A Data-Driven Approach for Estimating the Effectiveness of COVID-19 Non-pharmaceutical Intervention Policies across Different Communities

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Abstract

Non-pharmaceutical Interventions (NPIs), such as Stay-at-Home, Face-Mask-Mandate, are essential components of the public health response to contain an outbreak like COVID-19. However, it is very challenging to quantify the individual or joint effectiveness of NPIs and their impact on people from different racial and ethnic groups or communities in general. Therefore, in this paper, we study the following two research questions: 1) How can we quantitatively estimate the effectiveness of different NPI policies pertaining to COVID-19 pandemic?; and 2) Do these policies have considerably different effects on communities from different races and ethnicity? To answer these questions, we model the impact of an NPI as a joint function of stringency and effectiveness over a duration of time. Consequently, we propose a novel stringency function that can provide an estimate of how strictly an NPI was implemented on a particular day. Next, we applied two popular tree-based discriminative classifiers, considering the change in daily COVID cases and death counts as binary target variables, while using stringency values of different policies as independent features. Finally, we interpreted the learned feature weights as the effectiveness of COVID-19 NPIs. Our experimental results suggest that, at the country level, restaurant closures and stay-at-home policies were most effective in restricting the COVID-19 confirmed cases and death cases respectively; and overall, restaurant closing was most effective in hold-down of COVID-19 cases at individual community levels.

Introduction

Non-pharmaceutical Interventions (NPIs) are essential components of the public health response to control and contain an outbreak like COVID-19. NPIs include policies like *Stay-at-Home*, *Face-Mask-Mandate*, *Closing-and-Reopening-Businesses*, *Travel-Ban*, among others. These measures help suppressing the spread of the virus, thus as an outcome, reducing the infected population size and buying more time for the healthcare professionals to better handle the pandemic. Not to mention that during COVID-19 pandemic, those interventions also allowed us ample time to create potential vaccines and drugs to fight the virus. Recent research has shown that large-scale implementation of joint NPIs is effective in containing the virus [1], however, the impact of individual NPI is relatively under-explored. A reasonable way to estimate the effectiveness of an individual NPI is to adopt a data-driven approach to model the decay in COVID-19 cases/deaths as a joint impact function of multiple NPIs and then disentangle the weights of each individual NPI by fitting the target variable with NPIs impacts as independent variables and subsequently performing a detailed feature analysis. An additional challenge associated with this task is that there is always a lag between policy implementation and its effect on the targeted population [2]. Policy lag is well studied in economics [3], according to which we propose that, a delay between NPI implementation and its consequence is expected and thus should be considered for NPI impact modeling. Therefore, we also incorporate a lag effect in our estimation of effectiveness.

In terms of research questions, we investigate the following two questions in this paper:

1. How can we quantitatively estimate the effectiveness of NPI policies pertaining to COVID-19 pandemic?
2. Do these policies have significantly different effects on communities for different races and ethnicity?

In order to answer these questions, we considered the impacts of following five major policies related to COVID-19 NPIs implemented by the US government during the pandemic period from March'2020 to April'2021, i.e., *Stay-at-Home* [4], *Face-Mask-Mandate* [5], *Closing-and-Reopening-Restaurants* [6], *Closing-and-Reopening-Businesses* [7] and *Travel-Ban* [8].

Technically, we model the impact of an NPI over a duration of time as the product of stringency and effectiveness of the corresponding NPI over that particular time period. Consequently, we propose a novel stringency function for NPIs over a duration of time, which can provide an estimate of how strictly an NPI was implemented on a particular day. This stringency function has been designed by incorporating the Policy Stringency Index Value (PSIV) [9] provided by The Oxford COVID-19 Government Response Tracker (OxCGRT) and subsequently, assuming an exponential decay period after the policy is lifted.

Next, we trained two popular discriminative classifiers, i.e., Random Forest [10] and Gradient Boosted Trees [11], with the change in daily COVID cases and death counts as binary target variables and stringency values of different policies as features. We conducted this analysis with data from both country-level (Whole US) and community-level (refers to six races, *–White, Black or African American, Asian, American Indian and Alaska Native (AIAN), Native Hawaiian and other Pacific Islander (NHPI)*). Finally, we interpreted the learned feature weights as the effectiveness of COVID-19 NPIs. Our experimental results suggest that, on a country level, restaurant closures and stay-at-home was most effective in restricting the COVID-19 confirmed cases and death cases, respectively, and overall, restaurant closing was most effective in hold-down of COVID-19 cases at individual community levels.

Literature Review

According to a news article in Nature by Gibney, 2020 [12], *"working out the effectiveness of the measures implemented worldwide to limit the coronavirus's spread is now one of scientists' most pressing questions"*. In our paper, we aim to answer this pressing question by estimating the effectiveness of NPI (Non-Pharmaceutical Intervention) policies over a particular period. By far, to constrain the spread of the virus, governments from all over the world have responded with multiple NPIs such as *Face Mask Mandate*, *Social Distancing* and many more. However, the effectiveness of individual policies are still under-studied. Recent works focused on estimating the joint effect of policies using Reproduction number (R_t) [13, 14] or the mobility rate [15, 16] or the Ordinary Differential Equation (ODE) [17, 18, 19, 20].

