

Impact of the COVID-19 Policies on Morbidity and Mortality

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Dedicated to my parents, who sacrificed happiness for my higher studies abroad.

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ABSTRACT

This dissertation research deals with the panel data ordinary least square regression analysis to measure the impact of COVID-19 policies on morbidity and mortality. World Health Organization (WHO), the Center for Disease Control (CDC) USA, policymakers, medical scientists, and governments suggest various policies to reduce COVID-19-related morbidity and mortality. I aim to examine the effectiveness of those policies. I subdivided all policies into three groups: preventive policies, behavioral policies, and direct disease-related policies. The COVID-19 data set I used is extracted from the Oxford-Covid-19-government-response-tracker (OxCGRT) from January 01, 2020, to December 31, 2022. After performing the tests using the Python package, the results show that most of the policies' effects on morbidity are statistically significant except for the contact tracing and diseases-related information campaign policies. For the mortality, this research found that, except for the close public transport policy and diseases-related information campaign policy, the effect of other policies on mortality was statistically significant.

Keywords: COVID-19, Fixed effect model, Random Effect model, Hausman test

JEL Classification: H5, I1

BACKGROUND AND OBJECTIVE OF THE STUDY

Throughout the history of human civilization, humanity has faced various adverse circumstances at different times. Natural disasters such as hurricanes, floods, wildfires, droughts, famines, epidemics, and earthquakes have been notable. Alongside natural disasters, widespread outbreaks of epidemics have resulted in significant loss of life across the globe. However, in December 2019, the emergence of the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) from Wuhan, China, marked an unprecedented event, surpassing all previous pandemics. The uniqueness of COVID-19 lies in its global spread, affecting every continent. No country on Earth remained unaffected by COVID-19, and many suffered immense loss of life from the relentless pandemic.

The World Health Organization (WHO) officially identified the existence of the coronavirus on January 7, 2020. China declared the first death caused by the coronavirus on January 11, 2020. On February 25, 2020, the Center for Disease Control (CDC), USA, warned Americans to expect significant disruption from the virus, while the first US COVID-19 patient landed at Seattle-Tacoma International Airport (SEA) in January 2020. Finally, WHO declared COVID-19 a pandemic in March 2020. A pandemic is an epidemic that has spread over a large world region. WHO suggests some policies to prevent the spread of COVID-19.

According to World Meter's information, as of March 28, 2024, the total confirmed COVID-19 virus occurrences worldwide were 704,531,140, with 7,008,933 deaths. The USA is the most affected country; as of March 28, 2024, the total confirmed COVID-19 cases were 111,759,213, with 1,218,831 deaths. President Joe Biden signed a Republican-led resolution (229-

197) to end the national COVID-19 emergency a month earlier than initially planned, on March 29, 2023.

Although various countries have lifted the restrictions on COVID-19 and a readily available vaccine has been discovered, COVID-19 has not been eradicated. Even on March 28, 2024, 1575 new cases of COVID-19 have been reported, resulting in 32 deaths.

World Health Organization (WHO) and the CDC, USA, have advised various policies to prevent the spread of the COVID-19 virus and treat COVID-19-infected patients. They have recommended different policies to multiple countries, governments, and citizens. In this research, I have divided the mentioned 13 policies into three sub-groups. Among them, policies like staying at home, school closure, workplace closure, canceling public events, closing public transportation, restrictions on gatherings, restrictions on internal movement, and international travel controls are considered preventive policies. Additionally, the face-covering and contact-tracing policies are categorized as behavioral policies. Furthermore, testing, vaccination, and COVID-related information campaign policies are identified as directly addressing disease-related policies.

The main objective of this analysis is to dictate whether these policies impact mortality and morbidity. If they do, measure the effects, and identify which are more effective. These research findings will assist researchers, governments, communities, and policymakers better prepare for future pandemics, even if they are less severe.

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Chapter 1

Impact of the COVID-19 Preventive Policies on Morbidity and Mortality

Abstract

In this chapter, I will aim to assess the consequences of the COVID-19 preventive policies on morbidity and mortality. Most of the policies suggested in this study are highly effective in preventing disease and reducing death due to COVID-19. However, close transport 1 and 2, restrictions on internal movement 2, and international travel control 4 policies on mortality were not found to be statistically significant. Therefore, the results of this study say that the preventive policies for COVID-19 have been able to have a better impact on morbidity compared to mortality.

Keywords: COVID-19, Stay at home policy, School closure policy, Workplace closure policy, Cancel public events policy, Close public transport policy, Restrictions of gatherings policy, Restrictions of internal movement policy, International travel controls policy

JEL Classification: H5, I1

1. Introduction

COVID-19 is a type of virus that spreads to humans and causes illness. It is also called severe acute respiratory syndrome coronavirus 2, or more commonly, SARS-CoV-2. Among the types of epidemics that have occurred in the world to date, COVID-19 is unique because other epidemics were local or limited to one region. Still, the size of the COVID-19 epidemic is global; that is, from the Oceania region to North America, Covid-19 has spread out.

The leading cause of COVID-19 is the coronavirus, and its vaccine is no longer infectious. Still, it is spreading through the administration of the human body; the primary opinion of medical scientists is to prevent the spread of the seal in any way. That is to prevent the spread of COVID-19 so that the incidence of COVID-19 infection and loss of life decreases. Overall, preventive policies are essential to shorten the spread of coronavirus.

The "Stay at Home" or "SAHO" policy is one of the preventive policies against SARS-COV-2. People are restricted from protecting public health from infectious diseases during the COVID-19 pandemic, known as Stay-at-home. Essentially, the effectiveness of the Stay-at-Home policy is far-reaching, as it reduces social contact and prevents person-to-person virus spread. The stay-at-home policy can keep the person infected with the coronavirus in isolation, and the chain of transmission of the virus can be broken through the infected person, thereby preventing the spread of the corona during the outbreak of the COVID-19 stay-at-home policy. Communities are largely immune to transmission. It also protects vulnerable populations. This policy may call a proactive policy.

During the Covid pandemic, government orders have typically made the Stay-At-Home policy mandatory. There were different levels of restrictions. Also, legal penalties have been levied

for breaking the Stay-at-home policy. Due to this, the ordinary people were obliged to follow this policy.

The school closure policy is one of the preventive policies during the Covid period. We know that education and school are integral to any society or economy. However, the school closure policy that education (school, college, and university) through temporary shutdown helps a lot to intercept the widening of transmissible diseases, especially during a pandemic or outbreak. This policy aims to reduce contact rates with students, teachers, staff, and guardians. So that the school community, as well as society, reduces infectious disease. The efficacy of school closures has been tested earlier in the history of human civilization and during influenza, measles, and tuberculosis (TB) epidemics.

The school closure policy has been implemented by suspending in-person classes during the period. School closure policies have been implemented in different countries during different COVID periods, depending on the COVID-19 infection rate and healthcare capacity.

The workplace closure policy has worked as one of the preventive policies during the COVID period. Workplace policy is a strategy that an organization or authority temporarily prohibits physically from the workplace. A workplace closure policy is generally effective in a public health emergency because it reduces the transmission rate of disease outbreaks during a pandemic.

The real purpose of this policy is to reduce interpersonal contact. Besides, it protects employee and community health, facilitates social distancing, etc. The workplace closure policy has been proven historically. 1918, during the pandemic in Spain, many workplaces were

temporarily closed to avoid the pandemic. A workplace closure policy helps reduce close contact. Besides, it promotes social distancing.

Cancel public events policy plays a vital role in COVID-related preventive policy. One of the objectives of this policy is to reduce the transmission of the coronavirus and, at the same time, protect public health. When an infectious virus originates in a community, large crowds spread it. Because many people gather in a small place, there is a fear of spreading coronavirus at least quickly in a small place. Therefore, to prevent the coronavirus, the governments of various countries have been forced to adopt the cancel public events policy. Adopting this policy is the hope that the spread of the virus is within its level by gathering additional people in a small place.

Cancel public events policy can reduce the rate of coronavirus infection. At the same time, sensitive people, such as older people and individuals with underlying sickness. To avoid the spread of coronavirus, older people, children, and people with severe disease are restricted from attending public events.

Close public transport policy is another preventive policy for reducing the widening of COVID-19. Close public transport policy mainly refers to the restriction of public transport service and temporary or long-term suspension within a specific geographic area or jurisdiction. This policy reduces the spread of infectious diseases or mitigates any other hazards by limiting the movement of the public during public health emergencies, natural disasters, or any other crisis. In this closed transport policy, the operation of different ways of transport, such as buses, trains, trams, subways, ferries, etc., is closed or run on a reduced schedule.

In general, depending on the level of COVID-19 infection during COVID-19, the government and local authorities of different countries implemented this policy everywhere or in

the case of a specific route. Many goals are achieved through this policy, such as minimizing interpersonal contact. Because if the convenience of public transport decreases, then the tendency of the public to meet friends and relatives decreases. The ultimate result of which is the prevention of the transmission of contagious diseases. Social distancing is also promoted through a closed transport policy because we know that public transport is relatively crowded, and at the same time, passengers are in close contact. After all, public mobility is limited through closed transport policy, and public transport can be enhanced. Which generally helps to shrink the widening of COVID-19.

Another preventive policy is restrictions on gathering policy. Restrictions on gathering policy mean limiting the size of a public gathering, a social event such as a wedding, birthday, festival, or religious event where many people gather. Large gatherings have exposed people to outbreak virus transmission among attendees. Public gathering restrictions primarily aim to reduce the chance of widespread contamination diseases by lowering people's interaction. At the same time, limiting the tendency to become contagious is essential.

The government and authorities of various countries have adopted the prevention of coronavirus as one of the policies through the Restriction of Internal Movement policy. This policy has been effective as a companion policy to the stay-at-home policy. Mainly through Restrictions on Internal movement, the public has been discouraged from leaving the house except for urgent work. In general, this policy has played a fruitful role in preventing the widening of coronavirus from one region to another within a country.

The most crucial preventive policy to prevent the spread of coronavirus is the international travel control policy. Through this policy, a country has imposed control on land ports, water ports,

and airports in two ways. The ports were closed to stop the spread of the coronavirus, and the country's geographical borders were later opened on a limited basis.

Historically, we have seen epidemics take place at the local level. Still, in the current world, international travel is easy and low-cost, so the rate of people from one country traveling to another country is very high. Due to this, human-borne or animal-borne viral diseases can quickly spread from one region of the world to another. Similar things happened in the case of Covid-19. As a result, the governments and authorities of various countries have adopted this policy to reduce the rate of coronavirus infection through international travel control policy.

In this research, I examine these preventive policies' impact on mobility and modality. However, remain paper will be as follows: In section 2, I shall discuss the literature of the related research work, then section 3 describes the data and estimation strategy, and in section 4, I will discuss the research results. And finally, section 5 concludes this chapter.

2. Literature Review

Recently, researchers conducted several studies on the impact of COVID-19 policies, but most of them captured only few policies. According to Armitage & Nellums (2020), transmitting the disease from children was unclear; thus, closing schools might be an inappropriate decision because children, especially marginal children, might face the risk of dropouts, violence, child labor, and teen pregnancies as consequences. Also, for marginal children who cannot access digital technologies, the school provides education and is a place for subsidized meal programs, child health care, etc. Thus, without closing schools, we could initially take some measures like reducing

class size, hygiene and sanitation promotion, and physical distancing, which might be a better approach considering children's social, economic, and health.

The study by Bayham & Fenichel (2020) aimed to examine what effect closing schools had on healthcare providers' childcare responsibilities during periods of Social Distance in the USA. The investigators reviewed the U.S. Current Population Survey data to understand family composition and options for childcare available to healthcare workers. They found that some healthcare industry sectors were more affected by school closures because of differences in job type, geography, and household composition. The results showed that a large proportion (about 28.8%) of healthcare workers were caregivers to children between three and twelve years old. Approximately 15% still needed someone to take care of their kids when schools were not in session, regardless of other alternatives like non-working adults or elder siblings who could assist them with childcare at home. The article also points out extensive heterogeneity within a health system. By doing an analysis using models, they determined the critical threshold at which loss due to workforce absenteeism would balance out any positive impacts anticipated from school closings in reducing COVID-19 cases. Their findings suggested that if the mortality rate associated with COVID-19 rises with decreased workforce numbers, shutting down schools could cause more deaths than it prevents.

Manullang & Satria (2020), focused on the risks and challenges regarding the national policy of school closure during COVID-19 as most countries have undertaken the policy as a preventive measure so that they could fight the extend of the epidemic. The study considered the opinions, expectations, and comments of various voices of education stakeholders and parents and aimed to give insights for further decision-making and policy-making discourse.

Lee (2020) examined the upheld various aspects of school closures. It announced that children and adolescents with mental needs faced difficulties due to school closures as they lacked access to peer support groups and face-to-face interactions. Children with special education needs, like autistic children, are suffering more because they tend to show frustration and become agile when their daily routine is disrupted. The young generation of final years in study life or job seekers suffered mentally as their future became uncertain with school closure.

Suwantika et al. (2020) studied on the remunerative evaluation of combating the coronavirus pandemic in Jakarta, Indonesia, focusing on estimates such as social distancing (SC) and workplace closures (WC). They conducted the estimation process by comparing the baseline, which is "no intervention," with school and workplace closure to 2, 4, and 8 weeks. The work utilizes a modified Susceptible-Exposed-Infected-Recovered (SEIR) compartmental model to simulate the impact of different mitigation strategies. This research findings indicate that implementing a more extended school and workplace closure reduces the incidence and peak mortality rates.

Beck & Hensher (2020) presents the initial results of a survey that is being conducted to determine how Australian people's travel behavior is changing because of the government's stage 2 limitations. The final week of March 2020 was spent creating the survey. The company Pure Profile, which offered online panel surveys around Australia, was utilized to gather data to investigate the broader effects of COVID-19. Beginning on March 30, 2020, the survey received 1073 valid replies by April 15, 2020. This paper's conclusions show that the COVID-19 restrictions have a dynamic effect on people who can and cannot work from home. Fang et al. (2020) investigated to understand the impact of human mobility restriction, particularly in Wuhan. They used difference-in-difference model (DID) estimations to separate the lockdown effect from other

effects. Using the inter-city migration data from Baidu Migration (the travel map of the largest Chinese search engine), they saw a 76.98% decrease in the inflows to Wuhan and a 56.31% decrease in the outflows from Wuhan and a 55.91% decrease in within-Wuhan mobility. According to their estimate, on January 23, 2020, if Wuhan did not lock down, the COVID-19 cases would be 105.27% higher in the 347 cities in China.

Badr et al. (2020) evaluated the correlation between mobility patterns and COVID-19 imparting in the USA. Their study used mobility data from aggregated and anonymized cell phone data from January 1 to April 20, 2020. They used epidemiological data to compute the growth rate ratio of COVID-19 for a given county on a given day. Their study finds a strong correlation between mobility patterns and decreased COVID-19 cases. The Pearson correlation coefficient is above 0.7 for 20 of the 25 counties. They also saw a behavioral change due to the social distancing measures.

According to the study of Wakabayashi et al. (2020), the coronavirus pandemic made the whole world implement counteractive measures to prevent the transmission of infectious diseases among people. These measures include a stay-at-home policy, mandatory face masks, hand sanitizing, avoiding crowding places, etc.; in most countries, violating these restrictions would result in penalties. However, as for Japan, its government asked its citizens to abide by the regulations and implement them without penalties, though ignoring such restrictions is considered high-risk behavior. However, problem drinking and excessive taking of alcohol & drugs are also known as high-risk and self-harming behavior. But under the ongoing limits due to the COVID-19 outbreak, bars, nightclubs, and related shops closed the problem drinkers might face severe pressure. Hence, this study's objective is to scrutinize the alliance between alcohol use and precariousness in the COVID-19 ordinance, mainly focusing on the actions of problem drinkers.

A cross-sectional study used the data from the Japan COVID-19 and Society Internet Survey (JACSIS). In the survey, after data cleaning. Twelve thousand sixty-seven members were picked out as present drinkers. The drinkers were classified to identify whether a person suffers from alcohol use disorder. Then, their behavior (categorized into 18 behaviors) regarding compliance with the stay-at-home policy was analyzed. Stata software was used to perform 15 multivariable binary logistic regression models to research the guild-allying CAGE scores in the presence of each of the 18 behaviors. The results suggest that among the respondents, the highest number (66.9%) go shopping for unnecessary items. It also indicates a robust link between latent alcohol misuse or alcohol employ chaos, as indicated by elevated CAGE scores, and the propensity for high-risk actions from April to May 2020.

