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Analysis on Covid-19 Public Restrictions Using Granger Causality and Machine Learning

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Author's Declaration of Originality

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Abstract

This research examines the impact of COVID-19 policies on death rates across Canadian provinces, considering geographical, cultural, economic, and healthcare disparities. It analyzes the effectiveness of these policies over time, hypothesizing that their impact varies and that only certain measures are effective.

The study uses both traditional methods, like Vector Autoregression (VAR) and Granger Causality, and modern techniques, like eXtreme Gradient Boosting (XGBoost), to assess policy effectiveness. This approach goes beyond binary evaluations by quantifying the strength of policy impacts. By comparing these methods, the research identifies the most effective strategies for evidence-based decision-making.

Focusing on provincial-level data, the study aims to provide insights that are crucial for immediate policy decisions and future pandemic preparedness, contributing to a comprehensive understanding of effective pandemic response strategies and enhancing Canada's resilience to health crises.

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List of Abbreviations

Abbreviation	Full Form
GC	Granger Causality
GCI	Granger Causality Index
XGBoost	eXtreme Gradient Boosting
VAR	Vector AutoRegressive
OxCGRT	The Oxford Covid-19 Government Response Tracker
SCM	Synthetic Control Method
LSTM	Long Short Term Memory
GRU	Gated Recurrent Unit
RNN	Recurrent Neural Networks
MAPE	Mean Absolute Percentage Error
EV	Explained Variance
RMSLE	Root Mean Squared Log Error
OWID	Our World In Data
JHUCSSE	Johns Hopkins University Center for Systems Science and Engineering
DTR	Domestic travel restrictions
InFS	International flights suspension

Abbreviation	Full Form
IsoQ	Isolation and quarantine policies
RqPro	Requirement to wear protective gear in public
ADF	Augmented Dickey Fuller
AR	Auto Regressive
CGCI	Conditional Granger Causality
CGC	Conditional Granger Causality Index

Chapter 1

Introduction and Preliminaries

1.1 Introduction

On March 11, 2020, the World Health Organization officially labeled COVID-19 as a pandemic, signifying a crucial moment that highlighted the seriousness and global impact of the virus. In reaction to this declaration, countries worldwide promptly implemented various policies to deal with the pandemic, including measures like lockdowns, financial aid, and initiatives for testing and vaccination. [**1**]

Countries around the world exhibited varied responses to the COVID-19 pandemic. These responses were influenced by factors such as geographical variation, cultural and sociodemographic considerations, healthcare system disparities, and population density.

Geographical Variation: The diverse geography of countries played a pivotal role in shaping the efficacy of pandemic response policies. Urban, rural, and remote areas often required tailored approaches, considering the unique challenges each setting posed in terms of virus transmission and resource accessibility.

Cultural and Sociodemographic Factors: Varying cultural norms and sociodemographic conditions significantly impacted the compliance and effectiveness of implemented measures. Understanding and accounting for these differences became essential in designing policies that resonated with diverse populations and mitigated disparities in outcomes.

Healthcare Systems: Distinct healthcare systems across nations led to variations in testing, tracing, and vaccination strategies. The effectiveness of pandemic responses was closely tied to the resilience and adaptability of each country's healthcare infrastructure, emphasizing the need for a nuanced analysis of policy outcomes.

Population Density: Population density, whether in urban or rural areas, exerted a considerable influence on the transmission dynamics of the virus. Tailoring policies to accommodate these differences became imperative in controlling the spread of COVID-19 and minimizing its impact on public health.

Economic Disparities: The economic resilience and capacity of countries also played a pivotal role in their pandemic response. Wealthier nations could afford extensive testing, robust healthcare infrastructures, and substantial financial aid packages, while economically disadvantaged nations faced additional hurdles in implementing comprehensive measures.

Governmental Leadership: The effectiveness of pandemic responses was closely tied to the quality of governmental leadership. Proactive and transparent governance facilitated swift decision-making, clear communication, and coordinated implementation of policies, ultimately influencing the overall success of pandemic control efforts.

Global Cooperation: The interconnected nature of our world underscored the importance of global cooperation in pandemic response. Collaborative efforts in information sharing, resource allocation, and vaccine distribution became imperative to address the transnational nature of the virus and prevent its resurgence through international travel.

Vaccine Access and Distribution: The development and distribution of vaccines emerged as a critical milestone in the fight against COVID-19. Disparities in vaccine access and distribution underscored the need for equitable global strategies to ensure that all nations, irrespective of economic status, could achieve widespread vaccination coverage.

As we contemplate the diverse global responses to the COVID-19 pandemic, it becomes increasingly crucial to undertake country and province-focused studies. Such targeted investigations allow for the meticulous control of variations stemming from geographical, cultural, economic, and healthcare disparities. By delving into the specifics of each nation's and province's responses, we can effectively discern patterns, identify successful strategies, and learn from shortcomings. This focused analysis not only enhances our understanding of the pandemic's impact but also lays the foundation for a collective, adaptive approach to navigate future global health crises more effectively.

1.2 Define the Problem

Canada, like many other nations, implemented a variety of policy ranging from social distancing measures and lockdowns to vaccination and healthcare system reinforcements. Understanding the nuances of these policies and their effectiveness is essential for refining the government's health strategies and preparing for future pandemics. This research particularly focuses in on the variations in policy responses across provinces, recognizing that the diverse demographic, geographic, and socioeconomic factors may yield disparate outcomes.

The central problem addressed in this thesis revolves around assessing the impact of Covid-19-related public policies on death rates, with a focus on the provincial level.

We suspect that the effectiveness of Covid-19-related public policies may not be uniform across all measures and provinces. Our hypothesis suggests that only specific policies have proven to be effective in mitigating the impact on death rates.

