A MULTI-REGIONAL ANALYSIS OF THE ROLE OF NON-PHARMACEUTICAL INTERVENTIONS IN COVID-19 TRANSMISSION RATES ACROSS THE UNITED STATES

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ABSTRACT

With the emergence of COVID-19, state-level governments in the U.S. implemented various non-pharmaceutical interventions (NPIs). Despite this, there has been limited research on the linkage between COVID-19 transmission rates and NPIs. To that end, this research has the primary objective of employing observational, mathematical, and statistical methods to analyze if NPIs played any role in the transmission rates of COVID-19. To assess this problem, various estimators of the COVID-19 transmission rate (R_0) were developed under differing assumptions through the branching process model. The primary analyses included exploratory data analysis, ANOVA, and a change-point analysis (CPA). From the results, it was determined that NPIs did not play any observably significant roles in R_0, prompting further research. Finally, this research and its implications are primarily catered to an educated audience with a statistical background with interests in the cross-sections of topics such as COVID-19, epidemiology, mathematical modeling, and public health policy.

Keywords & Key Phrases: COVID-19, Non-Pharmaceutical Interventions, Epidemiological Transmission Rates, Branching Process, Change-Point Analysis

INTRODUCTION

In late 2019, the world was unexpectedly introduced to an outbreak of the novel Coronavirus Disease (COVID-19), a respiratory disease stemming from SARS-CoV2. Originating in China, the disease has since spread across the globe and further continues to affect society at large, well over a year after the disease was labeled a pandemic by the World Health Organization. In the United States, over 20 million cases and over 340,000 deaths were reported in 2020. Moreover, the effects of COVID-19 have overwhelmed more than just patients; COVID-19 has disrupted families, social norms, educational institutions, governments, and whole industries - a phenomenon unprecedented to many.

The initial transmission rate of the disease, coupled with the disease's long and short-term uncertainties, all acted as a catalyst encouraging governments around the world to implement novel policies. Though each government has reacted differently, most, if not all, have implemented some level of policy through non-pharmaceutical interventions (NPIs) or actions beyond the scope of traditional pharmaceutical measures (e.g., clinical research and vaccine development). Though such policies, or NPIs, vary across time, government, and region, they generally include mandating social distancing, mandating mask usage, establishing curfews and lockdowns, and much more. In the context of this research paper, NPIs are the specific type of policy investigated. Consequently, the terms 'NPIs', 'policy', and 'policies' are used interchangeably.

Unsurprisingly, COVID-19, with all of its direct and indirect impacts taken into consideration, has spawned into a research hotspot across many domains. Despite the topic of COVID-19 scattering across various research fields, there has been limited research on the topic and its intersection with NPIs, specifically in the United States (Ebrahim et al., 2020). Due to the gap in the literature, this particular research applies a mixed-methodology approach in assessing the relationship between COVID-19 transmission rates with NPIs in three distinct regions of the United States. The quantitative approach includes applying the branching process model to derive various estimators of COVID-19 transmission rates and further analysis. The qualitative approach entails analyzing the transmission rates alongside regarded policy changes, particularly by focusing on policy at various change-points in the COVID-19 transmission rates (i.e., significant spikes/drops in transmission rates over time). Ultimately, this research adds to the field by providing an in-depth analysis of a transmission estimator alongside policy comparison in a select handful of distinct U.S. regions.

The stated research problem and its complementary objectives are further outlined in the proceeding *Problem Statement and Objectives* section. Following that, the paper will cover a *Literature Review* to address similar literature, provide further insight on motivations, and cover gaps in the research space. From there, the *Methodology and Techniques* section will go into the mathematical details of the branching process model and further cover details on the dataset used and additional analyses. Finally, the *Results* section will provide insight on the analysis of the various transmission estimators and provide an analysis of the linkage of NPIs with a preferred transmission estimator. This research paper will finally conclude with final remarks on findings, limitations, and future recommendations in the *Discussion & Conclusions*. See Appendix A for frequently used acronyms.

PROBLEM STATEMENT AND OBJECTIVES

As stated, this project's high-level goal is in analyzing the role of NPIs in COVID-19 transmission rates. Specifically, the research question formulated is the following: *Do the transmission rates of COVID-19 in 2020 across 3 distinct regions of the United States relate to NPIs, and if so, in what ways?* Thus, it is intended that the scope of this project is limited to data in 2020 and on three particular regions in the United States. Nonetheless, due to restrictions on the format of existing datasets, particularly when dealing with policy, this research employs a mixed-methodology. Particularly, once estimates of transmission rates are calculated, we opt to look at certain time periods of interest (i.e., change-points) to better understand the NPIs introduced around those time periods.

In order to successfully address the research question at hand, a set of defining objectives were introduced as a means to guide the research process. The first objective was to identify a model to serve as the foundation for deriving COVID-19 transmission rate estimators. In this particular project, the branching process model was used to derive four different estimators of the transmission rate of COVID-19. The secondary objective was to simulate transmission rates independently of the COVID-19 data to support the use of the branching process model. A third objective was introduced to analyze and compare the four estimators against each other. The final objectives included comparing COVID-19 transmission rates over time, by region, and determining if there was a linkage with NPIs.

In total, this particular analysis includes 3 regions composed of a total of eight states as well as one federal district. The first region includes Iowa, Kansas, and Wisconsin, which is a subsection of the Midwestern region of the U.S. The second region includes New York, New Jersey, and Connecticut (and is commonly referred to as the Tri-State region). The final region includes The District of Columbia (D.C.)., Maryland, and Virginia (and is commonly referred to as the D.M.V. region). For future purposes, unless discussing specific states, any broader analysis will refer to the regions by their common regional names, such as the Midwest, the D.M.V., or the Tri-State area.

The primary reasoning for selecting these three specific regions is motivated by various factors. For instance, a subsection of the Midwest was included in this research due to their sudden spikes in COVID-19 cases toward the last quarter of 2020, possibly stemming from more relaxed NPIs in the region (Scott, 2020). On the other hand, the Tri-State area was included in this research primarily due to the fact that it includes the most populated metropolitan area in the whole country, New York City ("New York City, New York Population", 2021). Furthermore, in the early stages of COVID-19, this area was known for its large influx of cases in a short period of time (Centers for Disease Control and Prevention [CDC], 2020a). Knowing what role policy played in this region, if any at all, may provide the insights necessary to make statistical comparisons between areas of contrasting levels of impact of COVID-19. Finally, the D.M.V. region was selected as this region includes the capitol district of the United States, is one of the most educated and affluent areas in the United States, is densely populated, and finally, holds a personal stake to the researchers who live in the region (McCann, 2020).

Nonetheless, it is worthy to mention that the findings of these three selected regions may not necessarily draw generalizable conclusions on the entire country. Rather, the analysis of three distinct regions will provide insights on how policy affects COVID-19 transmission rates in said regions, if at all, and also how said effect varies by region.

LITERATURE REVIEW

General COVID-19 and NPIs Overview

Given the novelty and scalability of COVID-19, the respiratory disease has grabbed the attention of academics, scientists, and all other researchers worldwide since its offset. The motivations for the focus on COVID-19 across various domains are multi-fold. For instance, some cite the disease as "continuously evolving" leaving reason to believe that COVID-19 will continue to be a topic of interest to better understand (Fricker, 2021). However, despite the abundance of research, it is important to note a few drawbacks. For example, by creating an evidence map of the ongoing literature on COVID-19, researchers discovered that while the main topic of conversation centers around the disease itself, there is a gap in the focus on the disease and its interactions with policy (Liu et al., 2020). Specifically, of 550 mined journal articles, only an estimated 5.5% of the articles covered public health, which is a parent topic encompassing policy and hence NPIs. Findings as such, in which there is an emphasis on the lack of focus on policy in the space of COVID-19 literature, are further supported by other sources, and ultimately provide a foundational motivation for our broader research topic (Porter et al., 2020).

This is not to say, however, that the cross-section of policy and COVID-19 research is rare. For instance, in a U.K.-based research paper, researchers built an index measuring the policy measures taken by over 170 countries (over time) and regressed each country's death counts against the index to measure the role of policy in COVID-19 (Hale et al., 2020a). Overall, the research identified a set of key NPIs that closely align with the NPIs of interest to our research problem, as outlined in the *Methodology and Techniques* section. Nonetheless, studies such as the aforementioned U.K. research have general limitations. For instance, this particular study focuses on COVID-19 and NPIs from a global perspective, particularly with a focus on death rates as opposed to transmission rates. Furthermore, despite the existence of country-specific research (such as the role of masks in COVID-19 transmission in Korea or the role of NPIs in over 11 specific EU countries), there is a general discourse that points out that there is an extreme lack of research on the role of NPIs on COVID-19 in the United States (Ebrahim et al., 2020; See also Kim et al., 2020 & Flaxman et al., 2020).

United States Policy Overview

Given the motivation thus far, it is evident that there is a valid reason to focus on the role of NPIs in the United States when dealing with COVID-19. However, before delving into the *Methodology and Techniques* section, it is imperative to provide a high-level overview of the United States' unique political structure. Afterwards, the *Literature Review* will also cover the epidemiological context and terminologies pertaining to disease transmission rates.

In the U.S., there is generally high variation in the policy, given the nature of the dual federalism system in place. For instance, under Section 361 of the Public Health Service Act (42 U.S. Code § 264), the Secretary of Health and Human Services is authorized to take necessary measures to prevent the entry and spread of communicable diseases from foreign countries into the United States and between states (CDC, 2020b). Invocation of such a law is mandated at a federal level, meaning that all states must generally comply. However, there are also lower-level laws that vary by each state and county sovereignty, which is where the matter of NPIs and policy becomes convoluted in the United States. This incongruence in the U.S. results in a high variation of policy across the country (Ebrahim et al., 2020), which gives further reason to segment the available data on the U.S. into 3 distinct regions with 3 states (or federal districts) each.

Furthermore, due to the variability of policies across the U.S., datasets on the county-level policy are time-intensive to develop and are therefore extremely limited (Ebrahim et al., 2020). Nonetheless, a novel state-level time-series NPI dataset has been formulated by researchers at Oxford that is employed in this research paper (further detailed in the *Methodology and Techniques* section). Though the dataset's quantitative stringency indices have been used in global analyses, there is limited use of the index and the complementary textual policy for the purposes of change-point analyses on COVID-19 transmission rates in the U.S. (Hale et al., 2020b). Consequently, this further motivates the consideration of qualitative analysis like change-point analysis, rather than strictly relying on regression.

Epidemiological Notations and Overview

As for epidemiological terminology, the key focus of our research is on R_0, the epidemiological measure of the basic reproduction rate (transmission) of a viral disease. Specifically, this measure refers to the average number of nodes an infected node impacts. The transmission rate of R_0 has been historically used to classify a disease into 3 different categories: supercritical ($R_0 > 1$), critical ($R_0 = 1$), and sub-critical ($R_0 < 1$). In particular, when $R_0 > 1$, an individual infects more than one individual, and this leads to an exponential increase in the number of infected individuals with a disease. Conversely, if $R_0 < 1$, the number of cases does not increase and there will be a decline in the cases of a disease. Finally, with the case of $R_0=1$, the rate of growth of the disease is linear. Taking this into consideration, it is important to better understand the status of diseases such as COVID-19. For instance, understanding of the transmission rate (R_0) of COVID-19 yields two important implications, of many: (1) Early surveillance of transmission rates may have helped efficiently control the spread of the disease in the U.S., as done in China (Lipsitch et al., 2020), and (2) analysis of transmission rates, particularly at change-points, may yield a better understanding of whether NPIs played a role in such peaks/drops of $R_0$and how to better prepare for future viral diseases.

To properly estimate the viral transmission rate of disease (R_0), COVID-19 in this case, existing research calls for the use of branching process models. The branching process model, as compared with other modeling techniques, provides a mechanistic approach to model the spread of the virus (Yanev et al., 2020). In this model, the reproduction rate R_0 is the mean of the branching process. Furthermore, since the estimation of the mean of the branching process does not rely on the number of infections caused by a single individual (i.e., can rely merely on overall case counts and time), the model is popular in many domains including epidemiology (Slavtchova-Bojkova, 2020). However, despite this being the case, there is generally a small focus of branching process models in the space of COVID-19, which is another area our research strives to address (Slavtchova-Bojkova, 2020). Ultimately, while the full details of the branching process are described in the subsequent *Methodology and Techniques* section, it is imperative to cover the high-level motivation for its usage.

Taking all things into consideration from the existing literature, it is clear that there are many gaps in the space of COVID-19 research. The gaps include but are not limited to, reliable policy information, branching process modeling, understanding of NPIs/policy in the U.S., and more. By applying the branching process model to derive four estimators for R_0, we strive to compare the estimators of R_0while also analyzing the change-points in R_0 across three distinct regions to pinpoint any potential implications of NPIs. This particular methodology appears, at the moment, unique compared to existing literature. To that end, this ultimately allows us to investigate our posed research question on better understanding the roles of NPIs in COVID-19 transmission in the United States.

METHODOLOGY AND TECHNIQUES

Though the primary methodology centers on the branching process model, the methodology section will first introduce the datasets and pre-processing methods. From there, the branching process model will be introduced in-depth, coupled with mathematical formulations of the four derived estimators of R_0 and simulations that support the use of the branching process model. Finally, the methods will conclude with a discussion on state-level analysis techniques used to further explore NPIs and R_0.

Datasets

The primary dataset employed in this research project is the *us-counties* CSV file provided by the New York Times, which is publicly available in the NYTimes COVID-19 GitHub repository and updated on a daily basis (NYTimes, n.d.). This dataset is compiled by pulling data provided by local government health departments to create a historical time-series of county-level COVID-19 data across the U.S., dating back to the very first recorded case in the nation. To that end, the variables include Date, County, State, FIPS, Cases, and Deaths (see Appendix B). In general, FIPS is the Federal Information Processing Standards code used to numerically identify a county, and Cases and Deaths are the reported cumulative numeric counts at any given date. As for the covered regions, the dataset encompasses historical data for all 50 states, Washington D.C., and also four additional U.S. territories, which is more than sufficient for the objectives of this research paper. As a final note, since the dataset only includes holistic cumulative case data instead of individual case data, Institutional Review Board (IRB) approval of this research is not necessary.