Many studies have been conducted to analyze the joint impact of NPI policies through mathematical or statistical modeling of severity of the spread of COVID-19 virus. The most common method used to quantify the impacts of the policies to the model the spread through Ordinary Differential Equations (ODE) [17, 18, 19, 20]. For example, Johndrow et. al. [19] used simple SIR (Susceptible-Infected-Recovered) model to estimate the true count of confirmed cases with NPIs in consideration. They proposed the SIR model to estimate the disease spread using likelihood and suggested that the actual number of cases were 6-10 times higher than the reported cases and also accounted for the lag in time from infection to death and the infection fatality rate. Coughlin et.al. [20] used SEIR model for Wuhan, China and pointed that if the strictness of social mixing policies were prolonged till April'2020, then the peak of the spread of virus could have been delayed further. Spooner et.al. [21] used micro-simulation model that incorporate the susceptible and infectious individuals to estimate the transmission effect between them by building a model that mimics the population of the USA and the United Kingdom. However, these simulation-based models may explore the atypical behavior of the disease with a strong proposition that would be difficult to validate. Therefore, we rely primarily on data-driven approach to estimate the effectiveness of the NPIs.

Several other methods were also proposed to estimate the efficacy of the policies such as the Change Point Detection (CPD) model [15, 22], or the Bayesian models [13]. The CPD model finds the abrupt changes in the time series data by observing the change in mean and variance of the distribution of infection. Previously, this model was mostly used for the stock market analysis, genomics data modeling or segmentation. Later, researcher found similar abruptly changing trends in the distribution of COVID-19 infection like in stock markets. Bian et.al. [15] used the CPD model to estimate the impact of NPI's on the transportation system using mobility data and incorporated the lag time in the reported cases. Dass et.al. [16] assessed the impact of social gathering policies using the mobility data on the spread of the virus using the CPD method. Mbuvha et.al. [22] combined the Bayesian inference method with the simple SIR model to estimate the rate of spread of virus due to travel ban policy in South Africa. Brauner et.al. [13] used a bayesian hierarchical model to link the dates to cases and deaths and modeled each NPI effect as a multiplicative reduction in reproduction number (R) and estimated mean reduction in R across the countries. They suggested that a limit in gathering size up to 10 people, school closure and high exposure business closure were more effective in reducing the spread of virus than stay-at-home policy. Moreover, Cowling et.al. [14] estimated the NPI's impacts using the behavior change in population using reproduction number (R) and observed a decline in cases after the social distance and school closure policies were imposed.

In this paper, we analyze the effect of NPI's for the USA as this country has been a special case in terms of COVID-19 response as the US government gave authority to sub-national states governments to impose policies according to their will [23, 24]; in contrast to other countries like China, India, South Korea, where the implementation of each policy was centralized to the country. Moreover, the USA government had a delayed response for handling the pandemic and therefore, became the epicenter [24, 25]. To quantitatively estimate the effectiveness of the individual NPI policies on the country-level and individual race/community levels, we first computed how strictly a policy was implemented at a particular timestamp using our proposed novel stringency function. Next, we trained two tree based discriminative classifiers on daily COVID-19 cases and death counts as targets and stringency values of different policies as features. Finally, we interpreted the learned feature weights as the effectiveness of COVID-19 NPIs and performed qualitative analysis of our findings.

Problem Formulation and Effectiveness Model

During the pandemic, several NPI policies have been imposed and lifted to control the spread of COVID-19; as a consequence, we saw multiple ups and downs in the number of recorded cases. We assume that these variations primarily occurred due to the following two factors:

1. **Effectiveness Index:** How effective an NPI policy is in restricting the spread of the virus, if implemented properly. This is essentially our primary research question, let's call it *Effectiveness Index* and denote as α. We assume that the *Effectiveness Index* of an NPI does not change with time, which is a reasonable assumption.
2. **Stringency Index:** How strictly the NPI policy was implemented by the government and law-enforcement agencies. Let's call it *Stringency Index* and denote as β^t. Parameter t denotes a discrete timestamp (e.g., day as a unit) and captures the fact that the *Stringency Index* can and does change over time. For example, government can sometimes be more lenient / strict towards implementation of a particular law.

