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COVID-19 Response Measures

The Effect of National Non-Pharmaceutical Intervention on Hospitalizations: An Empirical Study of Governments Response to the COVID-19 Pandemic

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Preface

This thesis is written as a part of the MSc degree in Economics and Business Administration at the Norwegian School of Economics (NHH), where the authors are majoring in Business Analytics and Business Analysis and Performance Management. The process of writing this thesis has been educational both academically and in terms of learning the extent of writing an academic paper. It has been rewarding for us to challenge ourselves in applying the knowledge we have acquired at NHH to a completely unknown field. This challenge, more than anything, has really shown us the debt of knowledge the past five years at this great institution has provided us.

We sincerely express our gratitude to our supervisor, Associate Professor Floris Zoutman, for his constructive criticism and suggestions throughout the process. His belief in our abilities and expertise in our field of study has been a pivotal contribution to the result. Lastly, we would also thank friends and family for supporting us throughout the process of writing this master's thesis.

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Abstract

Throughout this thesis we will analyze the reaction in the growth rate of COVID-19 related hospitalizations following the implementation of Non-Pharmaceutical Interventions (NPIs), in order to estimate their effectiveness. Additionally, our thesis will investigate the effect of specific NPIs, and the difference in NPI performance throughout the pandemic.

Although previous studies have focused on the reproduction number R, case growth, and cumulative deaths as their dependent variable, our thesis focuses on the number of daily COVID-19 related hospitalizations. We believe this to be a more reliable indicator of the spread of infection within the population. In doing so, we use a moving average of daily COVID-19 related hospitalizations as our dependent variable in our analysis.

In order to carry out our analysis, we conduct our first regression on 64 events of NPI implementation. We undertake this regression in order to compute the difference in the growth rate of COVID-19 related hospitalizations, before and after NPI implementation. Furthermore, to conduct our second regression, we use the effect of each NPI in place as our dependent variable, which utilizes dummy variables for each active group of NPIs in order to find the effect of each NPI group. Lastly, our concluding regression introduces a final variable to determine if NPIs are getting increasingly more effective throughout the pandemic.

For our conclusion, we determine from the results of our event studies that not all NPI implementations were successful, and that the outcome of our second regression indicates that there are extensive differences in the effectiveness of NPIs. We understood from our regression that *school closures* and *lockdown measures* are the most effective NPI in order to reduce the growth rate in COVID-19 related hospitalizations. Furthemore, we conclude that the implementation of these NPIs was more effective in reducing the growth rate of COVID-19 related hospitalizations during the first wave of infection.

Keywords – COVID-19, Event Study, NPIs, Hospitalization

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1 Introduction

1.1 Background and Motivation

In the first months of 2020, the COVID-19 pandemic upended life as we knew it. Due to its highly infectious nature, COVID-19, caused by the severely acute respiratory syndrome coronavirus 2 (SARS-CoV-2), threatened to overwhelm the healthcare systems of countries worldwide. To respond to this imposing threat, many countries imposed Non-Pharmaceutical Interventions (hereafter known as NPIs) to reduce the spread of the virus. Some of these NPIs include: limitations and bans on private and public gatherings, school- and business closures, and travel restrictions. In a desperate attempt to reduce the rising infection rates, governments shut down societies overnight. The COVID-19 virus forced governments worldwide to take action, and although there were many similarities in how they did so, there were also many differences. Even within the European Economic Area, governments responded differently. Firstly, a factor that might have contributed to why they did is the general lack of preparation. Secondly, many governments predicted that long-lasting restrictions and lockdowns would result in vast economic costs. Finally, based on the available data on the virus, scientists and epidemiologists believed that there was not enough scientific basis for closing down society. While some governments decided to follow "the precautionary principle" and close down, others followed the advice of their scientific experts. Exemplified by Sweden and the famous quote made by their epidemiologist to international journal *Nature* (Paterlini, 2020):

"Closedown, lockdown, closing borders - nothing has a scientific basis, in my view. We have looked at a number of European Union countries to see whether they have published any analysis of the effects of these measures before they were started and we saw almost none." - Anders Tegnell, Swedish state epidemiologist

These different types of responses to the virus prompted our curiosity, and drove us to investigate the effectiveness of NPIs. In order to do so, we will estimate the effect that NPIs have on the growth rate of COVID-19 related hospitalizations.

Our studys' research question is:

How effective are Non-Pharmaceutical Interventions in reducing the spread of COVID-19 and thereby hospitalization numbers?

The answer to this question can be of substantial interest to government officials and health authorities, who would be responsible for NPI implementations in future virus outbreaks. Additionally, the negative impacts of NPIs are numerous, and for an accurate cost-benefit analysis, the effectiveness of NPIs are a crucial input. In the next section of our introduction, we present the hypotheses we have constructed to efficiently answer our research question.

1.2 Hypotheses

To thoroughly analyze our data and answer our research question, we define three specific hypotheses and elaborate on our expectations for the results.

Hypothesis 1: *All events of NPI implementation during increasing growth rate in COVID-19 related hospitalizations will result in a reduced growth rate when the NPIs are expected to be effective.*

Our hypothesis suggests that we will see an apparent reduction in the growth rate of COVID-19 related hospitalizations when the introduced NPIs are expected to be effective.

Hypothesis 2: *The introduction of any NPI effectively reduces the growth rate of COVID-19 related hospitalizations, yet some NPIs are more effective than others.*

We believe that the introduction of any of the NPIs in our sample effectively reduces the growth rate in hospitalizations. However, we hypothesize that some of our NPIs will be significantly more effective to reduce the growth rate of COVID-19 related hospitalizations than others. We predict that this will be especially present for the more intrusive NPIs, meaning that we expect a greater growth rate reduction for highly restrictive measures.

Hypothesis 3: *Events of NPI implementation in the later stages of the pandemic are more effective in reducing hospitalizations than events in the first wave.*

Our final hypothesis states that events of NPI implementation in later stages of the pandemic are more effective than those in the first wave. We base this hypothesis on the belief that governments with more substantial information and knowledge about the virus should make better decisions in NPI introduction.

1.3 Structure

The remaining content of our thesis is structured as follows. The following section will consist of a review of relevant literature and an introduction of fundamental concepts. The third section will elaborate on our data collection process and further present our final sample after filtering out the appropriate and trustworthy data in our sample description section. The fourth section will dive into the event study methodology and elaborate on the supplementary theoretical framework. Further, the fifth section will consist of our empirical results, where we will present and discuss the results of our regressions. In the following sixth section, we will conduct different robustness tests to see how adjustments in our model specifications will affect our event regression coefficients. Additionally, in the seventh part of our thesis, we will summarize our results and conclude whether our analysis findings align with our original hypotheses. Lastly, the final sections of our thesis will present the limitations of our study, followed by our references and appendix.

2 Literature Review & Fundamental Concepts

This section of our thesis starts by conducting a literature review on previously conducted research relevant to our study. Furthermore, we present fundamental concepts necessary to have a maximized benefit of our thesis. Based on our research, there have been no studies estimating the effects of Non-Pharmaceutical Interventions on hospitalizations in a large sample of European countries. This section will help clarify the contributions of our research.

2.1 Literature Review

As mentioned in the introduction to this thesis, an argument against lockdown or the use of NPIs is the lack of scientific basis for it. Although this is an argument that is less common now than it was in the early stages of the pandemic, it is an argument that is important to present. In early 2020, there was little knowledge on dealing with the COVID-19 virus, as there was still uncertainty on its infectiousness and mortality rate.

Now that the pandemic has passed its one-year mark, the publications and scientific basis are rapidly increasing in scope. As the pandemic has been the dominating factor in the news, economics, and everyday life, the number of reports made by scientists, universities and governments has drastically expanded. A COVID-19 response team from Imperial College added to the research on estimating reproduction numbers and measuring the impact of social distancing measures on 11 European countries (Ferguson et al., 2020). They compare the prediction of epidemiological modeling estimated on data before intervention to actual outcomes across the different countries, using the number of COVID-19 related deaths to compare the effects. The main contribution from their work, that we use in our thesis, is the estimation of the interval from the introduction of NPIs until the NPIs have an impact on hospital numbers (Ferguson et al., 2020). The response team found the interval between infection and reduction in hospitalization to vary from 2 to 3 weeks, which will be an essential estimate in our analysis.

Currently, there are numerous studies available regarding COVID-19 response measures and the use of NPIs. Yet, there is no clear consensus on which NPIs are more efficient. Therefore isolating the effects of the different NPIs would be a valuable addition to the overall research on the subject. Flaxman et al. (2020) conducted a study to estimate the effectiveness of five categories of NPIs on the spread of COVID-19 in 11 countries. The five categories they looked at were social distancing encouraged, self isolation, school closures, public events banned, and complete lockdown. As an indication for the number of people infected, they use mortality data collected between January and early May 2020. They concluded that only one of these NPI categories, the lockdown, had been effective in 10 out of the 11 European countries studied.

The research conducted by Bendavid et al. (2021) evaluates the effects of NPIs on epidemic growth, and separates the effect of more restrictive NPIs to those less restrictive.The research takes into consideration ten countries within the EU, South Korea, Iran and the US. The data used in the study is daily case numbers reported by subnational administrative regions of each country merged with the type and timing of policies in each administrative area (Bendavid et al. 2021). This data relies upon equal and correct reporting on a regional level. The implementation of any NPI was associated with significant reduction in case growth in 9 out of 10 countries. In conclusion, the paper did not find notable benefits that the more restrictive NPIs would have on limiting cases' growth numbers. Comparable reductions in case growth may be achievable with less-restrictive interventions.

The work of this thesis is also influenced by Juranek and Zoutman (2020) and their case study on the use of NPIs within the Scandinavian countries. In their difference-in-difference approach, Sweden serves as a counterfactual to Denmark and Norway due to Sweden being the only country that had not initiated strict lockdown measures. Limited to the Scandinavian countries, they find the more stringent measures reduce the number of hospitalizations and intensive care patients per capita, thereby decreasing the stress on the health care system.

Our thesis contributes to existing research by focusing on daily COVID-19 related hospitalizations as our dependent variable, as was used in the paper by Juranek and Zoutman (2020). A new perspective relative to the other studies mentioned above that analyze the effectiveness of NPIs with the reproduction number R, case growth and cumulative deaths. We believe that daily hospitalizations might be a more reliable estimate, as hospitals and health authorities have a great capacity for accurate registration of COVID-19 related hospitalizations. Hospitalized patients are also likely to be tested in all countries, as they will experience severe symptoms. Other measures, such as the number of confirmed infections, are likely to be affected by measurement error due to differences in the testing regime between the countries (Juranek & Zoutman, 2020).

Another contribution to the existing research is our use of the event study methodology and the manual identification of NPI implementation events. Additionally, the use of the pre- vs. post-treatment comparison in our event studies is different from most comparable studies, as most usually conduct event studies with treatment groups and difference-in-difference models. The pre- vs. post-treatment comparison does not require any assumptions regarding control groups. This trait enables us to include a larger number of events and groups than previous research to reduce the systematic time-varying components within countries, permitting us to isolate the effect of each NPI.

2.2 Fundamental Concepts

Within this section, we will provide information on Non-Pharmaceutical Interventions (NPIs) and COVID-19 disease progression. We will present the definition of Non-Pharmaceutical Interventions and elaborate on the use of NPIs to reduce the spread of a pandemic virus. The following COVID-19 disease progression section will substantiate the reasoning behind the time frames in our event study. The section will present estimates on the time frame between the initial COVID-19 infection and hospitalization.

2.2.1 Non-Pharmaceutical Interventions

Non-Pharmaceutical Interventions (NPIs) are defined by the *Centers for Disease Control and Prevention* (2020) as "actions, apart from getting vaccinated and taking medicine, that people can take to help slow the spread of illnesses like pandemic influenza". In other words, NPIs are interventions or restrictions that national authorities pose on communities to decelerate the spread of a virus. These restrictions are commonly referred to as lockdowns, response measures, and measures of social distancing. The use of NPIs is pivotal to reduce the spread of a virus. Particularly in the case of new viruses, like COVID-19, where the population has little or no immunity against it (CDC, 2021).

2.2.2 COVID-19 Disease Progression

In order to accurately measure the effects of NPIs, we find it necessary to determine the median time from a COVID-19 outbreak to a significant increase in the growth rate of hospitalizations. This would provide us with an accurate estimate of the time interval from NPI implementation to a reduction in the growth rate in hospitalizations. This measure is found by the following equation:

  Median incubation time
+ Median time from symptom onset to hospitalization
+ Median time hospitalized

=**Median time from transmission to a significant increase in the growth rate of hospitalizations**

The measurements are found in an article by the *American College of Physicians Public Health Emergency Collection* (Lauer et al., 2020). This data is collected from the initial coronavirus outbreak in the Hubei province in China prior to February 24th, 2020. The article found that the median incubation period was estimated to be 5.1 days, with a 95% confidence interval of 4.5 to 5.8 days. In the study, among those who developed symptoms, the median time from symptom onset to hospitalization was 1.2 days. These results indicate a median time from transmission to hospitalization of 6.3 days.

The last factor, the average time hospitalized has been the most challenging component to detect, as there has been considerable difference in estimates. In a report published by the Norwegian Public Institute of Health the results suggest an average hospitalization time of around 8.7 days during the first months of the pandemic. However, this estimate drops to 7.6 from June 2020 to January 2021 (NPIH, 2021), with the knowledge that treatment was the probable determining factor of this reduction.