Given that the branching process model can sufficiently be supported by the observed count data, this dataset was one of the few contenders for this research project. Nonetheless, there are a few caveats to discuss before delving into any further methods. First, for each state, there is an “unknown” county, which does include numeric data on cases and deaths. This occurrence is due to the fact that many health departments opt to report “unknown” for the county while patient residence information is still uncertain. Consequently, when the county is determined, a patient’s data is aggregated to the said county, which results in fluctuations in the “unknown” counties’ cumulative cases. Because of such fluctuations, the “unknown” county has been completely omitted from analyses in order to avoid any unusual fluctuations in estimator variances for each state. A second and third caveat deal directly with the observed regions for this research paper. In short, the dataset aggregates the data of D.C.'s 8 Wards and treats it as one massive county (“D.C.” in the dataset). Similarly for New York, the dataset aggregates the data from New York City’s 5 Boroughs (The Bronx, Brooklyn, Manhattan, Queens, and Staten Island) and again treats it as one county (“New York City” in the dataset). Since NY state has sufficient data on multiple other counties to explore the trends in transmission rates over time, the “New York City" county in the dataset was not delineated into its 5 respective boroughs. On the other hand, the “D.C." county data was delineated into its 8 respective wards (based on population proportions) since there is no other county-level data for D.C. A final caveat is that the FIPS value is listed as Not-A-Number (NAN) in python for various counties. Therefore, it is recommended to use both state and county names as keys to identifying specific counties of interest.

A secondary dataset used in this research is the *USA State Level COVID-19 Policy Responses* CSV file, as part of the Oxford COVID-19 Government Response Tracking (OxCGRT) project (Hale et al., 2020c). For each day in 2020, for each state, the dataset encapsulates various NPIs introduced and classifies them as either containment/closure policies (C), economic policies (E), health system policies (H), or miscellaneous policies (M). The particular measures of interest in our research are C1-C8 and H1 (C1: School Closings; C2: Workplace Closings; C3: Public Event Cancelations; C4: Restrictions on public gatherings; C5: Public Transportation Closings; C6: Stay-at-Home Requirements; C7: Restrictions on Internal Movements; C8: International Travel Controls; H1: Public Information Campaigns*)* (see Appendix B). Such classifications are provided in both an encoded scale of stringency (e.g., from 0-3) as well as raw textual NPI data with cited government press releases and news articles. The encoded scales of these 9 particular variables are integrated in a mechanism that systematically quantifies the measure of the NPIs as a stringency index variable ranging from 0-100 (with 100 being the strongest response). Other classified variables such as E1-E4, H2-H8 and M1 are used to construct other indices that are beyond the scope of this research project (e.g., economic support index). Finally, other variables, such as geography and date, are provided for basic organization of the NPIs. Ultimately, this dataset is employed as a centralized point of information access for COVID-19 related NPIs in the states and federal district observed. More specifically, the stringency index is used in an analysis of association with the estimated R_0, whereas the raw textual NPIs are reviewed in-depth as part of the change-point analysis.

Software: Pre-Processing and Analysis Techniques

As for pre-processing and analysis of the *us-counties* dataset, the primary software used was Python. In particular, Python was employed for general branching process simulations, for pre-processing the *us-counties* dataset, and for deriving the four estimators via the branching process. Moreover, Python was used to compute the means and variances of each estimator over time and over each state. Finally, Python was used for the generation of confidence intervals and temporal hypothesis testing of the estimators (as based on the means/variances computed) to identify change-points.

The general pre-processing phase began with converting the *us-counties* time-series data from its original daily format into a weekly format. Though estimators of R_0 could be computed on a daily basis, this would yield increased variability in the estimated R_0, so instead, weekly data was preferred. In order to achieve this, the *date* variable's type was converted to Python's DateTime type and then a new column was created to specify the day of the week. Since this research is only limited to 2020, the data was filtered down explicitly to "Thursday", considering that 2020 ended on a Thursday. This was done with the goal to ensure as much 2020 data could be encapsulated in the final dataset (any earlier day of the week would have omitted cumulative data from the last few days of the week). The second general pre-processing step taken was to divide the data into distinct datasets for each of the states of interest. A simple filtering approach was not feasible for calculations of estimators due to the aforementioned caveat with the FIPS variable.

Finer pre-processing was also performed to create new numerical columns that served as the key components for deriving the estimators (see Appendix B). In short, the dataset at hand provides cumulative data, however, three of our four estimators depend on new weekly or bi-weekly data. In order to address this, new columns were created to account for just the new cases in a given week (as opposed to the cumulative cases). This was done by grouping each state by county and then calculating the difference between each week's cumulative cases (see Appendix C for code samples). The result of this calculation did result in a few nonsensical values (e.g., between the last date of one county and the first date of the next county), which were reverted back to their sensical values of 0 afterward.

As for pre-processing and analysis of the Oxford dataset, Microsoft Excel and JMP were used. In particular, Excel was used to filter down the data into the regions of interest and also into a weekly basis to match that of the pre-processed COVID-19 case dataset (*us-counties)*. JMP was then used to group the stringency index of the filtered data into three different levels. This was done due to the nature of the index of being constant for multiple weeks at a time. In particular, these three levels of stringency index were derived by dividing the range of 0 to 100 into three intervals (i.e., Group A included indices between 0 and 50, Group B included indices between 50 and 70, and Group C included indices between 70 and 100). Though the stringency index could have been further broken down into more levels, three was an appropriate number in order to ensure each level had a sufficient sample size. For instance, when grouping to thirteen levels by intervals of size eight, certain levels often only had a sample size of one or two, leading to non-interpretability of the results. Furthermore, a two week shift in the indices were applied since it was assumed that the NPIs would take up to two weeks to be effective after initial implementation. Finally, a preferred estimator of R_0 (i.e., Estimator 1) was appended to the NPI data on JMP in order to perform an analysis of variance of R_0 against the varying levels of the stringency index. This was done to assess the significance of any high-level relationships between NPIs and R_0.

Finally, once the pre-processing of the COVID-19 and NPI datasets were complete and estimator derivation concluded, Tableau was used for additional exploratory data analysis (EDA) purposes. The EDA consists of plotting state R_0 data to identify trends between different states and R_0 estimators.

Moreover, Tableau was also used for visualizing the NPI data trends over time as well as the stringency index. Such plots are outlined in the *Results* section with additional plots being found in the various appendices. To that end, the EDA is conducted between various stages of the methods employed.

Branching Process Model Overview

At a high level, the branching process is used to model the growth of COVID-19 cases by county, particularly by estimating R_0 at each generation. The branching process, or the Bienaymé-Galton-Watson process, is a stochastic process that is parameterized by a probability distribution and is based on the branching rule to describe a population's evolution. Specifically, the branching rule indicates that each individual in a generation produces a random number of offspring in the next generation based on a specific probability distribution, independent of each other and of the previous generations.

The process begins with generation zero (Z_0), which is assumed to have one individual (i.e., $Z_0 = 1$). In the case of COVID-19, given that there is uncertainty in the notion of a "patient zero", or the first-generation, as well as underlying factors pertaining to testing, it may be the case that $Z_0 > 1$. That said, each offspring of Z_0 produces a random number of children which are considered a part of generation one (Z_1), and the process continues for each n^{th} generation. When $Z_n = 0$, it is said that the population is extinct and all generations Z_m such that m >= n are also zero (i.e., $Z_m = 0$). Otherwise, Z_{n+1} happens to simply continue and is equal to the random number of new offspring in that generation.

Estimators: Mathematical notation of COVID-19 Transmission Rate Estimators (R_0)

The branching process is then used as a foundational model for deriving various estimators of R_0 for each county, on a week-by-week basis, where each week is treated as a generation. For instance, with estimator 1, the mean of the branching process, M, is equal to $E(Z_n|Z_{n-1})/Z_{n-1}$, where M serves as an estimator for R_0 (i.e., M=R_0). In simpler terms, M or R_0can be treated as the average number of new individuals an infected individual infects. Consequently, the mean of the branching process is also representative of the criticality level of transmission. In this context, the branching process is said to be supercritical if $R_0 > 1$, subcritical if $R_0 < 1$ and critical if $R_0 = 1$. The true paths of infection are beyond the scope of this research, due to its difficulty and reliance on graph theory as well as its dependency on successful contact tracing techniques. That said, R_0 is rather estimated based on temporal data pertaining to the number of new cases or cumulative cases. As stated, in this research, four estimators of R_0 are derived using the branching process. Given that COVID-19's mechanism of transmission is ever changing and thus uncertain, these four estimators are valid based on varying assumptions (He, Pascual, & Subramanian, 2021; See also "The Basics of SARS-CoV-2 Transmission*"*, 2021).

The first estimator of R_0, or E1, simply relies on the number of new positive COVID-19 cases (offspring) in a given week (generation). The formulation of E1 is as follows:

$$E1(R_0) = \frac{Z_n}{Z_{n-1}}$$

With this estimator, the estimated R_0 is treated as the number of newly discovered cases in a given week, n, divided by the number of cases from the previous week, n-1. At week 1 of COVID-19 data for a given county, the estimate is treated as 0, given that it is assumed to be the first generation. Finally, this estimator relies on the assumption that the infection of individuals in a given week depends only on the newly infected individuals of the previous week. This implies that people infected for longer than one week have also been discovered (aside from asymptomatic individuals who may never be discovered). In short, this estimator assumes that the complete knowledge of cases and infections is contained on a week-by-week basis.

The second estimator of R_0, or E2, relies on the cumulative positive COVID-19 cases in a given week, as opposed to the actual generation sizes. The formulation of E2 is as follows:

$$E2(R_0) = \frac{\sum_{i=0}^{n} Z_i}{\sum_{i=0}^{n-1} Z_i}$$

Specifically, this estimator is computed by dividing the cumulative cases of a week, n, by the cumulative cases of the previous week, n-1. This estimator relies on the assumption that the estimated R_0 remains the same over time, which in a sense is that the total number of infected individuals in a given n week depends on the total number of infected individuals in week n-1.

The third estimator of R_0 considered in this research, E3, expands on E1. Instead of confining the window of infections to one week, this estimator provides consideration to the number of new cases for the previous two weeks combined. This is done as it more accurately reflects the existing literature that COVID-19 may be transmitted in a 14-day window to another individual. The formulation of E3 is as follows:

$$E3(R_0) = \frac{Z_n}{Z_{n-1} + Z_{n-2}}$$

This estimator is computed by dividing the number of new cases in a given week, n, by the number of new cases of the previous two weeks combined. In terms of assumptions, this estimator relies on the assumption that the disease of interest does have a two week incubation period and also may result in asymptomatic individuals. Because the timeframe of new cases is expanded to two weeks, it is expected that this estimator will be more stable than E1 but will also underestimate the true mean because the denominator is continuously increasing as long as the number of new cases increases.

Finally, as an attempt to combat the underestimation of the third estimator of R_0, a fourth and final estimator was developed, E4. This estimator expands on the concept of a window of infections for both the current generation and the previous generation. The formulation of E4 is as follows:

$$E4(R_0) = \frac{Z_n + Z_{n-1}}{Z_{n-2} + Z_{n-3}}$$

This estimator is computed by dividing the combined number of new cases of a given week, n, and the previous week, by the combined number of new cases from the two weeks prior to week n-1. In particular, the numerator is increased in value in an attempt to balance the increased denominator seen in E3. This estimator, like E3, is expected to be more stable than E1, while also mitigating the optimistically underestimation of R_0 by E3.

Estimators: Simulation of Branching Process Model

Prior to using the various estimators on COVID-19 data, various simulations were performed using synthetic offspring derived from various probability distributions. This was done in order to demonstrate the assumptions of each estimator and further motivate the usage of the branching process for this research. That said, our simulations relied on the Bernoulli and Poisson distributions, though the branching process may also consider other distributions like the Geometric, Normal, and Exponential distributions.

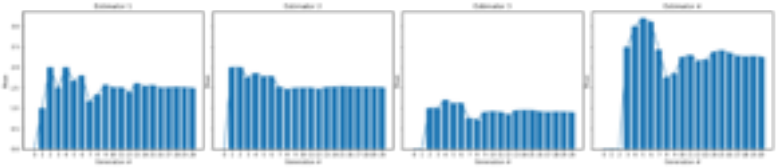
As for the Bernoulli distribution, the simulation was run n times (n = 1, 100, or 1000), such that at each generation, the number of new offspring produced by each individual was constructed using the following Bernoulli model:

$$X = \begin{cases} 1, & probaility\ p \\ 2, & probability\ q = 1 - p \end{cases}$$

Where E(X) = p+2q

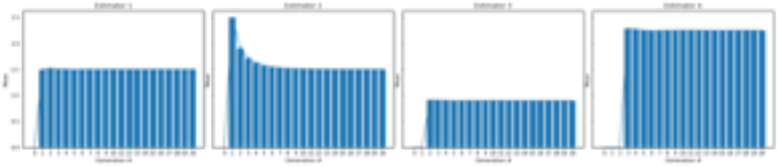
In the simulations, p was treated as 0.5, making q also 0.5, giving each individual an equal chance of producing one or two children. Figure 1 below shows the change in the estimated means (i.e., E1, E2, E3, and E4) over 20 consecutive generations (via a single Bernoulli simulation):

Figure 1
Bernoulli Model Simulation: Generation # vs. Means (1 Run)



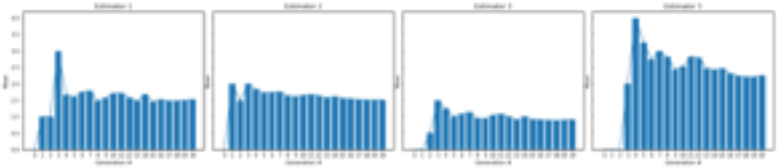
As can be seen in Figure 1, E1 converges to a mean of 1.44 and is relatively unstable compared to E2 (which converges to a mean of 1.52). Furthermore, it is evident that E3 appears more stable than E1, but it underestimates the true expected value of the distribution, 1.5. Contrary to its expected behavior, E4 actually tends to overestimate the expected value of the distribution, which may be viewed as overly pessimistic (or supercritical) in the context of R_0. Figure 2 below demonstrates the Bernoulli simulation using the average of the estimators for 1000 runs to simulate the true expected distributions:

Figure 2
Bernoulli Model Simulation: Generation # vs. Means (1000 Runs)



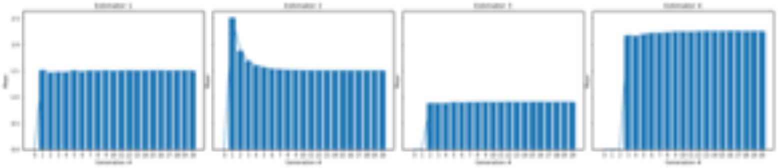
Simulations were also performed using the Poisson distribution, where various values of lambda were employed, ranging from 1.5 to 2.1 (with a 0.1 increment). This distribution simulates the mean based on the probability that a given person infects X individuals based on the value of lambda and the size of the current generation. Figure 3 below plots the means (E1, E2, E3, and E4) for a single run of the Poisson distribution over 20 generations (lambda = 1.5):

Figure 3
Poisson Model Simulation: Generation # vs. Means (1 Run; Lambda = 1.5)



Once again, it is seen that E2 is the most stable, followed by E3 and then E1. Similar to the trend seen with the Bernoulli distribution, E3 tends to underestimate the true mean while E4 tends to overestimate the true mean. Finally, Figure 4 shows the 1000 simulations of the Poisson distribution to demonstrate the expected distribution over repeated runs:

Figure 4
Poisson Model Simulation: Generation # vs. Means (1000 Runs; Lambda = 1.5)



See Appendix D for further simulations of the Poisson model with other levels of lambda ranging from 1.6 to 2.1.