The impact of a NPI policy P at timestamp t is defined as $I_t(P) = \alpha\beta^t$. Next, we define the target as a temporal binary random variable $X(t)$, where, $X(t) = 1$ means decay in number of positive cases at timestamp t and $X(t) = 0$ means otherwise. Finally, when multiple policies (P_1, P_2, ..., P_k,) are considered jointly, the target variable can be defined as the following function:

$$X(t) = f\left(I_t(P_1), I_t(P_2), ..., I_t(P_k)\right) = f\left(\alpha_1\beta_1^t, \alpha_2\beta_2^t, ..., \alpha_k\beta_k^t\right) \tag{1}$$

As our primary goal is to estimate α's (effectiveness index), we first computed $X(t)$ from publicly available CDC infection database. We then proposed a novel stringency function for NPIs to compute values for $\beta_k(t)$. Next, we trained two popular discriminative classifiers, i.e., Random Forest and Gradient Boosted Trees, with daily COVID cases and death-counts as targets and stringency values of different policies as features. Finally, the learnt feature weights from the training process are interpreted as our estimates of α_1, α_2, ..., α_k.

Proposed Stringency Function

Devising an accurate Stringency Index (how strictly a policy is implemented at a particular moment) is very challenging as it can changes with time and depends on various social and external factors. To provide a comprehensive definition of *Stringency*, we considered the following possible cases. For notations, we use t as the current timestamp, P_{Start} as the timestamp when the policy was imposed and P_{Lifted} as the timestamp when the policy was lifted.

Case 1 : When the policy has not yet been implemented, i.e., current timestamp *t* is smaller than the timestamp when policy was imposed, i.e., $t < P_{Start}$ We assume that there is no stringency as well as impact of a policy, i.e., $\beta_t = 0$. Therefore, $I_t(P) = 0$.

Case 2 : When the current timestamp *t* lies in-between the policy start day and policy end day, i.e., $P_{Start} + w_1 < t < P_{Lifted}$, we assume the stringency index (β_t) of a policy to be equal to the Policy Stringency Index Value (PSIV) [9] provided by the Oxford COVID-19 Government Response Tracker (OxCGRT). The PSIV ranges between

Algorithm 1: Computation of Stringency Index

Data:
(1) t: input timestamp (discrete timestamp)
(2) P: a particular policy
(3) $PSIV$: Policy Stringency Index Value (PSIV) [9] provided by the Oxford COVID-19 Government Response Tracker (OxCGRT)
(4) P_{Start}: timestamp when policy P was imposed
(5) P_{Lifted}: timestamp when policy P was lifted
(6) w_1: Assumed delay effect in PSIV (set to 5 days)
(7) w_2: Aftermath effect of a policy after lift (set to 10 days)
(8) γ: decaying rate (set to 0.01)
Result: β_k^t (Stringency Index of a Policy k at timestamp t);

```
if t < P_Start + w_1 then                                      // Case 1
    β_k^t ← 0;
else if P_Lifted ≠ ∞ then
    if P_Start + w_1 < t < P_Lifted then                       // Case 2
        β_K^t ← PSIV_P[t] ;
    else if P_Lifted < t < P_Lifted + w_2 then                 // Case 3
        β_k^t ← PSIV_P[P_Lifted];
    else                                                       // Case 4
        β_k^t ← PSIV_P[P_Lifted] × exp^(−γ×[t−w_2−P_Lifted])
else                                                           // Case 5
    β_k^t ← PSIV_P[t]
```

0 and 1 where, 0 being no strictness of a policy and 1 being very strict policy administration. Note that, we assumed a lag of w_1 days before using PSIV as the stringency index, which captures the fact that the impact of a policy is not immediately observed. In other words, any cases reported on current timestamp is a result of the infection received w_1 days ago. w_1 essentially models the incubation period [26] which is set to 5 days as per CDC guidelines.

Case 3: When current timestamp is in between Policy lift date and w_2 days after lifting,, i.e., $P_{Lifted} < t < P_{Lifted} + w_2$. This case captures the fact that the effect of a policy does not immediately disappear when it is lifted, rather it vanishes gradually and the vanishing effect is often observed after a certain lag period. Therefore, we assumed a lag period of w_2 before observing the decay of stringency. During this period, we assumed the stringency index of a policy to be equal to same PSIV value on the lift day.

Case 4: More than w_2 days since the policy was lifted, i.e., $t > P_{Lifted} + w_2$. As the state officials lift the policy, we assume that a policy would still have diminishing impact over time. This effect is expressed as a exponential decay function (β^t = PSIV[P_{Lifted}] $\times \exp^{-\gamma \times [t - w_2 - P_{Lifted}]}$). Note that, here we are multiplying the PSIV of the policy lifted day, which remains the same till the end of analysis period.

Case 5: When the state official didn't lift the policy before the analysis period. In this case, the policy effect would be equal the PSIV on that particular day.

Algorithm 1 combines these five cases into a single function which takes as input a particular timestamp t and returns the *Stringency Index* at timestamp t. The stringency indexes of different NPI policies are then used as features to represent the joint impact of NPIs on a particular day and further classified by a discriminative classifier like Random Forest, Gradient Boosted Trees etc. into a binary output which represents whether there is a decay in the COVID-19 positive cases/deaths or not.

