Effectiveness of Governments’ Non-Pharmaceutical   
Interventions on Covid-19 Spread

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Abstract

This paper examines the effect of various non-pharmaceutical interventions (NPIs) that governments utilized to reduce Covid-19 spread. This paper serves to differentiate between NPIs that work versus those that do not and can inform policymakers in the continuing fight against Covid-19 or future pandemics. Data were compiled from 36 countries from April 2020 to October 2021. Policy effectiveness was measured by the reduction of the Covid-19 reproduction rate, using lagged first-difference estimates. We found evidence to support policies such as school closing, workplace closing, limitation on gathering, limitation on domestic and international travels, debt relief, increase testing availability, facial covering mandate, and elder protection policies. We found no evidence to suggest policies such as stay-at-home mandate and contact tracing to be effective. There is some evidence for policies' complementary effect and substitution effect.

Keywords: Covid-19, non-pharmaceutical interventions

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The Covid-19 pandemic has been and will likely be one of the worst crises of the 21st century, leaving massive losses in human lives and the world economy. Prior to the creation of Covid vaccines, governments are limited in their toolkits to combat the pandemic, and among such tools is a class of non-pharmaceutical interventions (NPIs). NPIs here define policy interventions for Covid-19 that are not related to vaccination or treatment regime. Since governments employ many of these different strategies at once, it is important to differentiate between policies that work versus those that do not, as to inform policies makers on their continuing fight against Covid-19, as well as future pandemics. Previous studies have been somewhat limited in their scope as well as vulnerable to bias. This paper seeks to discuss common issues faced by researchers when estimating the mitigation effect of NPIs as well as proposing its own solution. As there are now plenty of data regarding Covid-19 case numbers as well as governments’ responses, we aim for a data-driven approach, fully transparent in our modeling choices and results, as well as discussing its limitations. Another area that this paper explores is the interaction effect between different NPIs. The intuition here is that governments may enact policies that are not intended to mitigate Covid directly, but rather to increase the effectiveness of existing policies. The goal of this paper is not to conclusively evaluate the effectiveness of NPIs, but to add to the bigger conversation in the scientific community. This paper is structured as follows: Firstly, it will discuss previous literature and that informed the approach of this paper. Secondly, it will go through the data collecting and processing methodology. Thirdly, this paper will run multiple regression and talk about the results. Finally, there will be some concluding remarks and discussion for further research on this topic.

# Literature Review

Previous literature vastly supports different measures of mitigating Covid-19 spread, but they differ in approaches as well as exactly which NPIs do they prescribe. Some papers based their approach on case studies and comparisons. Chen et al. (2020) took the approach of examining China, Korea, Japan, Italy, the USA, and Brazil, compare their success combating Covid-19, and concluded that policies adopted by China and Korea, such as contact tracing and lockdown are effective. Li et al. (2020) compared the trend of the Covid-19 cases in 15 US states with periods in which local governments adopt policies. They showed that some case trends changed direction once when local governments start implementing lockdown, and again when masking mandate starts. However, these approaches are not data-driven and vulnerable to omitted variable bias. There was also a lack of discussions about statistical significance and assumptions. Castillo et al. (2020) has taken a more data-driven approach by using the difference in difference framework to look at Covid-19 infection rate among US states before and after the states issued Covid-19 NPIs. They found out that policies like workplace closing, school closing, furlough, travel restriction, and prohibition of public events help to reduce the infection rate. However, they note that a limitation of their approach was omitted variable bias due to other policies also implemented between before and after period, impossibility of separating the effect of individual policy in the stay-at-home mandate, endogeneity between infection rate and policies, and measurement issue with countries rapidly increase testing capacity toward the beginning of the outbreak. Brauner et al. (2021) does a looks at global data, and found evidence that limiting gathering, closing of businesses and schools was more effective than stay-at-home order. Woshkie et al. (2021) took a different approach, to avoid endogeneity, they measure the effect of containment policies on population mobility, before linking population mobility to Covid-19 spread, limited to data from European countries. They found out that stricter policies do in fact reduce more social mobility subsequently, with the strictest being mandatory stay-at-home order, and the weakest being large gathering bans. Perhaps one of the ongoing debates, as shown by these study results is that does strict lockdown policies works. Most papers highlight the importance of workplace closing and school closing policies, but they disagree whether a lock-down/stay-at-home order will be necessary. In implementation, this policy is also controversial, with high economic cost and authoritative nature.

This paper will seek to expand on works of previous paper, by contributing on four points:

1. This paper will discuss endogeneity concerns and propose a solution to solve endogeneity. We found that while NPIs response might reduce Covid-19 spread, high Covid-19 spread also push governments to take on more and more drastic NPIs. Without dealing with endogeneity, we expect an underestimate of the true effect or even a positive effect on Covid-19 spread.
2. This paper seeks to improve on other papers by including more NPIs in the modeling. Since governments typically employ various NPIs to combat Covid-spread, any exclusion in the modeling could lead to an overestimate of the policies that are included in the model.
3. Related to the topic of endogeneity, we will discuss the time horizon of different policies. The idea is that policies, especially Covid-19, has a certain lag before it has the indented effect. For Covid-19 spread, due to the lag between when exposure and diagnosis, we can expect up to 2 weeks to see the effect of policies. However, other policies might take longer to see an effect on the infection rate.
4. We will explore the interaction between some policies. We hypothesize that policies such as income support pair well with policies that increase the financial burden on citizens, such as workplace closing and stay-at-home mandate. We also hypothesize that public information campaign improves the effectiveness of compliance dependent policies, such as limiting gathering, stay-at-home mandate, and face-covering mandate.