Estimators: State Level Means and Variances (COVID-19 Data)

Given that the simulations provide a general overview of how the branching process is used, the process is then used to similarly compute the four estimators in the context of the COVID-19 data. Initially, the four estimators are computed at a county-level in order to roughly estimate R_0 of each county in the observed states and federal district. Then, the county-level estimates of R_0 are used to compute the means and variances of the estimators at a state-level, on a weekly basis. For instance, since there are over 43 weeks of data for NY state in 2020, then there are 43 means and 43 variances for the estimators (E1, E2, E3, and E4). These means and variances are dependent on the R_0 of all of NY State's county means in each given week. Below is an overview of the formulation of the means and variances of R_0 for a given state:

$$\overline{E_{\jmath\imath c}} = \sum_{n=1}^{total\ number\ of\ counties\ (c)} E_j / \ c$$

$$Var\ (E_j\ \widehat{for}\ week\ \imath) = \sum_{n=1}^{total\ number\ of\ counties\ (c)} (E_{jin} - \overline{E_{\jmath\imath c}})^2\ /c - 1$$

Where E_j *=Estimator* $j \ \exists\ j \in [1,4]$

Where $\overline{E_{\jmath\imath c}}$ *= Estimated mean of* R_0 *using the* j^{th} *estimator of the* i^{th} *week using the c counties*

Where E_{jin} *= Estimator for the* i^{th} *week and* n^{th} *county using the* j^{th} *estimator*

As seen, the mean of the estimator is based on aggregation from a given state's counties, consequently giving the estimated R_0 for an entire state (as opposed to a county). The variance is similarly computed.

NPI Analysis Approach 1: Analysis of Variance

To recap, the primary goals of this research are to assess the relationship between NPIs and R_0. Using a preferred estimator of R_0, an analysis of variance (ANOVA) is performed between the grouped levels of the NPI stringency index and the estimated R_0 for each state and federal district. To reiterate, JMP is used to assess if different states' and federal district's R_0 have a relationship with the various levels of the NPI stringency index. Below are the general hypotheses (respectively for a given state), tested at a level of significance of 0.05 (α=0.05)

H0: E_i *is the same for all blocks of the NPI stringency index*

H1: There is a difference in E_i *between at least one pair of blocks of the NPI stringency index*

Where E_i*=True* R_0 *for* i^{th} *NPI stringency index (Notation used in results)*

In these ANOVA tests, the sample size is typically the total number of weeks analyzed in a given state (or in the context of the branching process, the total number of generations). Given that these sizes are typically small (e.g., n≈40 weeks/generations), a Shapiro-Wilks Test is performed to determine whether the sample's residuals follow a normal distribution. Below are the hypotheses for the Shapiro-Wilks Test, also tested at α=0.05):

H0: The data is normally distributed

H1: The data is not normally distributed

To that end, this analysis approach is just a preliminary primer in understanding if any relationship exists between NPIs and R_0 in the observed regions. The primary analysis is the change-point analysis, which is covered in-depth next.

NPI Analysis Approach 2: Confidence Intervals and Change-Point Analysis

The sample mean and variance of the R_0 estimators in each state are further used in creating 95% confidence intervals on a weekly basis to hypothesize the true value of R_0 on a given week. Below is the formulation of the confidence interval for a single week in a given state (with c counties) (Harris, 1964):

$$C.I.(week\ i) = \underline{E}_{jic} \pm t_{(df=c-1,\alpha=0.025)}\sqrt{Var(\widehat{\underline{E}_{jic}})/c}$$

By plotting these confidence intervals for the three states (or D.C.) in a given region, comparisons can be drawn between states on R_0 , between the state's variability of R_0 , and also more generally between the 3 estimators of R_0 . Moreover, the confidence intervals shine a light on which particular points in time COVID-19's transmission rate could be classified as sub-critical, critical, and super critical. Sample plots and tables can be found in the *Results* section and further plots can be found throughout the appendices.

Of greater interest is the implication of the confidence intervals of R_0 on the determination of change-points for the purpose of NPI analysis. Given what may be considered as a peak or drop is subjective, we have determined that change-points are considered to be R_0 values that are statistically different than the R_0 of the previous week (at a significance level of α=0.05). Moreover, given the time-series nature of this analysis, it is important to clarify that there may be multiple peaks and drops. That said, a peak is a time point (week) when R_0 is greater than the upper-bound limit of the confidence interval of the previous week's R_0. Below are the hypotheses tests for identifying peaks using confidence intervals (used on a weekly basis for each estimator in each state):

$$H0\colon E_{jic} = E_{j(i-1)c}$$
$$H1\colon E_{jic} > E_{j(i-1)c}$$

On the other hand, a drop is considered a time point where the R_0 is less than the lower-bound limit of the confidence interval of the previous week's R_0. Below are the hypotheses tests for identifying drops:

$$H0\colon E_{jic} = E_{j(i-1)c}$$
$$H1\colon E_{jic} < E_{j(i-1)c}$$

Using these particular change-points, an in-depth review of the raw NPIs is conducted at those given weeks (as well as up to two weeks prior). This is primarily done to assess whether any conclusions could be drawn on NPIs relationship with R_0. Like the ANOVA analysis approach, the change-points analysis depends on a single preferred estimator due to the limitations of the other estimators (further explanations outlined in the *Results* section).

RESULTS

To address the proposed research question, the *Results* section first identifies a preferred state-level estimator of R_0 (i.e., $\overline{E_1}$) through EDA for subsequent analysis alongside NPI data. The subsequent analysis entails the outlined methodologies of EDA, ANOVA testing, and change-point analysis for each of the 8 states and federal district (D.C.). To reiterate, the analysis of these 8 states and D.C. is performed based on three regions in the U.S. (Midwest, Tri-State, D.M.V.) and for the year of 2020.

Exploratory Data Analysis: Comparison of Estimators of R_0

In order to determine a preferred estimator of R_0, an initial visual analysis comparing the trends of the four estimators of R_0 by region is conducted. These comparisons can be seen in the time-series in Figures 5-8 below, running from week 17 of 2020 to the end of 2020 (The full plots can be found in the Appendix E).

The regional R_0 seen in Figures 5-8 were computed as weighted averages of means of all the states in a given region. For instance, the Midwest region had n=276 counties ($n_{IA} = 99$, $n_{KS} = 105$, $n_{WI} = 75$), the Tri-State region had n=87 counties ($n_{NY} = 58$, $n_{NJ} = 21$, $n_{CT} = 8$), and D.M.V. had n=118 ($n_{VA} = 95$, $n_{MD} = 23$). D.C. was excluded from the D.M.V. region for this particular comparative analysis of the estimators by region, primarily due to the aforementioned fact that the COVID-19 dataset treated the data of all 8 wards in D.C. as a single county. Though data manipulation measures were taken to redistribute the case counts based on population proportions of the wards, we did not want D.C. to be lumped with Maryland and Virginia due to the 8 wards not being completely representative of similar data of MD and VA.

Figure 5

$\overline{E_1}$ across the Three Regions

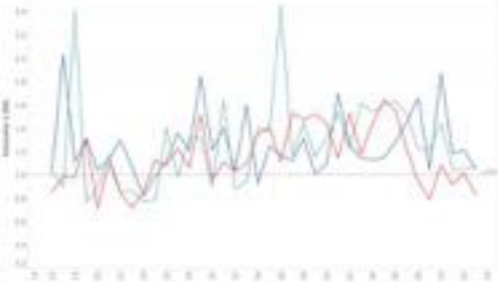


Figure 6

$\overline{E_2}$ across the Three Regions

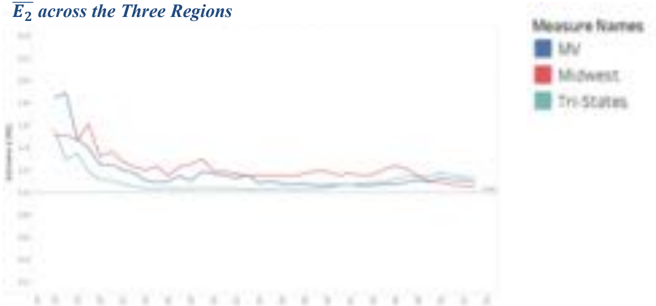


Figure 7

$\overline{E_3}$ across the Three Regions

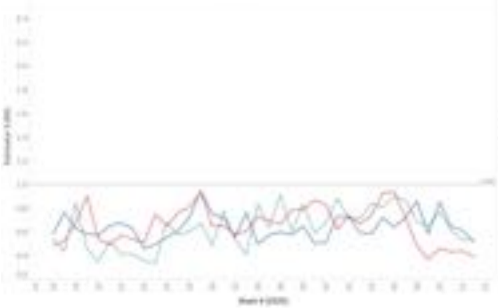
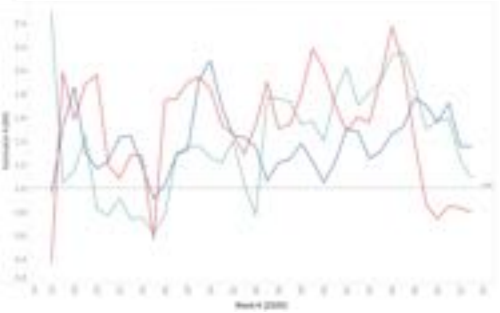


Figure 8

$\overline{E_4}$ across the Three Regions



At a glance of Figures 5-8, there are noticeably different trends between the four estimators. For instance, in Figure 5, $\overline{E_1}$ is seen to demonstrate moderate fluctuations over time. Conversely, $\overline{E_2}$ is seen to be stabilize and converge toward R_0= 1 in Figure 6. Nonetheless, $\overline{E_2}$ still remained slightly above 1 for most weeks, tending to constantly demonstrate a mildly supercritical behavior. On the other hand, $\overline{E_3}$ tends to be very optimistic in the weekly estimates of R_0, given all regions R_0s never exceeds 1. Specifically, with $\overline{E_3}$, the estimated growth of transmission is always classified as subcritical. Finally, in contrast to $\overline{E_3}$, $\overline{E_4}$, tends to slightly overestimate R_0, with many estimates converging beyond R_0 of 1.5 (Figure 8). Nonetheless, such behaviors were expected. In particular, the underlying assumptions of the estimators support the behaviors as well as the simulations of the estimators with data synthetically produced via two different probability models.

To that end, given these findings, $\overline{E_1}$ was decided as the best candidate estimator for subsequent analysis in the context of NPIs. The fluctuations in R_0 may serve as candidate change-points, which may not be of great amplitude in $\overline{E_2}$. Meanwhile, though there were fluctuations over time with $\overline{E_3}$ and $\overline{E_4}$, they may be biased from the truth, as noted by the particularly high and low estimates of R_0. This trend was similarly observed in the simulations using Bernoulli and Poisson models. Consequently, the remainder of the *Results* section will rely on $\overline{E_1}$ for analysis.

Beyond the derivation of the preferred estimator of R_0 (i.e., $\overline{E_1}$), Figures 5-8 also conveyed a few other mentionable results. For instance, it is seen that in the greater span of the year, the three regions generally tend to follow similar trends. Moreover, it was discovered that weeks with suddenly large spikes in R_0 for a particular region tended to be due to high variability of estimates for a given state. For instance, in weeks 13-16 (seen in the full plots in Appendix E), it was discovered that the Tri-State region had particularly high estimates of R_0 compared to the other regions across each estimator. Further investigation indicated that this was due to high variability between the counties of NJ during those weeks, potentially stemming from the influx of initial COVID-19 reported cases. As another example, in week 28 of $\overline{E_1}$, all three regions demonstrate a visible peak in R_0. Granted this analysis does not indicate if the peak is significant, the change-point analysis later on will show that it was. Similarly, in $\overline{E_2}$'s plot, to reiterate, it can be seen that the three regions generally continue to persist a mildly supercritical classification of R_0 of COVID-19. Nonetheless, when focusing on more specific points in time, the estimate trends of R_0 are evidently differing by region, which gives motivation to conduct further analysis alongside the NPIs, as seen in the remainder of the *Results* section.

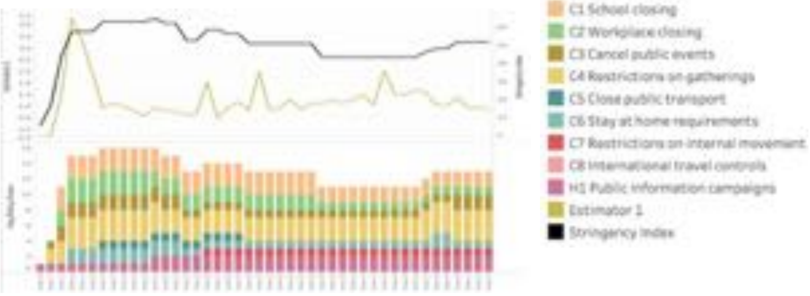
As a final comparison of the estimators, in terms of the variances of estimators, all estimators generally demonstrated low variances with the exception of a few off weeks (see plots in Appendix F). For instance, in Figure 1F, it can be seen that there are certain spikes in variability common to all observed states and D.C. with $\overline{E_1}$. With the few weeks with slightly higher variances, there is potential for this to be associated with NPIs. However, this may also be due to a host of other confounding variables beyond the scope of this research question, as further outlined in the *Discussion & Conclusions* section (Hanlon & Vidyashankar, 2011).

Exploratory Data Analysis: NPIs Over Time

Having identified $\overline{E_1}$ as a preferred estimator for subsequent analysis of NPIs, a secondary exploratory data analysis was performed, this time in the context of NPIs. In particular, visualizations were generated to compare the NPI stringency index alongside $\overline{E_1}$ as well as the individual NPIs over time (e.g., School closings, public even cancellations, etc.).