Figure 1 demonstrates the stringency of five NPI policies in 3 states [California (CA), Maryland (MD), and Wyoming (WY)] of USA during the analysis period from March'14'2020 to April'10'2021. Here, x-axis represents the number of days and y-axis shows the stringency of individual NPI policies. Note that, we have evaluated the stringency of the policies across 48 states of the USA and Figure 1 shows three states only due to lack of space. To interpret Figure 1,

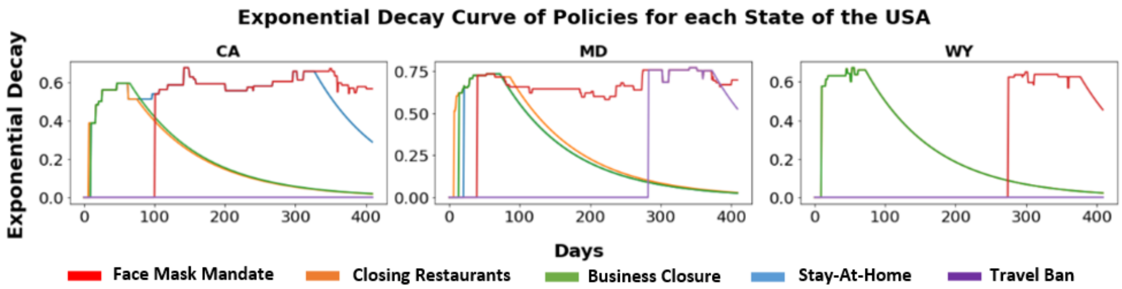

Figure 1: The Figure demonstrates the effect of policies on three states during the span of analysis period i.e. March'14'2020 to April'10'2021. The three states are California (CA), Maryland (MD) and Wyoming(WY). MD has implemented all the five polices, CA implemented 4 policies and WY has implemented 3 policies. The decay curve begins the next day of a policy lift and showcase the aftermath effect of a policy.

day 1 starts from March'14'2020 and last day represents the 410^{th} day i.e. April'10'2021. First, if we observe the CA state, we can notice that out of 5 policies, 4 policies were imposed except for the "Travel Ban" policy. The CA state government did not impose the "Travel Ban" policy during the analysis period and therefore, the policy did not have any impact (hence no stringency as well) in refraining the COVID-19 infection in CA. Second, if we observe the "Face Mask Mandate" Policy in state CA and MD, we will notice that the state officials did not lift the policy after imposing it, therefore, we consider the policy stringency value until the last day of the analysis period without any exponential decay. In-state WY, state officials procrastinated the implementation of the "Face Mask Mandate" policy and later lifted the policy quickly. As a result, the Face Mask policy was imposed for a very short period, and later after the policy was lifted, we observe the exponential decaying effect in the WY state. Third, many of the states imposed Stay-At-Home, Closing Restaurants, and Business Closure on the same day, for instance, state CA and WY had imposed "Closing Restaurants" and "Business Closure" policies on the same day, and thus, we see similar trends for those NPI policies.

Estimation of NPI Policy Effectiveness

Target Labels: Unfortunately, we do not have ground truth labels for the joint impact of NPIs at any given timestamp. To address this limitation, we applied the following heuristics:

Given a particular timestamp t, the change in daily confirmed cases and deaths counts can serve as a good indicator of the joint impact of NPIs at that particular timestamp.

This is a reasonable assumption because if one or more NPIs are effective, they must help decrease the number of confirmed cases and deaths counts. Otherwise, they will be deemed as ineffective. According to CDC, the average incubation period is around 5.6 days [26] and in the work, we captured this incubation period with the lag period w_1 which was set to 5 days. This means that, any person reporting a positive case today could have gotten the infection around 5 days ago (as per CDC). Consequently, we labeled the data in the following way: on a particular timestamp t, if we observe a decline in number of cases in terms of the moving average of preceding 5 days from current timestamp t, then timestamp t is assigned label 1, otherwise 0. Label 1 indicates that, the cases are reducing on average for past 5 days, whereas Label 0 indicates that cases are non-decreasing. We created two different target variables, i.e., decay in confirmed cases and deaths, separately using the same strategy and formulated a binary classification problem which was trained using tree-based methods.

Estimation of NPI Policy Effectiveness: After constructing the feature vectors using algorithm 1 and creating the the binary target variables as described above, the data-set is ready to be used for the classification task. Since, our data is non-linear, we used tree based methods to perform the binary classification task and then ranked the policies based on the learnt weights (α_i). Two tree based methods we experimented include 1) Random Forest and 2) Gradient Boosted Trees. The learnt feature weights are finally interpreted as the effectiveness of individual NPI policies.