Abdullah et al. (2020) explored the impacts of COVID-19 on travel behavior and mode preferences. For this study, they collected data from around the world through an online questionnaire survey, which covered different questions like trip purpose, mode of choice, how much distance traveled, and frequency of trips before and during COVID-19. There was a significant move from public transport to private transport.

Shi et al. (2020) estimated the results of airline travel restrictions on the risk of coronavirus transmission. In this research, they gathered passenger volume data from a global airline network and measured the distance output between every airport and the city of Wuhan; they patterned the risk of COVID-19 ingress by calculating survival chance. The research findings suggest that travel restrictions play a minor role in preventing the spread of SARS-CoV-2 but are insufficient to prevent global spread.

The objective of the survey of Akeju et al. (2021) is to bring indications for recognizing the design of obligation with the Stay Home policy, and people are uncovering the chance of

coronavirus. The survey was regulated through links via WhatsApp, Facebook, messenger, and other virtual platforms, and it included both closed-ended and open-ended questions. It was an in-depth interview, and the participants were 18 or above. Quantitative data were analyzed through SPSS version 22. Places where the respondents visited were coded from high-risk areas to low-risk areas. To explore the socioeconomic component accompanied with evidence and display the empirical proof of coronavirus multiple regression. A thematic analysis was adopted to understand qualitative data. Findings suggest that educated people with regular and stable incomes are likelier to abide by the regulations and thus show increased compliance. Poor people and people engaged in small-scale businesses do not comply with the strict restrictions to meet their family needs. The author termed the policy of Staying at Home as "caging animals without feeding them." On top of that, the difference between the stay-at-home policy and partial confinement is much lower than that of the full lockdown policy. This study also suggests that females, widows, and unemployed were more likely to comply; as for the exposure to risks, the marketplace was identified as the high-risk zone since the respondents most visited it.

Sogbe (2021) aims to examine Ghana's public transportation system, which places riders close to one another and restricts their movement, as well as the epidemic's impact on the system. The data for this study was collected from 1005 observations from September 1, 2020, to October 31, 2020, using an online survey tool called Google Forms. The use of statistical analysis includes quantitative comparison and descriptive analysis. Social distancing was noted as the significant impact of the pandemic on public transportation, a conclusion from this study that needs sufficient attention in policy and practice. This effect caused a change in the manner of public transit.

Wu & Wu (2022) investigate the effectiveness of stay-at-home orders and face mask policies in lessening the spread of coronavirus in the US. In other words, the study aims to analyze

the association between state-level mitigation policies and strategies and COVID-19 consequences in the US by using available pandemic data and the entire population. The study collected various types of data relating to COVID-19 cases, hospital capacities, fatalities, policy mandates, etc. Data were sourced from the CDC, state health departments, and government websites. The study first categorized the states based on stay-at-home (SAH) and mandated face mask (MFM) policies. Then, it analyzed the incidence and fatality rates of COVID-19. The research used an event study design to compare the effects of these policies on COVID-19 transmission between states with mandates and those without. The study gave a comprehensive evaluation of COVID-19 data without theoretical modeling or regional databases focusing only on state-level policies. It observed the trends in COVID-19 cases and fatalities following the implementation of SAH and MFM policies. The potential influence of population density on transmission rates was also observed. It addresses the effectiveness of various preventive measures, i.e., diagnostic testing, patient isolation, and contact tracing, in controlling the spread of the virus. The study's authors argue that there is insufficient evidence to support the effectiveness of SAH and MFM policies in reducing the spread of the virus. They further opine that other factors may be more influential during the pandemic.

Ali and Balme (2022), study explore the changing behavioral attitudes towards festivals. Additionally, the authors look at the probable long-term institutional changes that might emerge in the festival industry. The authors don't predict where the industry is heading but rather a discussion of possible possibilities.

Marra et al. (2022) explored the impact of the COVID-19 pandemic on public transportation and route selection: findings from a long-term monitoring study in an urban environment were the subject of a report in Zurich, Switzerland. This essay attempted to

demonstrate how transportation and route selection impact the COVID-19 pandemic. Data from Zurich, Switzerland, was collected for this study using a GPS tracker in February 2020 and spring 2019. One hundred seventy-two individuals' data were gathered in the spring of 2019 by installing a smartphone app that continuously gathers GPS data; each participant was watched for 22 days on average. A few weeks before the February 2020 pandemic breakout in Switzerland, the study's participants were called once more, and 48 were chosen to participate. They were followed up for an average of 112 days until July 2020. In this study, the researchers attempted to compare travel patterns before and during the epidemic. The purpose of the route choice model in public transportation is to analyze the selected routes inside the network. This study adds to our understanding of how travel behavior changes during the COVID-19 pandemic.

According to Bairoliya & İmrohoroglu (2023), the coronavirus pandemic has revealed that the world's healthcare facilities are inadequate to support the mass population. This study compared two different lockdown scenarios. When lockdown is implemented randomly, healthy, and less healthy individuals in the working-age population are affected. Another scenario targets lockdown based on the working population's age and health status. In another instance, singles are sanctioned to identify and alleviate the prospect of contamination by not attending to the labor force or shrinking the workforce. In this study area, labor supply declines by 4.15%, and 1.53% lessens output. When an unsystematic lockdown is executed, another 2% of the labor force is bound to stay at home, which causes 3.5% output. In the second case, targeted lockdown, where the risky and aged sole with less productivity is quarantined, total workforce supply declines by 4.85%, and output declines by 2.01%. The main findings suggest that the planned lockdown policy output showed a 43% smaller decline than the unsystematic lockdown. This study also shows the

government can incentivize working people to self-mitigate risks by achieving isolation via a tax and shift plan that almost gives a similar outcome to the systemic lockdown.

Valgañón et al., (2023) also worked on this ground. The novel coronavirus SARS-Cov-2 was first detected in Wuhan, China in December 2019. Later, as the infection spread worldwide, the WHO declared a pandemic on March 11, 2020. A range of regulations were employed to stop the transmission of the diseases, such as lockdowns, stay-at-home policies, mandatory face masks, travel restrictions, prohibition on social gatherings, maintaining social distancing, etc. However, according to some research, unlike developed countries, low-developing countries cannot bear the burden of these preventive measures, as people in the latter countries are vulnerable to financial challenges. They faced food insecurity, loss of jobs, and inadequate health services. Some literature suggests that transmissibility depends on many factors, such as population density, income inequality, urban areas, household size, etc. The objective of this study is to evaluate the effectiveness of such non-pharmaceutical policies across various countries. This paper employs the Susceptible-Exposed-Infected-Recovered (SEIR) model on the framework of a discrete-time model, which includes six compartments: Susceptible (S), Exposed (E), Infectious (I), Recovered (R), Pre-deceased (Pd), and Deceased (D). For model calibration, Approximate Bayesian Computation (ABC) solves the Bayesian Inference problem. The findings of this paper suggest that while Spain and Colombia have employed similar lockdown policies, the outcomes are different. Though Spain managed to stop the spread, Colombia experienced steady increases in casualties. Another interesting finding is that GDP per capita and social permeability are negatively associated, implying that people from high-income countries comply with policies more than those from low-income countries. Therefore, the pandemic has exposed existing social and economic disparities within countries, and the obstacles, such as inadequate infrastructure, lack of public

trust, and a high percentage of informal workers, make it challenging to implement effective prevention measures in low-income countries.

Hanzl & Rehm (2023), focused on finding the gendered effect of school closure in the time of the pandemic on paid work hours in Austria. The study examined the impact of school and daycare closures on labor market outcomes by using panel data from the Austrian Corona Panel Project (ACPP) supplemented with data on school closures obtained from OECD and COVID-19 containment measures from the European Centre for Disease Prevention and Control. The dependent variable was weekly paid hours, while control variables comprised socioeconomic characteristics, work time conditions, and pandemic-related factors. Among employees and self-employed individuals only, the sample included 17,892 observations for the total number of respondents, which amounted to 1,702. The primary independent variable was school closures, as well as other variables such as parental status, age, educational attainment, migration background, household income level, the possibility of working remotely at home during lockdowns implemented in response to the COVID-19 in Austria, etc., furloughing or short-time working schemes that were introduced in emergency circumstances; finally, a dummy variable was included which represented non-essential shops and restaurants being closed throughout several consecutive weeks' periods. Descriptive statistics illustrated variations in hours worked between mothers versus fathers versus those without children, also considering adjustments made to childcare practices when schools had to close due to the COVID-19 outbreak temporarily. In graphs, we can see density differences and gender-specific work-hour adjustments linked with closing off school premises. Econometric analysis was used for this research purpose. The study found that mothers reduced paid working hours more than fathers due to school closure. Also, fathers reduced work

hours less than individuals who did not have any children. The additional burden of unpaid care work on women was said to be a potential reason for this outcome.

According to the study of Gu & Zhong (2023), half of the US workforce switched to working from home by the first weeks of April 2020 as the stay-at-home policy was enacted. Around 40 states adopted Stay at Home Orders (SAHO) in the spring of 2020 with short-term SAHO (28 days) and long-term SAHO, which is 97 days, with a mean of 44 days. The findings suggest that the effect of the duration of SAHO was more on the types of work than the content of work. To conclude, this study implies that temporary closure in the workplace during the coronavirus pandemic has an endless effect on the applied-for potential lab.

The COVID-19 and ensuing governmental measures aimed to alleviate the health threat, such as closing schools, had disrupted school meal programs and necessitated an inquiry into the effects on school food service revenue identified in the paper of Zafari et al., (2023). This study performed a longitudinal cohort examination of state and federal reimbursements and sales revenues for all public local education agencies or LEAs in Maryland during SY 2018-2019 and 2019-2020. They analyzed changes in monthly reimbursements under various Child Nutrition Programs such as the School Breakfast Program (SBP), Child and Adult Care Food Program (CACFP), and Summer Food Service Program (SFSP). The outcomes showed a significant decrease in entire earnings from federal coupled with state repayments for SY 2019-2020 as opposed to SY 2018-2020, amounting to an appreciable fall of 11.4%. Between March and June, when schools remained closed due to the pandemic outbreak, the average decline in monthly reimbursements was equal to \$450,385 per LEA month, which is approximately a decrease of 41 percent.

3. Data and Estimation Strategy

The data for this research, I collected COVID-19-related data from January 01, 2020, to December 31, 2022, from the Oxford-covid-19-government-response-tracker (OxCGRT). This data source covered COVID-19-related daily data for all countries of the World. OxCGRT also collects all the policy information on indicators of government response. Finally, OxCGRT codes all the policy variables on an ordinal scale in the following manner:

(1) Stay-at-home policy: '0' no measures; '1' recommends not leaving the house; '2' requires no leaving the house with exceptions for daily exercise, grocery shopping, and essential trips; and '3' requires not leaving the house with minimal exceptions.

(2) School closures: '0' no measures; '1' recommends closing; '2' requires closing only some levels, and '3' requires closing all levels.

(3) Workplace closures: '0' no measures; '1' recommends closing or working from home; '2' requires closing for some sectors; and '3' requires closing all but essential workplaces.

(4) Cancel public events: '0' no measures; '1' recommends canceling; and '2' requires canceling.

(5) Close public transport: '0' no measures; '1' recommended closing or reducing volume/route; and '2' requires closing.

(6) Restrictions on gatherings: '0' no restrictions; '1' restrictions on huge gatherings (the limit is above 1000 people); '2' restrictions on gatherings between 100-1000 people; '3' restrictions on gatherings between 10-100 people; and '4' restrictions on gatherings of less than 10.

(7) Restrictions on internal movement: ‘0’ no measures; ‘1’ recommend movement restrictions; and ‘2’ restrict movement.

(8) International travel controls: ‘0’ no measure; ‘1’ screening; ‘2’ quarantine arrivals from high-risk regions; ‘3’ ban for high-risk regions; and ‘4’ total border closure.

In this research, the main challenge is that some data must be made available. Then, I compiled eight COVID-19 preventive policies that were only available. For this reason, I took daily data from July 5, 2020, to April 15, 2022 (a total of 640 days) for the eighteen countries (covered all continents): Argentina, Australia, Belgium, Canada, Denmark, Finland, France, Italy, Japan, Luxembourg, Malaysia, South Africa, South Korea, Spain, Sweden, Switzerland, United Kingdom, and the United States of America.

Table 1.1
Summary Statistics

	new deaths per million	new cases per million	icu patients per million	positive rate
count	11520	11520	11520	11520
mean	1.425022694	203.2090141	18.48175312	0.069501512
std	1.415402706	198.1201461	16.91464395	0.065263654
min	0	0	0	0.0001
25%	0.229	37.36	5.264271784	0.019
50%	0.918	138.595	11.6185	0.0487
75%	2.383	317.43475	29.339	0.1092
max	5.062	690.24	60.927	0.289

Data Source: Oxford COVID-19 Government Response Tracker (2023)

Table 1.2
Summary statistics of each category for each policy variable

Policies	0	1	2	3	4	5	mean	std
stay_home	0.33498	0.3316	0.33333	0.00009	N/A	N/A	0.25	0.16661
school_closures	0.09679	0.52153	0.21589	0.1658	N/A	N/A	0.25	0.18749
workplace_closures	0.08056	0.32535	0.47222	0.12188	N/A	N/A	0.25	0.18274
cancel_public_events	0.06936	0.43429	0.49635	N/A	N/A	N/A	0.33333	0.23070
close_public_transport	0.55729	0.40061	0.0421	N/A	N/A	N/A	0.33333	0.26410
restriction_gatherings	0.14523	0.0566	0.06918	0.18351	0.54549	N/A	0.2	0.20020
restrictions_internal_movements	0.5296	0.1684	0.302	N/A	N/A	N/A	0.33333	0.18263
international_travel_controls	0.01441	0.22535	0.15174	0.44141	0.1671	N/A	0.2	0.15554
facial_coverings	0.04722	0.10955	0.25113	0.46693	0.12517	N/A	0.2	0.16657
contact_tracing	0.01884	0.4362	0.54497	N/A	N/A	N/A	0.33333	0.27774
testing_policy	0	0.05312	0.44939	0.49748	N/A	N/A	0.33333	0.24386
vaccination_policy	0.27769	0.02786	0.08967	0.09748	0.08108	0.42622	0.16667	0.15297
public_information_campaigns	0.00061	0	0.99939	N/A	N/A	N/A	0.5	0.70624

Note: 'N/A' indicates not applicable

Table 1.3
Descriptive statistics with sample mean for the key variables according to the policy variables

	new_deaths_ per_million		new_cases_ per_million		icu_patients_ per_million		positive_rate	
	mean	std	mean	std	mean	std	mean	std
stay_home								
0	1.258	1.264	257.628	219.321	12.913	12.06	0.078	0.07
1	1.018	1.274	149.175	176.158	13.533	13.498	0.051	0.053
2	1.997	1.507	202.322	180.755	29.005	19.095	0.079	0.067
3	0.115		10.352		1.146		0.005	
school_closures								
0	1.498	1.471	287.338	237.639	9.171	7.773	0.108	0.075
1	1.252	1.312	201.776	200.392	16.931	15.722	0.065	0.061
2	1.557	1.471	179.924	174.759	21.893	18.41	0.064	0.064
3	1.753	1.537	188.923	180.854	24.354	19.08	0.068	0.065
workplace_closures								
0	1.517	1.51	254.932	216.735	10.628	11.08	0.099	0.074
1	1.186	1.275	201.55	205.997	14.301	13.81	0.066	0.064
2	1.515	1.448	199.647	192.198	21.376	18.003	0.07	0.065
3	1.653	1.491	187.254	180.59	23.619	18.864	0.058	0.058
cancel_public_events								
0	1.656	1.493	303.798	207.13	13.153	12.359	0.119	0.075
1	1.165	1.239	205.005	208.343	13.835	12.641	0.066	0.063
2	1.621	1.509	187.582	182.918	23.292	19.218	0.066	0.063
close_public_transport								
0	1.182	1.317	195.046	198.488	16.939	16.237	0.064	0.063
1	1.613	1.446	209.451	200.892	17.422	15.311	0.068	0.063
2	2.858	1.25	251.868	152.664	48.99	10.136	0.153	0.068
restriction_gatherings								
0	1.551	1.373	285.233	225.189	15.187	14.175	0.095	0.07
1	1.012	1.209	188.29	223.089	11.429	10.082	0.065	0.061
2	0.638	1.031	89.92	135.947	7.179	6.033	0.049	0.057
3	1.194	1.263	193.962	195.327	13.932	12.815	0.069	0.068
4	1.612	1.482	200.399	186.17	23.055	18.67	0.066	0.063
restrictions_internal_movements								
0	1.433	1.361	238.302	205.596	16.687	15.083	0.073	0.068
1	0.922	1.182	135.278	179.025	13.399	12.596	0.062	0.054
2	1.693	1.547	179.548	180.835	24.464	20.106	0.069	0.066

Table 1.3 (Continued)

	new_deaths_ per_million		new_cases_ per_million		icu_patients_ per_million		positive_rate	
	mean	std	mean	std	mean	std	mean	std
international_travel_controls								
0	1.77	1.259	370.077	208.005	8.727	5.401	0.126	0.07
1	1.688	1.363	273.393	212.642	16.527	12.858	0.104	0.071
2	1.189	1.303	208.376	213.86	13.067	11.705	0.063	0.066
3	1.477	1.467	193.76	182.415	22.767	19.083	0.057	0.053
4	1.112	1.367	114.439	153.799	15.557	17.425	0.056	0.066

Since this research deals with the panel data and I want to measure the effect of the COVID-19 preventive policies on morbidity and mortality, I apply panel data ordinary least square regression model. To do this, I have two alternatives, one is the fixed effect model (FEM), and another is the random effect model (REM). To select FEM or REM, I apply the Hausman test; if the p-value is less than 0.05, then FEM is preferred. Otherwise, REM is applicable.