Our thesis investigates the reduction in the growth rate of COVID-19 related hospitalizations. It is therefore important to estimate the time interval from when NPIs are implemented, until when we expect to see a significant effect on the growth rate of hospitalizations. The median time from transmission to hospitalization is 6.3 days, and the estimated time hospitalized is approximately 8 days. As our estimations are based on 7-day moving averages of hospitalizations, we will therefore not be able to see a significant effect on the growth rate until the hospital discharges outweigh the influx of patients. Therefore, we believe the findings of the Imperial College response team of 2-3 weeks from NPI implementation until NPI effect to be an accurate estimate (Ferguson et al., 2020).

3 Data Collection and Sample Description

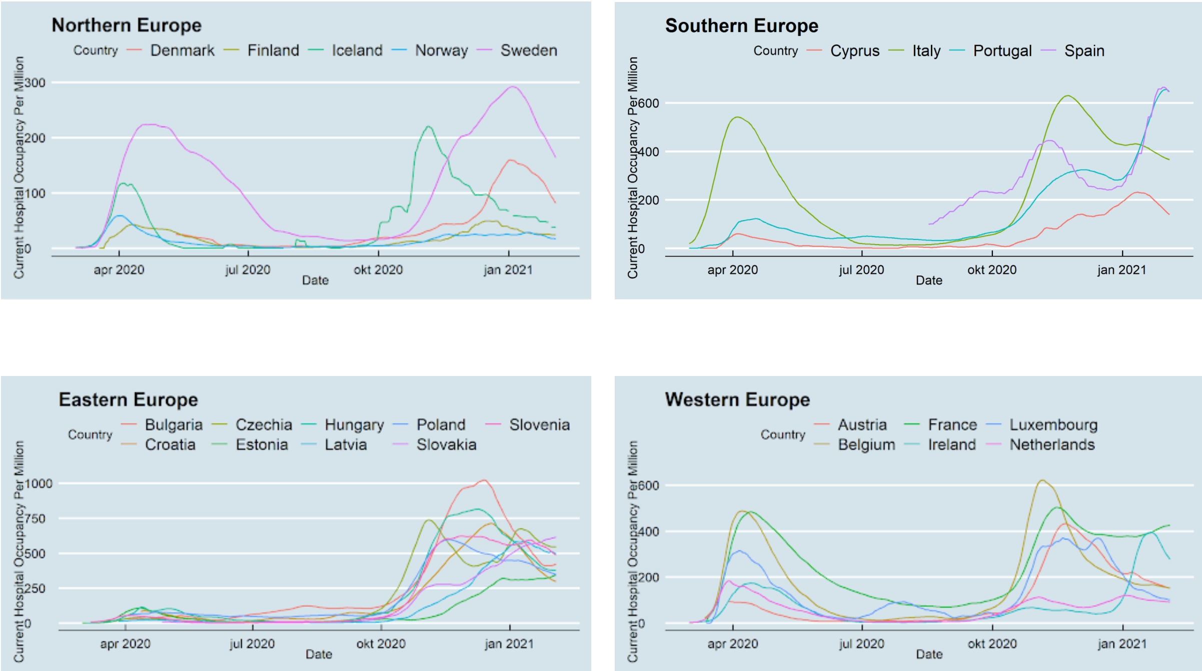
The data sample studied in this thesis consists of the daily hospitalization data from 24 countries from March 2020 to March 2021. The sample further includes data on all Non-Pharmaceutical Interventions implemented in Europe during the same time frame. This section will elaborate on our data collection and selection process. In the development of our final sample we have encountered challenges in collection, reliability and coherence. The following subsections will show how we have encountered these impediments and how we are able to minimize their influence.

3.1 Data on Daily Hospitalized COVID-19 Patients

The data on "Daily Hospitalized Patients" has been the most arduous part of the data collection process. This was a challenge for us because the data has been unavailable for many European countries and non-existent for others. There has been no sole data source that has collected and made this data available. While most of the data were collected from *Our World in Data*, outliers and missing data from specific countries have been found elsewhere (OWID, 2021). A large portion of the data is collected separately from individual sources, namely health departments and institutes of the sampled countries. Although a single source would have been beneficial, directly collecting data from individual government websites can add to the reliability of the data itself.

However, there is uncertainty within the individual countries' accuracy in recording daily hospitalized COVID-19 patients, as their method of hospitalization registration differs. This is because many countries do not register on a daily basis, or over weekends. Considering that the daily hospitalized COVID-19 patients is an uncertain estimate, all our analysis is based on a 7-day moving average. This is to avoid the issue of outliers and missing values and account for the differences in registering. The 7-day moving average for COVID-19 related hospitalizations for each country is presented in the figures below:

Figure 3.1: Hospital Occupancy in European Countries Per Million



For the purpose of enhancing the credibility of our analysis, during our data collection process, we have been in contact with numerous health authorities of different European countries. We did so in order to collect data and acquire information on the data already available in our sample

3.2 The Response Measures Data

To test the effect of different comparable Non-Pharmaceutical Interventions, it is necessary to find data that has assembled and compared different NPIs across different European countries. The data is found at the European Centre for Disease Prevention and Control (ECDC, 2021). This dataset, which is collected from official public websites of different countries, contains every NPI implemented in all European countries, with their respective date ranges. The response measures data come with four disclaimers. Firstly, there is substantial heterogeneity within measures related to physical distancing and how these NPIs are implemented between countries, principally in the level of enforcement and the amount of exceptions. Secondly, the response measures in the dataset are the ones reported nationally. For most countries, if there is a significant local outbreak, regional or local measures precede national ones. Thirdly, the dates introduced in the data might not be precise. It is not clearly stated whether the date presented is the date of informing the public of impending NPIs or the actual date of NPI implementation and is in our thesis regarded as the implementation date. Lastly, the response measures in the dataset might be difficult to count for, because unfortunately, the COVID-19 social measures that are no longer in force are removed from the official website. (ECDC, 2021).

Not all the measures that are shown in the dataset are relevant to our study. Therefore, presented in Table 3.2 below are the actions taken to condense the response measures data. Firstly, the response measures that were defined as "partially relaxed measures" were removed from the sample. Secondly, we remove all NPIs that have been active in less than three countries and are not similar to any other NPI. An example is the NPI *Closure Of Public Transport*, which was only active in Croatia and Slovenia. Response measures with limited observations do not provide us with reliable estimates on their efficiency and are therefore removed. Lastly, we consolidate NPIs that we consider to be highly homogenous and that we expect to have a limited difference in disease transmission. An example is the NPIs that restricted large indoor gatherings. *IndoorOver500* and *IndoorOver1000* were merged into *IndoorLargeGatherings*. See the measures underlined in the appendix *Measures To Identify Events* for the complete sample of NPIs.

Table 3.1: NPI Cleaning

Action No.	Action Taken	Number of NPIs
1	All NPIs Registered in Europe	64
2	Remove Partial NPIs	36
3	Remove NPIs Active in Less Than 3 Countries	34
4	Merge NPIs Considered Too Similar	28
5	Complete Sample of NPIs	28

The complete sample of 28 NPIs is used to identify our events, which we will elaborate on within the *Identifying the NPI Events* section of our thesis. It is evident that with only 25 countries, we are unlikely to identify enough events to be able to run a regression containing variables for all 28 NPIs in our sample. In the next section, we will correct this matter.

3.2.1 NPI Grouping Variables

With variables for all 28 NPIs, the explanatory power of our regression is expected to be low. For this reason it is necessary to sort NPIs into groups in order to reduce the number of variables. The NPI will be sorted based on similarity and intensity. Some groups are dummy variables that are activated if one or more of the similar NPIs are active. The remaining groups are based on intensity. That means that if few similar variables are activated for an event a "low intensity variable" is activated, while if many similar variables are activated the "high intensity variable" is activated. The *StayHomeOrder* NPI is the only one that is a dummy variable for a singular NPI, as this is an extensive and unique measure that does not fall within any of the other NPI groups. See the explanation for the event groups variables below:

WorkRestrictions. Dummy variable that indicates if one of the measures AdaptationOfWorkplace, Teleworking or WorkPlaceClosures are active. These are all NPIs that result in the implementation of office restrictions and thereby a work-from-home demand for most non-essential workers.

SchoolCloseLow. Dummy variable that indicates low intensity of the variables ClosDayCare, ClosHigh, ClosPrim and ClosSec. Low intensity means that less than three out of four of the educational institutions' NPIs listed are active at the time of the event.

SchoolCloseHigh. Dummy variable that indicates high intensity of the variables ClosDayCare, ClosHigh, ClosPrim and ClosSec. High intensity means that more than two out of four of the educational institutions' NPIs listed are active at the time of the event.

CloseVBLow. Dummy variable that indicates low intensity of the variables EntertainmentVenues, GymSportsCentres, HotelsOtherAccommodations, NonEssentialShops, PlaceOfWorship and RestaurantsCafes. Low intensity means that more than three out of six of the visitation based businesses NPIs listed are active at the time of the event.

CloseVBHigh. Dummy variable that indicates high intensity of the variables EntertainmentVenues, GymSportsCentres, HotelsOtherAccommodations, NonEssentialShops, PlaceOfWorship and RestaurantsCafes. High intensity means that less than four out of six of the visitation-based businesses NPIs listed are active at the time of the event.

GatheringsLow. Dummy variable that indicates if one of the measures OutdoorLargeGatherings, IndoorLargeGatherings, MassGather are active. These are all NPIs that put restrictions on the public gathering of large groups of people.

GatheringsHigh. Dummy variable that indicates if one of the measuresBanOnAllEvents, OutdoorSmallGatherings, IndoorSmallGatherings, MassGather50 are active. These are all NPIs that put restrictions on gathering of smaller groups of people.

PrivateGatherings. Dummy variable that indicates if one of the measures SocialCircle and PrivateGatheringsRestriction is active. These are both NPIs that put restrictions on gatherings in the private home.

StayHomeRec. Dummy variable that indicates if one of the measures StayHomeRec and StayHomeRiskG is active. These are both NPIs that involve stay-home recommendations for the population.

StayHomeOrder. Dummy variable that indicates if the NPI StayHomeOrder or commonly referred to as “lockdown” is active.

Figure 3.4: Overview of NPI Groups Implemented Per Country

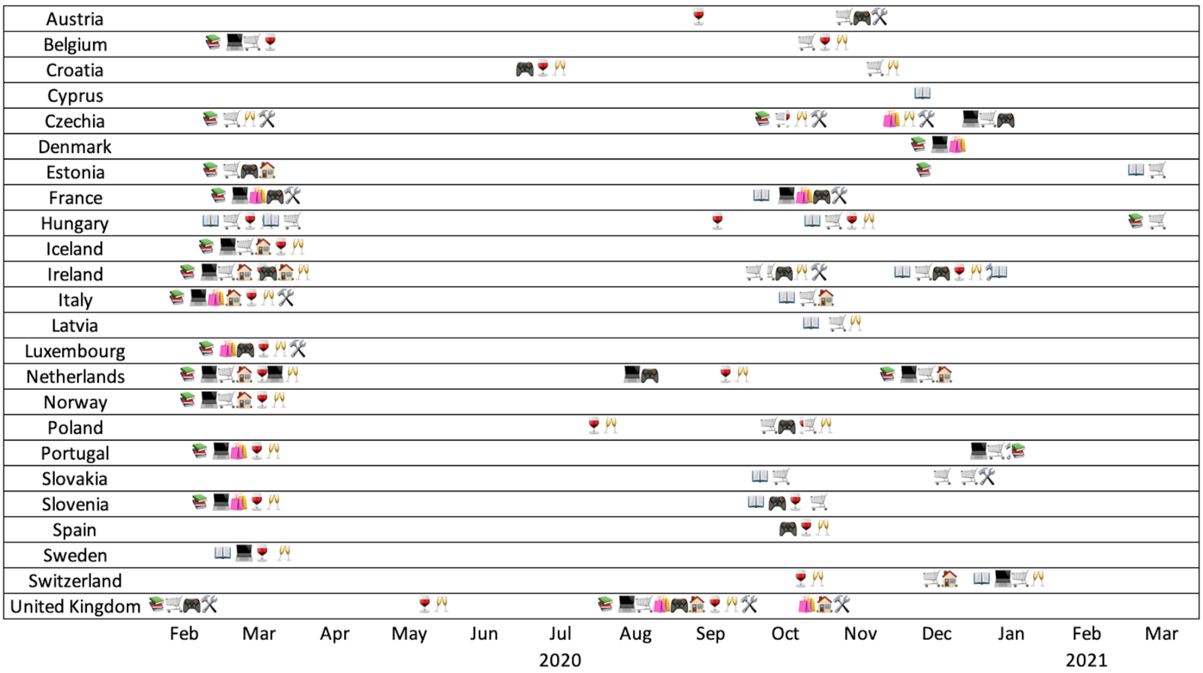


Figure 3.4: Overview of NPI groups implemented per country. NPI indicators are given by SchoolCloseLow:📖 , SchoolCloseHigh:📚 , WorkRestrictions:💻 , CloseVBLow:🛒 , CloseVBHigh:🛍️ , PrivateGatheringRestrictions:🎮 , StayHomeRec:🏠 ,GatheringsLow: 🍷, GatheringsHigh:🥂, StayHomeOrder:🛠️ .