Policy Effectiveness on Different Races: Generally, a policy is implemented to benefit all communities equally; however, during the pandemic era, it has been reported that different communities and races were impacted differently [27]. Indeed, the impact of the COVID-19 pandemic in the Country has shed light on inequities among different races and ethnicity. The official report by Commonwealth Fund analysis [27] suggests that there are high disparities in COVID-19 cases and deaths in communities. Therefore, to quantify the disparities in policy impacts across different races, we computed the effectiveness index of each policy at individual race levels. Next, we computed the squared difference between race-specific effectiveness index and country-level effectiveness index normalized by the country-level effectiveness index. This squared difference signifies how differently a particular race/community was impacted by a policy in comparison to the whole country level impact.

$$Squared\_Difference = \left\{ \frac{1}{\alpha_k^C} * \left(\alpha_k^C - \alpha_k^r \right) \right\}^2 \tag{2}$$

where, k is a specific policy; r is a specific race, α_k^C = effectiveness index of policy k on Country-Level and α_i^r = effectiveness of each policies on race r.

Results and Discussions

Data-set: We used four different publicly available data-sets dated from March'14'2020 to April'10'2021, to analyze the effects of NPI policies on the COVID-19 confirmed cases and deaths across 48 states of USA. The datasets are (1) Daily reported cases and death counts by each state [28], (2) Policy implementation records [29], (3) Policy Stringency Index value (PSIV) [9] records; and, (4) COVID-19 reported cases of different races and ethnicity [28]. The analysis is first performed at the country level and then, further extended to the individual race-level.

Country-Level Analysis: Table 1 showcases the effectiveness indexes estimated by two tree-based methods, i.e., 1) Random Forest and 2) Gradient Boosting, using country-level confirmed cases and death counts as target variables separately. As we observe from table 1 that nearly both methods suggest that the policy *Closing Restaurants* was most effective in refraining from the spread of COVID-19 cases (number of confirmed cases). According to Forbes [30] and Stanford University [31] report, if restaurants were allowed to open, then they would have been responsible for more than 600K infections in major cities. Additionally, in retrospect, it was concluded that 10% of leniency in restaurant opening could cause more than 85% of the cases according to the same reports. Therefore, we believe that *Closing Restaurants* policy was a vital in hindering the spread of COVID-19 on the country-level.

On the other hand, if we observe the death cases, both methods confidently suggest that the *Stay-At-Home* policy has reduced the risk of death in the country most. Although the effectiveness indexes from both methods differ slightly in Random Forest (0.280) and Gradient Boosting (0.307), they are pretty close, suggesting that the *Stay-At-Home* policy has distinctly contributed to reducing the death toll in the country. It is very intuitive that, to reduce the number of death, the infected people need to be isolated and therefore, the *Stay-At-Home* policy would be the right action. According to a report from University of Alabama, Birmingham(UAB) [32], with the absence of a *Stay-At-Home* policy, the death rate could have been 22% higher as opposed to if the policy was implemented nationwide. Additionally, according to the same reports, a quick stringent lockdown was very effective in controlling the early death toll due to its immediate effect.

On the other hand, other policies have contributed a fair share of the amount in controlling the death toll. It can be observed that the *Face Mask* policy was also very effective following the *Stay-At-Home* policy. *Closing Restaurant* policy was not found to be as effective for death count reduction as it was for containing the spread of the virus. This finding is supported by CDC [33] as well which stated the following about *Closing Restaurant* policy: *"0.7 percentage point decrease (p=0.03) in the daily death growth rates 1-20 days after the implementation, a decrease of 1.0, 1.4, 1.6 and 1.9 percentage points 21-40, 21-60, 61-80 and 81-100 days respectively"*. Additionally, *Restaurant Reopening* did not have a significant impact on death counts until day 60 of policy lift. It was observed that after day 60, CDC [33] saw an increase of only 2-3 percentage points in death cases.

In summary, if we compare the effectiveness of policies on reducing confirmed cases and deaths counts on country-level, the effects of different policies appears to be somewhat different. For containing the spread, closing restaurants/ businesses was found to be very effective; while for reducing death counts, stay-at-home was the most useful.

Method	Stay Home	Closes Restaurant	Closes Business	Face Mask	Travel Ban
RF	0.221	0.257	**0.258**	0.177	0.087
GB	0.207	**0.285**	0.216	0.198	0.093

(A) Policy Effectiveness on Confirmed Cases

Method	Stay Home	Closes Restaurant	Closes Business	Face Mask	Travel Ban
RF	**0.280**	0.173	0.204	0.199	0.144
GB	**0.307**	0.158	0.184	0.216	0.134

(B) Policy Effectiveness on Death cases

Table 1: Effectiveness of the policies on Confirmed Cases and Death on the Country-level estimated using Random Forest (RF) and Gradient Boosting (GB).

Individual Race-Level Analysis: We further extended our analysis to the individual races using the target variable "confirmed cases". It was observed that some races have been impacted differently compared to the overall population of the country. From the country-level analysis, it was found that policy *Restaurant Closing* has the highest effect in containing the COVID-19 confirmed cases, and from table 2 it is observed that the country-level analysis results do not apply to all races. Indeed, for some races, *Closing Restaurant* didn't have the maximum impact. Our findings on the effectiveness of NPI policies on individual races and comparison against country-level analysis is presented below.