Consider the Figure 9 below, which compares $\overline{E_1}$ in new New Jersey against New Jersey's NPI stringency index over time. As seen in the figure's upper plot, there is a sharp rise in the stringency index from weeks 16 to 23 in 2020. Interestingly, despite the sharp rise in the NPI stringency index (black), $\overline{E_1}$ in New Jersey persisted to rise. Though this may be due to other reasons, it may be a sign that the government acted too slow in combating the fast growing disease. Further analysis showed this trend occurred in every state and D.C. as well. Looking further in time in the upper plot, it can be noted that New Jersey's stringency index dropped slightly during weeks 24 and 25 (early June). Cross-reference to the lower plot at the same time seems to indicate that this drop in the cumulative stringency index was due to the relaxed component stringency of stay-at-home mandates. Looking two weeks later at the $\overline{E_1}$ in the upper plot, it can be noted that $\overline{E_1}$ in New Jersey increased, from 1.0 to 1.8. It is important to emphasize that such changes in $\overline{E_1}$ cannot truly be said, for certain, to be due to the changes in NPIs. Likewise, simple exploratory data analysis as such may not even indicate if there is any statistical association between the two variables. Nevertheless, it remains an interesting observation to potentially consider.

Figure 9
New Jersey: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)



As a second example, Figure 1G (Appendix G), shows a similar visualization in the context of Iowa from the Midwest region. It can immediately be seen that Iowa compared to New Jersey has more fluctuations in $\overline{E_1}$ over time. Moreover, the same trend of the concurrent rise in stringency index and $\overline{E_1}$ at the start of the pandemic, persists, as seen in New Jersey (and all other states and D.C. for that matter). Interestingly, around the same time of New Jersey's initial drop in stringency index, Iowa similarly saw a drop in stringency index (June/Week 24). However, unlike New Jersey, whose drop was slight, Iowa's was much more drastic, dropping from the low 60s to the mid 20s. Two weeks later, it can be seen that the $\overline{E_1}$ in Iowa goes from 1 to 1.4. Once again, though an interesting phenomenon, it is not clear with certainty that the lagged NPI is related to changes in $\overline{E_1}$. Finally, as the stringency index remains in the mid 20s until week 46, $\overline{E_1}$ continues to fluctuate in terms of peaks and drops. This also may be attributed to other factors beyond NPIs, such as those covered in the *Discussion & Conclusions.*

Table 1 provides additional examples of high-level and interesting observations occurring in the remaining states not covered above (see Appendix G for full plots). It should be stressed that the examples in Table 1 merely cover a sample of observations of potential interest. Looking at such examples, it appears that sometimes there is a related trend between the lagged stringency and $\overline{E_1}$. However, in truth, these are actually only a few times visual analysis such as the ones above provided insights with plausible interpretations. In fact, there are many other points in times where $\overline{E_1}$ fluctuates where there are no changes at all to the stringency index, with weeks 24 to 46 in Iowa being a prime example. Conversely, there are plenty of weeks where the stringency indices changed or even remained consistently high, but there were no changes in the estimated transmission rate of COVID-19.

Table 1
EDA Sample Observations: NPIs and E1(R0)

Region	**State**	**Week Number(s) (2020) Pertaining to Stringency Index**	**Sample Observation**
Midwest	Kansas	23	$\overline{E_1}$ dropped immediately after stringency index decreased
		24-53	$\overline{E_1}$ remained supercritical while stringency index remained below 50
	Iowa	24	$\overline{E_1}$ increases from 1.0 to 1.4 two weeks after stringency index drops by 35 points
	Wisconsin	35-40	$\overline{E_1}$ remained supercritical while stringency index decreased as low as 33.8
Tri-State	New York	all	$\overline{E_1}$ remained supercritical most of the year, despite high stringency index
	New Jersey	24-25	$\overline{E_1}$ spiked up two weeks after stringency index dropped
	Connecticut	28	$\overline{E_1}$ spiked up two weeks after to 3.2 after stringency index hit a plateau
D.M.V.	D.C.	22	$\overline{E_1}$ spiked up five weeks after the stringency index began to decrease (week 27)
		30	$\overline{E_1}$ dropped one week after stringency index began to increase again (week 31)
	Maryland	22	$\overline{E_1}$ spiked up two weeks after the stringency index started decreasing (week 22)
	Virginia	26	$\overline{E_1}$ spiked up two weeks after the stringency index started decreasing (week 28)
		35-50	$\overline{E_1}$ remained supercritical while stringency index remained below 45

From such high-level exploratory data analysis, it is clear that while there sometimes appears to exist a visual relationship between $\overline{E_1}$ and the NPI stringency index, nothing can be deduced with statistical certainty. Specifically, there is no statistical evidence pertaining to significance of the relationship between the stringency index and $\overline{E_1}$, of the classification of the transmission rate of COVID-19 (e.g., supercritical), or even of the identification of peaks and drops. Additionally, despite seeing how certain types of NPIs change in terms of component stringency, there is no insight provided by the plots on the actual policy changes being made (merely a high-level change in the type of NPI). That said, to address these two primary concerns, the next two sections of the *Results* outline the findings from an ANOVA analysis and a change-point analysis.

On a final note, pertaining to exploratory data analysis, Figure 9G (Appendix G) demonstrates some interesting comparisons between the stringency indices of the 8 states and D.C. Interestingly, all observed states and D.C. had varying levels of stringency year round. Moreover, in April and May of 2020, all observed regions demonstrated peaks in stringency indexes, with shared relaxations in summer that bounced back with increased stringency toward the holiday season (November and December of 2020). Furthermore, despite COVID-19 having well demonstrated its presence in Asia and Europe earlier in 2020, it is interesting to see all regions had delayed responses in stringency, including in March of 2020. Specifically, no state/district surpassed a stringency index of 35 until March of 2020. Additionally, it is evident that the stringency indices within a region tend to be at similar levels. For instance, the Midwestern states have consistently lower stringency indices compared to the Tri-State states. Finally, it is worthy to note that New York state appeared to have the highest of stringency indices year round.

Results of Analysis of Variance

Visual analysis of the role of NPIs in the transmission rate of COVID-19 merely provides high-level insight on the research question. Consequently, this next section of the *Results* analyzes the statistical findings from the ANOVA tests conducted between each state's $\overline{E_1}$ and leveled NPI stringency index. Consider the example of Kansas in the Table 2:

Table 2
Kansas ANOVA Results

Source	Degrees of Freedom	Sum of Squares	Mean Squares	F Ratio
Model	2	2.5644457	1.28222	11.1742
Error	36	4.1309395	0.11475	Prob > F
Total	38	6.6953852		0.0002*

*p<0.05

As evident, given the p-value of <0.0002 and α=0.05, there is statistically significant reason to believe that the different groups of the stringency index in Kansas have different $\overline{E_1}$. In order to further validate the results of the ANOVA, a Shapiro Wilks Test for normality was performed. Specifically, given the resulting p-value of 0.9031 being above the level of significance of 0.05, there is no sufficient reason to reject the null hypothesis that the distribution is normal in Kansas. Hence Kansas exhibits a meaningful statistically significant association between its $\overline{E_1}$ and the NPI Stringency Level.

Table 3
ANOVA and Shapiro Wilks Test Summary (All States and D.C.)

Region	State	n	ANOVA Significance (p-value)	Normality Assumption (Shapiro Wilks Test)	ANOVA Summary
	Iowa	39	0.8872	0.4211	*ANOVA results are NOT significant*
Midwest	**Kansas**	**39**	**<0.0002***	**0.9031**	***ANOVA results ARE significant***
	Wisconsin	**40**	**0.0205***	0.0006*	***ANOVA results ARE significant***
	New York	40	0.4671	<0.0001*	*ANOVA results are NOT significant*
Tri-State	New Jersey	40	0.2387	<0.0001*	*ANOVA results are NOT significant*
	Connecticut	39	0.9971	<0.0001*	*ANOVA results are NOT significant*
	D.C.	36	0.2737	0.0628	*ANOVA results are NOT significant*
D.M.V.	Maryland	40	0.1133	0.0015*	*ANOVA results are NOT significant*
	Virginia	39	0.6849	0.0011*	*ANOVA results are NOT significant*

*p<0.05

Similar analysis was repeated for all the states and D.C., as summarized in Table 3 above. Per the findings of the ANOVA tests, it is clear that only Kansas yielded significant results that could be interpreted as meaningful due to the normality assumption being met. Nonetheless, as mentioned, Kansas had a low R-squared value, indicating that the simple model regressing $\overline{E_1}$ against levels of the NPI stringency index may not have been sufficient. Wisconsin also demonstrated significant differences in $\overline{E_1}$ based on the level of the NPI stringency index. However, unlike Kansas, the normality assumption was not met in Wisconsin, indicating that the ANOVA results may be questionable in interpretation. For Iowa and D.C, while the ANOVA tests were not significant, this could be interpreted as meaningful due to the normality assumption being met. Finally, the remaining states did not yield significant results for the ANOVA tests, which may not be meaningful given that their normality assumptions were also violated.

Of the three regions, the Midwest region was the only region where there was a significant association between NPI stringency index and $\overline{E_1}$ values. Even though Wisconsin did not meet the normality assumptions, Kansas did. When not considering the normality assumption, this may indicate that NPIs play a more prevalent role in the Midwest region of the U.S. compared to other regions. Moreover, this analysis provides slight insight that NPIs play different roles in different states, which is not surprising given the variability of U.S. policy by region, state, and county. Nonetheless, further testing would be required to draw more definitive conclusions, as discussed in the *Discussion & Conclusions*.

Results of the Change-Point Analysis

Although the ANOVA analysis provided some insight into the roles NPIs play in the transmission rate of COVID-19, further analysis was sought to look deeper into the actual NPIs implemented at specific change-points. To reiterate, change-points are classified as peak or drop estimates of R_0 on a given week (i.e., $\overline{E_{1,\iota}}$ that are significantly different compared to the previous week $\overline{E_{1,\iota-1}}$). For instance, consider the plots below in Figures 10 and 11 from the Tri-State region as an example. Figure 10 shows the confidence intervals of $\overline{E_1}$ for the region since the first observed case on March 5th, whereas Figure 11 is zoomed in to 28-39 weeks after the first observed case on March 5th (i.e., September to late November).

Figure 10

Tri-State Region: 95% Confidence Interval for $\overline{E_1}$

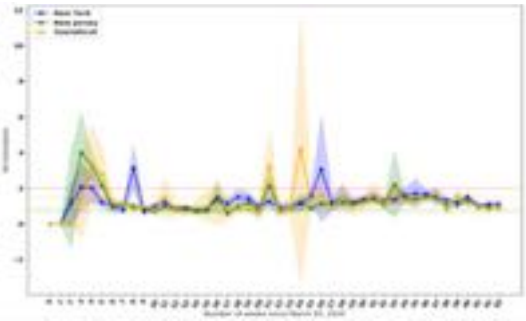
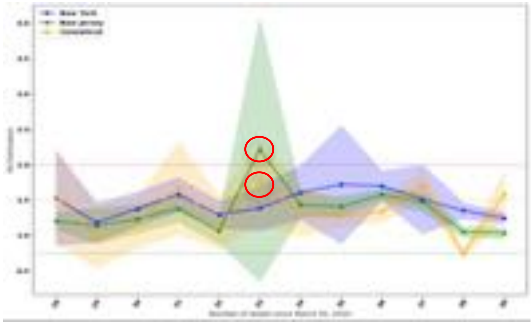


Figure 11

Tri-State Region: 95% Confidence Interval for $\overline{E_1}$: Sept to Nov



As evident from a high-level glance of Figure 10, there are various change-points visible to the eye. As outlined in the *Methodology and Techniques* section, to confidently determine such points, significance testing was performed by comparing confidence intervals of different points. In all, the Tri-State region had 43 particular change-points, with further breakdowns provided in Table 1I (see Appendix I). In Figure 11, it can be seen that both New Jersey and Connecticut share change-points on the week of October 22 (circled in red). When looking at the specific NPIs implemented in the two weeks leading up to that change-point, it was noted that there were in fact no new changes or modifications to NPIs in New Jersey. On the other hand, in Connecticut, the state entered Phase 4 of its reopening plan, which did include increased capacity of indoor gatherings, including weddings. This point draws a few observations of interest. First, it can be seen that NPIs do indeed vary by state, even if they do fall in the same region. Second, despite sharing a change-point peak, only one state seems to have a possible observational linkage to NPIs. And third, among many more observations, there is the possibility that reopenings in Connecticut played a role with the spike in the transmission of COVID-19 at that time. To reiterate, however, it cannot be said with statistical certainty if such findings were due to the relaxation of public gathering NPIs in the state. Moving beyond the general change-point analysis, the confidence bounds in Figures 10 and 11 also demonstrate that Connecticut experienced higher variability over time compared to its peer states. This is not surprising, given the state only had 8 counties, whereas the other two states had many more.

Given that the change-point analysis was extensive in nature, Table 1I (See Appendix I) intends to summarize other such findings for the observed regions. Such sample observations in the table are merely selected to demonstrate the general variability of NPIs and are by no means intended to provide any definitive explanations. To reiterate, the table is merely a sample of findings. For the most part, it was observed across all three regions that most weeks had no clear linkage between NPIs and change-points in the transmission of COVID-19. However, when there did appear to be a linkage, interesting findings emerged. As expected, the Tri-State region had drastically more stringent NPIs compared to the other regions observed. For instance, in New York State, gyms and restaurants rarely opened until much later in the year, as compared to the Midwest which had already opened up such services by May.

Moreover, there appeared to be much greater coordination between the three governors in the Tri-State area, whereas this trend did not appear in the other two regions. As another difference, of the weeks observed, there were only two references to mandates of NPIs through fines, and these appeared strictly in the Midwest. Of course, this may just be an observational finding, given that not every single NPI was examined (only those near change-points were analyzed). It nevertheless remains an interesting observation worthy of mention, as it emphasizes the variability of NPIs between different regions across the country. As a final comparison, among many others, a common trend observed with some of the peaks was reopenings. For instance, of the few change-points of transmission with plausible linkages with NPIs in the D.M.V., reopenings were a common trend. For instance, reopenings of public settings and relaxed restrictions of social gatherings in the summer were often observed with peaks in the transmission rates. This trend was also frequently observed in the analysis of the other two regions. Nonetheless, to reiterate once more, these trends are merely observational and representative of a small sample of all the NPIs implemented in these regions. Observing all NPIs and conducting more statistical analyses to validate the linkage between transmission rates and NPIs is beyond the scope of this paper's timeframe.