3.3 Panel Data

The data set used in our thesis is a panel data set. Using a panel data set enables us to create more extensive models and estimate more accurately the inference of model parameters, instead of purely analyzing cross-sectional data or time series. Additionally, in most cases, it will contain more sample variability and more degrees of freedom than cross-sectional data. The use of cross-sectional data and time series is not relevant for our study because we seek to analyze the change in hospital admissions over time. Therefore our best option is to work with panel data. Our panel data refers to the time from March 2020 to March 2021. Within this range, we will isolate the effect of COVID-19 measures variables while isolating the effect on the growth rate of daily hospitalizations as the dependent variable.

Panel data models sometimes include variables that vary across individuals and over time. Additionally, they may also include variables that are constant for all individuals but vary over time. This counts for most of our data, such as the timing of active COVID-19 response measures and hospitalization data. Finally, in many cases, models with panel data also contain variables that vary across individuals but are constant over time. These variables can often be difficult to observe and are referred to as unobserved heterogeneity, which is the part of the model's error term (Hsiao, 2006).

3.4 Pandemic Data Collection

We have collected the data used for this thesis throughout the spring of 2021, and throughout this time, the availability of data has increased. Collecting data from the beginning and during a pandemic has been challenging. Health departments and hospitals register infection data in different ways. This means that the reliability of our hospitalization data relies on the assumption that these institutions have registered and categorized their data uniformly. Additionally, the data from the beginning of the pandemic is uncertain and void.Therefore, in each of the individual data collection sections above, we present measures we have taken to reduce the margin of error. For this reason, the data we present has been cleaned to contain only values that present an appropriate estimation. In the final part of our thesis we reflect on the limitations of our study, that will further elaborate on the issues that occur in pandemic data collection.

4 Empirical Methods

Within our thesis, we follow the event study methodology aligned with additional theory to conduct our analysis. We use event studies to measure the effect of NPI implementations on the growth rate of hospitalizations. In this section, we elaborate on the event study methodology. Furthermore, we define our use of pre- vs. post-treatment comparison to estimate each individual event's effect. Lastly, we illustrate the use of OLS-regression, and how we derive the regressions in our thesis.

4.1 Event Study Methodology

The purpose of using the event study is to observe and analyze the impact of an event on a specific return variable before and after the event (Aktas et al., 2007). Although the method is more commonly used in finance, the methodology has increasingly been applied to other research areas. This is because it is easily applicable to all studies that aim to analyze how an event affects any variable. For instance, this method has been used to analyze the effect of the American 1971 cigarette advertising ban, and the Effect of Social Distancing Measures on Intensive care Occupancy in 2020 (Lamdin, 1999; Juranek & Zoutman, 2020).

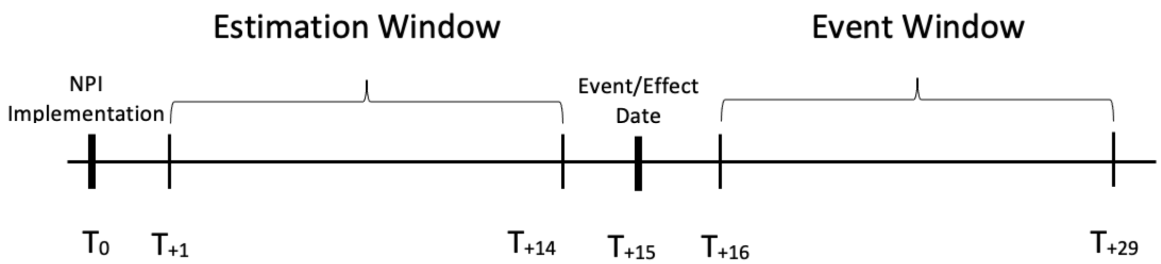
Throughout our thesis, the event study methodology is applied to analyze to what extent the introduction of different NPIs causes a reduction in the growth rate of COVID-19 related hospital admissions. The calculations are based on the estimation of growth rate coefficients for daily COVID-19 related hospitalizations. The "before event" coefficients will be estimated in the estimation window and serve as a counterfactual for the growth rate, had the NPIs not been implemented. The "after event" coefficients will be estimated in the event window. In our further analysis, the event coefficients will be used to estimate the effects of the distinctive NPI groups presented in our *Data Collection and Sample Description* section.

4.1.1 Defining The Events and Identify The Time Periods

The first step in conducting an event study is to define the event (or events) of interest and establish which surrounding time frames are to be included in the event study (Campbell et al., 1997). An event in this thesis is defined as the day on which the implemented NPIs are expected to affect the growth rate in COVID-19 related hospitalizations. Although in finance, the event date usually refers to the day of a shock creating announcement, the nature of the COVID-19 virus does not allow us to use the announcement of NPI implementation as our event date. The logic behind this is outlined in Section 2.2.2 of our thesis, as there is a time lag from the NPI implementation to the time of expected NPI effect.

As illustrated in Figure 4.1 below, in our further analysis, we will treat the "fifteen days after the implementation of NPIs" as our event/effect date. The two weeks between NPI implementation and the event/effect date will function as our estimation window. Furthermore, the two weeks following our event/effect date will function as our event window. The following subsections will elaborate on the calculations of the event study windows.

Figure 4.1: Event Study Timeline



Identifying the NPI Events

The first part of the event study is to identify the events. In our thesis a drastic increase in the number of active NPIs is the first defining criteria in order to identify an event, where all increases of more than 2 NPIs during a short day-span is considered drastic. The full sample of the NPIs used in our event identification process are presented in our appendix, and consists of a total of 28 NPIs. The NPIs might sometimes be introduced over a number of days, often irregularly and without any apparent plan behind it. Therefore, if the introduced measures are spread over a limited number of days, the event date will be chosen based on the median day of implementation.

The second important criteria for event identification is that the NPIs are introduced during a period of rising infection. In other words, when the growth rate of COVID-19 related hospitalizations are increasing. We chose this as a criteria in order to exclude events where NPIs are introduced as relaxing measures to others NPIs. These events would potentially cloud the data, because the estimation period could include a time span of decreasing hospitalizations, and the event period an interval of increasing/flat rates of hospitalization. It is also important to note that the introduction of new NPIs during a period of decreasing infection often occurs closer to the summertime, where there is an apparent seasonal effect on the spread of the virus. As seen in our raw data and on the online medical information cite *Medscape* that estimates a peak infection period for coronaviruses from December to April (Meneghetti, 2020).

Furthemore, within the data set, there are substantial differences between each countries' number of defiable events, and the number of NPIs implemented for each of these events. While most countries have one clear wave of infection during the spring and another during the fall of 2020, a considerable number of countries only have one definable event. An example of this is Norway, with the 12th of March being the only day that had more than one of the NPIs in our sample implemented. In Table 4.1.1 below we present the actions taken in our event selection process.

Table 4.1: Event Cleaning

Action No.	Action Taken	Number of Events
1	Identify Events of 2 NPIs or More	107
2	Events With Positiv Growth Rate on Implementation Day	76
3	Merge Events Within a 7 Day-Span	64
4	Complete Sample of Events	64

Estimation Window

The first time interval to choose in an event study is the estimation window. The purpose of the estimation window is to estimate the expected progression of the observations in the sample. Additionally, in order to not be affected by the event, the estimation window should always be before the event window. Choosing the length of the estimation window demands precision in balancing. A longer window is preferable as it increases the precision in what is considered expected progression, while on the other hand a shorter window is a stronger indicator of the current situation. Even though in finance it is common to choose an estimation window that ranges from 250 to 30 days before the event occurred, there is no set length for estimation windows (Aktas et al., 2007).

However, the length of the estimation window will be shorter in the case of an epidemiological event study. Regrettably, we do not have any available data on COVID-19 related hospitalizations before the virus started spreading at scale, and NPIs were implemented. Nonetheless, data prior to the substantial rise in hospitalizations would not be relevant for our study, since we are considering an expected progression in growth rate for COVID-19 related hospitalizations during the virus outbreak. Therefore, our estimation window is set from the date that the NPIs are implemented, until the day the NPIs are expected to be effective, namely fourteen days.

The determination of the estimation window is rather limited by our data. For many of the events in our sample, it could be highly beneficial to experiment with an estimation window that stretched further beyond the day of NPI implementation. This is because the NPI implementation is a result of rising infections and thereby hospitalizations. Unfortunately, a substantial part of the countries in our sample started registering the related hospitalization numbers at the time of NPI implementations. Therefore, a longer estimation window would greatly reduce the events in our sample.

Event Window

The next important step in the event study methodology is to establish the event window. The purpose of the event window is to capture the effect of the event. This can sometimes be challenging, since it is usually difficult to predict the exact time period in which the effect of the event is most present. Choosing the length of the event window is, as for the estimation window, about finding the right balance. A short event window could potentially exclude some of the NPI effect as well as not account for a potensial random drop in growth rate. However, if the event window is too long it could potentially include a time period where the event is no longer effective, as well as include other factors irrelevant to the event itself.

As mentioned in the *Disease progression* section of our thesis, the effects of the NPIs are estimated to occur after 2-3 weeks. Therefore, an appropriate event window is set to start immediately after the time in which the NPI implementations are expected to be effective. In order to capture the full effect of the event, we find it reasonable to use an event window of 14 days. This choice gives us the opportunity to compare two time periods of identical length in our event study.

Although the length of our event study windows had to be based on assumptions and doubtable estimates, we find them to be pertinent for the purpose of our paper, in order to estimate the effect of NPIs on hospitalizations. The event study windows presented in this section are the ones that will be used for the rest of our analysis. Moreover, we will test the strength of our assumptions in our *Robustness Tests* section later in our thesis.

4.2 Estimating Event and NPI Groups Effects

With the intention to build on the event study windows we use the pre- vs. post-treatment comparison to compare those windows, and to estimate the effect of each event. These estimated effects will be used in our further analysis. In the following section we will go over our methodology for identifying and isolating the effects of the events and NPI groups.

4.2.1 Pre- vs. Post-Treatment Comparison

When estimating the effect of the implemented NPIs, we use a pre- vs. post-treatment comparison, a particular type of simple difference evaluation (Pomeranz, 2017). It is an arduous and uncertain job to identify a standard control group to compare the treatment with, in this case NPI implementation. This is because NPI implementations take place in different countries, times and in various stages of the pandemic. Ideally, we would use a country that has not had any NPIs implemented as a control group, to compare growth rate in hospitalization. However, since there is no European country that allows us to do so, we have to compare each country with itself, before and after NPI implementation. This enables us to evaluate how the growth rate changes over time, and estimate the difference in growth rate before and after the event/effect date.

While a simple pre-post comparison could lead to biased results, there are certain settings in which a pre-post analysis can yield credible estimates while only analyzing one group (Pomeranz, 2017). The key assumption of this method is that the treatment is the only factor that influenced a change in outcomes over that time period. Without the treatment, the outcomes would have remained the same. However, this is often not the case in real life. Over time many factors can affect an outcome, which contradicts the key assumption made above. Therefore, in order to use this method, we must assume there are no other systematic changes over time other than the treatment. To account for this, we observe several different events, in order to cancel out any systematic time-varying components. The event study windows are also limited to a relatively short time-span, where we assume that each country's growth rate would have remained stable without any NPIs implemented. Therefore, any change in growth rate will be attributed to the treatment. Furthemore, the benefit of this method is that it does not require information on the groups that are not receiving treatment. Therefore, we can look at the effects the NPI implementations have on the individual countries separately.

4.2.2 OLS-Regression

In order to estimate the NPI effects, we use an ordinary least squares regression (OLS). The OLS model is a method for estimating a linear regression model, in which the estimates for the parameters are acquired through a minimization of the sum of squared residuals (Woolridge, 2018). The residuals are the differences between the observations and the values of the dependent variable estimated by the OLS model. To answer the hypotheses of the thesis, we use different OLS models for exploring each hypothesis.

Hypothesis 1: *All events of NPI implementation during increasing growth rate in COVID-19 related hospitalizations will result in a reduced growth rate when the NPIs are expected to be effective.*

For this hypothesis we examine a data set containing all the events and their corresponding 7-day moving average growth rate of hospitalization. Assuming that the effect of the implementation will be present after 14 days, we include dummy variables into the data set representing the time after implementation. The model is as presented below:

$$G_t = \gamma_0 + \gamma_1 * Week1_t + \gamma_2 * Week2_t + \gamma_3 * Week3_t + \gamma_4 * Week4_t + e_t \quad \textbf{(4.1)}$$

G_t, the dependent variable represents the 7-day moving average growth rate of COVID-19 related hospitalizations. *Week1* is a time dummy variable, and will be 1 for days 1-7 in the event study window, equal to two weeks prior to the effect date. *Week2* will be 1 for days 8-14 in the event window, equal to one week prior to the effect date. *Week3* and *Week4* will follow the same logistics, just after the effect date.

The intercept γ_0 indicates the average growth rate on the effect date for all events included as we look at this day separately for this regression. Coefficients γ_i for each week indicator represent the average difference for that given week relative to the effect date. We use this method of comparing averages across all events to be able to grasp an overview of the development of the growth rate in the period after the introduction of NPIs, relative to what we assume to be the effect date. Since the events are independent, the average will give a clear indication of the effect of NPI implementation in general, without saying anything about which of the events or NPIs that are effective. In order to understand how effective each event has been, we use a different regression in the following section.