Therefore, the primary objective of this research is to identify, assess, and select the most effective policies on a per-province basis. Through rigorous analysis and comparison, we aim to uncover patterns and trends that describe the policies with the greatest impact, providing valuable insights for policymakers and public health officials. This investigation will contribute to a detailed understanding of pandemic response strategies, enabling evidence-based decision-making for future upcoming pandemics.

1.3 Research Questions

In this section of the thesis, we will elaborate on a focused exploration on the key research questions that serve as the guiding compass for our investigation. The clarity and precision of these inquiries are very important in unraveling the dynamics between policies implemented in response to the Covid-19 pandemic and the resulting impact on death rates for the provinces of Canada. Our overarching goal is to contribute nuanced insights that go beyond traditional analyses by closely examining the time-related aspects of these connections.

The first set of questions revolves around the identification of effective policies—seeking to discern not only which policies manifest a tangible impact on death rates but also probing the temporal intricacies, such as the lag associated with this impact. The exploration extends further to understand whether the effects of these policies are immediately evident or if a delayed response, perhaps observed three weeks after implementation, plays a crucial role.

In the ensuing stage of our inquiry, we aim to compare the impact of different policies, discerning which one wields a more significant influence. Specifically, we seek to identify the policy with the strongest impact and explore potential associations with other policies. This comparative analysis delves into the nuanced dynamics of policy effectiveness, providing insights into the interplay between various strategies in influencing death rates across provinces.

These meticulously crafted research questions not only guide our exploration but also underscore the depth and complexity of our endeavor. By navigating through these questions, we aim to uncover valuable insights that transcend the immediate circumstances of the Covid-19 pandemic, offering a framework for evidence-based decision-making and strategic preparedness for future health crises in Canada.

1.4 Significance of the Study

The significance of this study lies in its distinctive approach to analysis of the impact of Covid-19-related public policies on death rates within the diverse provinces of Canada, particularly at the provincial level, sets our research apart.

This study holds paramount significance for Canada as it attempts to comprehensively understand the effectiveness of its Covid-19 response policies and the associated lag effects across its diverse provinces. By lag, we mean the interval between the occurrence of a cause (implementation of a policy) and its observable effect (changes in death rates).

The insights gained from this research are not only instrumental in shaping immediate policy decisions but also contribute to the nation's preparedness for future pandemics. By delving into the details of policy effectiveness and temporal dynamics, our study equips Canadian governments and public health professionals with critical knowledge essential for crafting informed and adaptive strategies. This proactive approach is indispensable for enhancing the nation's resilience and responsiveness to emerging health crises, ensuring that Canada is going to be well-prepared to manage the challenges of future pandemics.

Chapter 2

Review of Related Literature and Research

The current landscape of research on the effectiveness of policy responses to the COVID-19 pandemic provides a variety of methodologies and insights. To validate our method with robust academic backing, it is essential to thoroughly study both the merits and drawbacks of previous research efforts.

2.1 Evaluation of the Strategies to Control COVID-19 Pandemic in Four European Countries using VAR and Granger Casaulity

A research with topic of "Evaluation of the Strategies to Control COVID-19 Pandemic in Four European Countries" was published in 2021 [**2**]:

This study aims to explore the relationship between specific interventions and incident cases during the second wave in multiple countries. Utilizing data from the Oxford COVID-19 Government Response Tracker (OxCGRT) from October 1st, 2020, to January 10, 2021, they considered thirteen indicators related to the adopted measures.

Thirteen specific indicators were analyzed: eight were related to closures and containment measures while five to health measures. All of them are related to measures imposed to limit the transmission of COVID-19. All the indicators C1, C2, C4, C7, C8, H3, were analyzed. The other indicators (i.e., C3, C5, C6, H1, H2) were not analyzed since the four considered countries deployed these interventions over the entire time span without any different intensity.

C1: Record closings of schools and universities

C2: Record closings of workplaces

C3: Record canceling public events

C4: Record limits on private gatherings

C5: Record closing of public transport

C6: Record orders to "shelter-in-place" and otherwise confine to the home

C7: Record restrictions on internal movement between cities/regions

C8: Record restrictions on international travel Note: this records policy for foreign travelers, not citizens

H1: Record presence of public info campaigns

H2: Record government policy on who has access to testing Note: this records policies about testing for current infection (PCR tests) not testing for immunity (antibody test)

H3: Record government policy on contact tracing after a positive diagnosis Note: we are looking for policies that would identify all people potentially exposed to Covid-19; voluntary Bluetooth apps are unlikely to achieve this

H6: Record policies on the use of facial coverings outside the home

H7: Record policies for vaccine delivery for different groups

Four European countries were taken into account: Italy, German, Spain and UK.

This study employs a methodology based on a Vector Autoregression (VAR) model and the Granger Causality test to evaluate the effects of various policies during the COVID-19 pandemic.

Only workplace closures (C2) and imitations on private gatherings (C4) showed a significant correlation with incident cases in UK and restrictions on internal movement (C7) in Germany. The Granger causality also tested that C2 and C4 forecasted the decrease of incident cases after a time lag of 6 days in UK and C7 after 30 days in Germany. Other analyzed indicators did not show any significant correlation, thus they were not reported in significant results.

This research doesn't deploy any machine learning techniques, and only relies on a linear model. It doesn't consider vaccine data either. Notably, the study relies solely on p-values without quantifying the strength of the causal relation between a policy and fatality, suggesting a potential need for a more nuanced evaluation of policy effectiveness.

2.2 Investigate the effect of face masks on COVID-19 cases in Germany

Timo Mitzea, Reinhold Kosfeldb, Johannes Rodec, and Klaus Wälden did a research on Face masks effect on COVID-19 cases in Germany. [**3**] The authors used the synthetic control method (SCM) to estimate the effect of mandatory face masks on the development of registered COVID-19 infections in Germany. They found that the early introduction of face masks in Jena resulted in a drop in newly registered COVID-19 cases of around 75% after 20 days.