Results of Confidence Intervals Analysis

A final analysis relating to the change-point analysis pertains to the usage of the confidence intervals for other general regional comparisons. As Table 2I (See Appendix) demonstrates, the number of significant peaks and drops (or change-points) was more or less the same across the different regions. However, neither this nor the other analyses shine light on two other areas of analysis pertaining to the estimated transmission rate of COVID-19: (1) inter and intra regional overlaps of change-points and (2) inter and intra regional overlaps of epidemiological classifications of transmission. Beginning with intra-regional change-points, Table 4 highlights the week numbers of intersections:

Table 4
Regional Intersections of Peak and Drop Change-Points (Weeks)

Region	Shared Peak Weeks	Shared Drop Weeks
Midwest	42, 44, 50	30, 47, 48, 53
Tri-State	31	32
D.M.V.	17	39, 51

From Table 4, it appears that of the many change-points, very few actually were shared by the states in a region. This provides insight indicating that other confounding factors specific to each state (or district) may have played a role in the estimated transmission rates of COVID-19. Moreover, when comparing all three regions, not a single one shared a peak or drop. Nonetheless, this does not mean to say that peaks and drops were not shared by any two regions. In fact, the general exploratory data analysis plots from the earlier sections of analysis still tended to signify that there were more broader time periods (e.g., summer) where trends were the same.

In regard to the epidemiological classifications of the estimated transmission rates, Table 5 aims to provide insights. In particular, the confidence intervals of the estimated transmission rates were used to assess at a level of significance of 0.05 whether the transmission should be classified as subcritical, critical, or supercritical. In particular, Table 5 primarily looks at the intersection of these classifications between the states of a given region.

Table 5
Regional Intersections of Epidemiological Classifications of $\overline{E_1}$

Region	Shared Subcritical Weeks	Shared Critical Weeks	Shared Supercritical Weeks
Midwest	11, 12, 13, 15, 49	25, 26, 36	38, 39, 40, 42, 43, 44, 45, 46
Tri-State	N/A	16,17,18,19,23,25,26,27,28,32,36,40,42,53	47,50
D.M.V.	10, 11	16, 21, 30, 33, 34, 36, 37, 39	14, 41, 44, 46, 47

As Table 5 shows, in terms of regions, states in the Tri-State region tended to have significantly critical levels of transmission on the same weeks more often than states of the other two regions. Moreover, a sequence of back-to-back weeks from September to December in all three states of the Midwest appeared to have significantly super-critical levels of transmission. To that end, though further analyses could be provided on such findings, they only play a minor role in comparison of the regions in terms of change-points and classifications of transmissibility. As the complex findings of the various analyses have shown, NPIs and estimators of transmissions vary by states and regions in many different ways, prompting further research outlined in the *Discussion & Conclusions* section.

DISCUSSION & CONCLUSIONS

To recap, after identifying a preferred estimator of COVID-19 transmission rates for subsequent analyses such as ANOVA and change-point analysis, various findings emerged. Generally speaking, the exploratory data analysis of the NPIs alongside the estimated state-level transmission rate overtime set the scene, indicating that while certain time points may have had interesting relationships with NPIs, this was generally not true for most of the remaining time points. The statistical test results (i.e. ANOVA) further supported this, given that only two states demonstrated statistical significance in the relationship between the estimated transmission rate ($\overline{E}_1$) and the stringency index of NPIs. Even then, at best, only one of those two states with significant results could be deemed as meaningful given the normality assumptions. Finally, while the change-point analysis provided more nuanced insights on the actual NPIs themselves, the general analysis reaffirmed the uncertainty in the role of NPIs in the transmission of COVID-19, as there were ultimately no clear trends that emerged between the two variables of interest.

These findings are of relevance as they ultimately indicate that while COVID-19's transmission rate may have been influenced to some extent by NPIs in the focused areas, there are no definitive conclusions. A speculated reason for the lack of definitive conclusions is due to the complexity and variability of U.S. policy, as noted by existing literature (Ebrahim et al., 2020). The incongruence of NPIs was certainly observed by the in-depth change-point analysis, as it was noted that different states had different NPIs and stringency levels during the same time frames. Moreover, though the Oxford's NPI dataset was organized by state, it was evident that county level governments varied in their NPIs related to COVID-19. This particularly highlights the variability of policy in the U.S. due to its unique approaches in implementing policies. Alternatively, this may have also been due to issues in data being used in estimating R_0. The data observed in this research project relied on open source public health data which may often be messy and changed overtime due to integrity of COVID-19 test results (e.g., cases may not have been truly confirmed). Consequently, such unpredictability in the data may have resulted in biased peaks/drops that may have demonstrated trends contrary to the true changes of R_0 over time. One such implication of this is that greater research is necessary in gathering more reliable case data, such as direct hospital data. In particular, hospital data on COVID-19 cases may be more credible, given the centralized distribution of reliable tests, consequently allowing researchers to formulate more reliable estimators of R_0 while exploring its linkage with other variables such as NPIs.

That said, there are various potential confounding variables to consider in such an analysis. The most notable confounding factor is the actual enforcement of NPIs. Though this research focused on the implementations of NPIs, it is important to consider that implementations and enforcements are very different in nature. When dealing with enforcement of NPIs, it is unclear how exactly the NPIs are being enforced by the different regions, states, and counties. For instance, from our observation, there was a minimal mention of fines or imprisonment for violating the implemented NPIs. Secondly, there is no clear indication based on this research or the data used as to how long it actually takes for NPIs to succeed, if at all. Moreover, the complexities of enforcement of policies raises further underlying confounding factors. For instance, culture and geographic demographics to mention a few. It may be possible that policy enforcement varies by urban and rural demographics. Moreover, political beliefs, cultural values, and general shock may have also played a role into whether individuals in the U.S. actually abided by such NPIs or not. In fact, a Cornell study briefly indicated that miscommunication by political and public health figures played a role in the transmission of COVID-19 (Fricker, 2021). This opens up the discussion for the need for further statistical analysis of the general effectiveness of and adherences to policies (not necessarily restricted to NPIs).

Aside from this subtle difference between enforcement and implementation, there are many other potential confounding variables. For instance, the data does not account for which type of tests were provided by the various health departments of the U.S. As the summer rolled out, it was inevitable for travel plans to be made, requiring non-traditional COVID-19 tests such as the Rapid-PCR Tests. With such tests, those tested trade-off reliability for speed, which may unfortunately be reflected in data-based studies such as this. The same holds for different antibodies used in testing as well as the physical means of testing (e.g., blood samples versus respiratory samples) (Capuzzo et al., 2020). Variations transcend the testing process and into the diseases itself. Specifically, variants of COVID-19 itself may have also acted as a confounding factor, especially in the later half of 2020 with the introduction of variants of the virus. In particular, B.1.1.7, speculated to have originated in the U.K., has been identified as spreading more easily compared to the original disease (CDC, 2021). Aside from such variations, it is also reasonable to believe that such test data does not reflect everything going on in all the observed states. For instance, regions such as Northern Virginia, D.C. and Baltimore are tightly interconnected, so movement between states may have played a role as well. The same may be considered for the Tri-State area, wherein the states are closely packed in close proximity. Finally, travel by individuals between states due to holidays, seasons, and other reasons unbounded by NPIs may have also played underlying roles in the transmission rates of COVID-19.

Limitations & Future Work

Taking into account the implications and confounding factors of this research problem, it is imperative to provide considerations into limitations of the research, namely, to identify paths forward. Beyond the need for more reliable data, this research was limited in terms of resources needed for further analysis, specifically due to time and labor constraints. Previous studies as such have been contributed to by many more researchers, in wider time frames, and with the help of volunteers to collect and analyze the data. Consequently, given this constraint, our research limited its focus to merely a few statistical analyses of a single estimator of R_0. Though mentioned that $\overline{E_3}$ and $\overline{E_4}$ were more biased in their fluctuations, it nevertheless would have been interesting to conduct ANOVA and change-point analyses using those estimators of R_0. Furthermore, such estimators may have provided different insights on the roles of NPIs on the transmission rate of COVID-19. Similarly, such limitations also narrowed the scope of estimators analyzed. With the ever growing changes in assumptions of COVID-19 transmission mechanisms, other estimators of R_0 could have been explored if time permitted.

Shifting to future research, it is firstly highly recommended to expand this research to encompass other regions in the U.S. The obstacles that limited the scope of analyses and estimator assumptions also limited the scope of the regional analysis. In our paper, the majority of the regions were located in the east coast, providing no consideration to the role of NPIs in the transmission rate of COVID-19 in other regions of the U.S. Such regions include, but are not limited to the west coast, additional states in the Midwest, the southwest, central states, and also non-inland territories. By conducting further analysis into additional regions, if not the whole U.S., more regional comparisons may have surfaced regarding the role of NPIs in the transmission of COVID-19. An alternative recommendation for research would be to narrow the scope of focus to a particular state. As discovered, NPIs vary by state and county, often obscuring the analysis of linkages between NPIs and COVID-19 transmission rates. Research on a particular state/region would allow for more refined policy analysis, consequently enabling more nuanced conclusions. Final alternatives would be to draw on existing research such as the one described in this paper. For example, it is recommended to compare such a study against a similar study in countries or regions that implement NPIs more uniformly. This would provide further insights on the topic at hand. Similarly, one could draw on this research to develop more improved estimators of R_0 as continuing research on the transmission mechanisms of the disease and its variants continues to surface. Above all, it would be recommended to conduct further assessments on the associations, particularly with non-parametric methods such as the medians-test for state's whose residuals do not satisfy the normality assumptions for ANOVA.

All in all, despite recent developments of pharmaceutical measures such as vaccines, continued research needs to be done at the intersection of public health policy such as NPIs alongside COVID-19. In 2020, the world was undoubtedly blindsided by the infectious disease, wrecking disruptions to societal norms of living and economic markets among other realms. Though the prediction of a future pandemic unrelated to COVID-19 is not feasible, extensive research into mechanisms that help minimize the disruptions of such diseases may prove to be worthwhile for all people, policymakers and public health specialists.

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APPENDICES

Appendix A: Frequently Used Acronyms

Table 1A
Acronym Meanings

Acronym	**Meaning**
D.M.V	District of Columbia, Maryland, Virginia
NPI	Non-Pharmaceutical Interventions
COVID-19	Coronavirus 2019
CPA	Change-Point Analysis
EDA	Exploratory Data Analysis
ANOVA	Analysis of Variance

Appendix B: Variable Names and Descriptions

Table 1B
NYT COVID-19 us-counties Dataset Used Variables

Variable Name	Type	Description
Date	String	String representing daily date of positive cases and deaths for each county
County	String	U.S. county in a given state
State	String	U.S. State (also including D.C. and federal territories)
FIPS	Int	Federal Information Processing Standards Code assigned to each county
Cases	Int	Cumulative number of cases in a given county

Table 2B
Appended Variables to us-counties Dataset by Researchers

Variable Name	Type	Description
Day_of_Week	String	String representing weekday (i.e., “Thursday”) used to filter down data
Diff_cases	Int	Difference of cumulative cases of two consecutive weeks to derive the approximate number of new cases in a given week (as opposed to cumulative)
Mean_cases_E1	Float	Estimated R_0 in a single county using estimator 1 derivation
Mean_cases_E2	Float	Estimated R_0 in a single county using estimator 2 derivation
Mean_cases_E3	Float	Estimated R_0 in a single county using estimator 3 derivation
Mean_cases_E4	Float	Estimated R_0 in a single county using estimator 4 derivation

Table 3B
OxCGRT Dataset Used Variables

Variable Name	Type	Description	Coding
Stringency index	Float	Records the strictness of “lockdown” style policies that primarily contain/restrict people’s behaviors (scaled 0-100)	
C1_School closing	Int (Ordinal)	Records closings of schools and universities	0 - no measures 1 - recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations 2 - require closing (only some levels or categories, e.g. just high school, or just public schools) 3 - require closing all levels Blank - no data
C2_Workplace closing	Int (Ordinal)	Record closings of workplaces	0 - no measures 1 - recommend closing (or recommend work from home) or all businesses open with alterations resulting in significant differences compared to non-Covid-19 operation 2 - require closing (or work from home) for some sectors or categories of workers 3 - require closing (or work from home) for all-but-essential workplaces (e.g. grocery stores, doctors) Blank - no data
C3_Cancel public events	Int (Ordinal)	Record cancelling public events	0 - no measures 1 - recommend cancelling 2 - require cancelling Blank - no data
C4_Restrictions on gatherings	Int (Ordinal)	Record limits on gatherings	0 - no restrictions 1 - restrictions on very large gatherings (the limit is above 1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings of 10 people or less Blank - no data
C5_Close public transport	Int (Ordinal)	Record closing of public transport	0 - no measures 1 - recommend closing (or significantly reduce volume/route/means of transport available) 2 - require closing (or prohibit most citizens from using it) Blank - no data
C6_Stay at home requirements	Int (Ordinal)	Record orders to "shelter-in-place" and otherwise confine to the home	0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips 3 - require not leaving house with minimal exceptions (e.g. allowed to leave once a week, or only one person can leave at a time, etc.) Blank - no data
C7_Restrictions on internal movement	Int (Ordinal)	Record restrictions on internal movement between cities/regions	0 - no measures 1 - recommend not to travel between regions/cities 2 - internal movement restrictions in place Blank - no data
C8_International travel controls	Int (Ordinal)	Record restrictions on international travel	0 - no restrictions 1 - screening arrivals 2 - quarantine arrivals from some or all regions 3 - ban arrivals from some regions 4 - ban on all regions or total border closure Blank - no data
H1	Int (Ordinal)	H1_Public information campaigns	Ordinal scale

Appendix C: Sample Code

Code 1C

Sample Pre-Processing and Estimator Derivation of Estimators in NY State

```
NY_data = covid_data[covid_data.state == 'New York']


#NY Compute Differences
NY_data['diff_cases'] = NY_data.groupby('county')['cases'].diff()
NY_data['diff_deaths'] = NY_data.groupby('county')['deaths'].diff()


#Sort Data first by county then date
NY_data = NY_data.sort_values(by=['county','date'])


#first estimator - new cases in week n / new cases in week (n-1)
NY_data['mean_cases_E1'] = NY_data.diff_cases/NY_data.diff_cases.shift()


#second estimator - cumulative cases in week n / cumulative cases in week (n-1)
NY_data['mean_cases_E2'] = NY_data.cases/NY_data.cases.shift()


#third estimator - new cases in week n / new cases in week (n-1) + new cases in week (n-2)
NY_data['mean_cases_E3'] = NY_data.diff_cases/(NY_data.diff_cases.shift(1) + NY_data.diff_cases.shift(2))


#fourth estimator - new cases n + n-1 / n-2 + n-3
NY_data['mean_cases_E4'] = (NY_data.diff_cases + NY_data.diff_cases.shift(1))/(NY_data.diff_cases.shift(2) + NY_data.diff_cases.shift(3))


#post-estimator derivation cleans up
NY_data.replace([np.inf, -np.inf], np.nan, inplace=True)
NY_data.fillna(0, inplace=True)
NY_data.loc[NY_data.groupby('county')['mean_cases_E2'].head(1).index, 'mean_cases_E2'] = 0
NY_data.loc[NY_data.groupby('county')['mean_cases_E3'].head(2).index, 'mean_cases_E3'] = 0
NY_data.loc[NY_data.groupby('county')['mean_cases_E4'].head(3).index, 'mean_cases_E4'] = 0
```