We view each implementation with different combinations of NPIs as a treatment, and use a pre vs. post treatment event study to estimate the effect on reducing the growth rate of COVID-19 related hospitalizations. The effects are estimated using the following OLS-regression:

$$Y_{i,t} = \beta_0 + \beta_i * After_t + e_{i,t} \tag{4.2}$$

The dependent variable Y_i, trepresents the 7-day moving average growth rate of COVID-19 related hospitalization for event i. Because we are taking into account a two-period event, pre- and post treatment, the intercept coefficient β_0 represents the average growth rate in the period before the NPIs are expected to be effective. Furthemore, $After_t$ is a dummy variable that indicates whether we expect the effect of the NPIs to have an impact on a given day. This dummy variable will be "1" for all days after the effect date (14 days after implementations). Our goal for the regression is to find the coefficient β_i for this dummy variable as an indicator of the effect of the NPI implementation for each event i. This coefficient will represent the change in 7-day moving average growth rate of hospitalization after the effect date for event i. With the obtained effects of each event, we are able to analyse the differences in the events by identifying the NPIs responsible for an effective or ineffective implementation.

Hypothesis 2: *The introduction of any NPI effectively reduces the growth rate of COVID-19 related hospitalizations, yet some NPIs are more effective than others.*

The obtained coefficients representing the effectiveness of the event are included into a data frame containing the characteristics of the event, e.g. the implemented NPIs for the given event. We intend to identify the NPIs present in the most successful events, and look for statistical significance so we can conclude on the effectiveness of the different NPIs. To do so, we use the following OLS model:

$$E_i = \delta_0 + \sum \delta_j * NPIgroup_j + e_i \tag{4.3}$$

In this model, E_i represents the effect of the event, given by the coefficient β_i from equation 4.2. Additionally, $NPIgroup_j$ represents dummy variables for the different NPI groups j identified and presented in section 3.1.2, equal to 1 if the given NPI group was implemented in event i, and 0 otherwise. The intercept δ_0 represents the expected growth rate when no NPIs are implemented. Therefore, in order to answer our hypothesis we are interested in the coefficient δ_j , that represents the estimated effect NPI group i has on the 7-day moving average of COVID-19 related hospitalizations across all events. Moreover, we will use this equation in order to investigate our third hypothesis.

Hypothesis 3: *Events of NPI implementation in the later stages of the pandemic are more effective in reducing hospitalizations than events in the first wave.*

In order to inspect the difference between the effect of NPIs implemented in the first pandemic wave, we include a dummy variable into equation 4.3 to indicate whether the event took place in the spring of 2020 or not. The model is then:

$$E_i = \delta_0 + \sum \delta_j * NPI\_group_j + \delta_f * FirstWave + e_i \qquad (4.4)$$

All variables are explained in the section about hypothesis 2, other than the coefficient and dummy variable for the first wave. With the intent of answering our hypothesis we aim to identify the coefficient δ_f which indicates the difference in effect, with all NPIs taken into consideration.

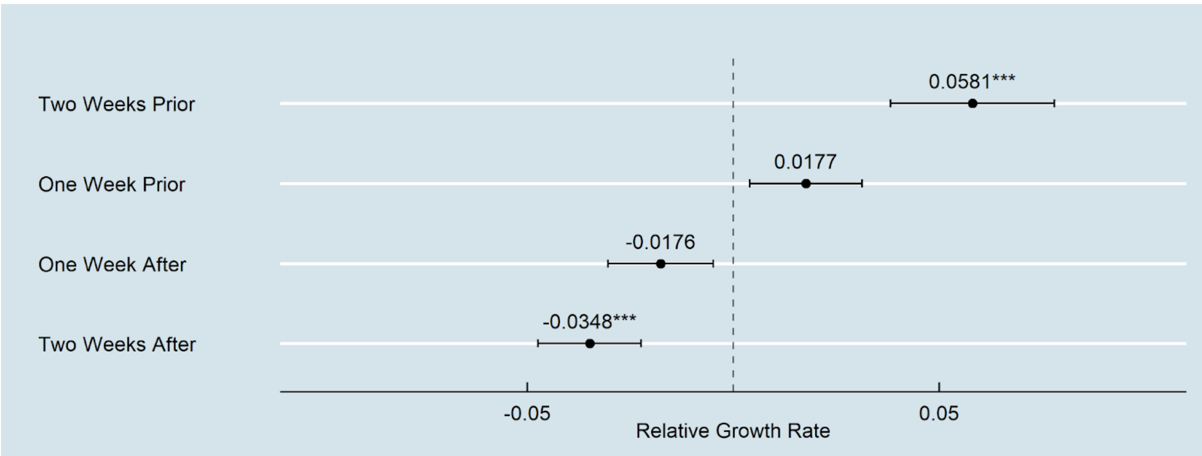
5 Empirical Results

In this section of our thesis we present the results of our regressions in order to provide concrete answers to our hypotheses and respond to our research question: *How effective are Non-Pharmaceutical Interventions in reducing the spread of COVID-19 and thereby hospitalization numbers?*. Our analysis utilizes the event study methodology and consists of three parts that address our hypotheses. Firstly, we will present the results of our event specific regression, that show the effect of each NPI implementation event. Secondly, we will present our NPI specific regression, and reflect on the most effective NPIs in our study. Lastly, we will present the results of our first wave indicator regression.

5.1 Event Regression

In this part of our empirical results section we present the outcomes of our event regressions. These regressions refer to our first hypothesis and analyze if the introduction of an NPI during a period of increasing growth rate in COVID-19 related hospitalizations will result in a reduced growth rate. Subsequently, in order to analyse the general effect of the implementations within our event window, we carry out the OLS regression from Equation 4.1. Within this model the 7-day moving average growth rate of hospitalization is the dependent variable, and the independent variables are dummy variables that represent the time around the effect date. The results of this regression are displayed below in Figure 5.1.

Figure 5.1: Weekly Average Growth Rate

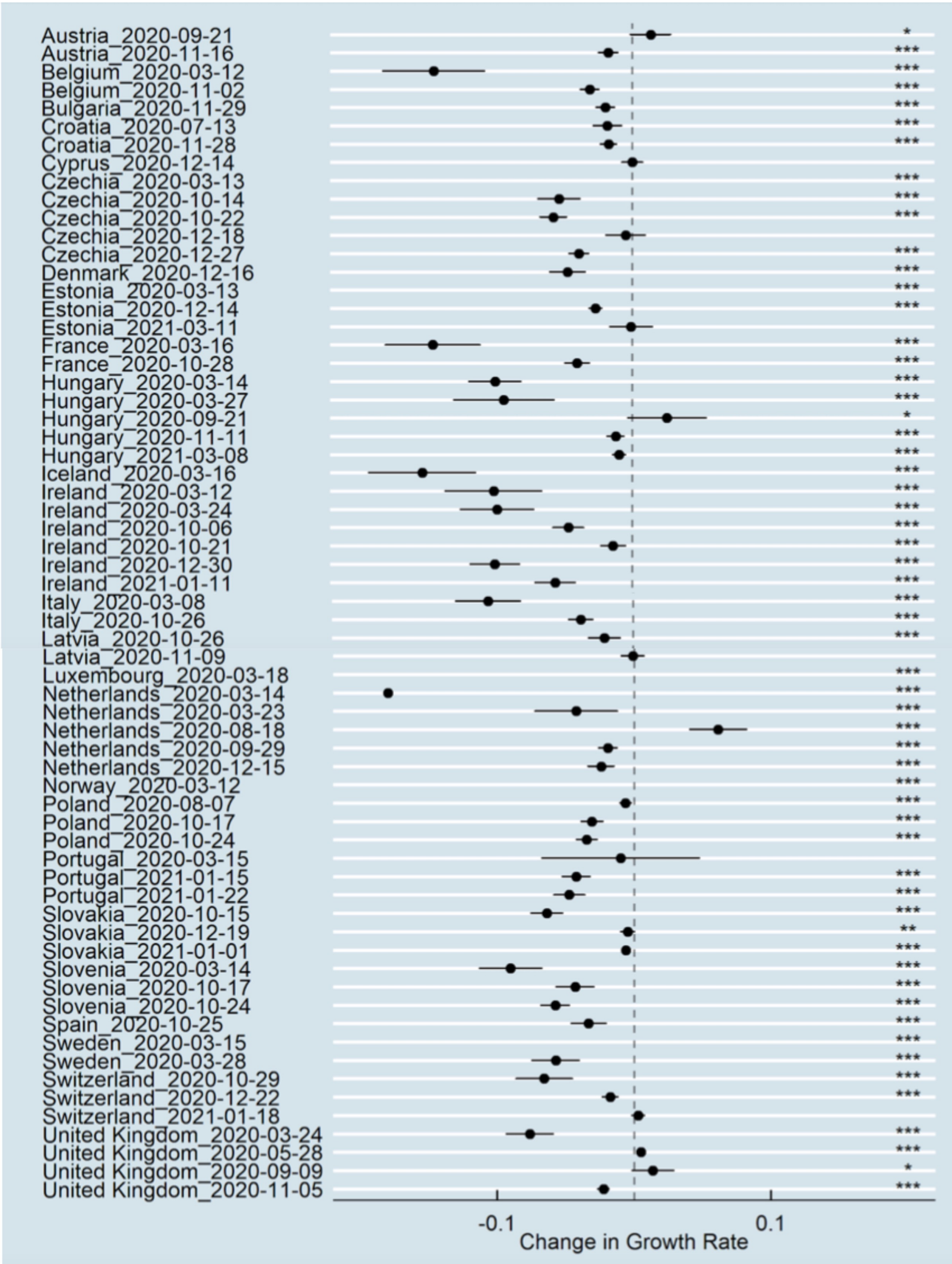


Note:*p<0.1; **p<0.05; ***p<0.01

The results presented in Figure 5.1 indicate a clear reduction in the growth rate of COVID-19 related hospitalizations during the time after the expected effect of the implemented NPIs. The week following the implementations, two weeks prior to expected effect, the results are positive and on average 5.81% higher per day in relation to the effect date. This growth rate is reduced in the second week, the week prior to the expected effect, but is still positive with an average of 1.77% per day. The relative growth rate turns negative in the third week, the week after the expected effect, with an average of -1.76% each day. Although these results are not statistically significant, they support the belief that NPIs will have a significant effect after approximately 14 days. The large growth rate reduction from the first week to the second implies that there is some effect of NPIs before 14 days. This can be due to the fact that most NPIs are announced to the public before they are implemented, and this can cause the population to adjust their behaviour before the official date of NPI implementation. Additionally, it is important to note that the growth rate is calculated as a 7-days moving average. Therefore, the average of one week is influenced to a certain degree by both the previous and subsequent week.

Furthermore, the regression reveals that the average decrease in growth rate per day increases from the third week to the fourth by -3.48%, suggesting a larger effect of the NPIs longer after they were implemented. From the outcome of our analysis, the results strongly indicate that the implementation of NPIs have a reducing effect on COVID-19 related hospitalizations. In order to identify the NPIs responsible for the effect, we find it necessary to carefully study each individual event. Figure 5.2 below presents the results of our regression from Equation 4.2. The coefficients represent the relative reduction of people hospitalized with COVID-19, within the event period compared to the estimation period of our event study.

Figure 5.2: All Event Coefficients



Note:*p<0.1; **p<0.05; ***p<0.01

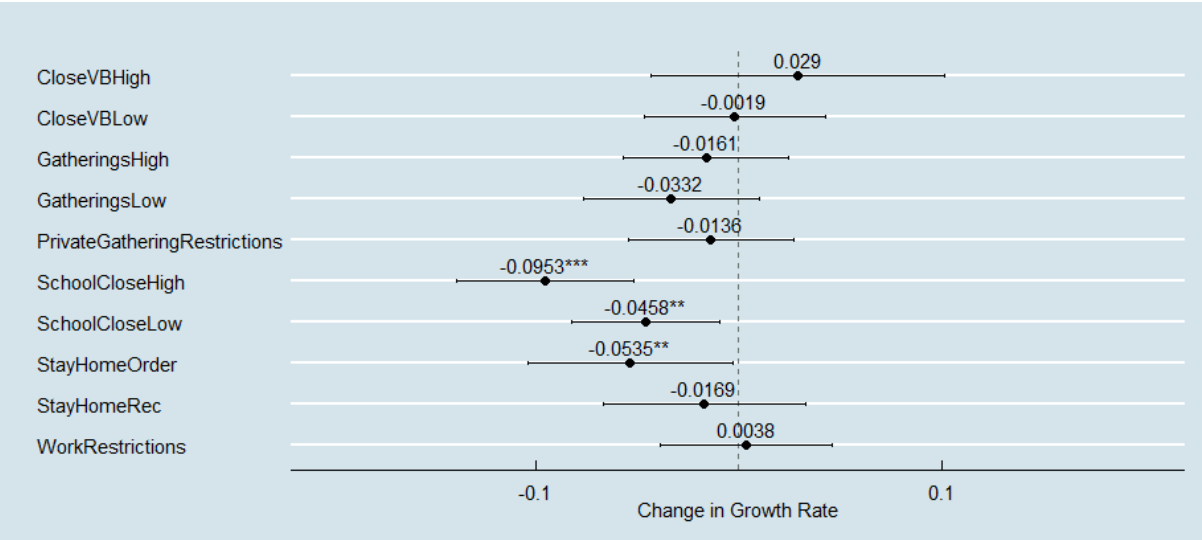
The plots presented above are limited to convey changes in growth rate within -0.2 and 0.2, in order to illustrate the confidence intervals for the "smaller" impact events. Therefore, the effects of some events are not present in the figures above, as the effects exceed the displayed interval. These events includes the implementations of NPIs in Czechia on 2020-03-13 (-0.356***), Estonia on 2020-03-13 (-0.202***), Luxembourg on 2020-03-18 (-0.399***), Norway on 2020-03-12 (-0.219***) and Sweden on 2020-03-15 (-0.276***).