The general equation of the fixed effect model for mortality is:

$$Y_{1it} = \beta_{10} + \beta_{11}X_{1it} + \beta_{12}X_{2it} + \sum_{j=1}^J \delta_{1j}D_{jit} + u_{1it}$$

The general equation of the fixed effect model for morbidity is:

$$Y_{2it} = \beta_{20} + \beta_{21}X_{1it} + \beta_{22}X_{2it} + \sum_{j=1}^J \delta_{2j}D_{jit} + u_{2it}$$

Here,

Y_{1it} and Y_{2it} are the dependent variables (new_deaths_per_million and new_cases_per_million, respectively) for individual i at time t .

β_{10} , β_{20} are the intercept term that represent the baseline category (policy at the zero level, that means no policy measures).

β_{11} , β_{12} , β_{21} , and β_{22} are the coefficients associated with the continuous independent variables.

X_{1it} and X_{2it} are continuous independent variables (icu_patients_per_million and positive_rate, respectively) for individual i at time t .

δ_{1j} and δ_{2j} are the coefficients associated with the policy variable.

D_{jit} are dummy variables representing the categories for a policy for individual i at time t . There are J categories in a policy variable.

u_{1it} and u_{2it} are the error terms specific to each dependent variable individual i at time t .

The general equation of the random effect model for mortality is:

$$Y_{3it} = \beta_{30} + \beta_{31}X_{1it} + \beta_{32}X_{2it} + \sum_{j=1}^J \delta_{3j}D_{jit} + w_{3it}$$

The general equation of the random effect model for morbidity is:

$$Y_{4it} = \beta_{40} + \beta_{41}X_{1it} + \beta_{42}X_{2it} + \sum_{j=1}^J \delta_{4j}D_{jit} + w_{4it}$$

Here,

Y_{3it} and Y_{4it} are the dependent variables (new_deaths_per_million and new_cases_per_million, respectively) for individual i at time t .

β_{30} , β_{40} are the intercept term that represent the baseline category (policy at the zero level, that means no policy measures).

β_{31} , β_{32} , β_{41} , and β_{42} are the coefficients associated with the continuous independent variables.

X_{3it} and X_{4it} are continuous independent variables (icu_patients_per_million and positive_rate, respectively) for individual i at time t .

δ_{3j} and δ_{4j} are the coefficients associated with the policy variable.

D_{jit} are dummy variables representing the categories for a policy for individual i at time t . There are J categories in a policy variable.

w_{3it} and w_{4it} are composite error terms. A composite error term consists of two components: ε_i for individual-specific or cross section error, and u_{it} for the idiosyncratic error.

The Hausman Test:

The Hausman test compares the estimates from the Fixed Effect model and a Random Effect model. It determines whether the assumptions of the random effects model are valid. We can express in an equation:

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})' (Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE}))^{-1} (\hat{\beta}_{FE} - \hat{\beta}_{RE})$$

Here,

$\hat{\beta}_{FE}$ are the vector of coefficient estimates from the Fixed Effect Model. $\hat{\beta}_{RE}$ are the vector of coefficient estimates from the Random Effect Model. $Var(\hat{\beta}_{FE})$ are the variance-covariance matrix of the coefficient estimates from the fixed effects model. $Var(\hat{\beta}_{RE})$ are the variance-covariance matrix of the coefficient estimates from the random effects model.

4. Estimation Results and Discussion

Estimation Results – Stay-at-home policies: Morbidity

Table 1.4
Hausman Test Results: stay_at_home
policy on morbidity

chi2	df	p-val
28.21061179	6	8.58E-05

Since the p-value is less than 0.05 so that here I apply the fixed effects model for the estimation.

Table 1.5
Parameter Estimates: stay_at_home policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	4.1778	0.1285	32.510	0.0000	3.9259	4.4297
positive_rate	1553.0	25.599	60.666	0.0000	1502.8	1603.2
const	64.828	3.1020	20.899	0.0000	58.748	70.908
stay_home_1	-61.421	3.6702	-16.735	0.0000	-68.616	-54.227
stay_home_2	-79.180	4.2576	-18.597	0.0000	-87.526	-70.834
stay_home_3	-86.027	137.05	-0.6277	0.5302	-354.67	182.62

Here, a decrease of approximately 61.421, 79.180, and 86.027 units in the morbidity rate per million, respectively, associated with stay-at-home policy 1, 2, and 3 compared with the stay-at-home policy 0 (baseline category). Stay-at-home policy 1 and 2 are statistically significant, whereas stay-at-home 3 is not statistically significant.

Estimation Results – Stay-at-home policies: Mortality

Table 1.6
Hausman Test Results: stay_at_home policy
on mortality

chi2	df	p-val
5.199524225	6	0.518489298

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.7
Parameter Estimates: stay_at_home policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0436	0.0009	47.826	0.0000	0.0418	0.0454
positive_rate	6.9441	0.1821	38.139	0.0000	6.5872	7.3010
const	0.1334	0.0895	1.4910	0.1360	-0.0420	0.3088
stay_home_1	-0.0830	0.0261	-3.1826	0.0015	-0.1342	-0.0319
stay_home_2	0.0927	0.00302	3.0643	0.0022	0.0334	0.1519
stay_home_3	-0.0058	0.9761	-0.0060	0.9952	-1.9191	1.9074

Here, a decrease of approximately 0.0830 and 0.0058 units in the mortality rate per million, respectively, associated with stay-at-policy 1 and 3, and an increase of roughly 0.0927 units in the mortality rate per million associated with stay-at-home policy 2 compared with the stay-at-home policy 0 (baseline category). Stay-at-home policy 1 and 2 are statistically significant, whereas stay-at-home policy 3 is not statistically significant.

Estimation Results – School Closures: Morbidity

Table 1.8
Hausman Test Results: school_closures
policy on morbidity

chi2	df	p-val
-28.0268	6	1

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.9
Parameter Estimates: school_closures policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	4.0036	0.1195	33.506	0.0000	3.7694	4.2378
positive_rate	1594.7	25.378	62.839	0.0000	1545.0	1644.5
const	83.065	14.870	5.5860	0.0000	53.917	112.21
school_closures_1	-45.550	5.0991	-8.9330	0.0000	-55.546	-35.555
school_closures_2	-102.78	5.6640	-18.146	0.0000	-113.88	-91.675
school_closures_3	-113.04	6.3839	-17.707	0.0000	-125.55	-100.52

Here, a decrease of approximately 45.550, 102.78, and 113.04 units in the morbidity rate per million, respectively, associated with school closures policy 1, 2, and 3 compared with the school closures policy 0 (baseline category). School closures policies 1, 2, and 3 are statistically significant in morbidity.

Estimation Results – School Closures: Mortality

Table 1.10
Hausman Test Results: school_closures
policy on mortality

chi2	df	p-val
5.193672	6	0.519224

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.11
Parameter Estimates: school_closures policy on mmortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0473	0.0008	55.675	0.0000	0.0456	0.0489
positive_rate	6.2958	0.1803	34.916	0.0000	5.9424	6.6493
const	0.4563	0.0994	4.5894	0.0000	0.2614	0.6512
school_closures_1	-0.3924	0.0362	-10.832	0.0000	-0.4635	-0.3214
school_closures_2	-0.3882	0.0402	-9.6469	0.0000	-0.4671	-0.3093
school_closures_3	-0.3235	0.0454	-7.1338	0.0000	-0.4124	-0.2346

Here, a decrease of approximately 0.3924, 0.3882, and 0.3235 units in the mortality rate per million, respectively, associated with school closures policy 1, 2, and 3 compared with the school closures policy 0 (baseline category). School closures policy 1, 2 and 3 are statistically significant on the mortality.

Estimation Results – Workplace Closures: Morbidity

Table 1.12
Hausman Test Results: workplace_closures
policy on morbidity

chi2	df	p-val
-12.378	6	1

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.13
Parameter Estimates: workplace_closures policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.8222	0.1218	31.387	0.0000	3.5835	4.0609
positive_rate	1636.6	24.997	65.473	0.0000	1587.6	1685.6
const	66.370	14.255	4.6559	0.0000	38.428	94.313
workplace_closures_1	-21.794	5.6718	-3.8426	0.0001	-32.912	-10.677
workplace_closures_2	-60.763	5.6600	-10.736	0.0000	-71.858	-49.669
workplace_closures_3	-96.545	7.2692	-13.281	0.0000	-110.79	-82.296

Here, a decrease of approximately 21.794, 60.763, and 96.545 units in the morbidity rate per million, respectively, associated with workplace closures policy 1, 2, and 3 compared with the workplace closures policy 0 (baseline category). Workplace closures policies 1, 2, and 3 are statistically significant in morbidity.

Estimation Results – Workplace Closures: Mortality

Table 1.14
Hausman Test Results: workplace_closures
policy on mortality

chi2	df	p-val
4.685424	6	0.584745

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.15
Parameter Estimates: workplace_closures policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0470	0.0009	54.722	0.0000	0.0453	0.0487
positive_rate	6.5664	0.1763	37.240	0.0000	6.2208	6.9121
const	0.4368	0.1021	4.2765	0.0000	0.2366	0.6371
workplace_closures_1	-0.3839	0.0400	-9.5958	0.0000	-0.4623	-0.3055
workplace_closures_2	-0.3504	0.0399	-8.7750	0.0000	-0.4286	-0.2721
workplace_closures_3	-0.3833	0.0513	-7.4750	0.0000	-0.4838	-0.2828

Here, a decrease of approximately 0.3839, 0.3504, and 0.3833 units in the mortality rate per million, respectively, associated with workplace closures policy 1, 2, and 3 compared with the workplace closures policy 0 (baseline category). Workplace closures policies 1, 2, and 3 are statistically significant in mortality.

Estimation Results – Cancel Public Events: Morbidity

Table 1.16

Hausman Test Results:

cancel_public_events policy on morbidity

chi2	df	p-val
-31.7476	5	1

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.17

Parameter Estimates: cancel_public_events policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.9798	0.1215	32.750	0.0000	3.7416	4.2180
positive_rate	1597.7	25.471	62.728	0.0000	1547.8	1647.7
const	62.084	13.810	4.4957	0.0000	35.015	89.153
cancel_public_events_1	-13.783	5.8086	-2.3729	0.0177	-25.169	-2.3972
cancel_public_events_2	-75.526	6.0198	-12.546	0.0000	-87.326	-63.726

Here, a decrease of approximately 13.783 and 75.526 units in the morbidity rate per million, respectively, associated with cancel public events policy 1 and 2 compared with the cancel public events policy 0 (baseline category). Cancel public events policy 1, and 2 are statistically significant in morbidity.

Estimation Results – Cancel Public Events: Mortality

Table 1.18

Hausman Test Results:

cancel_public_events policy on mortality

chi2	df	p-val
5.173041	5	0.395129

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.19

Parameter Estimates: cancel_public_events policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0466	0.0009	54.014	0.0000	0.0449	0.0483
positive_rate	6.5399	0.1810	36.140	0.0000	6.1852	6.8946
const	0.3997	0.1000	3.9966	0.0001	0.2037	0.5958
cancel_public_events_1	-0.3278	0.0413	-7.9424	0.0000	-0.4087	-0.2469
cancel_public_events_2	-0.2999	0.0428	-7.0118	0.0000	-0.3837	-0.2161

Here, a decrease of approximately 0.3278 and 0.2999 units in the mortality rate per million, respectively, associated with cancel public events policy 1 and 2 compared with the cancel public events policy 0 (baseline category). Cancel public events policy 1, and 2 are statistically significant in mortality.

Estimation Results – Close Public Transport: Morbidity

Table 1.20

Hausman Test Results:

close_public_transport policy on morbidity

chi2	df	p-val
289.5117	5	1.80E-60

Since the p-value is less than 0.05 so that here I apply the fixed effects model for the estimation.

Table 1.21

Parameter Estimates: close_public_transport policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.3245	0.1155	28.795	0.0000	3.0982	3.5508
positive_rate	1754.3	24.389	71.929	0.0000	1706.5	1802.1
const	27.584	2.8771	9.5876	0.0000	21.945	33.224
close_public_transport_1	-5.4750	4.2958	-1.2745	0.2025	-13.896	2.9456
close_public_transport_2	-131.83	11.109	-11.867	0.0000	-153.61	-110.05

Here, a decrease of approximately 5.4750 and 131.83 units in the morbidity rate per million, respectively, associated with close public transport policy 1, and 2 compared with the close transport policy 0 (baseline category). Close public transport policy 2 is statistically significant on the morbidity, whereas close public transport policy 1 is not statistically significant on the morbidity.

Estimation Results – Close Public Transports: Mortality

Table 1.22
Hausman Test Results:
close_public_transport policy on mortality

chi2	df	p-val
17.45336	5	0.003716

Since the p-value is less than 0.05 so that here I apply the fixed effects model for the estimation.

Table 1.23
Parameter Estimates: close_public_transport policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0444	0.0008	54.703	0.0000	0.0428	0.0460
positive_rate	6.8410	0.1716	39.868	0.0000	6.5046	7.1773
const	0.0742	0.0202	3.6680	0.0002	0.0346	0.1139
close_public_transport_1	0.1024	0.0302	3.3887	0.0007	0.0432	0.1617
close_public_transport_2	0.3105	0.0782	3.9723	0.0001	0.1573	0.4637

Here, an increase of approximately 0.1024 and 0.3105 units in the mortality rate per million, respectively, associated with close public transport policy 1, and 2 compared with the close transport policy 0 (baseline category). Close public transport policy 1, and 2 are positively statistically significant on the mortality.

Estimation Results – Restrictions on Gatherings: Morbidity

Table 1.24

**Hausman Test Results: restrictions_on_gatherings
policy on morbidity**

chi2	df	p-val
8.992713	7	0.25318

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.25

Parameter Estimates: restrictions_on_gatherings policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.8224	0.1224	31.218	0.0000	3.5824	4.0624
positive_rate	1599.4	25.063	63.814	0.0000	1550.3	1648.5
const	75.826	12.389	6.1203	0.0000	51.541	100.11
restriction_gatherings_1	43.638	7.5368	5.7900	0.0000	28.865	58.411
restriction_gatherings_2	-60.737	6.5648	-9.2520	0.0000	-73.605	-47.869
restriction_gatherings_3	-57.831	5.0745	-11.396	0.0000	-67.777	-47.884
restriction_gatherings_4	-77.136	4.4400	-17.373	0.0000	-85.839	-68.432

Here, a decrease of approximately 60.737, 57.831 and 77.136 units in the morbidity rate per million, respectively, associated with restrictions on gatherings policy 2, 3, and 4, and an increase of approximately 43.638 units in the morbidity rate per million associated with restrictions on gatherings 1 compared with the restrictions on gatherings 0 (baseline category). Restrictions on gatherings policy 2, 3, and 4 are negatively statistically significant, whereas restrictions on gatherings policy 1 is positively statistically significant.