# Descriptive Statistics

We utilize data from two sources. First, we got data about government NPIs from the Oxford Covid-19 Government Response Tracker (OxCGRT). They collect daily data from January 1st, 2020, of 180 countries about various NPIs. Various studies mention above also use this source, either as a variable directly, or as a resource to cross-examine their own data collection. The second source is the estimated reproduction rate of various countries, from Arroyo-Marioli et al. (2021). The reproduction rate here is defined as the average number of secondary cases produced by a primary case, thus the measure to go for when assessing Covid-19 spread. Brauner et al. (2021) also used this as the dependent variable in their paper, albeit they came up with their estimates.

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Description automatically generated However, we will not fully use all the observations from the two datasets. In detail, we will reduce the frequency to weekly, to avoid measurement errors in daily data. In addition, since countries start receiving Covid-19 cases at different times, we seek to include only countries that start roughly the same time, to account for global scientific and social development throughout the pandemic. To do this we tracked when countries had their 1000th case. Figure 1 illustrates this through a bar graph. We see that the bar plot peaked at the 13th week since Jan 1st, 2020, indicating in that week, a lot of countries reached 1000 cases. As a judgment call, we choose to include only countries that Map

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In addition, we choose the time range of data from April 8th, 2020 (15th week of 2020) to Oct 20th, 2021. We exclude the first few weeks of the pandemic due to governments’ rapid increase in testing capacity, which could lead to inaccuracy with the reproduction estimate.

Table

Description automatically generated Table 1 provides summary statistics for our data set. As per the description above, we are left with data from 36 countries over the period of 81 weeks. Variables from *SchoolClosing* to *EldersProtection* are ordinal indicators from the OxCGRT dataset. Lower numerical value indicates no policy or policy with lower intensity compared to higher value. The OxCGRT dataset also provides an index for overall government response, in our table referred to as *Response*. More details about how the index was calculated and what each indicator means can be found in the source material. Moreover, the variable *ReproductionRate* is from Arroyo-Marioli et al. (2021) will be our dependent variable.

# Table Description automatically generatedBasic OLS and FE Results

Let us start with a basic OLS result. Model (1) and (3) on table 2 display the result. Model (1) is simply regressing *ReproductionRate* on *Response* index, while model (2) replaces the index with individuals’ policy indicators. We see in model (1) that the overall response index does not have a statistically significant coefficient on reproduction rate, while in model (2) some policies have a positive statistically significant coefficient, except for *PublicEvents*. However, no well-informed statistician should take this OLS result seriously, due to the omitted variable bias. We can try to improve this regression by controlling for country fixed effect and time fixed effect. Model (2) and model (4) take this approach. While in model (2) the coefficient is statistically negative as we would hypothesize, the magnitude is minuscule. In addition, in model (4) where we break apart individual policy, we see that some policies, like *InternationalTravel, TestingAvailability,* and *EldersProtection* still have a positive statistically significant coefficient, suggesting that policies that restrict international travel, public information campaign, and elders’ protection scheme increase Covid-19 spread. However, one should still be skeptical of this result. One big issue we didn’t address is endogeneity. We hypothesize that NPIs will reduce the reproduction rate, however, when the reproduction rate is high, governments will be motivated to control the pandemic. As such if we don’t account for endogeneity, our estimate would be biased toward zero, or even show a positive effect.

# Chart, histogram Description automatically generatedFD and Lagged Independents Result

This paper suggests overcoming endogeneity by using the lagged value for policy indicators rather than the contemporaneous value. The idea is that the current Covid-19 spread can influence current NPIs response, but not policies choices made in the past, while the effect of policies made in the past will still be a valuable result. However, that approach will still produce bias if there is serial correlation in the dependent variable. Figure 3 gives us a time series plot of the reproduction rate for all 36 countries. We can see that indeed serial correlation will be a concern if we move with this approach without any adjustment.

Fortunately, we can also overcome this by using the first-difference estimator, where instead of running a regression on the dependent and the independents directly, we run a regression on the difference equation, which also implicitly controls for country fixed effect. This method is not unique to this paper, and Leszczensky and Wolbring (2019) discuss this approach’s viability and limitation. Lagged First-difference (LFD) estimator is a viable strategy to deal with endogeneity for panel data, however, there must truly be a lagged effect and the lag chosen in the model must be correctly specified.