From the results of Figure 5.2, it is clear to say that according to the regression results, not all NPIs implementations have been successful in reducing the spread of the coronavirus and subsequently the daily COVID-19 related hospitalizations. For instance, in comparison to our estimation period, for the NPIs implemented in the Netherlands on 2020-08-18 and in the United Kingdom on 2020-05-28, we see that there is an increase in the growth rate of hospitalizations in our event period. The difference in effects of each event will be the basis for further investigating the effect of the individual NPI groups.

5.2 NPI Regression

In this part of our analysis, we quantify the effect of each NPI grouping. Our objective is to analyze our second hypothesis, which states that all the NPIs in our sample are effective in reducing the growth rate of COVID-19 related hospitalizations. Additionally, we intend to discover which NPI groups are the most effective. In order to do so, we use the estimated event effects from our previous regression as the dependent variable in Equation 4.3, and we include the dummy variables for each NPI grouping as the independent variables. In Figure 5.3 below we present the result of the regression.

Figure 5.3: Regression Outcome NPI Group Specific Variables



Note:*p<0.1; **p<0.05; ***p<0.01

Although a regression analysis might not be able to give us the results to arrive at an absolute conclusion, it offers us a clear indication on which NPI groups are most significantly reducing the growth rate of daily hospitalizations in the event period of our study. Our model demonstrates that both high and low intensity of school closures are effective in reducing the COVID-19 related hospitalization numbers. Low intensity school closings indicating a 5.35% reduction of hospitalization and high intensity school closings indicating a 9.53%. These results coincide with contemporary research on the virus, which confers that the youth is the main spreader of the virus, due to many of the infected being asymptomatic. As an example, we refer to the remarks made by Dr. Takeshi Kasai at a WHO press conference (2020); who stated that the asymptomatic youth is increasingly driving the speed of the pandemic, with many of them being unaware that they are infected.

Lastly, the final significant coefficient of our regression is the NPI *StayHomeOrder*, that is more commonly known as the "lockdown measure". A significant reduction in hospitalizations from this NPI was expected, as it is one of the more intrusive NPIs. However, it is surprising that the reduction is as low as 5.35%, as one would expect it to be more effective than school closures. The relatively low effect of lockdown measures could be a result of possible side effects of this NPI. One side effect being, as stated in a study by Stanford researchers, that "it is possible that stay-at-home orders may facilitate transmission if they increase person-to-person contact where transmission is efficient such as closed spaces" (Bendavid et al., 2020). In countries where generation housing is more common, a lockdown could result in the youth spending more time with the elderly. Additionally, another side effect with the *StayHomeOrder* is that the enforcement of this NPI varies greatly between countries (BBC, 2020). It is also clear from our NPI implementation overview in section 3.2.1 that *StayHomeOrder* is often implemented at the same time as other NPIs, meaning that the strictness of the lockdown measure might be low. If the implementation of the *StayHomeOrder* NPI resulted in a full lockdown, other NPIs would have been excessive.

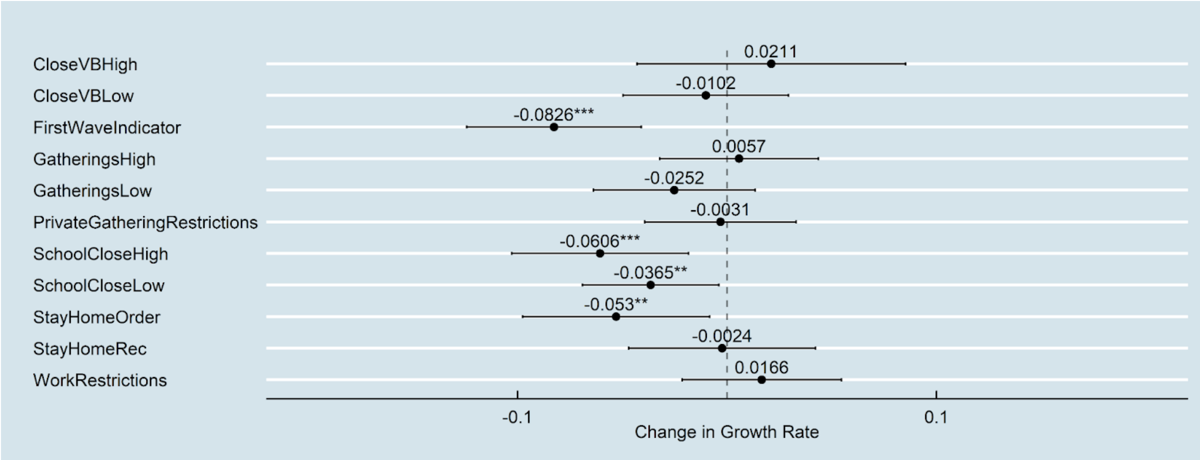
Furthermore, our regression demonstrates a clear indication that the lockdown measure and school closings are effective in reducing the spread of the virus. However, it is also important to consider the indications of effect of the other variables in our analysis. As expressed in our second hypothesis, we believed that all NPIs would be effective in reducing COVID-19 related hospitalizations to a certain degree. Nevertheless, the variables *WorkRestrictions* and *CloseVBHigh* imply the contrary. Although distinct conclusions are hard to obtain, our extensive analysis concludes that the measures stated above are ineffective in reducing the growth rate of daily hospitalization numbers.

To conclude, our regression suggests that not all NPIs are as effective in reducing the growth rate of COVID-19 related hospitalizations. The model indicates that strong restrictions on school closures result in a 9.53% reduction in the growth rate of hospitalized COVID-19 patients, and lockdown measures a 5.35% reduction. These percentages demonstrate that these two measures are the most effective NPI groups to implement in order to effectively reduce the spread of the virus. In accordance with our research, a recent study by *BMC Medicine* indicates that restrictions imposed on schools were found to be more effective than internal movement restrictions, such as lockdown (Liu et al, 2021).

5.3 First Wave Indicator

In the final part of our empirical results section we introduce the *First wave indicator* variable in our regression. The objective of this variable is to investigate whether events in the later stages of the pandemic are more effective in reducing the growth rate in COVID-19 related hospitalizations, as suggested by our third hypothesis. Figure 5.3 below shows the result of our regression with the "First wave indicator" variable.

Figure 5.4: Regression Outcome With First Wave Indicator Variable



Note: *p<0.1; **p<0.05; ***p<0.01

The results of the regression strongly indicate that our initial hypothesis is disproven. In the regression the estimated coefficient for the variable is -0.083, with significant p-values below the 0.1% level. These results demonstrate that a substantial part of the most effective events in our sample are from the first wave of the pandemic. The *First wave indicator* is the variable in our regression that results in the greatest reduction in growth rate in daily COVID-19 related hospitalizations. This result suggests that one of the most important factors in NPI implementations is to apply strict regulations early in the first wave of infection. This early application is to avoid implementations in the second wave, where the NPIs seem to be less effective. The results of the regression contradicts our initial hypothesis, in which we assumed that the use of NPIs would be more effective later on in the pandemic. To further analyze our initial hypothesis, we detected three grounds that could explain its seemingly erroneous nature.

Firstly, the events later on in the pandemic do not account for already active NPIs, as our events are only defined by the NPIs implemented at that specific time. Therefore, later events are lacking contributions from NPIs that would greatly impact both the event study windows and reduce the effect of these events.

Secondly, the effectiveness of NPIs might be reduced by factors unrelated to the NPIs themselves. One of them being the pandemic fatigue, a drop in adherence to Non-Pharmaceutical Interventions. In a recently published research in the medical journal *YAMA*, the authors estimate the effect of pandemic fatigue (Crane et al., 2021). The results of this research indicated a substantial reduction in adherence to response measures that reduced social contact. The only NPI that had increasing adherence from April until November 2020, was the use of masks and other face coverings.

Lastly, it is important to mention another possible contributing factor to the reduction in effectiveness of the NPIs in later stages of the pandemic, namely virus mutations. Throughout the pandemic we have seen new varieties of the COVID-19 virus, such as the mutations commonly referred to as the “British mutation” and “South African mutation” that originated in December 2020. These are mutations that have shown to have higher transmissibility than the earlier varieties of the virus (WHO, 2020). Therefore, it can be deduced that NPIs might be less effective in areas whereas a new mutation is dominating the infections.

In conclusion, the results of our *First wave Indicator* regression reveals that the NPIs were most effective in the first wave of the pandemic. This final regression concludes our *Empirical Results* section. In order to further solidify the conclusions drawn from our regression results, the following part of our thesis will test the robustness of our assumptions.

6 Robustness Tests

In this part of our thesis, we will conduct robustness tests to observe how our results react to changes in the specifications and assumptions in our model. In the first section we test our assumption of a 14-day delay, from NPI implementation to event/effect day, by introducing alternative days until the expected effects appear. In the second section we test alternative lengths of the two event study windows.

6.1 Alternative Expected Day of Effect

This thesis conducts analysis based on the assumption that the NPIs are effective after 14 days from implementation. In this part of our thesis we test the strength of our analysis and challenge this assumption.

Therefore, in this section we test different time intervals from NPI implementation until the NPI are expected to be effective. The robustness testing in this section is conducted only to assess the time interval in question. All other conditions and assumptions are constant. This conveys that, in this test, the length of the event study windows are kept at 14-days.

On the left side of Table 6.1 we set days after NPI implementation. The rates presented on the right side of the table presents the outcomes of our test, namely the difference in growth rate in hospitalizations between the two event study windows. All tests are based on the average event coefficients for all events in our sample.

Table 6.1: Alternative Interval of NPI Implementation Effect

Interval from NPI Implementation Until Event/Effect Day	Event Study Windows Length	Event Coefficient Average
14	14	-0.06306
16	14	-0.05404
18	14	-0.04516

In Table 6.1 above we see the result of testing with longer time-delay from NPI implementation to NPI effect. We observe that an increase in this delay from 14 to 16 and 18 days, decreases the average event coefficient. This means that increasing the time delay apprehends less of the effect of the NPI implementation.

This robustness test only analyzes the change in event coefficients for longer time delays. Testing for shorter time delays could be beneficial for our analysis. The difficulty with such a test is that we would be unable to conduct tests where the estimation window precedes our current day of NPI implementation. This is because of data availability, as many countries only started registering their daily COVID-19 related hospitalization numbers on the same day as they introduced their initial measures. Testing for 12 days until expected effect with a 14 day estimation window, would result in a great reduction of events in our sample. In a case of less events in our regression, the results of robustness tests would be uncomparable. Reducing the length of only the estimation window is not considered an option in this part of our robustness analysis, because the effect window should not be longer than the estimation window (Aktas et al. 2007).

Additionally, in order to strengthen our analysis, we include a scenario where we assume that it would take the NPIs 12 days to show significant effects. We limit our estimation and event window to 12 days prior and after the effect date. We reduce the event window to 12 days in order to handle the missing data prior to the day of NPI implementation from the earliest events. We apply this reduction in order to understand and observe what effects a shorter interval could have on our thesis analysis.

Table 6.2: 12 Day Interval Of NPI Implementation Effect

Interval from NPI Implementation Until Event/Effect Day	Event Study Windows Length	Event Coefficient Average
12	12	-0.05944

As it can be seen in Table 6.2 above, reducing the number of days to 12-days increases the average event coefficient. We disregard this option considering that for our event regressions we aim to have coefficients as negative as possible.

6.2 Alternative Event Study Windows

In our second robustness test, we adjust the length of our event study windows. In our preliminary analysis, the initial length of the estimation window and event window is set to be 14 days. In this section of our robustness test we run our event regressions on different event study windows. Testing different event study windows is crucial in order to see if we are able to capture the maximum effect of our events.

This robustness test will only test for different lengths of the event study windows, where we deduct that the assumption of 14 days from NPI implementation to event/effect day holds. Furthemore, our testing will keep the estimation window and event window at the same length, in order to keep the test results comparable to our initial analysis.

In Table 6.3 below we present the results we found by changing the length of our event study windows. On the right side of the table we present the event regression coefficients associated with the respective changes.

Table 6.3: Alternative Event Study Windows

Interval from NPI Implementation Until Event/Effect Day	Event Study Windows Length	Event Coefficient Average
14	14	-0.06306
14	12	-0.06125
14	10	-0.04352
14	8	-0.03589

The event coefficients from the table above displays that reducing the number of days in the event study windows results in lower relative difference in event effect, between the estimation window and the event window. A lower coefficient shows that more of the effect of the NPI implementations is captured. Therefore, reducing the number of days in our event study windows would not improve our model.

Optimally, this robustness test would also include testing for event study windows of more than 14 days. However, as mentioned in the robustness test above, due to lack of available COVID-19 related hospitalization data we are unable to test for estimation windows that stretch before the day of NPI implementation. The maximum time span of our estimation window with a 14 day lag until expected effect is then 14 days. Furthemore, increasing the number of days in our event study windows increases the possibility of effects irrelevant to the NPI implementation.

Our robustness testing could have been conducted under more fixed conditions. Meaning that we only test for events that have data available for a longer time period before the NPI implementation. More fixed conditions could have given us the opportunity to test longer time intervals for our event study windows. However, seeing that the events we would have to exclude from our analysis would mostly be events from the first wave of infections, we decided not to conduct this type of analysis. Due to the first wave events being the most effective ones, and containing the most NPIs implemented.