Estimation Results – Restrictions on Gatherings: Mortality

Table 1.26

Hausman Test Results: restrictions_on_gatherings policy on mortality

chi2	df	p-val
7.322489	7	0.396092

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.27

Parameter Estimates: restrictions_on_gatherings policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0456	0.0009	52.386	0.0000	0.0438	0.0473
positive_rate	6.5569	0.1779	36.866	0.0000	6.2082	6.9055
const	0.3016	0.0975	3.0949	0.0020	0.1106	0.4927
restriction_gatherings_1	0.0274	0.0535	0.5116	0.6089	-0.0775	0.1323
restriction_gatherings_2	-0.3914	0.0466	-8.4007	0.0000	-0.4827	-0.3001
restriction_gatherings_3	-0.2844	0.0360	-7.8969	0.0000	-0.3550	-0.2138
restriction_gatherings_4	-0.1769	0.0315	-5.6128	0.0000	-0.2386	-0.1151

Here, a decrease of approximately 0.3914, 0.2844 and 0.1769 units in the mortality rate per million, respectively, associated with restrictions on gatherings policy 2, 3, and 4, and an increase of approximately 0.0274 units in the mortality rate per million associated with restrictions on gatherings 1 compared with the restrictions on gatherings 0 (baseline category). Restrictions on gatherings policy 2, 3, and 4 are negatively statistically significant, whereas restrictions on gatherings policy 1 is not statistically significant.

Estimation Results – Restrictions on Internal Movement: Morbidity

Table 1.28

Hausman Test Results:

restrictions on internal movement policy on morbidity

chi2	df	p-val
-8.56823	5	1

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.29

Parameter Estimates: restrictions on internal movement policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.8411	0.1162	33.045	0.0000	3.6132	4.0689
positive_rate	1638.8	24.195	67.734	0.0000	1591.4	1686.3
const	60.131	12.545	4.7933	0.0000	35.541	84.721
rest_internal_move_1	-61.155	4.7289	-12.932	0.0000	-70.425	-51.886
rest_internal_move_2	-104.35	4.3776	-23.837	0.0000	-112.93	-95.769

Here, a decrease of approximately 61.155 and 104.35 units in the morbidity rate per million, respectively, associated with restrictions on internal movements policy 1, and 2 compared with the restrictions on internal movement policy 0 (baseline category). Restrictions on public movements policy 1, and 2 are negatively statistically significant on the morbidity.

Estimation Results – Restrictions on Internal Movement: Mortality

Table 1.30

Hausman Test Results:

restrictions_on_internal_movement_policy on mortality

chi2	df	p-val
5.583133	5	0.348916

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 1.31

Parameter Estimates: restrictions_on_internal_movement_policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0452	0.0008	54.298	0.0000	0.0436	0.0468
positive_rate	6.8343	0.1732	39.455	0.0000	6.4947	7.1738
const	0.1549	0.0886	1.7476	0.0806	-0.0188	0.3286
rest_internal_move_1	-0.1674	0.0339	-4.9444	0.0000	-0.2337	-0.1010
rest_internal_move_2	-0.0388	0.0313	-1.2377	0.2159	-0.1002	0.0226

Here, a decrease of approximately 0.1674 and 0.0388 units in the mortality rate per million, respectively, associated with restrictions on internal movements policy 1, and 2 compared with the restrictions on internal movement policy 0 (baseline category). Restrictions on public movements policy 1 is statistically significant on the mortality, whereas restrictions on public movements policy 1 is not statistically significant on the mortality.

Estimation Results – International Travel Control: Morbidity

Table 1.32

Hausman Test Results:

international_travel_control policy on morbidity

chi2	df	p-val
125.916	7	4.48E-24

Since the p-value is less than 0.05 so that here I apply the fixed effects model for the estimation.

Table 1.33

Parameter Estimates: international_travel_control policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.9576	0.1189	33.279	0.0000	3.7245	4.1907
positive rate	1498.8	26.375	56.828	0.0000	1447.1	1550.5
const	75.023	11.330	6.6216	0.0000	52.814	97.231
international_travel_controls_1	8.7900	11.278	0.7794	0.4358	-13.317	30.897
international_travel_controls_2	-32.380	11.677	-2.7730	0.0056	-55.268	-9.4912
international_travel_controls_3	-77.698	11.380	-6.8276	0.0000	-100.00	-55.391
international_travel_controls_4	-71.208	12.238	-5.8187	0.0000	-95.196	-47.220

Here, a decrease of approximately 32.380, 77.698 and 71.208 units in the morbidity rate per million, respectively, associated with international travel controls policy 2, 3, and 4, and an increase of approximately 8.7900 units in the morbidity rate per million associated with international travel controls policy 1 compared with the international travel controls policy 0 (baseline category). International travel controls policy 2, 3, and 4 are statistically significant, whereas international travel controls policy 1 is not statistically significant.

Estimation Results – International Travel Control: Mortality

Table 1.34

Hausman Test Results: international_travel_control policy on mortality

chi2	df	p-val
12.34605	7	0.089738

Since the p-value is higher than 0.05 so that here I apply the random effects model for the estimation.

Table 1.35

Parameter Estimates: international_travel_control policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0471	0.0008	55.954	0.0000	0.0455	0.0488
positive rate	6.3764	0.1874	34.029	0.0000	6.0091	6.7437
const	0.4737	0.1162	4.0775	0.0000	0.2460	0.7014
international_travel_controls_1	-0.2549	0.0802	-3.1792	0.0015	-0.4120	-0.0977
international_travel_controls_2	-0.3913	0.0830	-4.7147	0.0000	-0.5539	-0.2286
international_travel_controls_3	-0.4972	0.0809	-6.1461	0.0000	-0.6557	-0.3386
international_travel_controls_4	-0.1580	0.0869	-1.8183	0.0690	-0.3283	0.0123

Here, a decrease of approximately 0.2549, 0.3913, 0.4972 and 0.1580 units in the mortality rate per million, respectively, associated with international travel controls policy 1, 2, 3, and 4 compared with the international travel controls policy 0 (baseline category). International travel controls policy 1, 2, and 3 are statistically significant, whereas international travel controls policy 4 is not statistically significant at the 5% significance level.

5. Conclusion

In the recent history of the world, the COVID-19 epidemic has been a terrible experience for people. These three years, from 2020 to 2022, all the world's people must go through a terrible fear. Even the death of a close person could not be close to the work of charity. Medical scientists and the government have adopted various preventive policies to reduce COVID-19-related morbidity and mortality.

In this research, I have examined the effect of preventive policy on COVID-19-related morbidity and mortality. Most of the policies suggested in this study are highly effective in preventing disease and reducing death due to COVID-19. However, close transport 1 and 2, restrictions on internal movement 2, and international travel control 4 policies on mortality were not found to be statistically significant. Therefore, the results of this study say that the preventive policies for COVID-19 have been able to have a better impact on morbidity compared to mortality.

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Chapter 2

Impact of the COVID-19 Behavioral Policies on Morbidity and Mortality

Abstract

In this chapter, I aim to estimate the impact of the COVID-19 behavioral policies on morbidity and mortality. Here, behavioral policies include face covering policy and contract tracing policy. These policies mainly restrict the spread of the coronavirus and minimize the new cases of covid disease, which causes death by changes in human behavior. This study finds that face-covering 1, 2, and 3 policies' impact on morbidity is statistically significant, whereas the effect of contract tracing policies is statistically insignificant. Still, the impact of face covering- 2, 3, 4 policies, and contract tracing 2 policy on mortality are statistically significant, whereas face covering 1 and contract tracing 1 policies do not work on mortality.

Keywords: COVID-19, Face Covering Policy, Contract Tracing Policy

JEL Classification: H5, I1

1. Introduction

Behavioral policy is a framework that prevents diseases and promotes health. Centuries to centuries, pandemics have played critical aspects of human behaviors. As a government, policymakers have taken different steps to control pandemic illness. According to the World Health Organization (2023), in Africa, the Uganda government has strictly taken measures to control human immunodeficiency virus (HIV). There are lots of success stories in Uganda of taking strategies of different behavioral policies they got to control HIV. At present, many other countries like Zimbabwe are following effective strategies to reduce HIV pandemics.

Many countries can prevent pandemics by learning from the past. We must leave our house to earn a living. To meet people's basic needs, they must leave the house to go to the market to buy food, the hospital for medication, the school for education, and work for livelihood.

In that case, the coronavirus constantly threatens the human community. The government and policymakers decide on the face mask covering policy to prevent the coronavirus. Medical scientists say the coronavirus is transmitted through human sneezes, coughs, and droplets. So, the face mask policy plays a very influential role in preventing the spread of coronavirus.

The face mask covering policy plays an influential role in maintaining the social communication system for survival, for work that is for livelihood, as well as maintaining physical distance and preventing the spread of COVID-19. The face mask covering policy helps people control their health risks and avoid infection and coronavirus transmission from one person to another. Coronavirus spreads through breathing and coughing. Therefore, covering the face with a mask is an effective policy to avoid this. People still use face masks for COVID-19 infection and prevention. People remain in their habits because of the fear of covid.

Contract tracing policy is one of the countermeasures against COVID-19. The Ebola virus was first detected in South Sudan in 1976. Doctors adopt contract tracing policies since no vaccine has been discovered, and governments and policymakers work together to prevent transmission to other human bodies. Health workers and volunteers used this policy to identify and isolate people affected by epidemics to keep themselves healthy and prevent the virus from spreading to other people. History shows that contract tracing policies have been adopted throughout the ages to control epidemics. Those who were affected by the virus were identified and kept isolated.

When the coronavirus was discovered, there was no vaccination. The physicians first detected the corona through the test and arranged to keep those with positive corona in a separate room. Also, those who were in close contact, such as family members, office colleagues, and others who have been with the affected person for a long time, are identified under this contract tracing policy. Self-quarantine through contract tracing policy, monitoring if any COVID symptoms are observed, and re-checking everyone if necessary. Also, follow up through guidelines to the infected and those who were close to the infected during quarantine.

In the early days, when a person died of COVID-19, they were given a unique burial by volunteers because death can also spread through the person. Many times, if someone comes from abroad and does not maintain the quarantine, the whole family will be affected. If the doctors were not informed of the COVID-19 positive, people who encountered the infected person and their families would be at risk. Contract tracing policy plays a vital role in overcoming this problem.

Many countries have made the COVID test mandatory for surgery or hospital admission. The affected person has bound the office with the negative report of COVID-19 after the quarantine days are over. After COVID-19, the affected person is also monitored so they are not again affected. Governments and policymakers make contract tracing effective through various

guidelines. COVID-19 is limited through guidelines such as keeping shoes outside, washing vegetables and fruits from the market, washing hands, and sanitizing hands.

The prevailing policy is the contract tracing policy. Many countries still allow PCR COVID tests before traveling abroad. In the case of foreign travel during the Covid period, many countries have followed quarantine till the specified time after travel.

Contract tracing policy is a vital tool to control epidemics and pandemics. The contract tracing policy is working as an epidemic chain breakdown to prevent the rapid spread of COVID-19 in the community. As a result, timely identification of COVID-19-affected persons, timely guidelines, monitoring, and necessary support are possible under this policy. Contract tracing policy is very challenging because large-scale COVID breakdown people are limited by fewer volunteers, nurses, and physicians in a short period. These volunteers, nurses, and physicians have been trained by the government and policymakers. It is becoming possible to reduce the epidemic and pandemic rate through collective efforts.

In this research, I examine these behavioral policies' impact on mobility and modality. The remainder of this paper will begin as follows: In section 2, I will discuss the literature of the related research work, then section 3 describes the data and estimation strategy, and in section 4, I will discuss the research results. Finally, section 5 concludes this chapter.

2. Literature Review

Recently, many researchers have studied the impact of COVID-19 policies, but only some have captured all the policies. Mossong, J. et al. (2008) aimed to determine the impact of potential interventions; mathematical modeling of infectious diseases transmitted through the respiratory or

close-contact route (for example, pandemic influenza) is becoming increasingly popular. The study's primary objective is to examine social interactions and contact patterns pertinent to the transmission of infectious diseases. The surveys were administered from May 2005 to September 2006. The selection of participants ensured that the findings generally represented the entire population concerning age, gender, and geographic distribution. The participants were requested to document their interactions with others in a physical diary, encompassing details such as age, gender, whereabouts, duration, and frequency of contact. Diaries were made accessible in an assortment of languages for the participation of the individuals or their legal guardians. Physical contacts (including skin-to-skin contact) and non-physical contacts (including conversations) involving the interchange of three or more words were the subjects of the study. In general, the primary discoveries of the research underscore the significance of age-related assortative in contact patterns, the uniformity of contact patterns among European nations, and the necessity of integrating social contact information into transmission models to gain a more comprehensive comprehension of the dissemination of infectious diseases.

Numerous African countries have either implemented or are contemplating the utilization of Digital Contact-Tracing (DCT) as a component of COVID-19 containment strategies, prompted by the call for technological enhancements to traditional contact-tracing methods (Arakpogun et al., 2020). We explore the intricacies of employing Digital contact tracing (DCT) in Africa. This research contends that if the design and implementation of DCT are not carefully considered, it could lead to unintended consequences, especially in a continent like Africa, characterized by significant digital disparities and systemic disparity. This study proposes that any assumption of DCT by African nations should consider their similarity with community stocks, values, social structures, and domestic political dynamics. Consequently, we advocate for a process of translation

wherein DCT adaptation is tailored to suit the distinctive institutional and technological characteristics of African countries, drawing on local practices gleaned from previous pandemics such as Ebola to formulate a blended epidemiological approach to (digital) contact tracing.

The research work by Chung et al. (2021) tried to study whether the government policies of different countries to reduce the loss of COVID-19 were effective. For this research, they extracted COVID-19 data from December 31, 2019, to August 31, 2020, from the European Centre for Disease Prevention and Control (ECDC), which included daily confirmed cases and deaths in COVID-19 from 90 countries. The Poisson regression model was used to determine the effectiveness of government policy measures in the spread of Covid-19 across countries with different waves. Segmentation techniques were employed to detect peaks and breaks in daily confirmed case data, such as wave-specific analyses that could be conducted using dummy variables. This study's results demonstrated how government policies have helped reduce overall cases per day since the start of the pandemic. It is worth noting that massive testing and contact tracing strategies played a part in reducing these confirmed cases. However, many policies with significant coefficients indicated a positive relationship between policies and confirmed cases. A lot made it difficult to understand whether certain factors affect the spread of COVID-19 more than others. This was because changes in confirmed cases often took time before becoming observable due to lag effects associated with policy implementation. This study focused on specific waves of infection and pointed out the importance of containment policies, which was exceptionally high during the first wave when there was little knowledge about COVID-19. In subsequent waves, a range of other policies, such as economic ones, appeared significant, implying that an evolving grasp of what works better is emerging. The study concluded that although some

policies have direct negative relationships with confirmed cases, interpretation should be done in a broader context.

de Montjoye et al. (2021) examine the trade-offs linked to implementing contact tracing apps to aid pandemic response policies. Due to limitations in governmental enforcement, individuals' voluntary adoption of such apps becomes pivotal. This basic model underscores the significance of individuals' incentives to willingly utilize a reporting app, disclosing their infection status to authorities for contact tracing purposes. The study delves into the implications of different policy choices, such as security measures, communication strategies, and anonymization policies, on the volume and diversity of infection data samples generated by contact tracing applications. The study presents a straightforward framework to examine the trade-offs inherent in these inquiries and to analyze individual choices regarding app installation and adoption, as well as truthful reporting. The methodology employs fundamental economic theories to delineate inevitable trade-offs linked to the implementation of tracing apps aimed at gathering information to bolster pandemic response policies, the inclusiveness of data gathered from these apps, and the overall advantages gained. Based on the evidence available thus far during the COVID-19 pandemic, numerous countries face challenges in attaining substantial adoption rates of government-endorsed contact tracing apps. The study proposes a basic theoretical framework to delineate inevitable trade-offs linked to the implementation of such tracing apps aimed at gathering information to support policy responses. The framework emphasizes the interaction between the inclusiveness of the data collected from these apps and the perceived net benefits for users in downloading the apps. It underscores that achieving widespread adoption hinges on various factors, including the security of data collection processes and the assurance of user anonymity. Additionally, it assists in steering discussions regarding potential policy directions. The study

believes this area is crucial yet needs to be explored and anticipates that our initial contribution, in the form of a framework, will stimulate more comprehensive efforts to address these questions in the future.

The policy responses to COVID-19 in the United States compared to those of its G7 counterparts from March to September 2020. Despite economic and ideological alignment, the G7 nations have implemented diverse strategies to curb the disease's spread, with varying levels of adherence (Barari et al., 2021). This study calculates the beta coefficient for each country, representing the slope of daily new cases regressed against global new cases. Initially, it examines structural shifts in daily global case data using the Bai Perron method, identifying five break dates that allowed the segment of the timeframe into six intervals for separate beta estimations. Structural break and multivariate regression have been used. Subsequently, the G7 countries were ranked based on their beta values within each interval. Moreover, those with higher compliance rates showed improved rankings. Although the United States typically ranked the lower half of the G7 nations, it could have been more consistently the lousy performer. This empirical research demonstrates that implementing a universal mask requirement and ensuring widespread adherence to such policies are crucial factors in maintaining economic stability.