Method	Race	Stay Home	Closes Restaurant	Closes Business	Face Mask	Travel Ban
RF	Asian	0.225	0.265	**0.282**	0.150	0.078
	White	0.210	**0.274**	0.264	0.158	0.094
	Black	0.227	**0.258**	0.255	0.166	0.094
	AIAN	0.191	**0.275**	0.235	0.209	0.090
	NHPI	0.217	0.239	**0.267**	0.183	0.095
GB	Asian	0.200	**0.324**	0.257	0.119	0.104
	White	0.191	**0.350**	0.213	0.162	0.085
	Black	0.239	**0.253**	0.244	0.168	0.097
	AIAN	0.128	**0.385**	0.162	0.256	0.069
	NHPI	0.248	0.232	0.**297**	0.160	0.064

Table 2: Effectiveness of the policies on individual races estimated with Random Forest (RF) Gradient Boosting (GB).

Asian: Table 2 indicates that policy *Closing Business* (RF) and policy *Closing Restaurants* (GB) have the highest effectiveness indexes in terms of containing the spread with 0.282 and 0.324 scores, respectively, for the Asian race. These numbers are slightly different from the corresponding country-level scores, i.e., 0.258 and 0.285, respectively. This finding is consistent with the report published by August Census Survey [34] which states that Asian people were *"afraid to go or didn't want to go out and buy food"* implies that Asian community were themselves resisting to visit restaurants. Additionally, according to a study by the National Bureau of Economic Research [35], around 22% decline was observed in small Asian vendor businesses nationwide after the policy was implemented. Therefore, the reports advocate that both policies *Closing Business* and *Closing Restaurants* worked together in reducing the spread of COVID-19 infection with better effectiveness than other policies. On the other hand, we observed a significant drop in effectiveness index of *Face Mask* policy from the country-level to community-level. For country-level (see table 1) the effectiveness of *Face Mask* policy for GB is 0.198, whereas on community level, the score is 0.119, i.e., it dropped by 40%, which is significant. Therefore, we can say that *Closing Business/Restaurant* has impacted the Asian community more than the overall population, whereas, *Face Mask* policy has contributed lesser in comparison to the whole population. This is further substantiated by the bold numbers in the "Face Mask" column for Asian race (Table 3), where the squared differences (eqn. 2) for both methods (0.024 for RB and 0.162 for GB) show high values.

White: According to Table 2, both methods strongly suggest that the *Closing Restaurants* policy has been very effective for the white community to fight the infection. However, GB suggests a significant increase (23%) in the effectiveness index of *Closing Restaurants* policy for the White population, which is interesting. This is further

Method	Race	Stay Home	Close Rest.	Close Buss.	Face Mask	Travel Ban	$\sum Race\_SD$
RF	Asian	0.000	0.001	0.009	**0.024**	0.011	0.045
	White	0.003	0.004	0.001	**0.012**	0.007	0.027
	Black	0.001	0.000	0.000	0.004	**0.006**	0.011
	AIAN	0.019	0.005	0.008	**0.033**	0.001	**0.066**
	NHPI	0.000	0.005	0.001	0.001	**0.007**	0.014
	$\sum SD$	0.023	0.015	0.019	**0.074**	0.032	-
GB	Asian	0.001	0.019	0.028	**0.162**	0.013	0.223
	White	0.006	**0.051**	0.000	0.033	0.008	0.098
	Black	**0.025**	0.013	0.016	0.024	0.001	0.079
	AIAN	**0.144**	0.122	0.064	0.084	0.069	**0.483**
	NHPI	0.040	0.035	**0.138**	0.039	0.102	0.354
	$\sum SD$	0.216	0.240	0.246	**0.342**	0.193	-

Table 3: Effectiveness disparities of polices on race-level compared to the whole population.

substantiated by the bold number in the "Closing Restaurant" column for White race from Table 3, where the squared differences (equation 2) for GB method shows a high value, i.e., 0.051.

Black: From table 2, we observe that for the Black community, both methods suggest that *Closing Restaurants* has contributed the most in reducing the COVID-19 spread, which is consistent with the community-level results. However, findings for GB method in Table 3 is more interesting, which suggests that "Stay-at-home" had a significantly different impact (squared difference of 0.025) on the Black Community compared to the same for the whole population. This is consistent with the report from the Economics Policy Institute [36] which suggests that, less than one in five people from black community work on tele-platform (work from home meetings) which showcase lack of technical jobs in the community. Moreover, in pandemics many people from the community lost their job due of the shunt of in-person jobs. As a result, *Closing Restaurants* policy avoided customer-oriented jobs which results in helping the community to stay away from infection.

NHPI (Native Hawaiian and other Pacific Islander): From table 2, we can observe that both methods suggest that *Closing Business* has worked for the NHPI community in reducing the infection. However, if we compare the scores of GB methods on both levels (table 1 and table 2), we will notice that a significant difference in some policies effectiveness. For instance, the difference in score of *Closing Restaurants* policy is 0.083 which is significant. On the other hand, scores from RF methods differ slightly but follow the same policy effectiveness trend. Therefore, the estimations by the two methods do not quite agree with each other.