7 Limitations

In this part of our thesis we assess our data critically by discussing the size and data reliability of our sample. Furthermore, other limitations of our study are outlined by discussing factors of epidemiological growth and other relevant missing factors that could be relevant for our analysis.

7.1 Small Sample

A limitation within our thesis is our small sample size. As a result of our small sample size, of only 64 event observations, we reduced the number of NPI variables in order to adjust for a greater fit in our regression. A larger sample would have enabled us to use variables for every NPI in our response measures dataset and could have resulted in more precise results. Although 64 observations are sufficient in order to calculate the effectiveness of the events, we encountered a challenge in regards to our NPIs. While a large part of our NPI group of dummy variables were active in half our sample, others were only active in a fourth. This challenge becomes clear in regards to conducting other regression methods. Therefore, regression methods such as Lasso Regression are excluded from our analysis.

The reason behind the lack of a larger sample size is the absence of available data from numerous EU territories. Available data from all European countries would greatly increase our sample size, and subsequently result in more reliable estimates and stronger conclusions. To our surprise, considering their size and reputation, data that was necessary to our research was unavailable from countries like Finland and Germany. Therefore, the lack of data on hospitalization and measures is primarily due to the exclusions of data-deficient countries from our sample.

Our sample size could also have been expanded by including non-European countries like South Korea, China, Iran and USA. However, it was arduous to find comparable response measures in regards to data, as well as reliable statistics on hospitalizations for non-European countries. The collection of uncertain and uncomparable data could have made our findings inconsistent. Therefore, we chose to limit our data to European countries because the comparability advantage of the response measures outweighs the advantage of having data from countries outside the EU.

7.2 Unreliable Data

The second limitation of our analysis is the lack of reliable data. The response measures data set has restrictions because the data is based on a manual collection and sorting process of measures that are collected from numerous external sources. It is districtly probable that data might be absent and that source material might have been misinterpreted. Additionally, daily COVID-19 related hospitalizations, our main component of data, is at even greater risk of being unreliable. It is reasonable to believe that, within health institutions, the counting system of COVID-19 cases could be more prone to error because of the unprecedented pandemic. Furthemore, another limitation in the daily COVID-19 related hospitalizations data is that it fails to take into consideration that a reduction in number of hospitalizations is not necessarily due to the effectiveness of NPI measurements, but on the other hand could be due to a result of COVID-19 fatalities. Initially, our objective was to use the growth rate of daily hospital admissions as our dependent variable. However, only 11 countries had this data available, and some of them for only a brief period of time. Therefore, in order to go forward with our analysis, we were obligated to prioritise a larger sample over a more reliable dependent variable.

7.3 Epidemiological Growth

Another limitation within our analysis is that our model does not include a control group that regulates how the epidemic curve of the COVID-19 virus would naturally bend without any NPI intervention. Presented in the regression results section above, our model indicates, with a constant value of 0.019, that hospitalization numbers would grow exponentially. Yet, this is not the case because every epidemic curve is self-limiting in the long run (Kleczkowski & Kao, 2020). However, within the short time spans in which we conduct our analysis, we choose to allocate all the reduction in the growth rate of hospitalizations to NPIs. Furthermore, it is likely that other factors within the field of epidemiology are disregarded in our thesis. As this thesis is conducted from a purely empirical point of view, and not from the view of experts in epidemiology.

7.4 Missing Relevant Factors

Accounting for all relevant factors related to the spread of COVID-19 and the effects of NPIs requires a substantially larger model than the one used in this thesis. Our analysis introduced some broad assumptions, excluding numerous factors. It is a possibility that our analysis has overlooked relevant factors that could have greatly influenced the effectiveness of the NPIs in our sample. For example, a factor being the cross-sectional effect, that could have estimated the effect of combining NPIs to reduce the growth rate of COVID-19 related hospitalizations. Considering the results in our analysis regarding the first wave indicator, it is likely to assume that cross-sectional effects between NPIs are responsible for a considerable reduction during the first wave of the pandemic.

We believe that most country-specific factors, such as the age demographic, population health and population density, are irrelevant for our analysis. This is because the effect of these factors should be equal in the estimation window and the event window. However, some factors that directly contribute to the effectiveness of the NPIs are likely to be absent from our analysis. One of these factors could be the reliance that the population has on those who are responsible for implementing restrictions, such as the government and health authorities. Additionally, a contributing factor can be differences in the level of enforcement of the NPIs within different countries, and if the implementation is based on the population's trust or its fear of monetary fines or other repercussions.

8 Conclusion

Our objective within this thesis has been to expand the currently available research with information about the effect of NPIs in reducing the spread of COVID-19 and thereby lowering hospitalization numbers. Furthermore, by quantifying the effects of NPIs, we aim to provide crucial input for a cost-benefit analysis regarding pandemic responses.

Firstly, we used an event-driven approach to estimate the effects of 10 NPI groups on COVID-19 related hospitalizations in 25 European countries. We identified 64 events across these countries, which we used to explore our hypotheses. Firstly, we looked at *Hypothesis 1*, concerning the general effect of NPI implementations. From our results we saw a reduction in the growth rate of COVID-19 related hospitalizations after NPI implementation, which supported our first hypothesis and the general belief that NPIs reduce the spread of COVID-19. By using the pre-vs post-comparesaint method, we estimated the effect for each of the 64 events.

Secondly, we combined the effect of each event with their corresponding implemented NPIs, to quantify the effect of each individual NPI group. This was done to answer our second hypothesis that all NPIs are effective, while some are more effective than others. We found the NPI group *"SchoolCloseHigh"*, regarding high intensity of school closing, to have the highest significant effect. Reducing the growth rate of COVID-19 related hospitalizations by 9.53%. Other NPI groups with significant effect were *"SchoolCloseLow"* regarding low intensity of school closings and the lockdown NPI *"StayHomeOrder"*, reducing the growth rate respectively by 4.58% and 5.35%. We were not able to estimate the effect of the other NPI groups presented in our regression with a significance level of 0.05, however, most NPI groups indicated a reduction in growth rate.

Lastly, we looked at our third hypothesis which states that events of NPI implementation in the later stages of the pandemic were more effective in reducing COVID-19 related hospitalizations than events in the first wave. Our results indicate the opposite. They stipulate that the NPIs introduced in the first wave seemed to be the most effective. We argue that potential reasons for this can be “pandemic fatigue”, causing a drop in adherence to NPIs. Furthemore, another reason can be the reduced effect of individual NPI groups, when other NPIs are already active.

In conclusion, with our thesis we hope to add some groundwork to the already available research regarding the effectiveness of NPIs. We desire to do so in order to enable governments and policy makers to construct more informed decisions in the future. If more effective response measures will be chosen in the wake of a future pandemic, we firmly believe that lives will be saved and economic consequences will be minimized.

Further research

In order for future research to accurately estimate the effects that Non-Pharmaceutical Interventions have had on reducing COVID-19 related hospitalization numbers, we elaborate three propositions.

Firstly, even though we argue for the use of daily COVID-19 related hospitalizations as the dependent variable, a more accurate time specific variable could be the daily hospital admission of COVID-19 patients. We believe hospital admissions to be the most trustworthy dependent variable for this type of analysis as it is not affected by the time spent at the hospital by each patient. However, not enough countries register this kind of data. For statisticians and researchers to be able to conduct analysis on this variable in the future, it is necessary that health authorities and hospitals set a plan for a more accurate registration of daily hospital admissions. Through our data collection process, several health authorities indicated that these numbers will become available soon, opening up the opportunity for this variable to be used in future analysis.

Secondly, there is a great necessity for further research on the interval from NPI implementation to when they are expected to be effective. During our information collection process we corresponded by email with the Norwegian Institute of Public Health (NIPH) about this subject. Regrettably, they did not have a clear response to our question. However, NIPH displayed interest in collaborating with us on this particular issue if we were to further extend our research beyond our thesis. Their profound interest made us understand even further the contemporary necessity for this kind of research.

Lastly, we believe that, in future analysis, researchers should aim to include cross-sectional effects between NPIs. In order to include more variables in the analysis, the quantity of data must increase in scope. This type of research could have the ability to find the most effective combination of NPIs to reduce the spread of COVID-19.

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Appendix

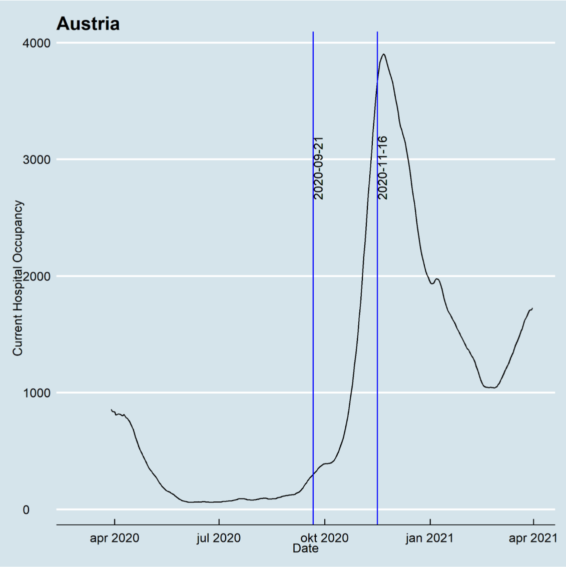
Description of Measures

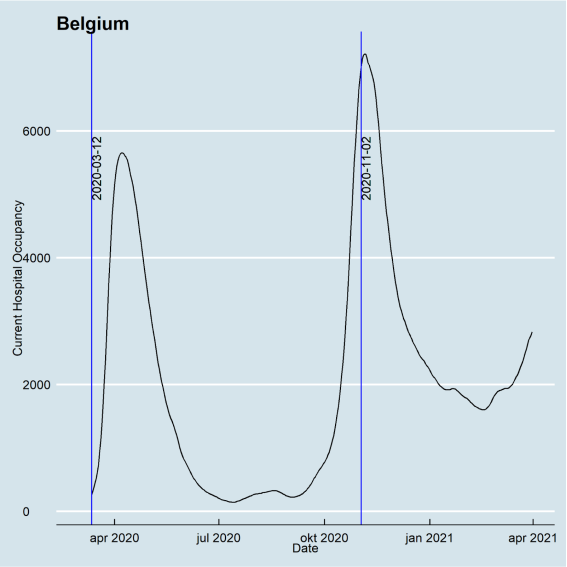
Response Measures	**Description**
AdaptationOfWorkplace	Adaptation of workplaces (e.g. to reduce risk of transmission)
BanOnAllEvents	Interventions are in place to limit all indoor/outdoor mass/public gatherings
ClosDaycare	Closure of educational institutions: daycare or nursery
ClosHigh	Closure of educational institutions: higher education
ClosPrim	Closure of educational institutions: primary schools
ClosSec	Closure of educational institutions: secondary schools
EntertainmentVenues	Closure of entertainment venues
GymsSportsCentres	Closure of gyms/sports centres
HotelsOtherAccommodation	Closure of hotels/accommodation services
IndoorSmallGatherings	
Indoorover50	Interventions are in place to limit indoor mass/public gatherings of over 50 participants
Indoorover100	Interventions are in place to limit indoor mass/public gatherings of over 100 participants

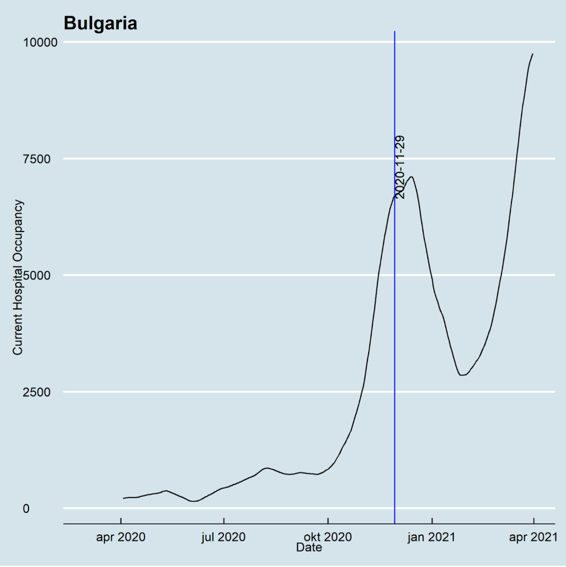
IndoorLargeGatherings	
Indoorover500	Interventions are in place to limit indoor mass/public gatherings of over 500 participants
Indoorover1000	Interventions are in place to limit indoor mass/public gatherings of over 1000 participants
MassGather50	Interventions are in place to limit indoor mass/public gatherings (any interventions on mass gatherings up to 50 participants included
MassGatherall	Interventions are in place to limit indoor mass/public gatherings (any interventions on mass gatherings up to 1000 participants included
NonEssentialShops	Closures of non-essential shops
OutdoorSmallGatherings	
Outdoorover50	Interventions are in place to limit outdoor mass/public gatherings of over 50 participants
Outdoorover100	Interventions are in place to limit outdoor mass/public gatherings of over 100 participants
OutdoorLargeGatherings	
Outdoorover500	Interventions are in place to limit outdoor mass/public gatherings of over 500 participants
Outdoorover1000	Interventions are in place to limit outdoor mass/public gatherings of over 1000 participants