The COVID-19 epidemic caused several states to impose stay-at-home orders, which resulted in a sharp fall in employment in the U.S. from March to April 2020—roughly 15%. In the late summer of 2020, employment rebounded to within 6% of pre-pandemic levels, ensuing the easing of the stay-at-home orders (Hornstein, 2021). Although it cost in terms of lost productivity, reducing social and professional connections linked to these stay-at-home orders may have contributed to the pandemic's containment and the number of disease-related deaths. The fundamental SEIR model of infectious disease dispersion was used in the study, along with random

testing, contact tracing, and quarantine regulations. To estimate the coronavirus transmission rate in the United States in 2020, a version of the model has been employed and calibrated to the known characteristics of the outbreak. The transmission rate is then divided into two parts: a residual component representing illness characteristics and any other factors influencing the disease's spread and a part reflecting observable changes in employment and social contacts. This study contends that a more focused strategy, like enhanced quarantine, an alternate career path that eschewed the harsh and unsettling circumstances, could have produced comparable or superior disease-related results for contact tracing and random testing. Additionally, the worth of the lives saved by using this alternate strategy outweighs any potential expenses. The efficiency of different measures to stop a pandemic's spread in an SEIR model adjusted for COVID-19's unique features. Expressly, the model permits including asymptomatic infectious persons, a strategy that recommends contact tracing provided that an efficient quarantine protocol is in place. When the disease transmission in the model is compared to the U.S. experience in 2020, effective quarantine can significantly reduce cumulative deaths, as can contact tracking and potentially random testing.

The contact tracing methods confront significant practical challenges, and precise data regarding their efficacy still needs to be found. The quasi-random variance in COVID-19 contract tracking is exploited in this paper from September 25 to October 2, 2020. On October 3, it was found that a row limit in an Excel spreadsheet had caused the case information to be cut off (Fetzer & Graeber, 2021). By coincidence, there is a significant difference in the extent to which various areas of England were exposed to delayed referrals of cases from COVID-19 to the contact tracking database. However, this paper has used a primary data set processed using the U.K.'s COVID-19 dashboard. Both specimen data and reported data have been used in the study. The quasi-experimental evidence has drawn the outcome of the study. Also, the non-linear least square

method has been used to estimate the fraction cases. The DID model is to measure the average number of new COVID cases. Specification tests were also run. This publication advances this field of study by offering a causal estimate that uses a unique source of variance from quasi-experiments. The major conclusions of our research are consistent with the body of prior research, which shows that despite several obstacles, including potential distrust among the people, non-adherence, and privacy issues, contact tracing systems can nevertheless be successful. Under the circumstances, England's non-timely referral to contact tracing at the start of a second pandemic wave probably moved the country to a different stage of COVID-19 spread. A data error caused this. According to our most cautious estimations, the data malfunction is directly responsible for over 1,500 additional COVID-19-related deaths and over 125,000 additional infections.

Nguyễn et al. (2021) discuss how, during the early months of the COVID-19 pandemic, state governments in the U.S. implemented social distancing policies that mandated the closure of specific venues to control virus spread. These actions and private risk-averse behavior effectively reduced much of the U.S. economic and social activity. The research touches on how human mobility is a significant factor in transmitting infectious diseases. It covers the effects of state and local mitigation actions on mobility and social interaction based on cell phone data. There were substantial increases in mixing activities following reopening events, with the most significant increases in mobility occurring in states that were early adopters of closure measures and hard hit by the pandemic, suggesting that psychological fatigue is an essential barrier to prolonged closure policies. After state reopening events, there was a substantial increase in human mobility and mixing behavior, measured using cellular device data. Specifically, there was a 13.56% increase in mixing activities in four days and a 48.65% increase in 4 weeks following the reopening events. Mobility outside the home began increasing even before state reopening policies were

implemented, suggesting that factors such as psychological fatigue from prolonged closure measures contributed to the changes in mobility patterns.

Mata et al. (2021), aims to understand the impact of the COVID-19 lockdown on mental health and the role of specific health behaviors in buffering against stress associated with the lockdown. It discusses the consequences of policy measures such as social distancing and school closures on mental health, including symptoms of depression, anxiety, and loneliness. By examining the effects on mental health over a period marked by repeated stressors, the study also touches upon learning processes like habituation and sensitization, highlighting how people with and without vulnerabilities to mental health issues respond to ongoing stress.

Howell & Potgieter (2021) focused on comparing two contact-tracing apps: Australia's Covid Safe and New Zealand's N.Z. Covid Tracer. These two mobile-based apps were released by these two countries' governments for contact tracing when they face a resurgence of COVID-19 infections. This study investigates the extent to which the two apps are fit for their purposes and compares their functional activities. This study evaluates the effectiveness of the two apps in improving their performance by using process mapping and analysis. This study also uses the framework that Verrall (2020) proposed to improve the performance of existing contract tracing systems across a range of efficiency. This paper finds that Bluetooth-based Australian apps are more convenient for that country's contact tracing system to perform more efficiently and effectively in the period of resurgence of COVID-19 than New Zealand's Q.R. code-based apps.

Stokes et al. (2022) analyzed the observational data from 130 countries to examine the impact of non-pharmaceutical interventions (NPIs) on mortality rates due to COVID-19. This study focused on the need for research on how different strategies (NPIs) affect COVID-related deaths. It emphasizes the importance of considering the specific effects of each strategy and how

they interact with other measures being implemented simultaneously. The study aims to fill this knowledge gap by analyzing how the timing and strictness of individual NPIs during the pandemic's first wave are related to COVID-19 deaths. They consider current interventions alongside the specific NPI being studied and aim to build on existing research to inform future policy choices. They exploited the time lag between intervention implementation and mortality to limit the reverse causality. They employed both linear and non-linear multivariate regression models to explore the connection between the timing of interventions and changes in mortality. The results were found by employing pooled cross-sectional regression analysis. Results show that in the early stage of the epidemic, earlier and stricter implementation of workplace closures (-0.26 daily deaths per million) and school closures (-1.23 daily deaths per million) was associated with fewer COVID-19 deaths. At the same time, other policies were not found to be significantly related.

Contact tracing has played a pivotal role in the non-pharmaceutical response to the COVID-19 epidemic, with countries worldwide allocating unprecedented resources to bolster testing and quickly identify abilities, which include the spread and placement of smartphone applications (Howell & Potgieter, 2022). However, despite significant investments, the scholarly literature assessing the impact of smartphone applications is unused, and other apps still need to deliver the anticipated benefits (Bano et al., 2021).

This COVID-19 discusses the impact of disclosing COVID-19 tracing information on consumer dine-out decisions (Gao et al., 2022). The main objective of this study is to reveal the exposure and uncover data on COVID-19 occurrences that could push to start food market recovery. For their analysis, they collect information from 87 restaurants across 10 cities for in-site dining transactions from December 1, 2019, to March 27, 2020, in China. The restaurants in

these 10 cities reach a potential market of 140 million people. They estimate the difference-in-difference (DID) model regarding regressions forms to know the effect of coronavirus infections and contact information tracing on economic activity as measured by daily transactions. Their investigation found how user purchases in a sample of 87 Chinese restaurants were affected by the approach and timeliness of COVID-19 contamination, showing that providing consumers with information does not seem to significantly allay their anxieties, which motivates them to eat out.

The COVID-19 pandemic has significantly impacted the tourism sector worldwide, presenting challenges and opportunities for human resources (H.R.) executives to adapt to the "new normal." This paper explores the essential practices implemented by H.R. professionals within the traversing industry and understands how organizations in this sector manage their personnel amidst disruptive times (Eftimov & Kitanovikj, 2023). The post-COVID-19 era necessitates a reset, restructuring, and redefinition of the H.R. role, focusing on enhancing employee deftness and etiquette to drive organizational performance and efficiency forward. Through theoretical and empirical analysis, this research aims to identify key H.R. challenges in the post-pandemic world within the tourism sector, develop a strategic H.R. management model, and highlight future trends. The paper presents theoretical and practical perspectives on recovering from COVID-19, mainly focusing on the tourism and hospitality industry in a Western Balkans nation. Through thoroughly examining existing literature in areas such as H.R. management, strategic H.R. management, crisis handling, and tourism resurgence, along with pertinent theories, the study identifies crucial H.R. strategies employed by H.R. directors (HRDs) during the recovery phase after the crisis. These strategies encompass job reallocation, talent retention, fostering collaboration, enhancing communication and negotiation skills, and refining performance management. A range of external and internal factors influences adopting these H.R. strategies.

This qualitative investigation involved conducting partially structured examinations with H.R. professionals, managers, and industry leaders in the tourism sector. Regarding managerial implications, our research provides practical insights into H.R. precautionary measures and regaining tactics. The theoretical framework and discoveries furnish actionable advice for companies seeking to formulate and implement effective plans for recovery post-COVID. The paper offers theoretical and practical insights into the belles' litters surrounding COVID-19 recovery, specifically within the context of a Western Balkans country and its tourism and hospitality sector. Drawing from existing research in Human Resource Management, Strategic Human Resource Management, crisis management, and tourism recovery, as well as relevant theories, we identify key H.R. practices that H.R. directors (HRDs) employ during recovery following a significant crisis during an epidemic. These practices encompass job redeployment, talent management, collaboration, communication and negotiation, and performance management. Various factors influence adopting these H.R. practices, ranging from external (less influential) to internal (more influential) factors. The provisional qualitative analysis involved semi-structured interviews with H.R. professionals, managers, and business leaders in the tourism sector. The managerial implications of this study lie in its practical suggestions for H.R. crisis management and recovery. The theoretical insights and framework offered actionable guidance for companies to develop and implement post-COVID recovery plans effectively.

Disease transmission occurs from infectious individuals to susceptible ones. A policymaker intervenes to control disease spread through two costly measures: social distancing and contact tracing (Pollinger, 2023). Social distancing reduces the disease's spread by minimizing social interactions across the entire community. Contact tracing minimizes the spread by diligently identifying and isolating infectious individuals from susceptible ones. The ideal policy integrates

these measures to economize associated with both control measures and infections. The effectiveness of contact tracing plays a crucial role in determining the properties of the optimal policy. Contact tracing technology is deemed efficient (or inefficient) based on whether the maximum detection rate of infectious individuals surpasses (or falls short of) the uninhabited swelling rate of the disease. This study investigates strategies for suppressing disease transmission within the SIR model while considering economic interactions.

3. Data and Estimation Strategy

The data for this research, I collected COVID-19-related data from January 01, 2020, to December 31, 2022, from the Oxford-covid-19-government-response-tracker (OxCGRT). This data source covered COVID-19-related daily data for all countries of the World. OxCGRT also collects all the policy information on indicators of government response. Finally, OxCGRT codes all the policy variables on an ordinal scale in the following manner:

(1) Face covering policy: ‘0’ no policy; ‘1’ recommended; ‘2’ required in some specific shared or public spaces outside the home; ‘3’ required in all shared or public spaces outside the home; and ‘4’ always needed outside the home regardless of the location.

(2) Contact tracing policy: ‘0’ no contact tracing, ‘1’ limited contact tracing, and ‘2’ comprehensive contact tracing.

In this research, the main challenge is that some data must be made available. Then, I compiled two available COVID-19 behavioral policy data. For this reason, I took daily data from July 5, 2020, to April 15, 2022 (a total of 640 days) for the eighteen countries (covered all continents): Argentina, Australia, Belgium, Canada, Denmark, Finland, France, Italy, Japan,

Luxembourg, Malaysia, South Africa, South Korea, Spain, Sweden, Switzerland, United Kingdom, and the United States of America.

Since this research deals with the panel data and I want to measure the impact of the COVID-19 preventive policies on morbidity and mortality, I apply panel data ordinary least square regression model. To do this, I have two alternatives, one is the fixed effect model (FEM), and another is the random effect model (REM). To select FEM or REM, I apply the Hausman test; if the p-value is less than 0.05, then FEM is preferred. Otherwise, REM is applicable.

Table 2.1
Descriptive statistics with sample mean for the key variables according to the policy variables

	new_deaths_ per million		new_cases_ per million		icu_patients_ per million		positive_rate	
	mean	std	mean	std	mean	std	mean	std
face_coverings								
0	1.403	1.582	212.590	220.956	6.235	6.814	0.087	0.075
1	0.837	1.178	138.741	187.983	7.307	4.707	0.063	0.056
2	1.130	1.275	223.900	205.545	15.191	14.569	0.062	0.068
3	1.519	1.387	200.453	193.563	20.314	16.963	0.075	0.068
4	2.189	1.524	224.859	186.538	32.648	18.687	0.065	0.047
contact_tracing								
0	1.058	1.184	218.052	194.788	5.391	5.719	0.087	0.069
1	1.614	1.383	235.848	196.553	20.878	16.431	0.068	0.058
2	1.287	1.430	176.571	195.535	17.016	17.180	0.07	0.071

4. Estimation Results and Discussion

Estimation Results – Face Covering Policies: Morbidity

Table 2.2
Hausman Test Results: face_cover policies
on morbidity

chi2	df	p-val
35.06072	7	1.09E-05

Since the p-value is less than 0.05 so that here I apply the fixed effects model for estimation.

Table 2.3
Parameter Estimates: face_cover policies on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.1473	0.1214	25.926	0.0000	2.9094	3.3853
positive_rate	1722.7	25.241	68.251	0.0000	1673.2	1772.2
const	-0.0171	9.3388	-0.0018	0.9985	-18.323	18.289
face_coverings_1	37.231	10.649	3.4962	0.0005	16.357	58.105
face_coverings_2	27.811	9.6180	2.8915	0.0038	8.9576	46.664
face_coverings_3	31.548	10.628	2.9685	0.0030	10.716	52.380
face_coverings_4	-3.7265	11.451	-0.3254	0.7449	-26.173	18.720

Approximately 3.473 per million morbidity increases for a one-unit increase in the ICU patient per unit and 1722.7 per million morbidity increases for a one-unit increase in the COVID-19 positive rate. Here, face-covering policy 1; face-covering policy 2; and face-covering policy 3 are positively statistically significant, whereas face-covering policy 4 is not statistically significant on the morbidity.

Estimation Results – Face Covering Policies: Mortality

Table 2.4
Hausman Test Results: face_cover policies
on mortality

chi2	df	p-val
12.83431	7	0.07625

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 2.5
Parameter Estimates: face_cover policies on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0450	0.0008	53.350	0.0000	0.0433	0.0466
positive_rate	6.7643	0.1755	38.549	0.0000	6.4203	7.1083
const	0.5764	0.1108	5.2004	0.0000	0.3592	0.7937
facial_coverings_1	0.0425	0.0736	0.5778	0.5634	-0.1017	0.1867
facial_coverings_2	-0.6320	0.0664	-9.5229	0.0000	-0.7621	-0.5019
facial_coverings_3	-0.5347	0.0731	-7.3171	0.0000	-0.6780	-0.3915
facial_coverings_4	-0.3886	0.0789	-4.9224	0.0000	-0.5433	-0.2338

Approximately 0.0450 per million mortality increases for a one-unit increase in the ICU patient per unit and 6.7643 per million mortality increases for a one-unit increase in the COVID-19 positive rate. Here, face-covering policy 2, 3, and 4 are statistically significant, whereas face-covering policy 1 is not statistically significant on the mortality.

Estimation Results – Contact Tracing Policies: Morbidity

Table 2.6
Hausman Test Results: contact_tracing
policy on morbidity

chi2	df	p-val
8.989733	5	0.109474

Since the p-value is less than 0.05 so that here I apply the fixed effects model for estimation.

Table 2.7
Parameter Estimates: contact_tracing policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	2.9476	0.1135	25.971	0.0000	2.7252	3.1701
positive_rate	1745.0	24.449	71.372	0.0000	1697.1	1792.9
const	26.181	10.722	2.4418	0.0146	5.1644	47.198
contact_tracing_1	20.729	10.595	1.9566	0.0504	-0.0383	41.496
contact_tracing_2	-14.261	11.260	-1.2666	0.2053	-36.333	7.8100

Approximately 2.9476 per million morbidity increases for a one-unit increase in the ICU patient per unit and 1745.0 per million morbidity increases for a one-unit increase in the COVID-19 positive rate. Here, contact tracing policy 1 and contact tracing policy 2 are not statistically significant at the 5% level of significance on the morbidity.