The SCM approach is used to estimate the effect of a policy intervention (treatment) which only targets a small number of treated units (in this case, one or a few regions). Treatment effects are identified by comparing the development of outcomes in treated and control regions during the treatment period. Statistical significance of the estimated treatment effect is based on permutation. The SCM estimates a series of placebo treatment effects for all regions in the donor pool, that is, each region in the donor pool is treated as if it had been treated. The distribution of placebo effects is then compared with the treatment effect for the treated region. If the magnitude of the latter effect is large relative to the distribution of the placebo effects, the treatment effect is considered not to be observed by chance, that is, it is deemed to be significant.

This research doesn't deploy any machine learning techniques, and only relies on a linear model. It has considered only one policy. The SCM approach might not capture complex and non-linear relationships that could be present in the data, which modern machine learning algorithms are better equipped to handle. It might not be the best choice when the goal is prediction and understanding complex relationships in high-dimensional data with more policies.

2.3 Time series forecasting of new cases and new deaths rate for COVID-19 using deep learning methods

Nooshin Ayoobi et al. conducted a study on Time series forecasting of new cases and new deaths rate for COVID-19 using deep learning methods in 2021. [**4**] This study is notable for its application of advanced machine learning techniques to predict Covid19 outcomes. The primary focus is on the evaluation of three different methods, Long Short-Term Memory (LSTM), Convolutional LSTM, and Gated Recurrent Unit (GRU) methods, including their bidirectional extensions, for forecasting new cases and new death rates in Australia and Iran.

Here's a more detailed exploration of the study's key components:

Model Selection and Evaluation: The study employs three popular types of recurrent neural networks (RNNs) – LSTM, Convolutional LSTM, and GRU. These models are known for their ability to capture temporal dependencies in time series data. Bidirectional extensions of these models are also considered, which can enhance the ability to capture information from both past and future time points. The performance of the models is evaluated comprehensively using a range of evaluation metrics such as such as Mean Squared Log Error (MSLE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Log Error (RMSLE), and Explained Variance (EV).

Dataset and Time Series Splitting: The World Health Organization (WHO) dataset is utilized, and specific time series data for new cases and new deaths in Australia and Iran are chosen for analysis. The time series data are split, into training and testing sets, to facilitate model training and subsequent evaluation.

Prediction Horizons: The study investigates different prediction horizons, specifically forecasting for 1, 3, and 7 days ahead. This approach allows for a nuanced understanding of how well the models perform over short to medium-term forecasting periods.

Limitation – Absence of Policy Data: One notable limitation highlighted in the study is the absence of policy data. While the deep learning models effectively forecast COVID-19 outcomes based on historical data, the lack of information on implemented policies hinders a holistic evaluation of the interplay between policy interventions and pandemic outcomes. This limitation suggests that the study, despite its advanced forecasting techniques, doesn't consider the broader context of policy impacts on the observed trends in COVID-19 cases and deaths.

2.4 A global analysis of the effectiveness of policy responses to COVID-19 using Correlation Analysis

K. Agyapon-Ntra and E. McSharry worked on a global analysis of the effectiveness of policy responses to COVID-19. They also tried to answer to this question of which policy measures are most effective for managing COVID-19. [5]

In this paper, they took a more high level approach and moved from single countries and international economic organizations like the OECD to pursue a more global view of the effects of COVID-19 and the effectiveness of policies. They used used Pearson correlation coefficient method. This method was used to calculate the policy impact based on the negative correlation between policies and the percentage change in case counts.

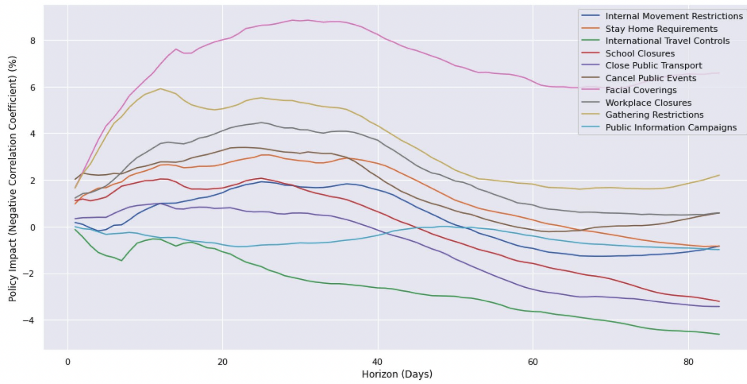
The datasets analyzed during this study is from the Oxford COVID-19 government response tracker (OxCGRT) repository [6], The Google Mobility Trends datasets can be accessed from Google's COVID-19 Community Mobility Reports. [7] Finally, the data used to estimate the emergence of COVID-19 variants was found on the Word Health Organization's official web page. [8]

Non-pharmaceutical interventions, NPIs, range from facial coverings to restrictions on mobility, and these are compared using an empirical assessment of their impact on the growth rate of case numbers. They used country-level daily time series from Our World In Data (OWID) platform. [9] Using information about the stringency of a particular policy and the number of cases for each day and country allowed for the quantification of the impact over different temporal horizons. It provided a comparison of the impact of various policies and the horizon over which they take maximum effect. The Policy impact was quantified using the correlation between government policies and relative changes in normalised case counts for various horizons.

This study showed that most policies require well over 20 days to yield any effect, and that the impact is marginal for some of these policies. It is also worth noting that they showed it takes at least 12 days for any single policy to effectively contribute to a decline in case counts as seen in the case of Gathering Restrictions and Closure of Public Transport.