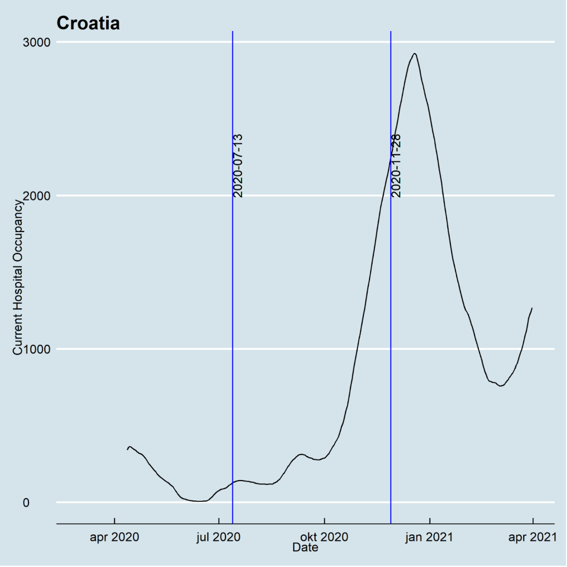
PlaceOfWorship	Closure of places of worship
PrivateGatheringRestrictions	Restrictions on private gatherings
RestaurantsCafes	Closure of restaurants and cafes/bars
SocialCircle	Social circle/bubble to limit social contacts e.g. to limited number of households
StayHomeGen	Stay-at-home recommendations for the general population (which are voluntary or not enforced)
StayHomeOrder	Stay-at-home orders for the general population (these are enforced and also referred to as 'lockdown')
Teleworking	Teleworking recommendation
StayHomeRiskG	Stay-at-home recommendations for risk groups or vulnerable populations (such as the elderly, people with underlying health conditions, physically disabled people, etc.)
WorkplaceClosures	Closures of workplaces

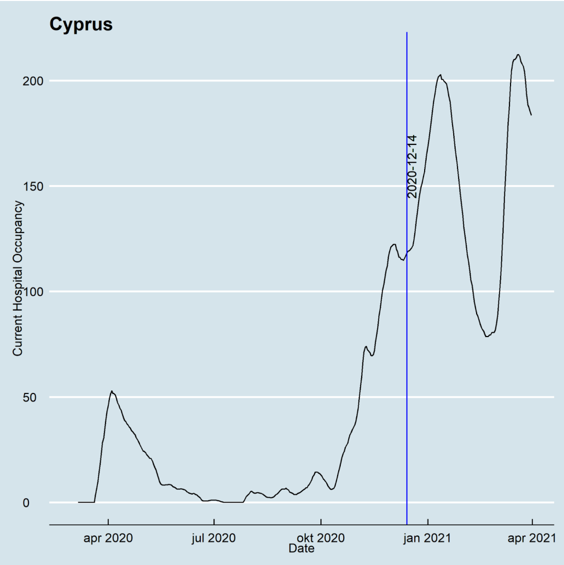
Event Presentation Per Country







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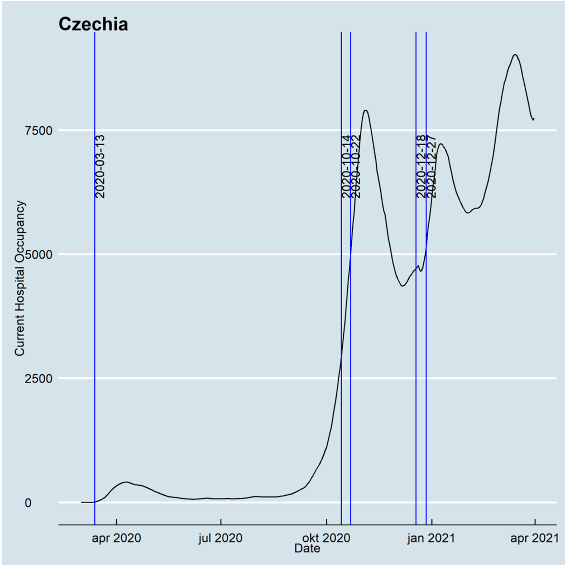
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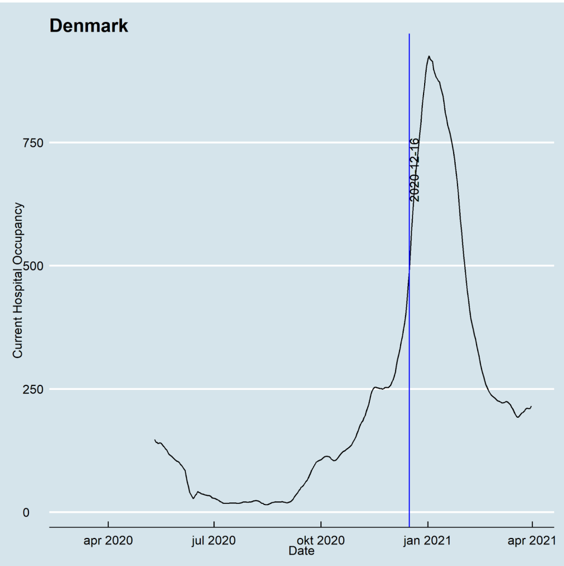
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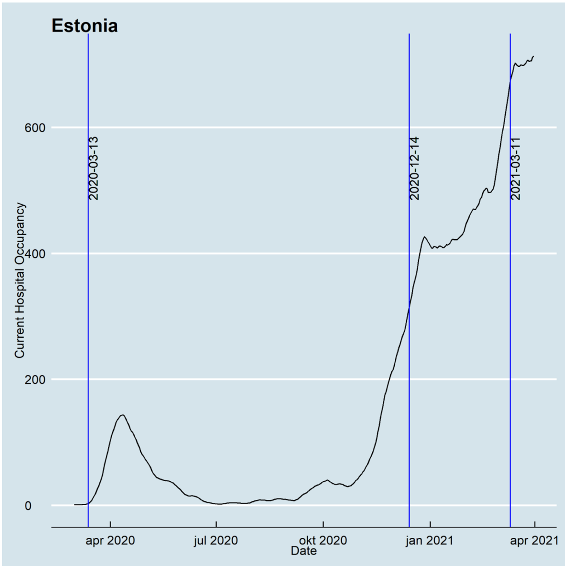
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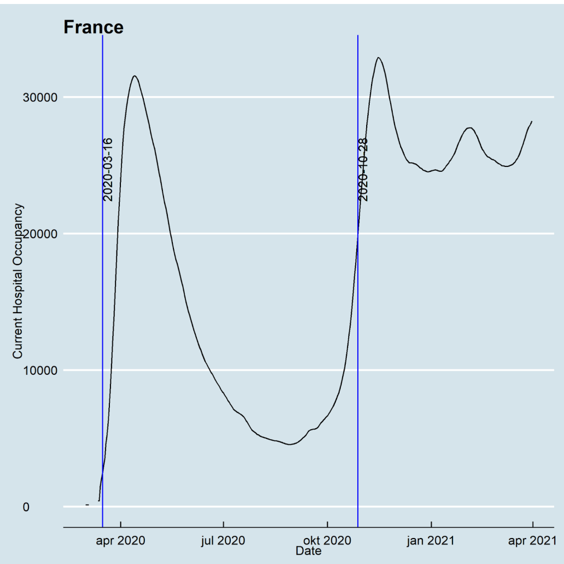
Date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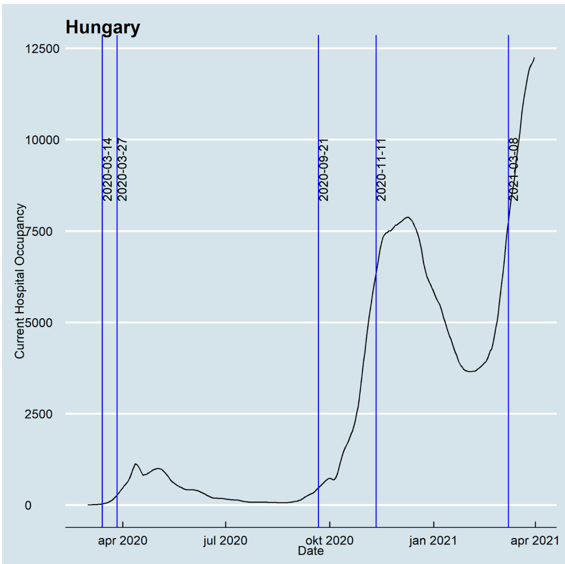
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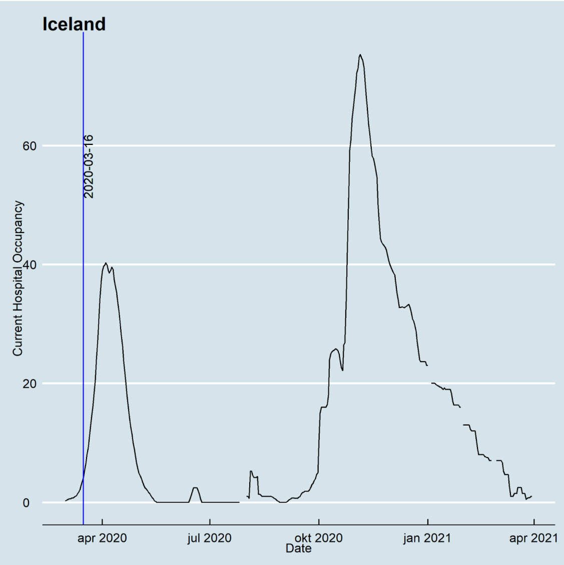
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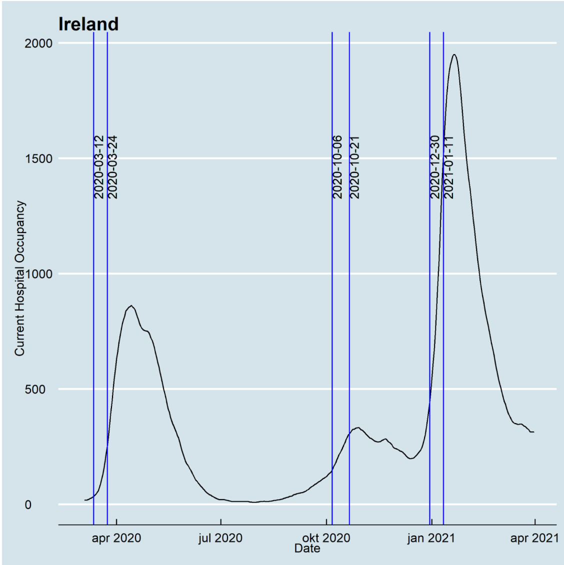
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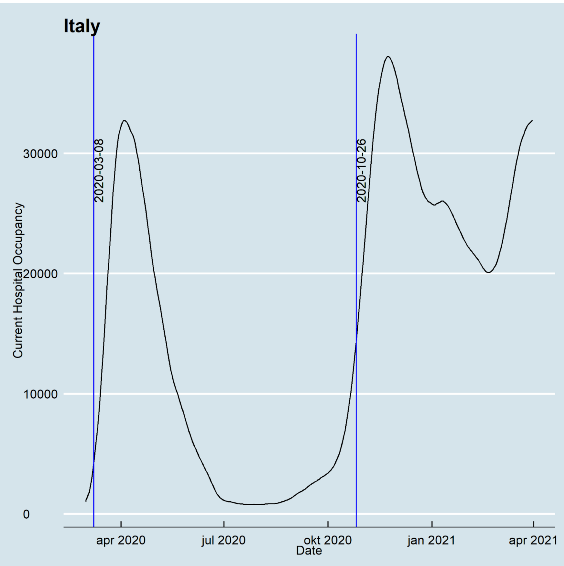
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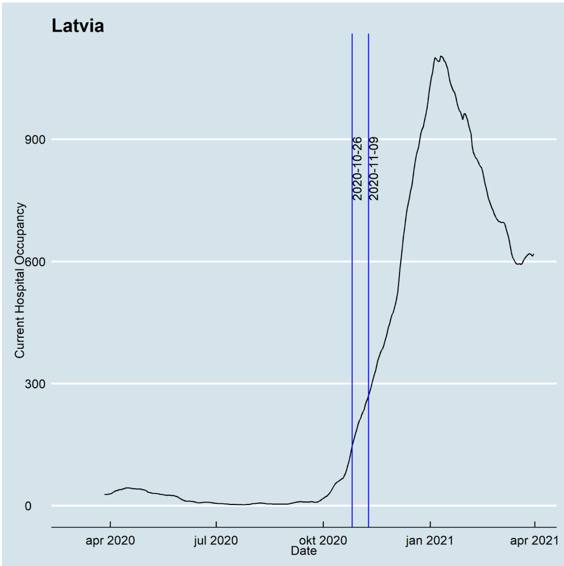
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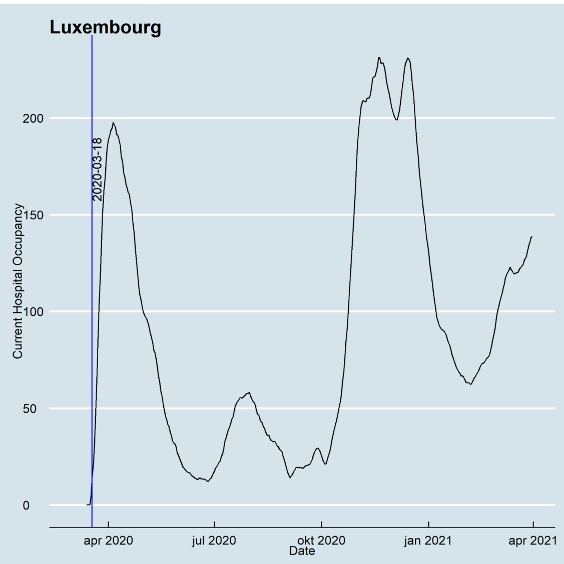
Date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200
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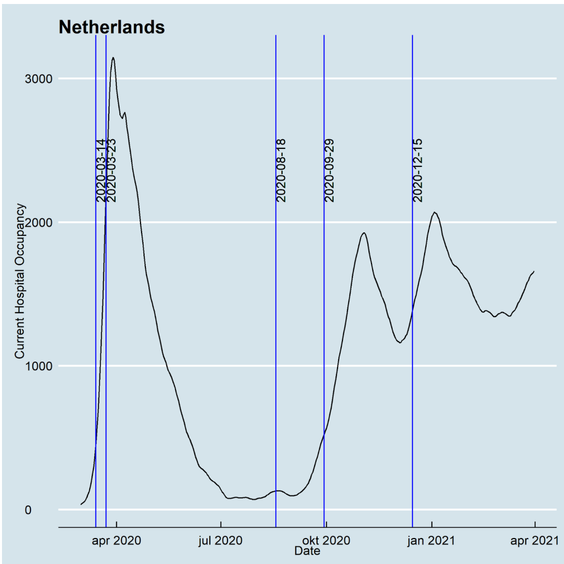
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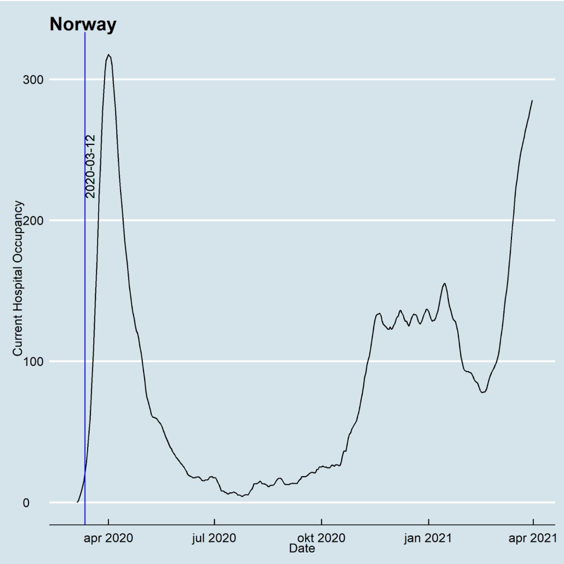
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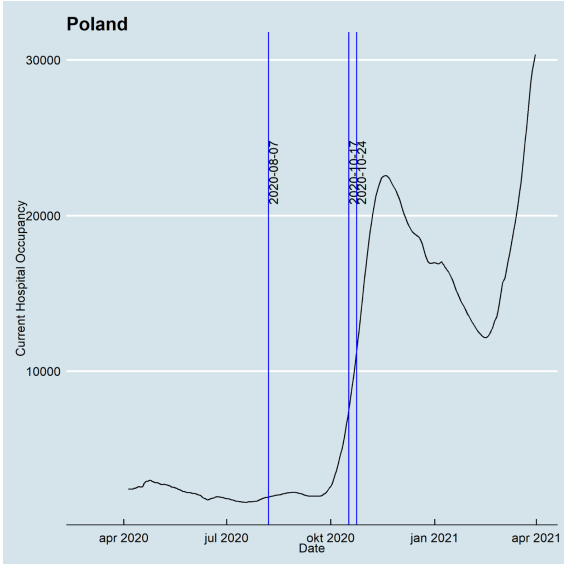
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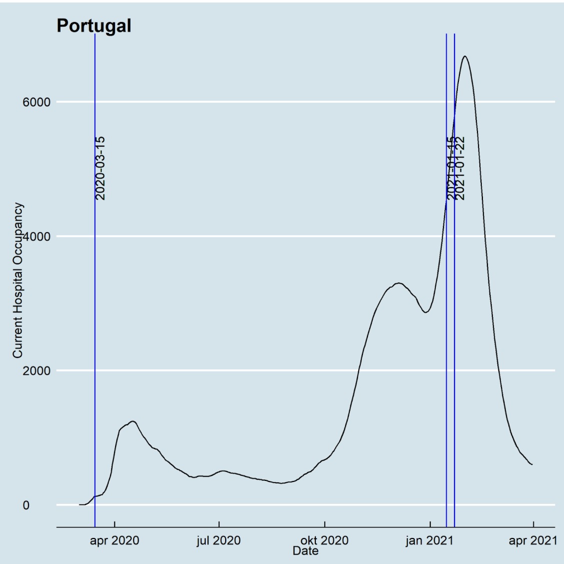
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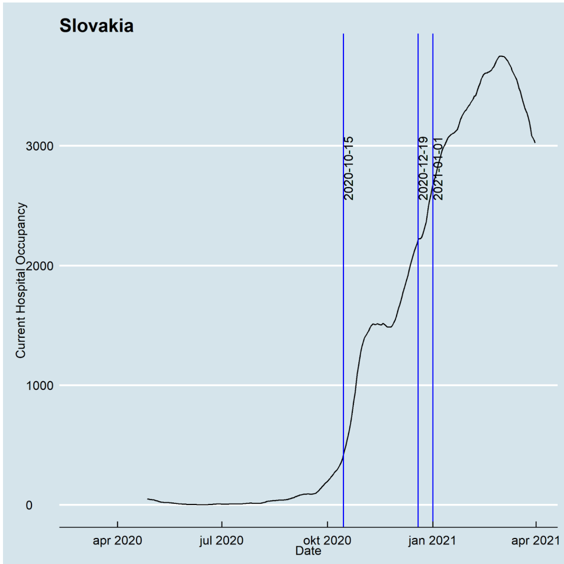
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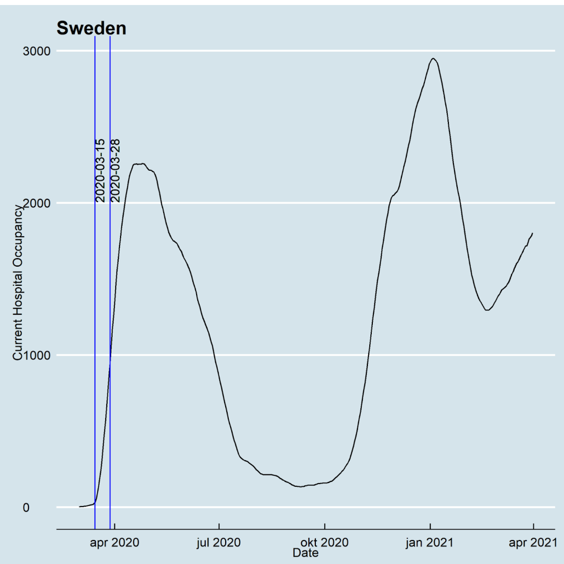
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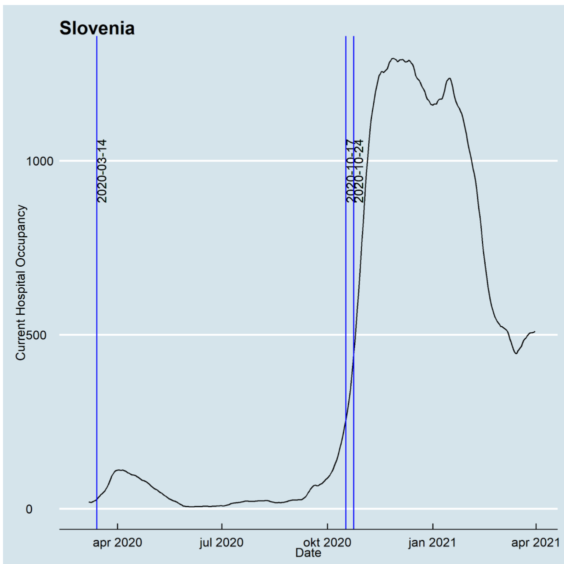
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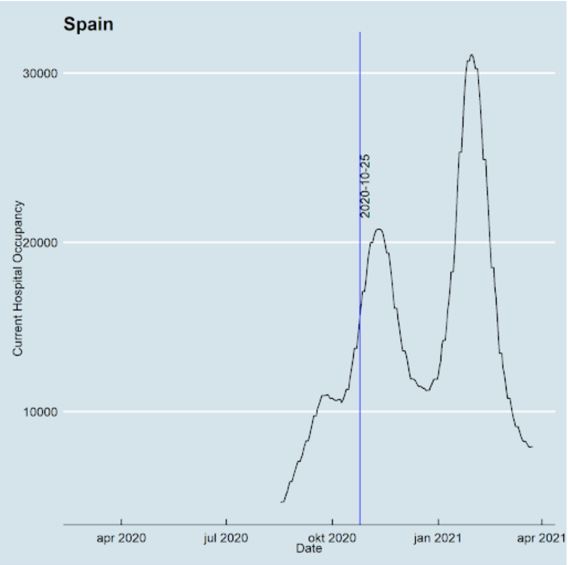
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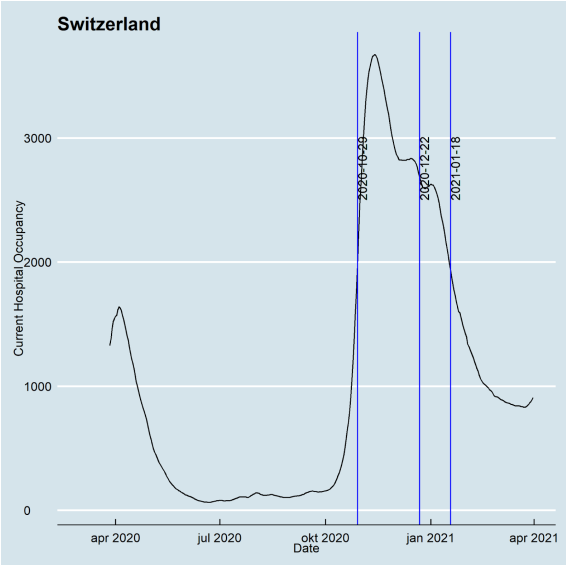
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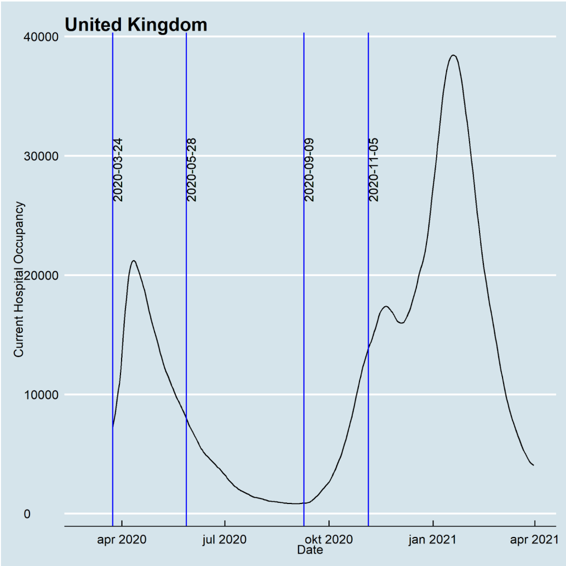
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Date