Estimation Results – Contact Tracing Policies: Mortality

Table 2.8
Hausman Test Results: contact_tracing
policy on mortality

chi2	df	p-val
26.17442	5	8.25E-05

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 2.9
Parameter Estimates: contact_tracing policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0452	0.0008	56.960	0.0000	0.0436	0.0467
positive_rate	6.9054	0.1714	40.298	0.0000	6.5695	7.2413
const	-0.0367	0.1138	-0.3222	0.7473	-0.2598	0.1865
contact_tracing_1	0.1040	0.0742	1.4015	0.1611	-0.0415	0.2496
contact_tracing_2	0.1861	0.0787	2.3643	0.0181	0.0318	0.3404

Approximately 0.0452 per million mortality increases for a one-unit increase in the ICU patient per unit and 6.9054 per million mortality increases for a one-unit increase in the COVID-19 positive rate. Here, contact tracing policy 2 is statistically significant at the 5% level of significance on the mortality, whereas contact tracing policy 1 is not statistically significant.

5. Conclusion

COVID-19 has brought different experiences into people's daily lives. Even after the end of the COVID pandemic in 2024 and people's COVID period, habits or precautionary measures still exist among many. Face-covering behavior still exists in many people and is a habit among many, especially when traveling and going to work outside. In this study, the impact of face-covering policy and contract tracing policy on morbidity and mortality has been examined. Unfortunately, the study results show that the effect of contract tracing policies on morbidity are statistically insignificant. Still, the impact of face covering 1, 2 & 3 policies on morbidity are statistically significant. The face-covering 2, 3, and 4 policies are highly significant on the mortality, whereas the contract tracing policy 1 do not work on mortality.

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Chapter 3

Impact of the COVID-19 Direct Diseases-related Policies on Morbidity and Mortality

Abstract

In this chapter, I am measuring the impact of the COVID-19 direct diseases-related policies on morbidity and mortality. Here, direct disease-related policies include the COVID-19 testing policy, vaccination policy, and public information campaign policy. These policies mainly minimize the COVID-19 causes of hospitalizations and deaths. However, this study finds that the effect of the public information campaign policy is statistically insignificant on morbidity and mortality. Still, the impact of testing policy 3 is statistically significant on morbidity and mortality. Moreover, vaccination policy 1, 2, 3, 4 & 5 are highly significant for mortality, whereas vaccination policy 1, 2, 3, & 5 is highly significant for morbidity.

Keywords: COVID-19, Testing policy, Contract Tracing Policy, Public information campaign policy

JEL Classification: H5, I1

1. Introduction

Medical scientists have identified the transmission of the coronavirus from one human body to another as one of the reasons for the spread of COVID-19. That is, if a person is infected with Covid-19, there is a risk of infecting others through them. Many people are COVID-19 positive, but their symptoms are not observed. For this reason, experts think COVID-19 is the fastest-expanding disease in the world. As a result, the World Health Organization (WHO) has given suggestions to the policymakers and governments of each country to have people tested for COVID-19 as soon as possible; also, with the discovery of COVID-19 vaccines, WHO has advised to bring everyone under vaccination.

At the same time, since COVID-19 is a human-borne disease, it is necessary to encourage and force ordinary people to follow the various policies announced by the government to intercept the expansion of COVID-19. Hence, various persuasive media, such as radio, television, newspaper, signboards, billboards, and notice campaigns, have adopted warning messages in different public places.

The COVID-19 testing policy was important during the pandemic period. The testing policy is called the disease screening policy, which I have identified as a direct disease policy. The primary purpose of this testing policy is to identify SARS-CoV-2 virus-infected and non-infected persons and, at the same time, isolate the infected person (quarantine) so that others are not affected. This means the virus can be detected early, and preventive measures can be taken immediately.

Those who are COVID-19 positive might have a fever, cough, shortness of breath, fatigue, muscle or body aches, headache, loss of taste or smell, sore throat, congestion or runny nose,

nausea or vomiting, and diarrhea. Moreover, they might not have any symptoms, but by testing, they may discover they are COVID-19 positive. During the pandemic, volunteers, NGO technical teams, and medical teams got to know people's diseases by testing, self-reporting, and symptom questionnaires.

If a person has positive antigens, infected people should be isolated, monitored, and given COVID-19 guidelines to follow. International travelers may test for COVID-19 upon arrival and departure times, including at airports, seaports, or border crossings. Travel restrictions, quarantine requirements, and testing protocols implemented depend on the destination country. Employees must do their COVID-19 symptom tests to protect their health before joining the workplace. Sometimes, people around the infected must stay in quarantine. Schools may conduct COVID-19 tests among students, teachers, and staff to reduce coronavirus infection.

In short, testing policy is essential to public health policy, involving disease detection, surveillance, prevention, and control. In addition to diagnosing the patient's disease through testing policy, taking appropriate steps in the case of intervention is necessary for making decisions promptly. Above all, a testing policy will prevent many people from infecting others with the disease.

Severe acute respiratory syndrome coronavirus-2 causes COVID-19, and it was recognized in January 2020. By December 2 of that year, a vaccine was developed by BioNTech, and the United States of America accepted Pfizer. Depending on age group, vaccine availability, and physical condition, medical scientists and the government determine the vaccination policy. The government and policymakers bought bulk vaccines from vaccine-making countries, international organizations, pharmaceuticals, and clinics.

Despite the financial status of different levels of people, the government ensures a free vaccination policy to encourage people. Some countries have provided extra facilities to those vaccinated and implemented specific laws and orders to give vaccines to those with religious prejudice regarding vaccination. This way, government and policymakers can protect public health and prevent outbreaks.

Overall, vaccination policy plays a vital role in preventing the COVID-19 outbreak. During crises of epidemics, public health authorities and international policymakers can implement vaccination strategies to achieve global efforts to eliminate vaccine-preventable diseases.

Public awareness is a powerful medium through which the public can be educated about the COVID-19 virus and prevent the pandemic outbreak. Information campaigns teach People about transmission, symptoms, prevention measures, testing, treatment, and vaccination. This knowledge can be shared through various channels, such as television, radio, social media, websites, posters, leaflets, and SMS messages.

They are training the community through information campaigns such as enervating masks, carrying out hand hygiene, continuing physical distance, staying away from large gatherings, and staying home when they or people around them are ill. Volunteers, NGOs, and medical and public health authorities will inform the community to help prevent the spread of diseases, how they can get available treatment options, supportive care, COVID-19 symptoms, and all the information people need to know. In that case, people should be informed about every information related to COVID-19. Through this campaign, people of all levels have been told about the availability of vaccines and where to get the vaccine. Trust and invention should be increased to avoid hearing wrong information.

The primary purpose of the public information campaign is prevention, safety, knowing about COVID-19 symptoms, and, above all, preventing COVID-19. To motivate people, they should be told about COVID-19 and how to protect themselves through mass media, storytelling, and role models. Also, because of the pandemic, many people are suffering from mental health problems, but these public information campaigns can help them overcome this. Providing accurate information, dispelling myths, and fostering community engagement can save people's lives.

In this research, I examine the impact of these direct disease-related policies on mobility and mortality. The rest of this study follows: in section 2, I will elaborate on the literature research work; then, section 3 will describe the data and estimation strategy; and in section 4, I will discuss the research results. Finally, section 5 concludes this chapter.

2. Literature Review

Recently, many researchers have studied the impact of COVID-19 policies, but only some have captured all the policies. Borjas (2020) aims to examine the impact of business closures and activity restrictions on coronavirus results in New York City. The experiment evaluated whether these steps slowed down the spread of the virus, as it is vital in forming public health policies. The study used an analytical analysis of testing data sourced from the New York City Department of Health and Mental Hygiene (DOH) at the zip code level. It covered the timeline from April 1, 2020, to May 31, 2020. The daily cumulative counts of tests were provided from the data and residents for 177 zip codes. These testing data were integrated with smartphone location information from Safe Graph, a private company that gathers anonymous location data from 35

million mobile devices. Data collected indicated each zip code, which incorporated daily counts of visitors to certain places or locations. It also included residents' mobility patterns. The study employed a regression model to analyze how people were spread by coronavirus due to business closures and out-of-home activity restrictions in New York City by investigating variations examining results over time and overall zip codes. This research found that the test positivity rate peaked at 71% on March 28. However, the number gradually declined to 4% by March 31. The index of economic activity and stay-at-home had a statistically significant effect on the positivity rate. It was deduced that a one-hundred-unit increase in the commercial activity index was related to a 12.4 percentage point increase in the positivity rate. On the other hand, a one hundred unit increase in the stay-at-home index was associated with a 2.0 percentage point decrease. The relapse explained 82% of the variation in the positivity rate, which is relatively high. The combined effect of the two symptoms is considered for approximately 25% of the observed reduction in the positivity rate from early April to early May.

Pasdar et al. (2021) explore the association of public health policies with the graveness of the COVID-19 epidemic. This study worked with various community health policies, i.e., social distancing measures, mask mandates, travel restrictions, vaccination rates, etc. This research put an ecological analysis method into action to delve into the connection between public health policy measures and the COVID-19 pandemic's severity in 22 nations. The research shed light on numerous outcomes linked to the pandemic trajectory, such as average death rates during the increasing period, time until the peak hit, maximum fatalities per 100,000 inhabitants, total deaths post-peak per 100,000 people, and the mean slope comparison of rising and falling death trends. Each evaluation was broken down by factors like age, economic status, and region to measure the effect of public health strategies on diverse demographic groups. This research found containment

methods proved successful in more affluent countries, and an emergency influx of funds into healthcare was most strongly linked with the average mortality rate. Internal movement restriction had the strongest association with positive outcomes, and investment in vaccines was attributed to negative consequences in European countries. On the other hand, school closures were productive against the average mortality rate, and peak deaths per 100,000 were given by testing policy in non-European countries.

Toffolutti et al. (2022) worked with 28 European countries to find a relationship uniting COVID-19 policy responses and mental well-being across the countries. It contemplated various policy responses such as segregation and closure measures, economic support, and health system measures. The study underscores the complex relationship between COVID-19 policies and mental well-being, suggesting the importance and need for balanced policy approaches to reduce adverse mental health effects during the time of the pandemic. The study used the Eurofound "Living, Working and COVID-19" (LWC) survey data. The WHO-5 Well-Being Index, which ranges from 0 to 25 and assesses feelings of cheerfulness, calmness, vigor, restfulness, and interest in daily life, was used to measure mental well-being (MWB). Individuals aged 18 and older were approached for data collection via e-survey in three waves. 13 NPIs were analyzed separately in the model, which included individual characteristics like gender, education, age, presence of children in the household, etc. Western Europe residency, national monthly unemployment rate, country fixed effects, wave fixed effects, and individual random effects were also present in the model. The study was controlled for lagged variables to account for the time delays. The findings portray those men, educated individuals, and individuals over 44 were reported to have high levels of mental well-being. High mental well-being was also experienced by those who lived with partners and had no children. There was an increase in MWB from the first to the second wave but

a decline from the second to third in the temporal variation. Findings also indicated that specific policies, such as restrictions on international travel, gatherings, and contact tracing, were negatively related to MWB, whereas workplace closures were positively associated. A notifying fact came from the study that said restrictions on international travel were strongly and negatively associated with MWB for those living with a partner and those not. As for geographical differences, Western Europeans were better under some NPIs than Eastern Europeans. Sensitivity analysis confirmed the robustness of the results, with consistent findings across different control variables and combinations of NPIs.

Negi et al. (2022) aims to generate the primary reproduction number by using future generations matrix technique. Next, the stability of equilibrium locations has been studied using the fundamental reproduction number. The impact of mediation policies, vaccination rates, vaccine efficacy, and quarantine has been investigated by adding a numerical simulation of the model. Lastly, by including quarantine and vaccine compartments, their research created a deterministic compartmental model for the dynamics of COVID-19 transmission.

The study by Wright (2022), "COVID-19 Vaccine Mandates in U.S. Transplant Centers," asked respondents about their role at the transplant center, the name of the center, and the center's vaccination policies for transplant candidates, their caregivers, and other members of their household. Using a list of non-ranked, non-exclusive options, centers were asked to justify their decision to implement or not implement a COVID-19 vaccine mandate. The poll was designed to target transplant providers at 250 transplant centers. Target participants included medical and surgical staff, transplant coordinators, administrators, and social workers. They were gathered through the professional connections of the researchers and professional society listservs. The survey was distributed from October 14, 2021, to November 15, 2021. Consent to take part in the

study was given by the participants when they decided to go ahead and finish the survey. By comparing their data with publicly available COVID-19 vaccination rates as of October 27, 2021, the authors evaluated if there was a relationship between local immunization rates and the choice to support or oppose a vaccine mandate. No association was discovered between vaccination rates and transplant centers' decisions to support or oppose a vaccine mandate, despite a correlation between county-level immunization rates and political voting patterns.

Amare et al. (2022) aim to investigate how Ethiopian bilateral trade flows are affected by different cases such as deaths, non-medicine policies, and remedy policies. They selected 133 trading partners, including Ethiopia, from the trade statistics database of the IMF's quarterly reporting states the effect of COVID-19 on bilateral trade flows. In 133 samples, we chose 90 nations for a reciprocal export sample and 80 countries for a reciprocal import sample. Using a Poisson pseudo, they estimated the effect of COVID-19 pandemic-induced outcomes of pharmaceutical and nonpharmaceutical strategy on Ethiopian bilateral export and import flows. This study calculated the impact on the Ethiopian trade of immunizations, nonpharmaceutical policies, and contamination cases and deaths. Bilateral exports and imports are statistically significantly negatively impacted by different affected cases, deaths, and the stringency index. Conversely, vaccinations positively affect bilateral imports and exports statistically considerably.

Kim et al. (2023) evaluated the impact of immunization rate and timing on the incidence of coronavirus. The incidence of COVID-19 considerably rose following the easing of face-covering mandates, according to the results. However, the vaccination rate was similar between nations, with higher and lower frequencies. It was discovered that rapid vaccinations postponed the incidence reappearance. The study concludes that face-covering policies are essential for reducing the spread of COVID-19 when paired with rapid vaccinations. The results emphasize

how crucial it is to preserve and modify public health initiatives, such as laws requiring face coverings, especially when combined with a successful vaccination campaign to minimize the virus's spread.

Fayaz-Farkhad and Jung (2023) devote distinct parts to analyzing and debating the effects of vaccination mandates, vaccination passports, and financial incentives—three significant measures implemented during the COVID-19 epidemic. A thorough review of the data shows that, far from backfiring, these strategies can effectively increase vaccination rates among the public. However, there are certain drawbacks to the rules as well. For example, they cannot encourage people adamantly opposed to vaccinations. Lastly, to combat pandemics and epidemics in the future, this study addresses the design and implementation of policy-level interventions.

Bautista-Arredondo et al. (2023) study aims to evaluate the effectiveness of a five-technology immunization program implemented per society hierarchy, which nation experiencing one of the worst COVID-19 epidemics. Facts on all patients suspected of having coronavirus contamination are included in Silver; that is, persons with at least one primary symptom (cough, fever, dyspnea, headache) and one minor symptom (myalgia, arthralgia, odynophagia, chills, chest discomfort, rhinorrhea, anosmia, dysgeusia, conjunctivitis). People sixty years of age or older provided the data. According to this investigation, the average effectiveness opposed to ensuring coronavirus cases was predicted to be 60.9%. Moreover, vaccination reduced hospital stays and fatalities by 62.7% and 62.6%, respectively. They observed a 79.1, 80.9, and 81.3% decrease in new cases, hospitalizations, and deaths among the vaccinated after controlling for vaccination coverage. This study connected the benefits of coronavirus vaccinations in a middle-income country that uses a multi-vaccine program.

Li et al. (2024) employed panel data from 21 nations for their investigation; data from 21 developed and developing countries were used in this study. This study implies that policymakers should choose a policy mix with vaccines as complementary rather than an alternative to intervention measures. The impact of immunization is unique in that it will not increase EPU like all other government response programs to COVID-19.

3. Data and Estimation Strategy

The data for this research, I collected COVID-19-related data from January 01, 2020, to December 31, 2022, from the Oxford-covid-19-government-response-tracker (OxCGRT). This data source covered COVID-19-related daily data for all countries of the World. OxCGRT also collects all the policy information on indicators of government response. Finally, OxCGRT codes all the policy variables on an ordinal scale in the following manner:

(1) Testing policy: ‘0’ no testing policy; ‘1’ only those who both (a) have symptoms and (b) meet specific criteria; ‘2’ testing of anyone showing COVID-19 symptoms; and ‘3’ open public testing.