They reported wearing facial coverings as the most impactful measure, showing a substantial 8.8% reduction in COVID-19 cases within approximately one month. Gathering restrictions yield the most significant short-term impact at 5%. Workplace closures, cancellation of public events, stay-at-home requirements, school closures, and internal movement restrictions all extend over a period of around 25 days, with decreasing impacts of 4.5%, 3.4%, 3.1%, 2.1%, and 1.9%, respectively. Public transport closures, lasting only 12 days, deliver a modest impact of 1.0%. Public information campaigns and international travel controls, however, exhibit negligible impact, making their justification challenging based on the global evidence from this study. Therefore, it is recommended to promptly implement facial coverings in response to a new airborne pandemic, considering its effectiveness, cost-efficiency, and minimal impact on mobility and economic growth. While school closures have a relatively small impact of 2.1%, it is advised to prioritize more impactful measures before resorting to this restriction, given its potential long-term effects on children's education. This aligns with the findings of previous studies, such as Viner et al., which indicated that "school closures alone would prevent only 2–4% of deaths, much less than other social distancing interventions.

This research doesn't deploy any machine learning techniques, and only relies on a linear model.



Policy impact quantified using the correlation between government policies and relative changes in normalised case counts for various horizons.

Policy	Impact (%)	Horizon (days)
Facial coverings	8.8	31
Gathering restrictions	5.9	12
Workplace closures	4.5	25
Cancellation of public events	3.4	23
Stay home requirements	3.1	26
School closures	2.1	25
Internal movement restrictions	1.9	25
Closure of public transport	1.0	12
Public information campaigns	0.0	49
International travel controls	−0.1	1

COVID-19 policy responses, impact, and horizon over which policies attain maximum efficiency.

2.5 Investigate Relations Between Implementation Date of Policies and The Spreading of COVID-19 using Cluster Analysis

W. Sirinaovaku worked on the Relations Between Implementation Date of Policies and The Spreading of COVID-19 as well. This study was published in 2020 [**10**]:

This research studied the relations of how public policy implementation might affect the onset and the spread of COVID-19 cases. They employed cluster analysis to identify data patterns associating with the policy implementation profiles.

They used Four datasets, namely JHU Coronavirus COVID-19 Global Cases, by country [**11**] from Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE), COVID-19 Government Measures Dataset [**12**] from Assessment Capacities Project (ACAPS), COVID-19 country lockdown days [**13**] and COVID-19 US Lockdown Dates Dataset [**14**] , were gathered for the most analysis advantages. The last two datasets [**13**] - [**14**] were gathered and provided as CSV files on Kaggle [**15**] - [**16**] , which we downloaded from there.

The COVID-19 data were extracted from the JHU Coronavirus COVID-19 Global Cases dataset. [**11**] the policy data are composed of the rest three datasets: COVID-19 Government Measures dataset [**12**] , COVID-19 Country Lockdown Days [**15**] , and COVID-19 US Lockdown Dates Dataset . [**16**]

These are the policies they studied: - CiP: Changes in prison-related policies - DTR: Domestic travel restrictions - Econ: Economic measures - HeScrn: Health screenings in airports and border crossing - InFS: International flights suspension - IsoQ: Isolation and quarantine policies - Psy: Psychological assistance and medical social work - RqPro: Requirement to wear protective gear in public - Test: Testing policy - Visa: Visa restrictions

They deployed two experiments:

1) Experiment I: After the two sets of data were consolidated, the value in each column of the policy data, which originally contained the implemented date, was changed to the number of days passing the date confirmed cases exceeding 100 cases. Then, the correlations were calculated. The policies that have a fairly high correlation score compared to other policies were examined. The result of this study would indicate how the implementation date of policies affects a country's overall statistics at the current stage .

They used K-means algorithm for clustering. To select the number of clusters and evaluate the quality of data clustering, the silhouette method was used. The optimized number of clusters was 3. They first classified countries into stages starting from the beginning to almost the end based on how a country performs in the latest week (7th June 2020) compared to the average and the peak week

First cluster is the countries in the stage of facing their peak. IsoQ, Psy, and RqPro have high levels of correlations. Second cluster is the countries that are in a steady stage.DTR, InFS, and IsoQ still have a moderate level of correlation. Third cluster is the countries that are reaching the ending stage. CiP, DTR, IsoQ, RqPro have a moderate level of correlation. Fourth cluster represents the countries that might be recently added to the data. It is because the number of days in this cluster is noticeably low compared to the other clusters. The number of countries in this cluster was relatively low compared to other clusters. Therefore, the correlation in this cluster could be biased and hard to conclude.

2) Experiment II: The correlation of the each-week clusters and policies. In this experiment, before joining the two sets of data, the implementation date of policies in the policy data were shifted by two weeks based on the assumption that policy would affect the spreading of COVID-19 after it has been implemented for two weeks. Then, the modified policy data were combined with the each-week clusters on the country, province/state, and week. Next, the correlations between the number of weeks from implementation date and features for each policy were computed. The result of this experiment would demonstrate how the implementation date of policies affects a country two weeks after it is implemented.

Firstly, the correlations of the before-peak group shows that HeScrn and IsoQ are the policies that have a high correlation compared to the others.

Next, the correlations of the peak group display three policies, namely IsoQ, Econ, and Visa, that have high correlations to the death rate. Furthermore, the testing policies (Test) had a moderate negative correlation .

The results suggest that the effectiveness of policy adoption relates to the onset spreading of COVID-19. This also indicates that the decision of public administrators was critical in the latter stage of the pandemic situation management.

While utilizing machine learning, the study has limitations, such as considering only a two-week lag, excluding vaccine data. These constraints suggest potential avenues for improvement in capturing the complexity of policy effects.

2.6 Evaluate the effectiveness of containment and closure policy on the epidemic using statistical signal processing framework

Y. Li, C. Chan et al. [**17**] proposed a statistical signal processing framework to evaluate the effectiveness of containment and closure policy on the epidemic dynamics and provided case studies on four countries: United States, United Kingdom, Italy, and Turkey. This study was published in 2021.