Appendix D: Additional Poisson Model Simulation Plots (With Various Lambda)

Figure 1D
Poisson Model Simulation: Generation # vs. Means (1 Run; Lambda = 1.6)

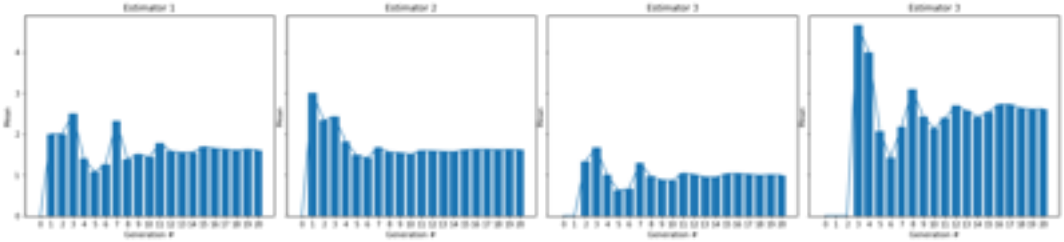


Figure 2D
Poisson Model Simulation: Generation # vs. Means (1 Run; Lambda = 1.7)

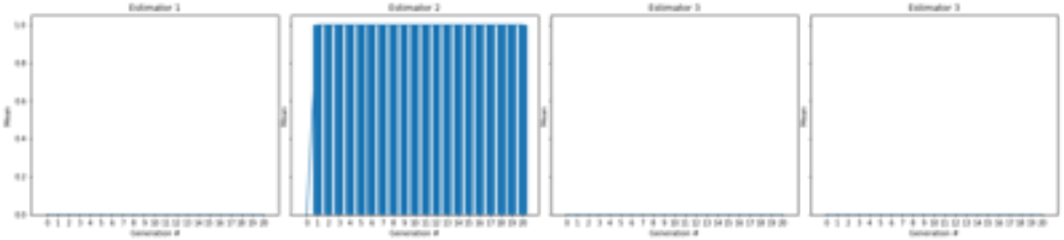


Figure 3D
Poisson Model Simulation: Generation # vs. Means (1 Run; Lambda = 1.8)

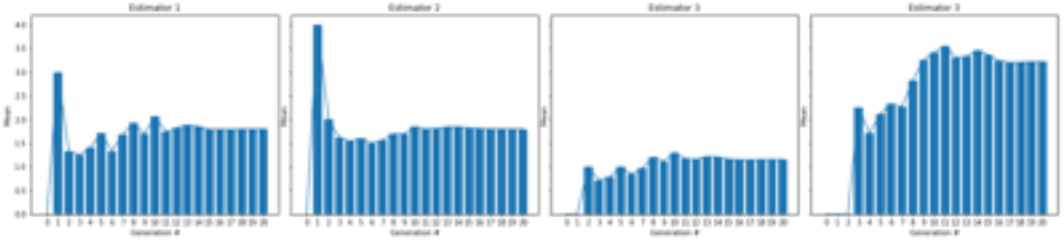


Figure 4D
Poisson Model Simulation: Generation # vs. Means (1 Run; Lambda = 1.9)

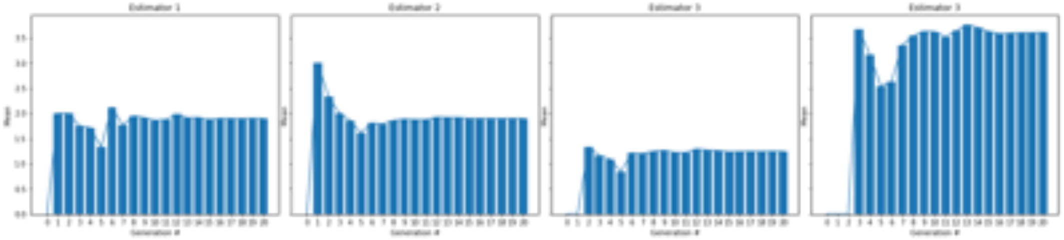


Figure 5D
Poisson Model Simulation: Generation # vs. Means (1 Run; Lambda = 2.0)

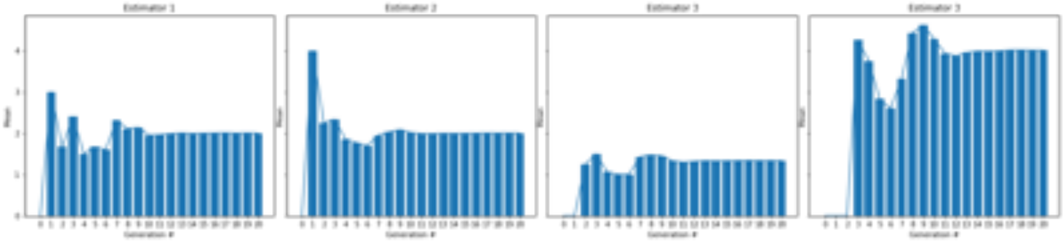


Figure 6D

Poisson Model Simulation: Generation # vs. Means (1 Run; Lambda = 2.1)

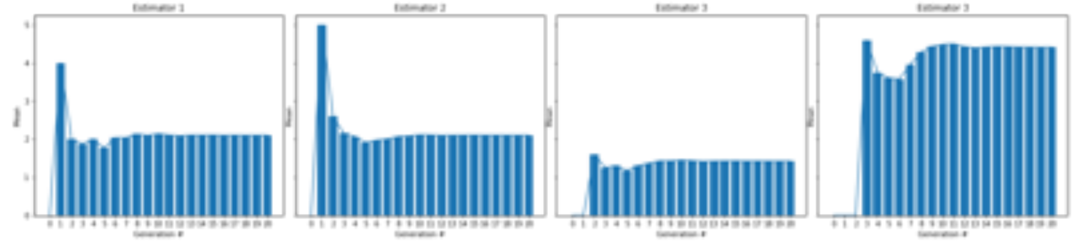


Figure 7D

Poisson Model Simulation: Generation # vs. Means (1000 Runs; Lambda = 1.6)

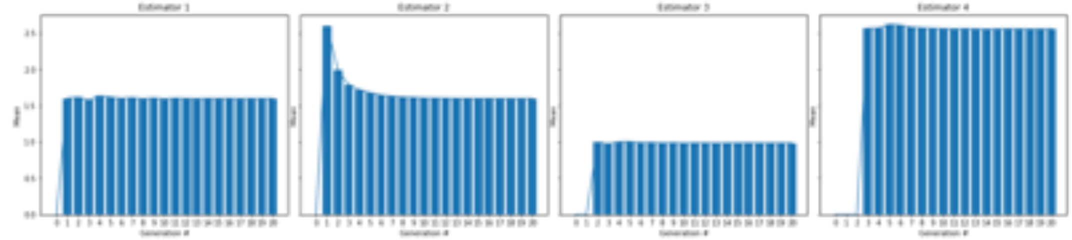


Figure 8D

Poisson Model Simulation: Generation # vs. Means (1000 Runs; Lambda = 1.7)

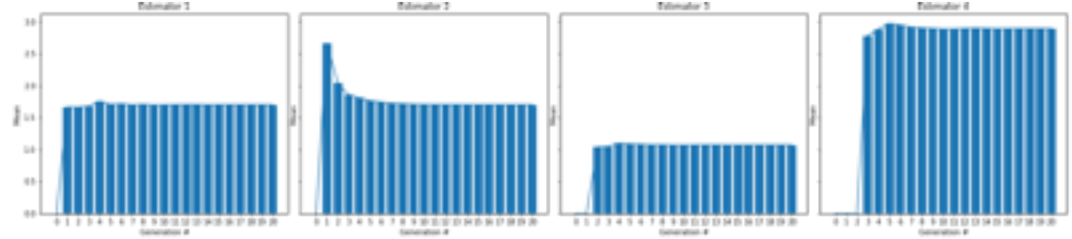


Figure 9D

Poisson Model Simulation: Generation # vs. Means (1000 Runs; Lambda = 1.8)

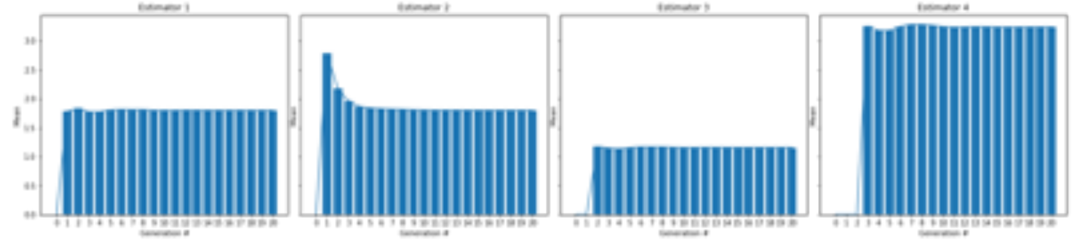


Figure 10D

Poisson Model Simulation: Generation # vs. Means (1000 Runs; Lambda = 1.9)

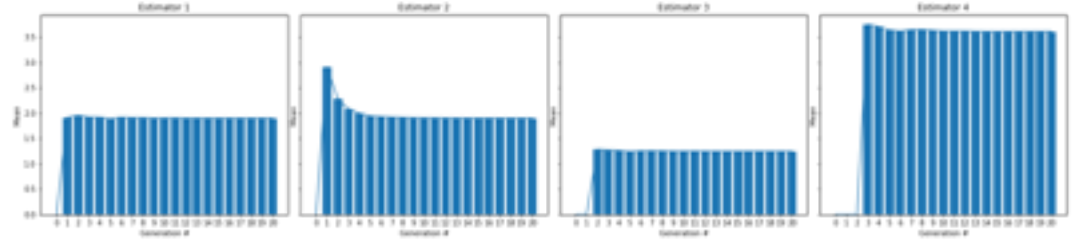


Figure 11D
Poisson Model Simulation: Generation # vs. Means (1000 Runs; Lambda = 2.0)

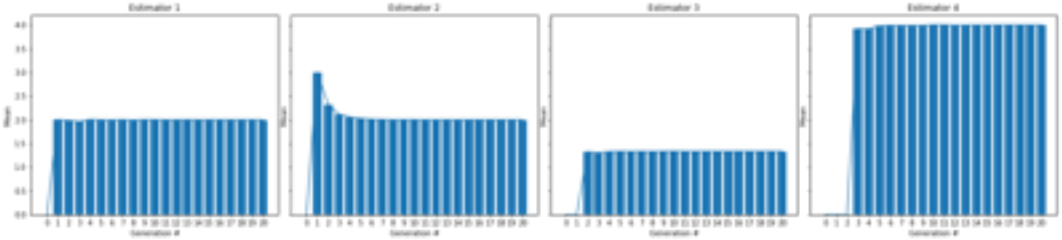
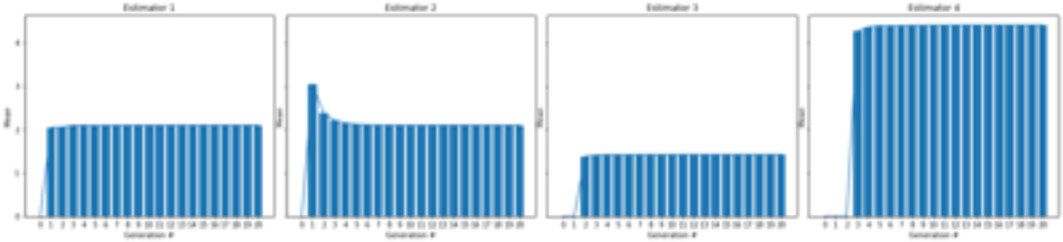


Figure 12D
Poisson Model Simulation: Generation # vs. Means (1000 Runs; Lambda = 2.1)



Appendix E: Full Estimator Plots (Regional)

Figure 1E

$\overline{E_1}$ across the Three Regions (Full)

Figure 2E

$\overline{E_2}$ across the Three Regions (Full)

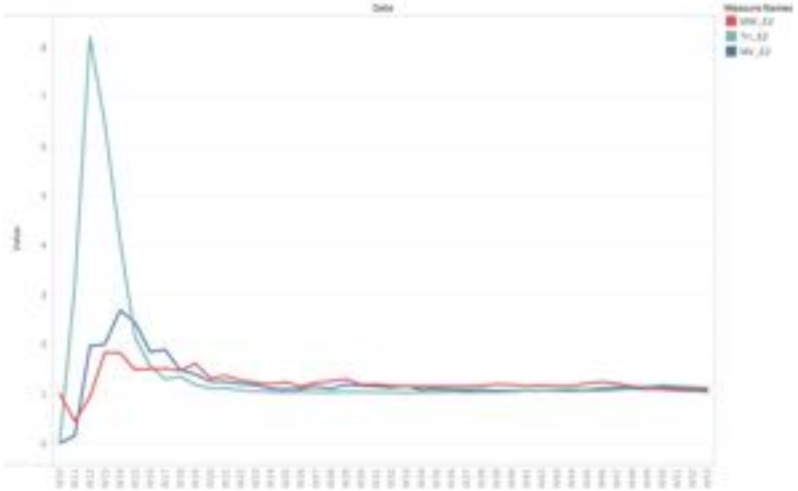
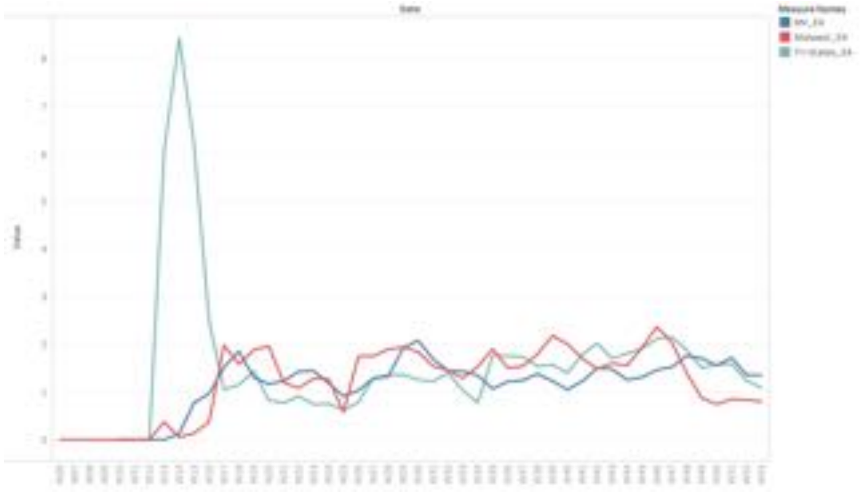


Figure 3E

$\overline{E_3}$ across the Three Regions (Full)

Figure 4E

$\overline{E_4}$ *across the Three Regions (Full)*



Appendix F: Additional Variance Plots

Figure 1F
Variances of $\overline{E_1}$ of 8 States and D.C.