(2) Vaccination policy: ‘0’ no availability, ‘1’ availability for one of the following: key workers/ clinically vulnerable groups/ elderly groups; ‘2’ availability for two of the following: key workers/ clinically vulnerable groups/ elderly groups; ‘3’ availability for all of the following: key workers/ clinically vulnerable groups/ elderly groups; ‘4’ availability for all three plus partial additional availability for select groups/ages; and ‘5’ Universal availability.

(3) Public information campaigns: ‘0’ no COVID-19 public information campaign; ‘1’ public officials urging caution about COVID-19; and ‘2’ coordinate public information campaign, for example, across traditional and social media.

Table 3.1
Descriptive statistics with sample mean for the key variables according to the policy variables

	new_deaths_ per million		new_cases_ per million		icu_patients_ per million		positive_rate	
	mean	std	mean	std	mean	std	mean	std
testing_policy								
0								
1	1.383	1.455	172.324	176.457	13.397	11.999	0.104	0.066
2	1.331	1.386	180.993	192.991	18.239	18.221	0.063	0.063
3	1.515	1.432	226.576	202.111	19.244	16.016	0.071	0.066
vaccination_policy								
0	1.171	1.460	127.196	162.127	15.488	18.201	0.058	0.062
1	2.186	1.536	178.283	192.590	31.353	18.750	0.090	0.055
2	2.094	1.430	206.507	164.823	28.488	16.614	0.069	0.044
3	1.647	1.512	205.008	173.675	26.302	19.0387	0.063	0.072
4	0.948	1.258	133.670	175.269	18.286	17.9526	0.045	0.056
5	1.440	1.295	266.486	213.039	15.735	13.0847	0.082	0.069
public_information_campaigns								
0	2.231	0.191	169.935	18.351	33.662	0.3619	0.065	0.002
1								
2	1.425	1.416	203.229	198.178	18.473	16.916	0.070	0.065

In this research, the main challenge is that some data are unavailable. Then, I compiled three COVID-19 direct disease-related policies using the available data. For this reason, I took daily data from July 5, 2020, to April 15, 2022 (a total of 640 days) for the eighteen countries (covered all continents): Argentina, Australia, Belgium, Canada, Denmark, Finland, France, Italy, Japan, Luxembourg, Malaysia, South Africa, South Korea, Spain, Sweden, Switzerland, United Kingdom, and the United States of America.

Since this research deals with the panel data and I want to measure the impact of the COVID-19 preventive policies on morbidity and mortality, I apply panel data ordinary least square regression model. To do this, I have two alternatives, one is the fixed effect model (FEM), and another is the random effect model (REM). To select FEM or REM, I apply the Hausman test; if the p-value is less than 0.05, then FEM is preferred. Otherwise, REM is applicable.

4. Estimation Results and Discussion

Estimation Results – Testing/ Disease screening Policies: Morbidity

Table 3.2
Hausman Test Results: testing_policy on morbidity

chi2	df	p-val
-25.29915591	5	1

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 3.3
Parameter Estimates: testing_policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.1591	0.1137	27.782	0.0000	2.9362	3.3820
positive_rate	1715.2	24.859	68.995	0.0000	1666.4	1763.9
const	-6.7609	15.673	-0.4314	0.6662	-37.483	23.961
testing_policy_2	12.114	7.1734	1.6887	0.0913	-1.9473	26.175
testing_policy_3	54.141	7.9576	6.8037	0.0000	38.543	69.739

Approximately 3.1591 per million morbidity increases for a one-unit increase in the ICU patient per unit and 1715.20 per million morbidity increases for a one-unit increase in the COVID-19 positive rate. Here, testing policy 3 is statistically significant, whereas testing policy 2 is not statistically significant at the 5% level of significance on the morbidity.

Estimation Results – Testing/ Disease screening Policies: Mortality

Table 3.4
Hausman Test Results: testing_policy on mortality

chi2	df	p-val
15.07648	5	0.01004

Since the p-value is less than 0.05 so that here I apply the fixed effects model for estimation.

Table 3.5
Parameter Estimates: testing_policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0465	0.0008	58.379	0.0000	0.0450	0.0481
positive_rate	6.4942	0.1739	37.355	0.0000	6.1534	6.8350
const	0.5377	0.0526	10.226	0.0000	0.4346	0.6407
testing_policy_2	-0.5294	0.0502	-10.541	0.0000	-0.6279	-0.4310
testing_policy_3	-0.3745	0.0558	-6.7072	0.0000	-0.4840	-0.2651

Approximately 0.0465 per million mortality increases for a one-unit increase in the ICU patient per unit and 6.4942 per million mortality increases for a one-unit increase in the COVID-19 positive rate. Here, testing policy 2 and 3 are statistically significant on the mortality.

Estimation Results – Vaccination Policies: Morbidity

Table 3.6
Hausman Test Results: vaccination_policy
on morbidity

chi2	df	p-val
-3387.487468	8	1

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 3.7
Parameter Estimates: vaccination_policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.9883	0.1206	33.076	0.0000	3.7519	4.2246
positive_rate	1492.2	25.118	59.408	0.0000	1443.0	1541.4
const	-18.542	11.311	-1.6394	0.1012	-40.713	3.6282
vaccination_policy_1	21.392	8.1686	2.6188	0.0088	5.3802	37.404
vaccination_policy_2	22.478	5.0405	4.4594	0.0000	12.597	32.358
vaccination_policy_3	15.193	4.8969	3.1025	0.0019	5.5941	24.792
vaccination_policy_4	3.7499	5.1433	0.7291	0.4660	-6.3318	13.832
vaccination_policy_5	93.694	3.1416	29.823	0.0000	87.536	99.852

Approximately 3.9883 per million morbidity increases for a one-unit increase in the ICU patient per unit and 1492.20 per million morbidity increases for a one-unit increase in the COVID-19 positive rate. Here, vaccination policy 1, vaccination policy 2, vaccination policy 3 and vaccination policy 5 are positively statistically significant on the morbidity. Whereas vaccination policy 4 is not statistically significant on the morbidity.

Estimation Results – Vaccination Policies: Mortality

Table 3.8
Hausman Test Results: vaccination_policy
on mortality

chi2	df	p-val
5.433039537	8	0.710446824

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 3.9
Parameter Estimates: vaccination_policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0446	0.0009	51.192	0.0000	0.0429	0.0463
positive_rate	6.8189	0.1815	37.571	0.0000	6.4631	7.1746
const	0.1022	0.0790	1.2946	0.1955	-0.0526	0.2570
vaccination_policy_1	0.1920	0.0590	3.2526	0.0011	0.0763	0.3077
vaccination_policy_2	0.3533	0.0364	9.7006	0.0000	0.2819	0.4247
vaccination_policy_3	-0.1051	0.0354	-2.9699	0.0030	-0.1745	-0.0357
vaccination_policy_4	-0.2652	0.0372	-7.1359	0.0000	-0.3381	-0.1924
vaccination_policy_5	0.0458	0.0227	2.0162	0.0438	0.0013	0.0903

Approximately 0.0446 per million mortality increases for a one-unit increase in the ICU patient per unit and 6.8189 per million mortality increases for a one-unit increase in the COVID-19 positive rate. Here, vaccination policy 1, 2, 3, 4 and 5 are significant at the 5% level of significance on the mortality.

Estimation Results – Disease related information campaign: Morbidity

Table 3.10
Hausman Test Results: campaign policy on morbidity

chi2	df	p-val
-66.47309063	4	1

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 3.11
Parameter Estimates: campaign policy on morbidity

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	3.0157	0.1128	26.728	0.0000	2.7945	3.2368
positive_rate	1735.4	24.456	70.961	0.0000	1687.5	1783.4
const	-67.190	55.021	-1.2212	0.2221	-175.04	40.661
public_info_campaigns_2	94.105	53.095	1.7724	0.0764	-9.9700	198.18

Approximately 3.0157 per million morbidity increases for a one-unit increase in the ICU patient per unit and 1735.40 per million morbidity increases for a one-unit increase in the COVID-19 positive rate. Here, public information campaign policy 2 is not statistically significant at the 5% level. These 18 countries were not imposed public information campaign policy 1 in the time frame (July 5, 2020, to April 15, 2022).

Estimation Results – Disease related information campaign: Mortality

Table 3.12
Hausman Test Results: campaign policy on mortality

chi2	df	p-val
4.135746931	4	0.387946116

Since the p-value is greater than 0.05 so that here I apply the random effects model for estimation.

Table 3.13
Parameter Estimates: campaign policy on mortality

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
icu_patients_per_million	0.0451	0.0008	57.247	0.0000	0.0436	0.0467
positive_rate	6.8983	0.1710	40.329	0.0000	6.5630	7.2336
const	0.3272	0.3823	0.8561	0.3920	-0.4221	1.0765
public_info_campaigns_2	-0.2162	0.3714	-0.5822	0.5605	-0.9442	0.5118

Approximately 0.0451 per million morbidity increases for a one-unit increase in the ICU patient per unit and 6.8983 per million morbidity increases for a one-unit increase in the COVID-19 positive rate. Here, public information campaign policy 2 is not statistically significant at the 5% level. These 18 countries were not imposed public information campaign policy 1 in the time frame (July 5, 2020, to April 15, 2022).

5. Conclusion

To reduce the risk of illness and death due to COVID-19, COVID-19 testing policies and vaccination policies have been adopted based on the advice of medical scientists worldwide. At the same time, government officials started public information campaigns. In this research, I measured the impact of testing, vaccination, and public information campaign policies on morbidity and mortality. Analyzing the overall results, although testing policy 2 is insignificant on morbidity, testing policy-3 is highly significant, and testing policy 2 and 3 are significant on mortality. In the case of vaccination policy, the effects of vaccination policy 1, 2, 3, and 5 are significant, and the vaccination policy 4 is insignificant. On the other hand, although vaccination policy1, 2, 3, 4, and 5 are significant in mortality. Surprisingly, I found no effect of the public information campaign policy on morbidity and mortality. In conclusion, testing and vaccination policies reduce morbidity and mortality, but public information campaign policy does not impact morbidity and mortality.

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APPENDIX

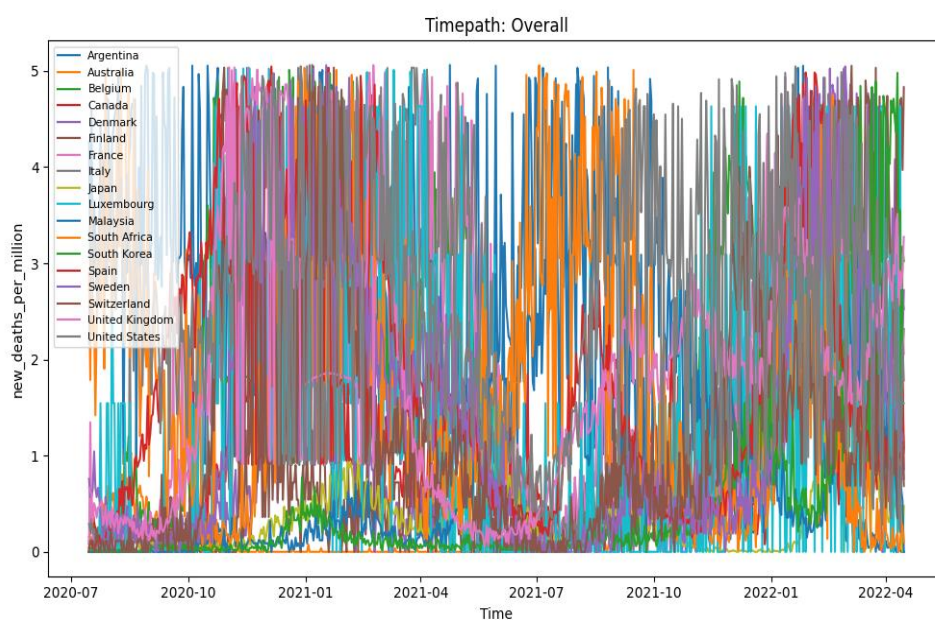


Figure A.1: New Deaths Per Million (all country)

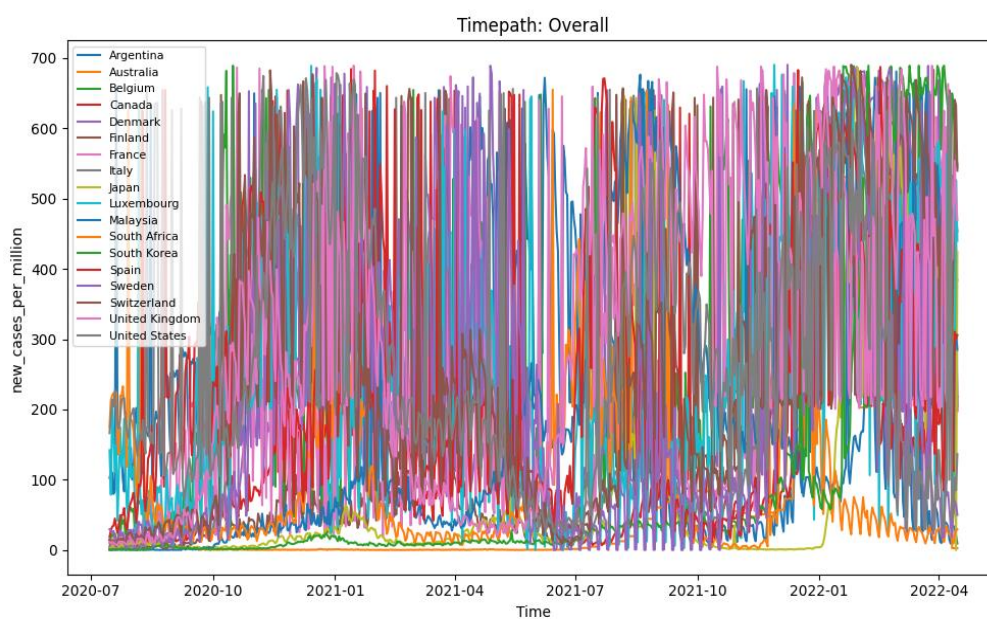


Figure A.2: New Cases Per Million (all country)

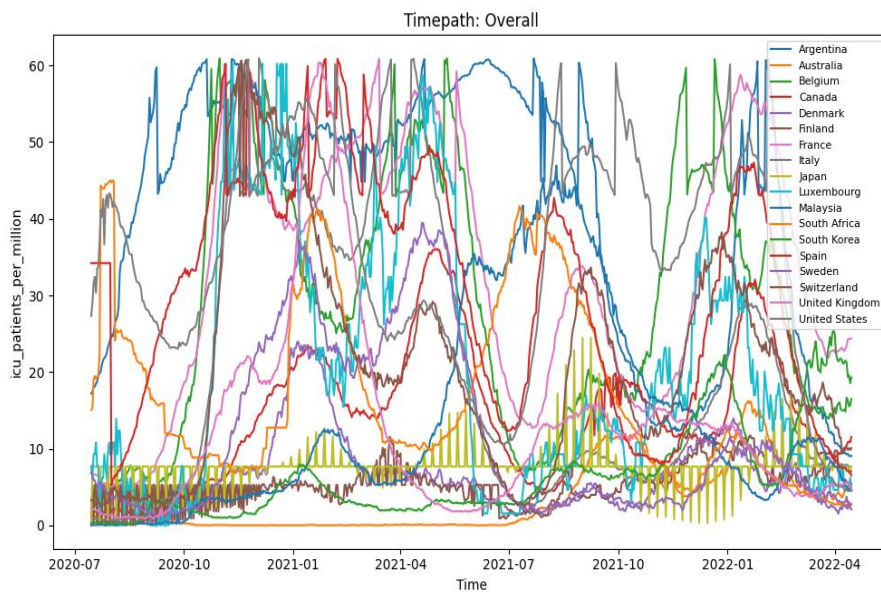


Figure A.3: ICU Patients Per Million (all country)