They used Oxford covid-19 government response tracker dataset for their analysis. They studied the effectiveness of stringency index on total cases rather than studying single policies. They implemented Dickey–Fuller test (ADF) to make the two time series stationary. They split the data set into four timelines: April 19 to October 28, March 23 to December 18, April 04 to December 18, March 25 to December 18 and used Kalman filter to estimate the cases. Next, they implemented GC test to see if stringency index granger causes the number of total cases. They observed that in United States and Italy, stringency index Granger-causes reproduction number. In United Kingdom and Turkey, however, stringency index does not Granger-cause reproduction number, suggesting that containment and closure policies taken by the

British and Turkish government seem to have little influence on the trend of COVID-19 pandemic.

This study utilizes the Granger Causality test and Kalman filter for predicting cases but does not incorporate machine learning. Also another limitation is the absence of studying the effectiveness of the individual policies and the exclusive reliance on p-values without quantifying the strength of impact. These limitations indicate a need for a more nuanced evaluation of policy effectiveness.

2.7 Literature Review Summary

Building upon this knowledge base, our study diverges by introducing a sophisticated approach to understanding causality. We aim to investigate not only the policies themselves but also the temporal dimension of their impact. Employing Granger causality test, we seek to delineate the time window during which policies show an observable influence on death rates. This temporal analysis aims to contribute a dynamic perspective, acknowledging that the efficacy of policies depends on time window and lag.

Additionally, our research introduces machine learning regression model as a complementary methodology to assess causality. By leveraging the predictive power of these models, we intend to compare and contrast results obtained from Granger causality tests, ultimately identifying the most robust and accurate approach to explain the causal relationships between implemented policies and death rates. This comprehensive integration of time-series analysis and machine learning techniques positions our study at the forefront of policy evaluation methodologies during public health crises.

Also, our extensive literature review underscores a notable gap in research work related to the impact of public policies on death rates within the Canadian context and the provincial level. Despite the international studies exploring Covid-19 response strategies, there exists an absence of investigations into the effectiveness of policies implemented across the diverse provinces of Canada. The absence of a comprehensive examination of Canada's Covid 19 response policy amid a global pandemic underscores the unique and crucial significance of our research attempt in contributing essential insights to the field. By analyzing the sophisticated interplay of policies and death rates in Canadian provinces, our research attempts to contribute novel insights and practical implications for governments and public health professionals navigating the distinctive challenges posed by the Covid-19 pandemic within the Canadian context.

Chapter 3

Methodology

In delineating the intricate relationship between policy interventions and the resulting impact on mortality during the COVID-19 pandemic, this chapter provides a comprehensive overview of the methodology employed in our research. With a focus on transparency, we present a thorough examination of the approaches employed to answer our research questions. The objective of this study is to answer these questions:

1- Can we estimate the number of death by policies implemented during the Covid-19?

2- Which policy measures are most effective for managing COVID-19 death rate?

3- Whether the effects of these policies are immediately evident or if a delayed response, perhaps observed three weeks after implementation, plays a crucial role.

Our comprehensive literature review has brought to light a conspicuous gap in the existing research landscape concerning the impact of public policies on death rates at both the national and provincial levels in the Canadian context. The scarcity of studies focusing on this critical aspect calls for a dedicated exploration, prompting our research to fill this void and contribute valuable insights to the understanding of pandemic management strategies within Canada.

Building upon this observation, a significant innovation in our methodology lies in the nuanced treatment of Granger Causality (GC). In contrast to existing studies that have predominantly relied on p-values to determine the presence or absence of an effect, our approach takes a step further by quantifying the strength of Granger Causality for each individual policy. The conventional focus on p-values, while informative, offers a binary understanding of the impact of policies – either effective or ineffective. By introducing the concept of GC strength, we transcend this binary paradigm, providing a more nuanced evaluation of the influence that each policy exerts on death rates. This quantitative assessment enables a richer comprehension of the magnitude and robustness of the causal relationships, thereby offering a more comprehensive view of the effectiveness of public policies. In essence, our research methodology not only acknowledges the presence or absence of causal links but delves into the subtleties of their strength. This methodological advancement aligns with the overarching objective of our research – to offer a more refined and granular understanding of how policies, both individually and collectively, impact mortality outcomes during the ongoing COVID-19 pandemic at the provincial level in Canada.

Moreover, our methodology stands out for its unique integration of Granger Causality (GC) with machine learning techniques, specifically eXtreme Gradient Boosting (XGBoost), applied to each individual policy. While the acknowledgment of Granger Causality in the literature is widespread, the novelty of our approach lies in its combination with a modern and sophisticated machine learning methodology. This distinctive strategy serves the dual purpose of capturing temporal dependencies and unraveling intricate relationships between policies and death rates.

By juxtaposing traditional linear methods, embodied by Granger Causality, with the advanced capabilities of machine learning, particularly XGBoost, we introduce a comparative dimension to our analysis. This allows us not only to assess the effectiveness of each policy individually but also to compare the performance of linear and machine learning approaches. The aim is to discern which method offers a more accurate and insightful understanding of the complex dynamics governing the relationship between public policies and mortality outcomes during the ongoing COVID-19 pandemic. This comparative analysis will enable us to identify the most effective strategies, thereby contributing valuable insights for evidence-based decision-making and strategic preparedness in managing public health crises.

The dual methodology employed — a traditional linear approach utilizing Vector Autoregression (VAR) and Granger Causality, coupled with the contemporary machine learning capabilities of XGBoost — is designed to provide a holistic understanding of the nuanced dynamics between public policies and their impact on mortality outcomes. Through this integrative approach, our research endeavors to bridge gaps in the current literature, offering a multifaceted perspective on the effectiveness of policies in mitigating the impact of the COVID-19 pandemic across different provinces in Canada.

3.1 Autoregressive Process

A statistical model is autoregressive if it predicts future values based on past values. It could be Univariate or Multivariate.