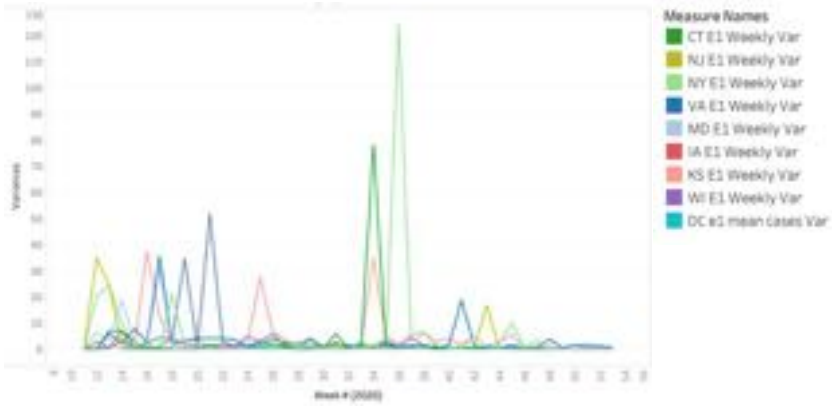


Figure 2F
Variances of $\overline{E_2}$ of 8 States and D.C.

Figure 3F
Variances of $\overline{E_3}$ of 8 States and D.C

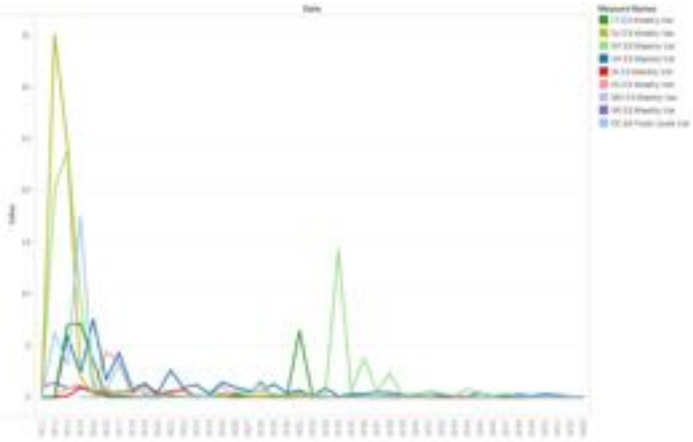


Figure 4F
Variances of $\overline{E_1}$ of Midwest Region

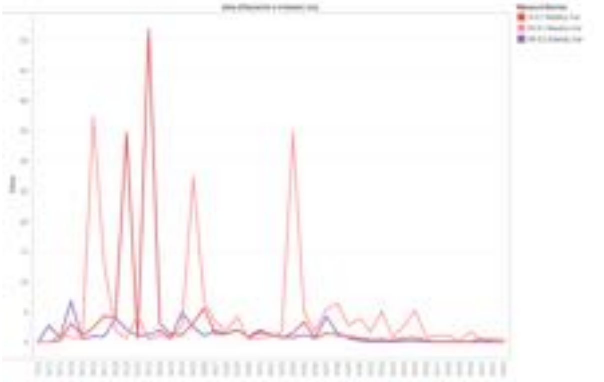


Figure 5F
Variances of $\overline{E_1}$ of Tri-State Region

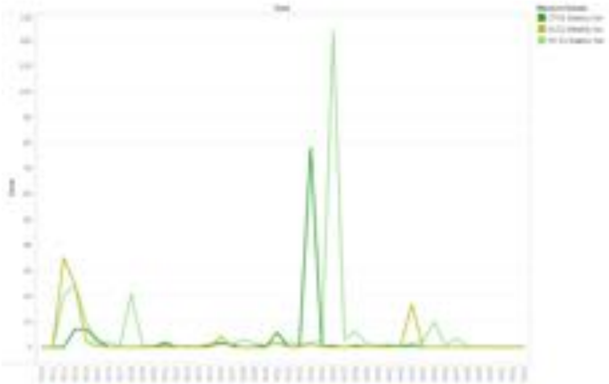
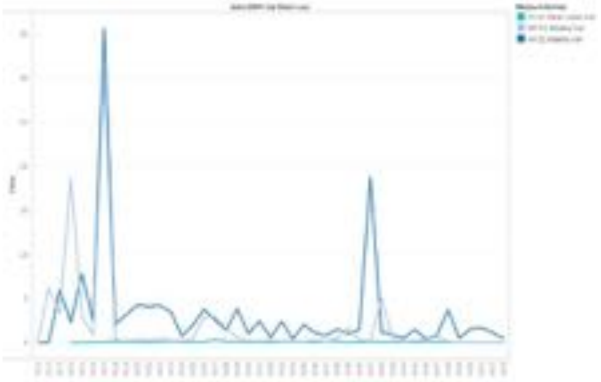


Figure 6F
Variances of $\overline{E_1}$ of DMV Region



Appendix G: Additional Comparison Plots of NPI breakdowns and E1

Figure 1G

Iowa: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)

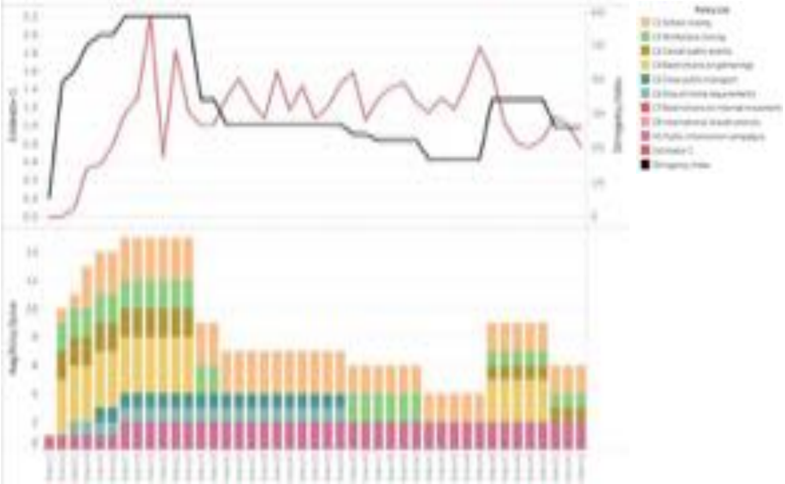


Figure 2G

Kansas: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)

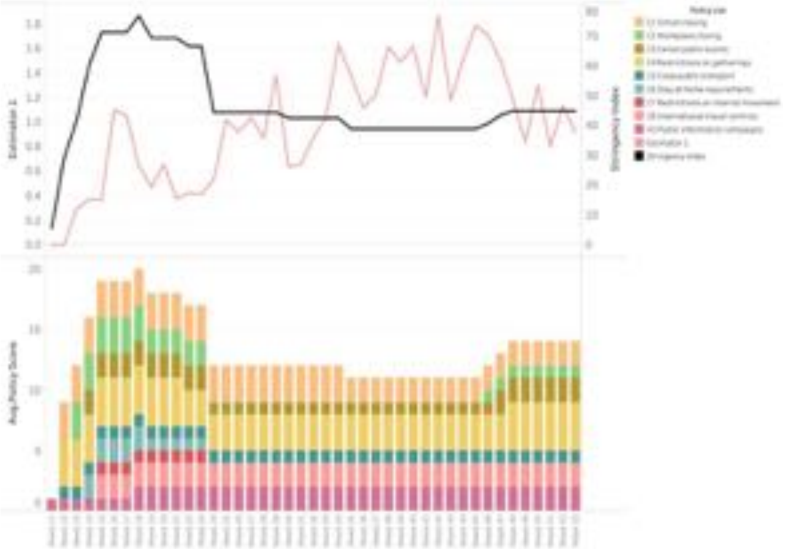


Figure 3G
Wisconsin: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)

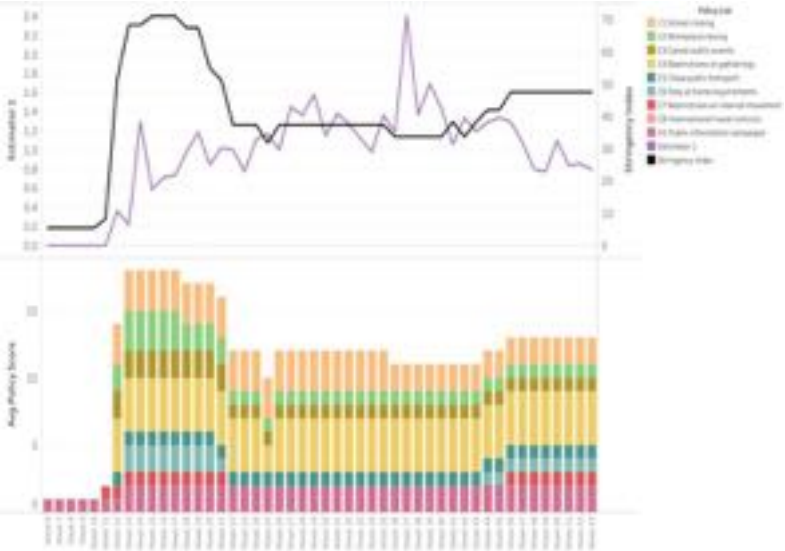


Figure 4G
New York: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)

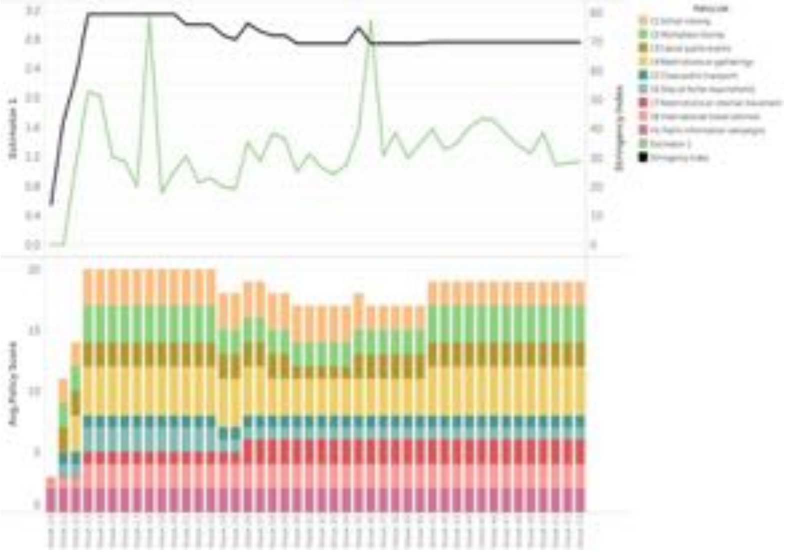


Figure 5G

Connecticut: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)

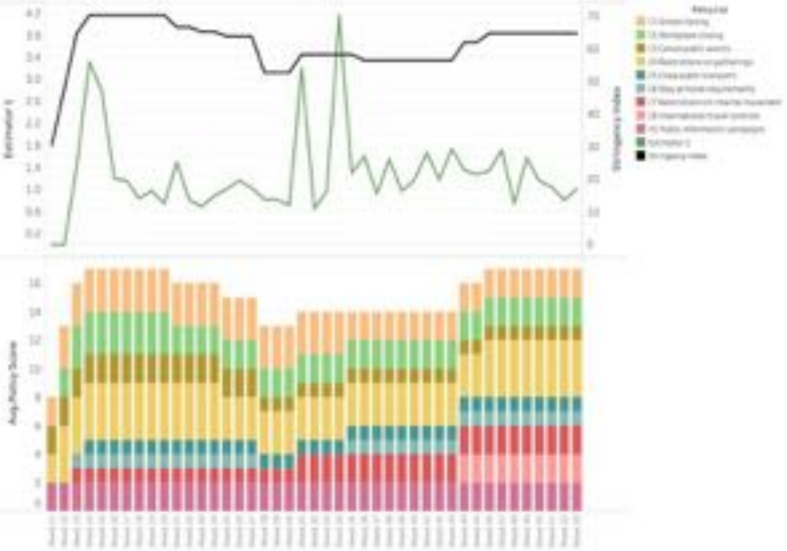


Figure 6G

Virginia: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)

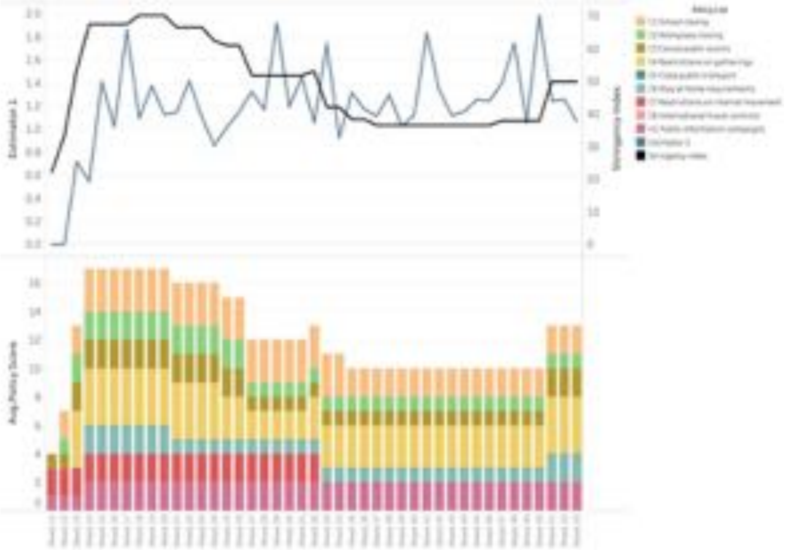


Figure 7G
Maryland: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)