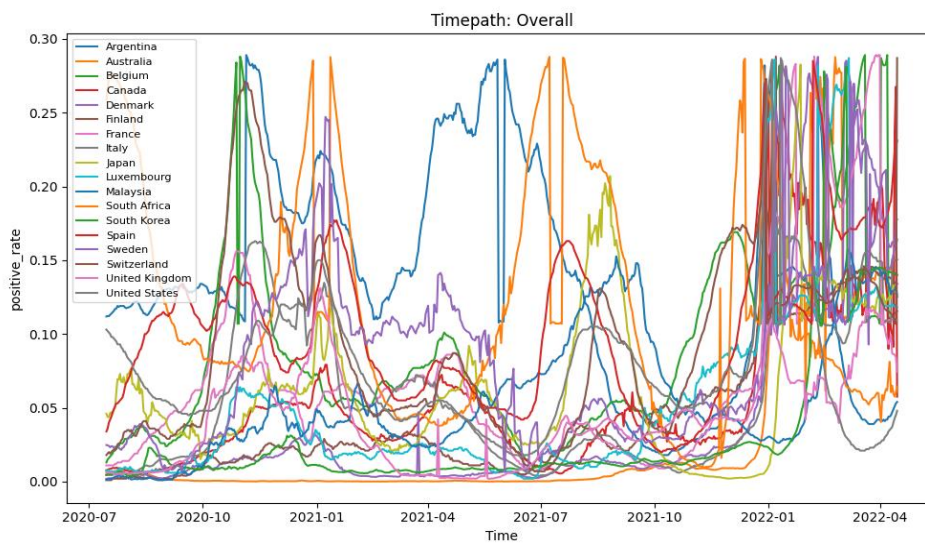


Figure A.4: COVID-19 Positive Rate (all country)

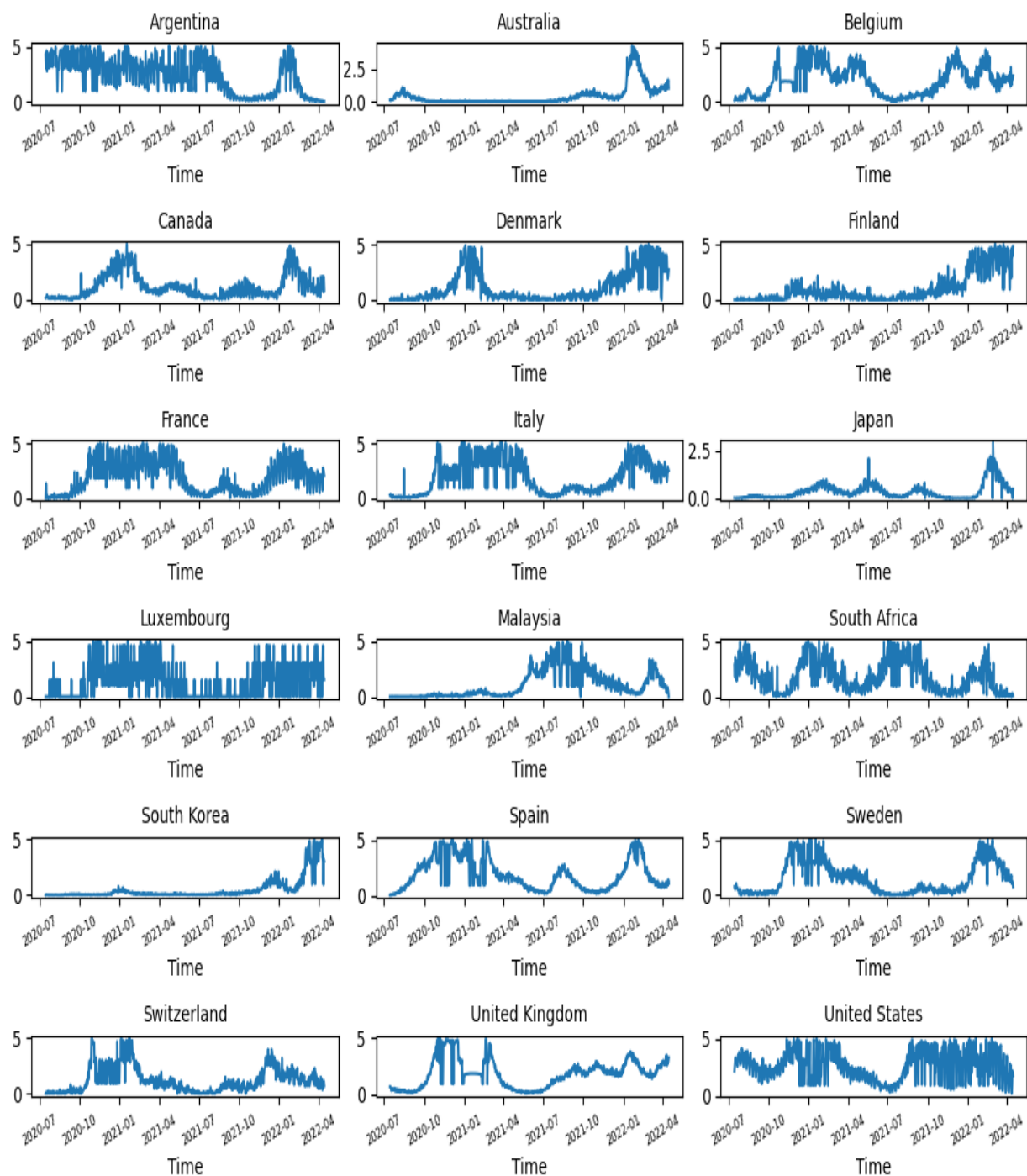


Figure A.5: New Deaths Per Million (individual country)

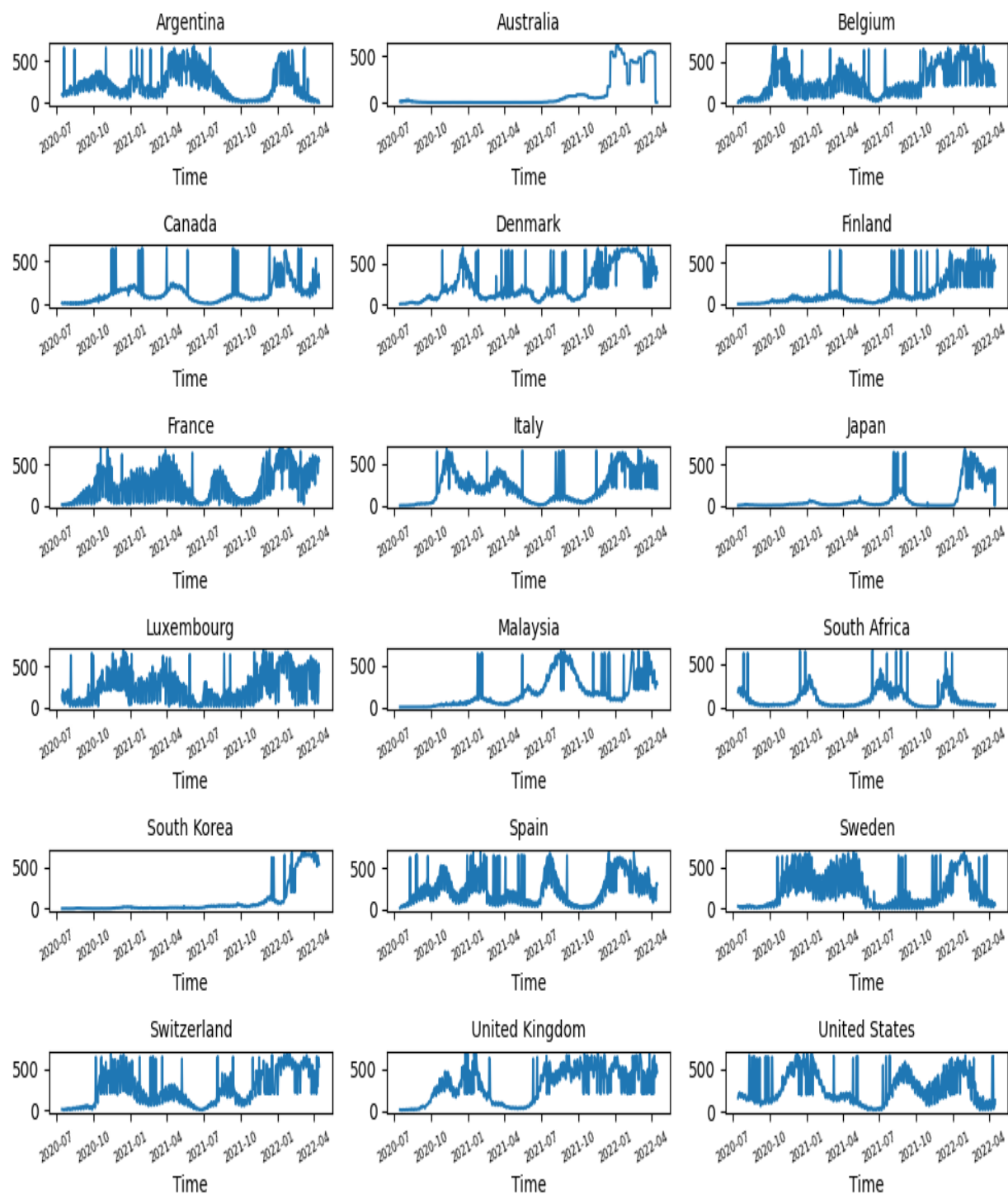


Figure A.6: New Cases Per Million (individual country)

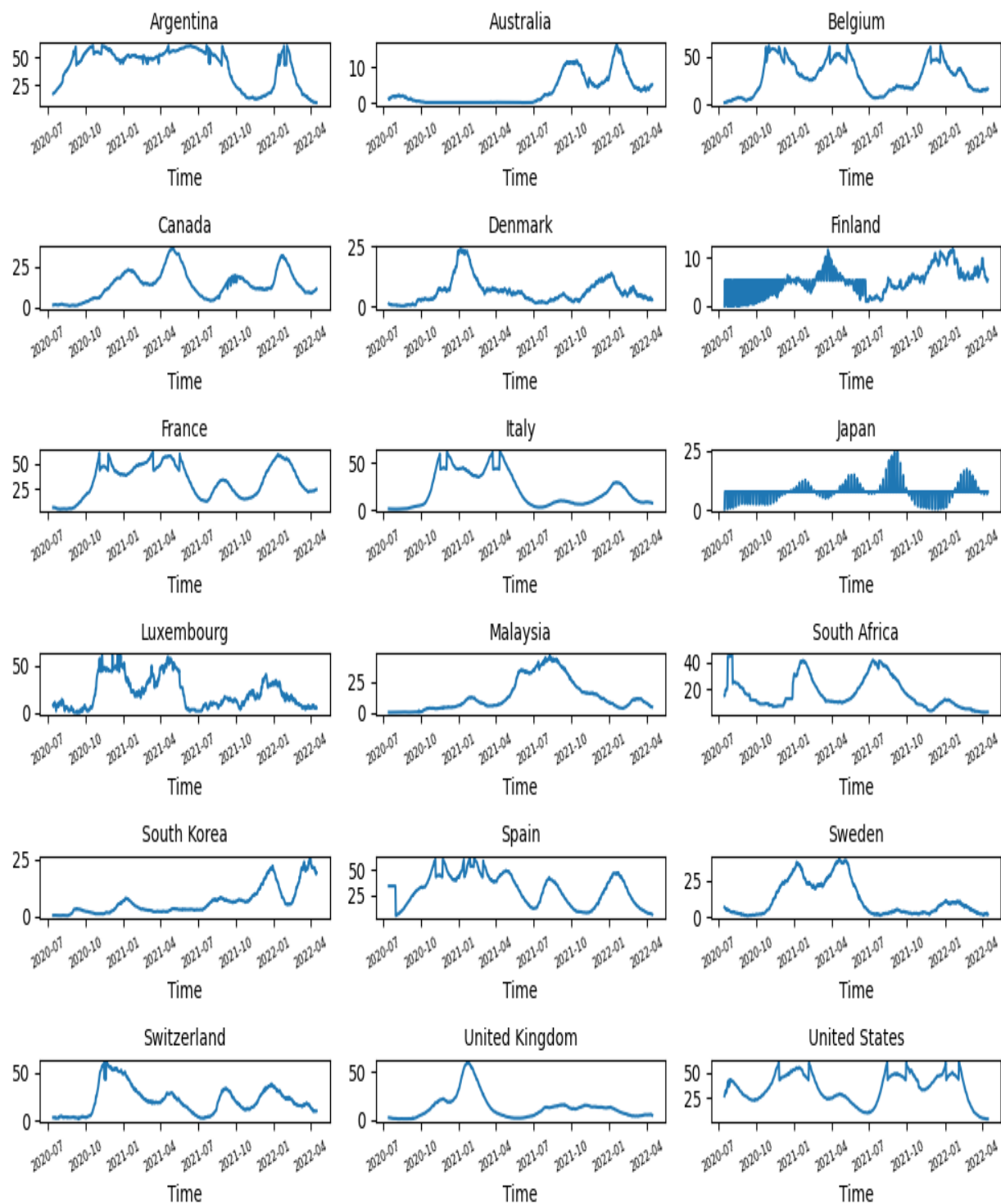


Figure A.7: ICU Patients Per Million (individual country)

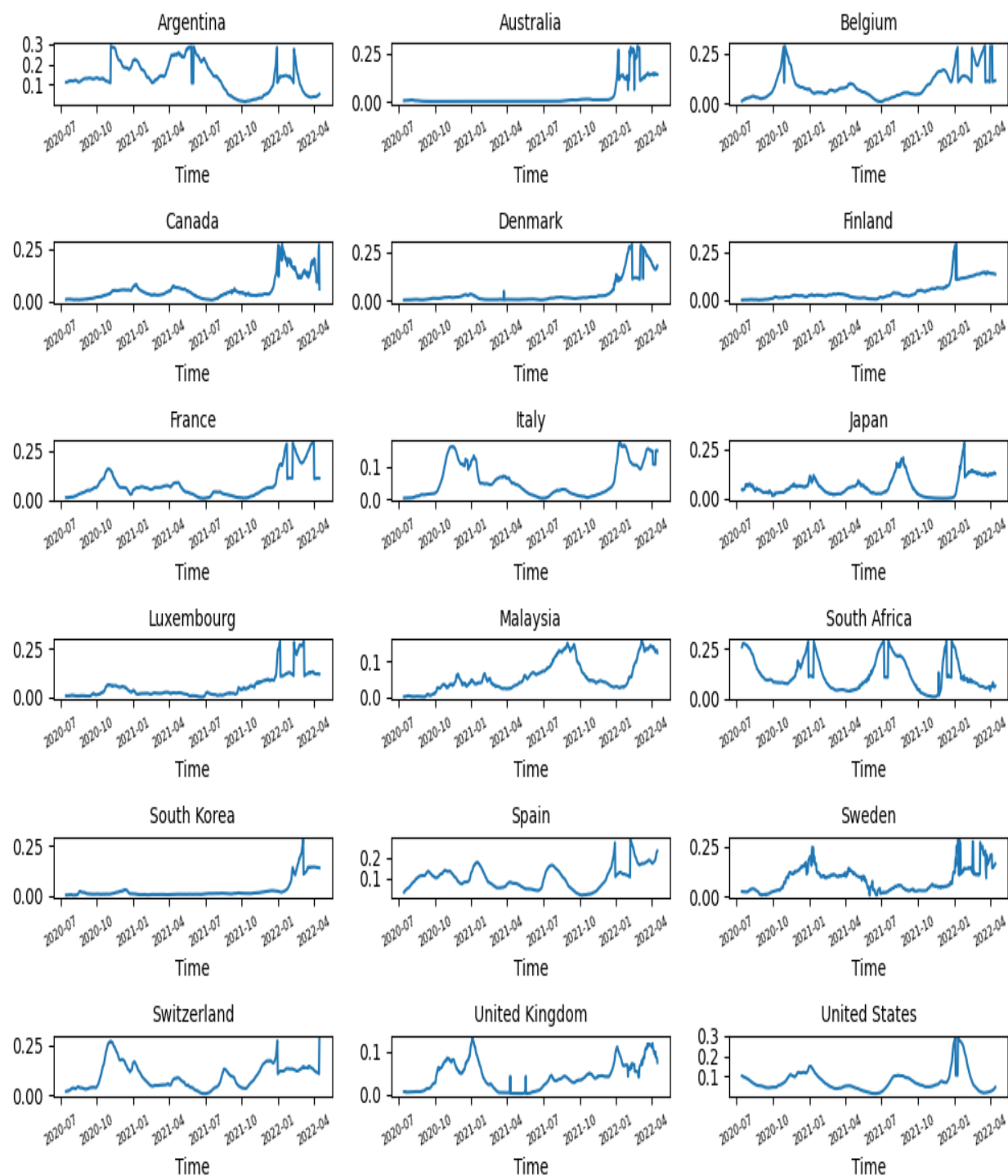


Figure A.8: COVID-19 Positive Rate (individual country)