AIAN (American Indian/Alaska Native): From table 2, we observe that both methods suggest that *Closing Restaurants* (RF) policy has proven to be effective for the AIAN community. However, in terms of squared difference in table 3, *Stay-at-home* policy had a very different impact on the AIAN population compared to the whole population.

Conclusion

In this work, we proposed a novel data-driven approach to estimate effectiveness of different COVID-19 related NPI policies for fighting the spread (confirmed cases) and severity (death counts) of the virus. To achieve this, we proposed a novel stringency function to estimate the strictness of the NPI policies on a particular day (timestamp). Next, we trained two discriminative classifiers on confirmed cases and death counts as the binary target variable separately and stringency scores of NPI policies as features. The learnt weights were then considered as the effectiveness of the NPI policies. We also performed a comparative analysis between race-specific effectiveness and country-level effectiveness to see whether different communities were impacted differently. Our findings are briefly summarized below.

Do the policies affect the races differently? Yes, policies are indeed affecting different races differently in comparison to the whole population. For instance, according to both tree-based methods, the Asian race were impacted significantly differently by the Face-Mask Policy in comparison to the whole population. Similarly, Black people saw a different impact of the Stay-at-home policy compared to the whole population.

Which policy was more impactful among all policies? *Closing Restaurants* and *Closing Businesses* policies were effective for refraining the spread of the virus. Whereas, we believe *Stay-at-home* was the most useful policy for decreasing the number of severe cases/deaths.

Going forward, the work can be extended to incorporate new target variables like the change of hospitalization rate, vaccination rate and many more features. One can also utilize the proposed method to estimate the effectiveness of other countries NPIs policies considering their local issues.

References

1. Banholzer N, van Weenen E, Kratzwald B, Seeliger A, Tschernutter D, Bottrighi P, et al. Impact of non-pharmaceutical interventions on documented cases of COVID-19. medRxiv. 2020. Available from: https://www.medrxiv.org/content/early/2020/04/28/2020.04.16.20062141.
2. Culbertson JM. Friedman on the lag in effect of monetary policy. Journal of Political Economy. 1960;68(6):617-21.
3. Jovanovski T, Muric M. The phenomenon of lag in application of the measures of monetary policy. Economic research-Ekonomska istraživanja. 2011;24(2):154-63.
4. Centers for Disease Control and Prevention. Stay-At-Home order By Centers for Disease Control and Prevention. Centers for Disease Control and Prevention;. Available from: https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Stay-At-Home-Orders-Marc/y2iy-8irm.
5. Centers for Disease Control and Prevention. Face Mask order By Centers for Disease Control and Prevention. Centers for Disease Control and Prevention;. Available from: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/about-face-coverings.html#:~:text=People%20may%20choose%20to%20mask,about%20how%20to%20protect%20yourself.
6. Centers for Disease Control and Prevention. Closing Restaurants order By Centers for Disease Control and Prevention. Centers for Disease Control and Prevention;. Available from: https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Orders-Closing-and-Reope/azmd-939x.
7. Centers for Disease Control and Prevention. Closing and Reopening of Business By Centers for Disease Control and Prevention. Centers for Disease Control and Prevention;. Available from: https://www.cdc.gov/coronavirus/2019-ncov/community/guidance-business-response.html.
8. Centers for Disease Control and Prevention. Travel Ban orders By Centers for Disease Control and Prevention. Centers for Disease Control and Prevention;. Available from: https://www.cdc.gov/coronavirus/2019-ncov/travelers/travel-during-covid19.html.
9. Hale T, Angrist N, Goldszmidt R, Kira B, Petherick A, Phillips T, et al. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nature Human Behaviour. 2021;5(4):529-38.
10. Biau G, Scornet E. A random forest guided tour. Test. 2016;25(2):197-227.
11. Friedman JH. Greedy function approximation: a gradient boosting machine. Annals of statistics. 2001:1189-232.
12. Nature. Whose coronavirus strategy worked best? Scientists hunt most effective policies. Nature;. Available from: https://www.nature.com/articles/d41586-020-01248-1.
13. Brauner JM, Mindermann S, Sharma M, Johnston D, Salvatier J, Gavenčiak T, et al. The effectiveness of eight nonpharmaceutical interventions against COVID-19 in 41 countries. MedRxiv. 2020.
14. Cowling BJ, Ali ST, Ng TW, Tsang TK, Li JC, Fong MW, et al. Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in Hong Kong: an observational study. The Lancet Public Health. 2020;5(5):e279-88.
15. Bian Z, Zuo F, Gao J, Chen Y, Venkata SSCP, Bernardes SD, et al. Time lag effects of COVID-19 policies on transportation systems: A comparative study of New York City and Seattle. Transportation Research Part A: Policy and Practice. 2021;145:269-83.
16. Dass SC, Kwok WM, Gibson GJ, Gill BS, Sundram BM, Singh S. A data driven change-point epidemic model for assessing the impact of large gathering and subsequent movement control order on COVID-19 spread in Malaysia. PloS one. 2021;16(5):e0252136.
17. He S, Peng Y, Sun K. SEIR modeling of the COVID-19 and its dynamics. Nonlinear dynamics. 2020;101(3):1667-80.
18. Dergiades T, Milas C, Panagiotidis T. Effectiveness of government policies in response to the COVID-19 outbreak.