Univariate Autoregressive Process only uses past time points from the same signal to predict future points. A variable $X(t)$ is autoregressive of order n (i.e., $AR(n)$) if its state at time t is a function of its n past states:

$$X(t) = \sum_{i=1}^{n} a_i X(t-i) + \epsilon(t) \tag{3.1.1}$$

where t is the time step and intiger, and the real coefficients a_i indicate the contribution from i steps in the past, to the current state t of X. The term $\epsilon(t)$ is a noise source with variance Σ that models any external additive contribution to the determination of $X(t)$. If Σ is large, then the process is weakly dependent on its past states and $X(t)$ may be regarded as just noise.

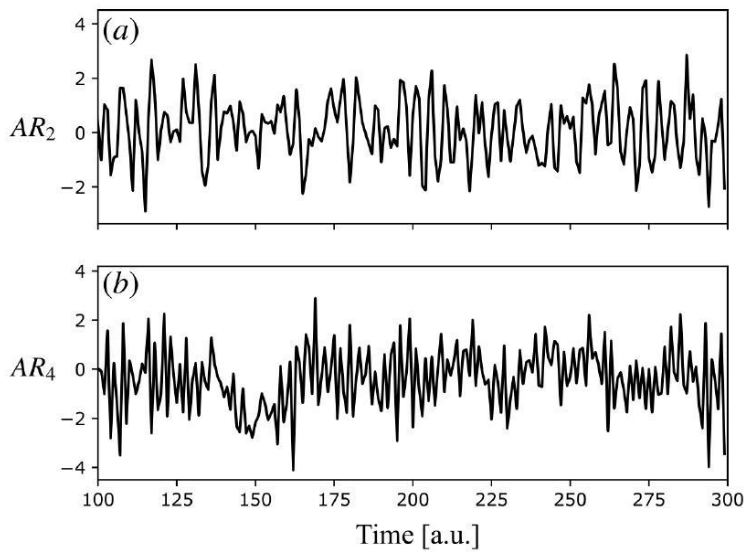


Figure Autoregressive processes. (a) time series of an AR_2 process with coefficients $(a_1, a_2) = (0.3, -0.5)$. (b) time series of an AR_4 process with coefficients $(a_1, a_2, a_3, a_4) = (-0.2, 0.5, 0.6, -0.2)$.

Multivariate Autoregressive Process Considers two signals of interest, another model of the data could use the past time points from both signals to predict future points of one.

$$X_1(t) = \sum_{i=1}^{n} a_i X_1(t-i) + \sum_{i=1}^{n} b_i X_2(t-i) + \epsilon^*(t) \tag{3.1.2}$$

3.2 Granger causality

The investigation of the causal relationships between a set of time series is a very important topic in many applications including neuroscience [**18**] , genomics [**19**] , econometrics [**20**] - [**21**] , climate science [**22**]- [**23**] , and social media analysis.

Introduced more than a half century ago, Granger Causality reveals interdependence structure in multi-variate time series. Clive Granger, a British economist, put forth a framework to assess whether past observations of one time series Y help to predict future values of another series X [**24**] . According to the concept originally introduced by Granger, a time series Y Granger causes another time series X if the prediction of X is improved when Y is included in the prediction model for X. The basic idea can be traced back to Norbert Wiener [**25**] who conceived the notion that, if the prediction of one time series could be improved by incorporating the history of a second one, then the second series is said to have a causal influence on the first , which needs to be distinguished from a true cause-and-effect relationship. We distinguish this definition from other standard definitions of causality by referring to it as Granger causality.

Granger causality has been applied in a wide variety of fields including economics [**26**] neuroscience [**27**] earth systems [**28**] , atmospheric systems [**29**] , solar indices [**30**] , turbulence [**31**] , and inference of functional networks of the brain using fMRI [**32**], MEG [**34**], and EEG [**35**].

The definition of Granger causality [**36**] is based on the theory of linear prediction [**37**] and its original estimation framework requires autoregressive (AR) modeling of time series data [**38**]. In this chapter, we will first introduce the basic concepts of autoregressive processes that form the basis of the parametric estimation of the GC. [**39**] Next, we will review one of the most frequently used solutions of this estimation problem, Yule-Walker set of equations [**40**].

3.3 Granger causality in time domain

In this section we develop the mathematical concepts and definitions of GC in time domain. Consider two stochastic signals, $X_1(t)$ and $X_2(t)$. We assume that these signals may be modeled by autoregressive stochastic processes of order n, independent of each other, such that their states in time t could be estimated by their n past values:

$$X_1(t) = \sum_{i=1}^{n} a_i X_1(t-i) + \epsilon_1(t)$$
$$X_2(t) = \sum_{i=1}^{n} c_i X_2(t-i) + \epsilon_2(t) \tag{3.3.3}$$

where the variances of ϵ_1 and ϵ_2 are, respectively, Σ_{11} and Σ_{22}, and the coefficients a_i and c_i are adjusted in order to minimize Σ_{11} and Σ_{22}.

However, we may also assume that the signals $X_1(t)$ and $X_2(t)$ are each modeled by a combination of one another, yielding

$$X_1(t) = \sum_{i=1}^{n} a_i X_1(t-i) + \sum_{i=1}^{n} b_i X_2(t-i) + \epsilon_1^*(t),$$
$$X_2(t) = \sum_{i=1}^{n} c_i X_2(t-i) + \sum_{i=1}^{n} d_i X_1(t-i) + \epsilon_2^*(t), \tag{3.3.4}$$

where the covariance matrix is given by

$$\mathbf{\Sigma} = \begin{bmatrix} \Sigma_{11}^* & \Sigma_{12}^* \\ \Sigma_{21}^* & \Sigma_{22}^* \end{bmatrix} \tag{3.3.5}$$

Here, $\Sigma_{11}^*, \Sigma_{22}^*$ are the variances of ϵ_1^* and ϵ_2^* respectively, and $\Sigma_{12}^* = \Sigma_{21}^*$ is the covariance of ϵ_1^* and ϵ_2^*. Again, the coefficients a_i, b_i, c_i and d_i are adjusted to minimize the variances Σ_{11}^* and Σ_{22}^*.