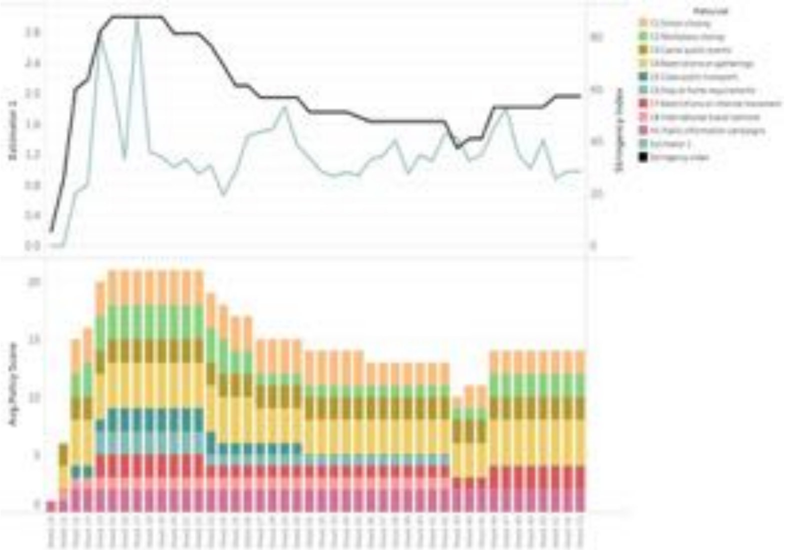


Figure 8G
Washington D.C.: COVID-19 NPI Stringency Index vs $\overline{E_1}$ (2020)

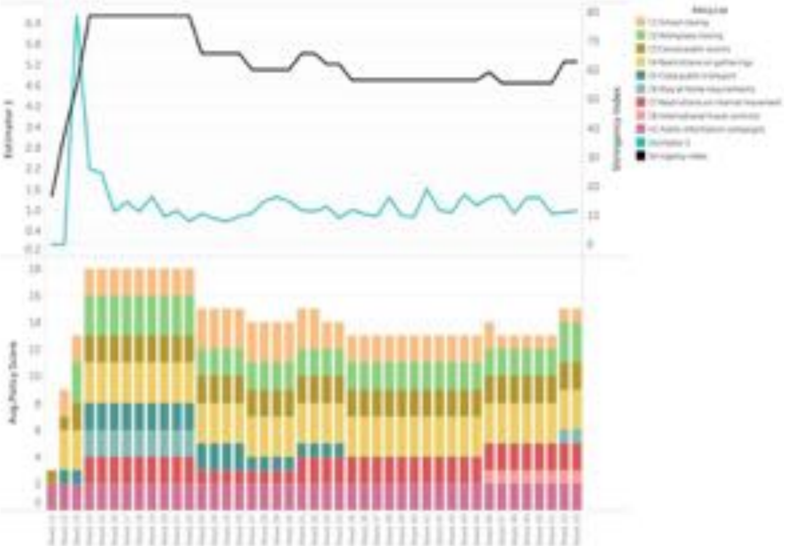
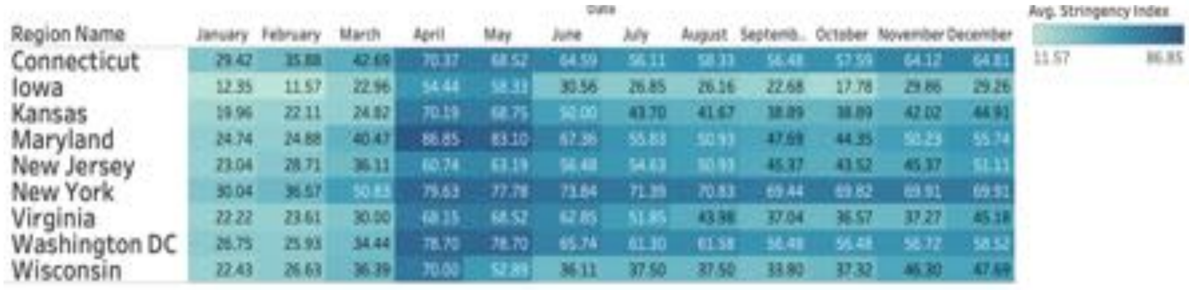


Figure 9G
Monthly Stringency Index of All States and D.C.



Region Name	January	February	March	April	May	June	July	August	Septemb..	October	November	December
Connecticut	29.42	35.88	42.69	70.37	68.52	64.59	56.11	58.33	56.48	57.59	64.12	64.81
Iowa	12.35	11.57	22.96	54.44	58.33	30.56	26.85	26.16	22.68	17.78	29.86	29.26
Kansas	19.96	22.11	24.82	70.19	68.75	50.00	43.70	41.67	38.89	38.89	42.02	44.91
Maryland	24.74	24.88	40.47	86.85	83.10	67.36	55.83	50.93	47.69	44.35	50.23	55.74
New Jersey	23.04	28.71	36.11	60.74	63.19	56.48	54.63	50.93	45.37	43.52	45.37	51.11
New York	30.04	36.57	50.83	79.63	77.78	73.84	71.39	70.83	69.44	69.82	69.91	69.91
Virginia	22.22	23.61	30.00	68.15	68.52	62.85	51.85	43.98	37.04	36.57	37.27	45.18
Washington DC	26.75	25.93	34.44	78.70	78.70	65.74	61.30	61.58	56.48	56.48	56.72	58.52
Wisconsin	22.43	26.63	36.39	70.00	52.89	36.11	37.50	37.50	33.80	37.32	46.30	47.69

Appendix H: Additional Change-Point Plots

Figure 1H

DMV Region: 95% Confidence Interval for $\overline{E_1}$: Sept to Nov

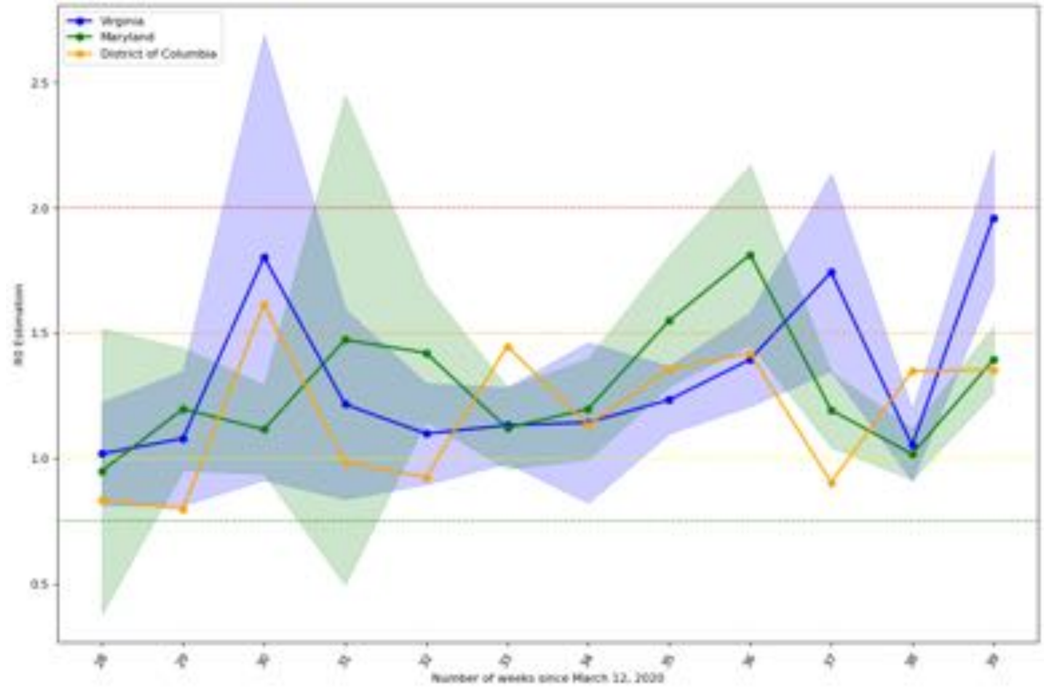
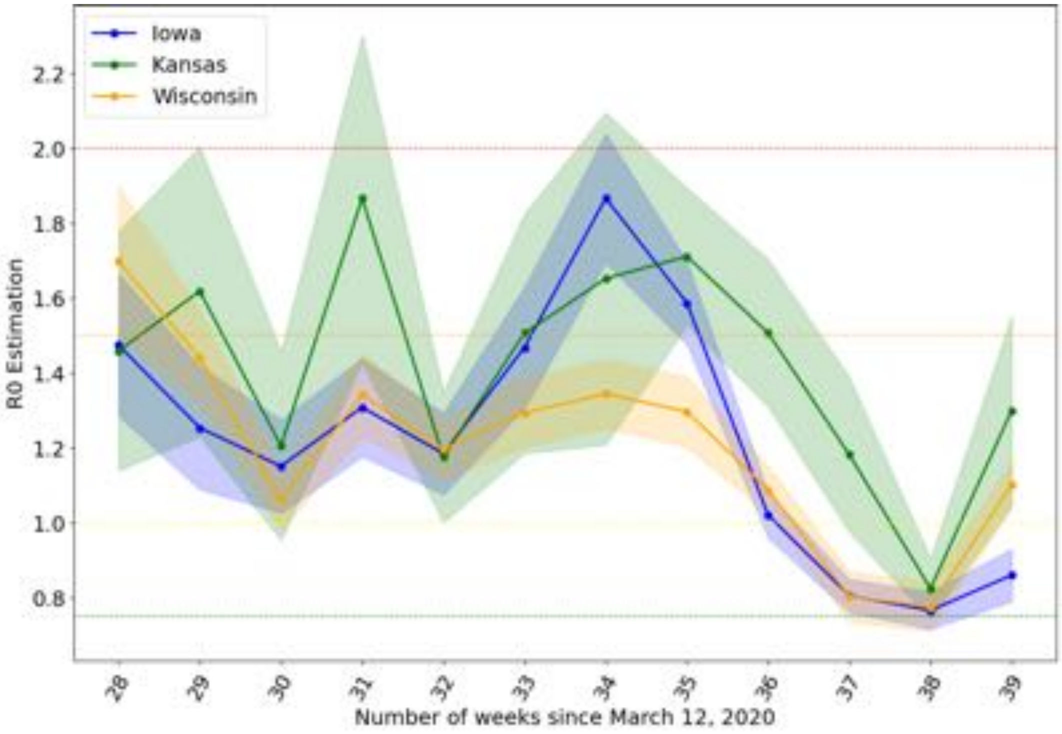


Figure 2H

Midwest Region: 95% Confidence Interval for $\overline{E_1}$: Sept to Nov



Appendix I: Change-Point Analysis Sample

Table 11
Regional and State-Level Breakdown of Change-Points

Region	State	Date of Change -Point	Type of Change (Peak or Drop)	NPI Changes Two Weeks Prior to Change-Point	NPI Changes One Week Prior to Change-Point	NPI Changes Week of Change-Point	Summary of NPI Linkage to Change-Point
Midwest	Iowa	5/7	Peak	None	Reopening of malls, restaurants, gyms)	None	Perhaps premature reopenings early in the summer played a role in the peak change-point
	Iowa	10/8	Drop	None	None	None	No clear linkage
	Kansas	10/15	Peak	None	Reopening of schools in multiple counties	None	Perhaps reopenings of public schools is linked with this peak change-point
	Kansas	5/14	Drop	None	Relaxation of stay at home measures	Increased public health campaigns through the launch of COVID-19 website	Contradictory NPI changes (relaxation of some, increase in others)
	Wisconsin	4/2	Peak	None	Closure of all public schools, non-essential businesses, and public gatherings	Fines for mass gatherings	Despite proactive measures in the first few weeks of COVID-19 cases in the state, there was still a peak
	Wisconsin	11/26	Drop	None	Limitations on public transportation and social gatherings	None	Perhaps increased stringency on social and public gatherings is linked with this drop change-point
Tri-State	New York	6/25	Peak	Relaxation of Social gathering restrictions (up to 50 people)	None	Regional reopenings of public pools and playgrounds	Perhaps increased reopenings in various contexts and intra-state regions is linked with this peak change-point
	New York	5/7	Drop	None	None	Governor releases executive order requiring masks in public	Perhaps public announcement led by the Governor is linked with this drop change-point
	New Jersey	7/16	Peak	None	None	Reopening of indoor dining and increased outdoor gathering capacity up to 500 people	Perhaps relaxations on previous indoor dining and outdoor social gathering restrictions are linked with this peak change-point
	New Jersey	8/6	Drop	None	None	None	No clear linkage; *There were no clear linkages for any drop change-point in New Jersey
	Connecticut	8/20	Peak	None	None	None	No clear linkage; *Note, even on peak change-points, there are no clear linkages
	Connecticut	4/16	Drop	None	Increased public health campaigns to stay home (including in Spanish)	None	Perhaps government-led campaigns are linked with this drop change-point
D.M.V.	D.C.	10/8	Peak	None	None	None	No clear linkage
	D.C.	5/30	Drop	Continued reopening of businesses	Start of reopening of non-essential businesses	Requirements of face masks in public transit	Contradictory results. Despite increased reopenings, there was a drop, perhaps linked with the mask mandate.
	Maryland	4/2	Peak	Closure of public buses	Closure of non-essential businesses and gatherings	Stay-at-home order limited to 10 individuals	Despite proactive measures in the first few weeks of COVID-19 cases in the state, there was still a peak
	Maryland	8/20	Drop	Reopening of college campuses (UMD)	None	Announcement of public schools being mostly online	Contradictory results between types of reopenings; No clear linkage.
	Virginia	7/16	Peak	None	None	Reopening of entertainment and recreational gatherings up to 250 individuals	Perhaps an increase in the number of individuals at gatherings is linked with this peak change-point.
	Virginia	12/3	Drop	None	None	None	No clear linkage; *Week after had the highest peak change-point in VA.

Table 2I
Regional Comparison of n weeks pertaining to peak and drop change-points

Region	State	n (change-points)	n (peaks)	n (drops)
Midwest	Iowa	17	10	7
	Kansas	12	6	6
	Wisconsin	12	7	5
Midwest Totals		**41**	**23**	**18**
Tri-State	New York	15	8	7
	New Jersey	16	7	9
	Connecticut	12	6	6
Tri-State Totals		**43**	**21**	**22**
D.M.V.	D.C.	8	4	4
	Maryland	16	8	8
	Virginia	16	10	6
D.M.V. Totals		**40**	**22**	**18**
Overall Totals		**124**	**66**	**58**