Available at SSRN. 2020;3602004.
19. Johndrow J, Ball P, Gargiulo M, Lum K. Estimating the Number of SARS-CoV-2 Infections and the Impact of Mitigation Policies in the United States. Harvard Data Science Review. 2020 11. Https://hdsr.mitpress.mit.edu/pub/9421kmzi. Available from: https://hdsr.mitpress.mit.edu/pub/9421kmzi.
20. Coughlin SS, Yiğiter A, Xu H, Berman AE, Chen J. Early detection of change patterns in COVID-19 incidence and the implementation of public health policies: A multi-national study. Public Health in Practice. 2021;2:100064.
21. Spooner F, Abrams JF, Morrissey K, Shaddick G, Batty M, Milton R, et al. A dynamic microsimulation model for epidemics. Social Science & Medicine. 2021;291:114461.
22. Mbuvha R, Marwala T. Bayesian inference of COVID-19 spreading rates in South Africa. PloS one. 2020;15(8):e0237126.
23. Warner ME, Zhang X. Social safety nets and COVID-19 stay home orders across US states: a comparative policy analysis. Journal of Comparative Policy Analysis: Research and Practice. 2021;23(2):176-90.
24. Haffajee RL, Mello MM. Thinking globally, acting locally—The US response to COVID-19. New England journal of medicine. 2020;382(22):e75.
25. Hodge JG. Federal vs. state powers in rush to reopen amid the coronavirus pandemic. Hodge JG Federal vs state powers in rush to reopen amid coronavirus pandemic Just Security. 2020.
26. Centers for Disease Control and Prevention. Clinical Questions about COVID-19: Q/A. Centers for Disease Control and Prevention;. Available from: https://www.cdc.gov/coronavirus/2019-ncov/hcp/faq.html#:~:text=Based%20on%20existing%20literature%2C,2%E2%80%9314%20days.
27. Getachew Y, Zephyrin L, Abrams MK, Shah A, Lewis C, Doty MM. Beyond the case count: the wide-ranging disparities of COVID-19 in the United States. A report prepared by The Commonwealth Fund doi. 2020;10.
28. CDC Covid Data tracker. Centers for Disease Control and Prevention;. Available from: https://covid.cdc.gov/covid-data-tracker/#trends_dailycases.
29. CUSP. COVID-19 US state policy database (CUSP). Centers for Disease Control and Prevention;. Available from: https://docs.google.com/spreadsheets/d/1zu9qEWI8PsOI_i8nI_S29HDGHlIp2lfVMsGxpQ5tvAQ/edit.
30. Dans E. There's no denying the evidence: Restaurants and bars are helping spread covid-19. Forbes Magazine; 2020. Available from: https://www.forbes.com/sites/enriquedans/2020/11/15/theres-no-denying-the-evidence-restaurants-and-bars-are-helping-spreadcovid-19/?sh=168c54db3353.
31. Lucas A. This chart shows the link between restaurant spending and new cases of coronavirus. Stanford University;. Available from: https://www.cnbc.com/2020/06/26/this-chart-shows-the-link-between-restaurant-spending-and-new-coronavirus-cases.html.
32. University of Alabama, Birmingham. Study suggests stay-at-home orders reduced COVID-19 infections and deaths - News — UAB. University of Alabama, Birmingham;. Available from: https://www.uab.edu/news/research/item/11642-study-suggests-stay-at-home-orders-reduced-covid-19-infections-and-deaths.
33. Centers for Disease Control and Prevention. Association of State-Issued Mask Mandates and Allowing On-Premises Restaurant Dining with County-Level COVID-19 Case and Death Growth Rates — United States, March 1–December 31, 2020. Centers for Disease Control and Prevention;. Available from: https://www.cdc.gov/mmwr/volumes/70/wr/mm7010e3.htm.
34. United States of Census Bureau. Asian Population More Likely to Report Fear of Going Out for Food as Reason They Did Not Have Enough to Eat During COVID. United States of Census Bureau;. Available from: https://www.census.gov/library/stories/2021/08/asian-households-cite-fear-of-going-out-as-reason-for-food-insufficiency-during-pandemic.html.
35. National Bureau of Economic Research. Racism targets Asian food, business during COVID-19 pandemic. National Bureau of Economic Research;. Available from: https://www.pbs.org/newshour/nation/racism-targets-asian-food-business-during-covid-19-pandemic.
36. Freeman RB. Planning for the "Expected Unexpected": Work and Retirement in the US After the COVID-19 Pandemic Shock. National Bureau of Economic Research; 2022.