If $\Sigma_{11}^* < \Sigma_{11}$, then the addition of $X_2(t)$ to $X_1(t)$ generated a better fit to $X_1(t)$, and thus enhanced its predictability. In this sense, we may say there is a causal relation from X_2 to X_1, or simply that X_2 Granger-causes X_1. The same applies for the other signal: if $\Sigma_{22}^* < \Sigma_{22}$, then X_1 Granger-causes X_2 because adding X_1 to the dynamics of X_2 enhanced its predictability.

We may summarize this concept into the definition of the total causality index, given by

$$F_{1.2} = \log\left(\frac{\Sigma_{11}\Sigma_{22}}{\det(\mathbf{\Sigma})}\right) = \log\left(\frac{\Sigma_{11}\Sigma_{22}}{\Sigma_{11}^{*}\Sigma_{22}^{*} - (\Sigma_{12}^{*})^{2}}\right) \tag{3.3.6}$$

If $F_{1.2} > 0$, there is some Granger-causal relation between X_1 and X_2, because either $\Sigma_{11}^{*} < \Sigma_{11}$ or $\Sigma_{22}^{*} < \Sigma_{22}$, otherwise there is correlation between X_1 and X_2 due to $\Sigma_{12}^{*} > 0$. If neither Granger-causality nor correlations are present, then $F_{1.2} = 0$.

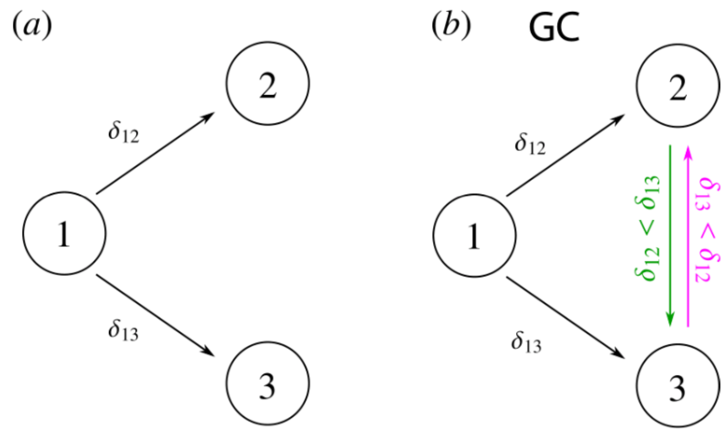
To know specifically whether there is Granger causality from 1 to 2 or from 2 to 1 , we may use the specific indices:

$$\begin{aligned} F_{1\to 2} &= \log\left(\frac{\Sigma_{22}}{\Sigma_{22}^{*}}\right) \\ F_{2\to 1} &= \log\left(\frac{\Sigma_{11}}{\Sigma_{11}^{*}}\right) \\ F_{1\leftrightarrow 2} &= \log\left(\frac{\Sigma_{11}^{*}\Sigma_{22}^{*}}{\det(\Sigma)}\right), \end{aligned} \tag{3.3.7}$$

such that

$$F_{1.2} = F_{1\to 2} + F_{2\to 1} + F_{1\leftrightarrow 2}, \tag{3.3.8}$$

where $F_{1\to 2}$ defines the causality from $X_1(t)$ to $X_2(t)$, $F_{2\to 1}$ is the causality from $X_2(t)$ to $X_1(t)$, and $F_{1\leftrightarrow 2}$ is called instantaneous causality due to correlations between



An interconnected system with 3 nodes, each subjected to distinct transmission delays

ϵ_1^* and ϵ_2^*. Just as for the total causality case, these specific indices are greater than zero if there is Granger causality, or zero otherwise.

3.4 Conditional Granger Causality

The complexity of interconnected systems often presents challenges for traditional Granger Causality (GC) analyses, particularly when attempting to analyze the causal relationships in the presence of a dependency. In this context, a notable limitation of GC becomes evident when applied to a system of three processes where one process drives the other two with differential time delays. Consider a system where Node 1 ($X_1(t)$) sends input signals to Node 2 ($X_2(t)$) and Node 3 ($X_3(t)$), each subjected to distinct transmission delays, $\delta_{12}(t)$ and $\delta_{13}(t)$. The conventional GC calculation, however, may infer causal links between Node 2 and Node 3 based solely on the temporal ordering of these delays, without accurately capturing the underlying dynamics. Such incorrect inferences arise due to the cross-correlation between $X_2(t)$ and $X_3(t)$, induced by their shared input from $X_1(t)$, thereby highlighting the inadequacy of GC in this scenario. [**41**]

To disambiguate these situations requires additional measures. Conditional Granger causality has the ability to resolve whether the interaction between two signals is direct or is mediated by another time series signal and whether the causal influence is simply due to differential time delays in their respective driving inputs.

Let $X_t = \{X_{1,t}, X_{2,t}, \ldots, X_{K,t}\}, t = 1, \ldots, N$, be a stationary time series with K dimensions and length N. Conditional Granger Causality index (CGCI) is calculated by assessing the influence of one variable (Xi) on another (Xj) while controlling for the impact of all other variables CGCI from a driving variable X_i to a response variable X_j involves two vector autoregressive (VAR) models for X_j, called also dynamic regression models [1] . [**42**] The first model is the unrestricted model (U-model) [**43**], given as

$$X_{j,t} = \sum_{k=1}^{K} (a_{jk,1} X_{k,t-1} + \cdots + a_{jk,p} X_{k,t-p}) + u_{j,t}$$

where p is the model order and $a_{jk,l}(k = 1, \ldots, K, l = 1, \ldots, p)$ are the U-model coefficients. The U-model includes all the K lagged variables for lags up to the order p. The second model is the restricted one (R-model) derived from the U-model by excluding the lags of X_i, given as