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Description automatically generated**To best meet this constraint, we will run a finite distributed lag model with the first-differenced reproduction rate and the government response index. The idea is to look if there is an actual lagged effect and which lag specification would be best in general. Figure 4 display the result of this regression. We see that lag of 2 weeks has the strongest effect. This also lies with the intuition that the lag between exposure and diagnosis is roughly 2 weeks, so there exists a true lagged effect. With this, we arrive at our LFD model specification:

Table 3 displays the regression result using the LFD estimator. Model (5) has the same specification as the above equation, while model (6) adds in time fixed effect, and model (7) adds in month-year fixed effect. We can see that the estimates are robust to both time-related fixed effect so we will focus on the result of model (5).

Table

Description automatically generated From model (5), we see policies such as school closing, workplace closing, limit on gatherings, internal movement restrictions, international travel restriction, debt relief scheme, increase testing availability, face-covering mandate, and elders’ protection measures have negative statistically significant coefficients, suggesting that these policies are effective at reducing Covid-19 spread. These findings are similar to those in the literature review. Moreover, this paper adds itself to the argument that stay-at-home policies are less effective at mitigating Covid-19 spread than other containment policies.

There are several reasons why a policy would not show a statistically significant result. One, if the coefficient is negative but not statistically significant, like in the case of public transport closing and income support, it could be the case that the true effect is small and lost in data noises. Two, if the coefficient is small in magnitude or positive, it could be due to there not being an actual effect, or due to misspecification of the lag, something that we can investigate later.

# Exploring Policies Interaction

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Now we will move on to test interactions between policies. We will start with the intuition that containment policies that create financial pressure will pair well with income support policy. The idea is that such containment policies might be less effective due to lack of compliance unless there is some income support scheme. In addition, public information campaigns may play a supporting role in increasing compliance in policies such as gathering, stay-at-home order, and public masking. Table 4 displays the result of this exploration, model (8) is the same as model (6) and is included here as a source of comparison. Overall, we have two types of interaction:

1. Where the interaction term is negative, and the main effects are closer to zero or turn positive
2. Where the interaction term is positive, and the main effects are more negative, sometimes statistically significant

In the first case, we can understand it as a complement effect where two policies work together, this is the case for the closing of workspace and income support. In the second case, we can interpret it as a substitution effect, where one policy could be used in place of another. This is perceived to be the case between limiting of gathering versus public information campaign and stay-at-home order versus public information campaign. However, this result is only exploratory, and a more thorough investigation of the interaction effect is needed.

# Relaxing for Different Lagged Independents

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Going back to the specification of the LFD model, we are required to correctly choose the lag for independent variables for the model to be correct. While using a distributed lag model on the overall response index works, we can also use a distributed lag model with all different indicators. This will allow us to account for different lag effects for different policies. Figure 5 to Figure 19 reports the coefficients, grouped by policies. We see that for *SchoolClosing, WorkplaceClosing, Gathering, InternationalTravel,* and *EldersProtection* we have correctly chosen the lag. For *InternalMovement, IncomeSupport, DebtRelief, TestingAvilability,* and *ContactTracing* we should have chosen a later lag for the LFD specification. Further investigation should try to run LFD again with the changed specification to see if it changed the result. We shouldn’t use the result of the distributed lag directly is due to the large standard error by having a lot of variables on the right-hand side.

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# Discussion

We argue that our strategy has tackled endogeneity effectively, while also controlling for country fixed effect and time fixed effect. The inclusion of various NPIs ensures that we limit omitted variable bias as much as possible. However, there are still limitations: Firstly, is the suboptimal utilization of data, given that our result is the same with or without time fixed effect, it discredits the concern to include only countries that start an outbreak at the same time. With this relaxation, we could include more countries in our analysis. Secondly, since the policy indicator variables are on an ordinal scale, the coefficient magnitude does not bring a practical interpretation. The interpretation is limited to the sign and significance of the estimate. Thirdly, or perhaps the biggest threat to the analysis, is that while we include a lot of different NPIs, there could still be unobservable confounding variables, however, given our various controls, it is unlikely that a confounding variable that we missed will have a large effect on the result.

There are also many angles to take this paper further. One would be to change the specification of the lag in the LFD model to see result changes. Another would be an in-depth investigation into the topic of policy interaction and synergy. We could also use this framework to explore related questions such as what the effect of NPIs on Covid-19 fatality is. And in the context of the debate about the stay-at-home mandate, we suggest investigating factors that influence the effectiveness of the policy. A factor that could affect policy effectiveness is compliance. Chan et al. (2020) argue that confidence in the healthcare system (or lack thereof) and trust in government are good indicators for policy compliance, and thus provide a way to proxy for compliance when modeling.

In conclusion, by using the LFD framework for panel data, we have tackled the endogeneity issue with measuring the effectiveness of non-pharmaceutical interventions on Covid-19 spread. We found evidence to support policies such as school closing, workplace closing, limitation on gathering, limitation on domestic and international travels, debt relief, increase testing availability, facial covering mandate, and elder protection policies. We found no evidence to suggest policies such as stay-at-home mandate and contact tracing to be effective. There is some evidence for policies' complementary effect and substitution effect.

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