Regression Results

Table A0.1: Weekly Average Growth Rate

		Growth Rate	
Predictors	Estimates	CI	P-value
(Intercept)	0.04	0.01 - 0.06	**0.002**
Week 1	0.06	0.03 - 0.08	<**0.001**
Week 2	0.02	-0.01 - 0.04	0.151
Week 3	-0.02	-0.04 - 0.01	0.153
Week 4	-0.03	-0.06 - -0.01	**0.005**
Observations	1796		
$R^2/R^2 adjusted$	0.130 / 0.128		

Table A0.2: Main NPI Regression

		Coefficient	
Predictors	Estimates	CI	P-value
(Intercept)	0.02	-0.02 - 0.06	0.354
ScoolCloseLow	-0.05	-0.08 - -0.01	**0.015**
ScoolCloseHigh	-0.10	-0.14 - -0.05	<**0.001**
WorkRestrictions	0.00	-0.04 - 0.05	0.856
CloseVBLow	-0.00	-0.05 - 0.04	0.933
CloseVBHigh	0.03	-0.04 - 0.10	0.425
PrivateGatheringRestrictions	-0.01	-0.05 - 0.03	0.504
StayHomeRec	-0.02	-0.07 - 0.03	0.498
GatheringsLow	-0.03	-0.08 - 0.01	0.130
GatheringsHigh	-0.02	-0.06 - 0.02	0.433
StayHomeOrder	-0.05	-0.10 - -0.00	**0.038**
Observations	64		
$R^2/R^2 adjusted$	0.450 / 0.346		

Table A0.3: First Wave indicator

Predictors	Estimates	Coefficient CI	P-value
(Intercept)	0.02	-0.02 - 0.05	0.399
ScoolCloseLow	-0.04	-0.07 - -0.00	**0.029**
ScoolCloseHigh	-0.06	-0.10 - -0.02	**0.006**
WorkRestrictions	0.02	-0.02 - 0.05	0.386
CloseVBLow	-0.01	-0.05 - 0.03	0.608
CloseVBHigh	0.02	-0.04 - 0.09	0.512
PrivateGatheringRestrictions	-0.00	-0.04 - 0.03	0.862
StayHomeRec	-0.00	-0.05 - 0.04	0.916
GatheringsLow	-0.03	-0.06 - 0.01	0.196
GatheringsHigh	0.01	-0.03 - 0.04	0.762
StayHomeOrder	-0.05	-0.10 - -0.01	**0.021**
First Wave Indicator	-0.08	-0.12 - -0.04	**<0.001**
Observations	64		
$R^2/R^2 adjusted$	0.578 / 0.489		