$$X_{j,t} = \sum_{k=1, k\neq i}^{K} (b_{jk,1} X_{k,t-1} + \cdots + b_{jk,p} X_{k,t-p}) + e_{j,t}$$

where $b_{jk,l}(k = 1, \ldots, K$ but $k \neq i$ and $l = 1, \ldots, p)$ are the coefficients of the R-model. The terms $u_{j,t}$ and $e_{j,t}$ are errors with the variances σ_U^2 and σ_R^2, respectively [2]. Then CGCI from X_i to X_j is defined as

$$\mathrm{CGCI}_{X_i \to X_j} = \ln \frac{\sigma_R^2}{\sigma_U^2}.$$

CGCI is at the zero level when X_i does not improve the prediction of X_j (the U-model and R-model give about the same fitting error variance) and obtains larger positive values when X_i improves the prediction of X_j indicating that X_i Granger causes X_j.

The statistical significance of CGCI is commonly assessed by a parametric significance test on the coefficients of the lagged driving variable X_i in the U-model [**44**]. The null hypothesis is $\mathrm{H}_0 : a_{ji,l} = 0$ for all $l = 1, \ldots, p$, and the Fisher statistic is

$$F = \frac{\left(\mathrm{SSE}^R - \mathrm{SSE}^U\right)/p}{\mathrm{SSE}^U/((N-p) - Kp)}$$

where SSE is the sum of squared errors and the superscript denotes the model, $N-p$ is the number of equations and Kp is the number of coefficients of the U-model. The Fisher test assumes independence of observations, normality and equal variance for

3.5 Granger causality in frequency domain

In order to derive the GC in frequency domain, we first define the lag operator L^k, such that

$$L^k X(t) = X(t-k), \tag{3.5.9}$$

delays $X(t)$ by k time steps, yielding $X(t-k)$. We may then rewrite equations 3.3.4 as:

$$\begin{aligned} X_1(t) &= \left(\sum_{i=1}^{n} a_i L^i\right) X_1(t) + \left(\sum_{i=1}^{n} b_i L^i\right) X_2(t) + \epsilon_1^*(t) \\ X_2(t) &= \left(\sum_{i=1}^{n} c_i L^i\right) X_1(t) + \left(\sum_{i=1}^{n} d_i L^i\right) X_2(t) + \epsilon_2^*(t), \end{aligned} \tag{3.5.10}$$

and rearrange their terms to collect $X_1(t)$ and $X_2(t)$:

$$\begin{aligned} \left(1-\sum_{i=1}^{n} a_i L^i\right) X_1(t) + \left(-\sum_{i=1}^{n} b_i L^i\right) X_2(t) = \epsilon_1^*(t) \\ \left(-\sum_{i=1}^{n} c_i L^i\right) X_1(t) + \left(1-\sum_{i=1}^{n} d_i L^i\right) X_2(t) = \epsilon_2^*(t). \end{aligned} \tag{3.5.11}$$

We define the coefficients $a(L) = 1 - \sum_{i=1}^{n} a_i L^i, b(L) = -\sum_{i=1}^{n} b_i L^i, c(L) = -\sum_{i=1}^{n} c_i L^i$ and $d(L) = 1 - \sum_{i=1}^{n} d_i L^i$, and rewrite equations 3.5.10 into matrix form:

$$\begin{pmatrix} a(L) & b(L) \\ c(L) & d(L) \end{pmatrix} \begin{pmatrix} X_1(t)X_2(t) \end{pmatrix} = \begin{pmatrix} \epsilon_1^*(t)\epsilon_2^*(t) \end{pmatrix} \tag{3.5.12}$$

where $a(0) = d(0) = 1$ and $b(0) = c(0) = 0$.

We apply the Fourier transform to equation 3.5.12 in order to switch to the frequency domain,

$$\underbrace{\begin{pmatrix} \tilde{a}(\omega) & \tilde{b}(\omega) \\ \tilde{c}(\omega) & \tilde{d}(\omega) \end{pmatrix}}_{A(\omega)} \underbrace{\begin{pmatrix} X_1(\omega) \\ X_2(\omega) \end{pmatrix}}_{\mathbf{X}(\omega)} = \underbrace{\begin{pmatrix} \epsilon_1^*(\omega) \\ \epsilon_2^*(\omega) \end{pmatrix}}_{\Sigma(\omega)}, \tag{3.5.13}$$

where ω is the frequency and $A(\omega)$ is the coefficient matrix whose elements are given by

$$\begin{aligned} \tilde{a}(\omega) &= 1 - \sum_{i=1}^{n} a_i \exp(-j\omega i) \\ \tilde{b}(\omega) &= - \sum_{i=1}^{n} b_i \exp(-j\omega i) \\ \tilde{c}(\omega) &= - \sum_{i=1}^{n} c_i \exp(-j\omega i) \\ \tilde{d}(\omega) &= 1 - \sum_{i=1}^{n} d_i \exp(-j\omega i). \end{aligned} \tag{3.5.14}$$

The expressions above are obtained by representing the lag operator in the spectral domain as $L^i = \exp(-j\omega i)$. This derives from the z-transform, where the representation of the z variable in the unit circle ($|z| = 1$) is $z^{-i} = \exp(-j\omega i)$. [**45**]- [**46**]

To obtain the power spectra of $X_1(\omega)$ and $X_2(\omega)$, we first isolate $\mathbf{X}(\omega)$ in equation 3.5.13:

$$\begin{pmatrix} X_1(\omega) \\ X_2(\omega) \end{pmatrix} = \underbrace{\begin{pmatrix} H_{11}(\omega) & H_{12}(\omega) \\ H_{21}(\omega) & H_{22}(\omega) \end{pmatrix}}_{\mathbf{H}(\omega)} \begin{pmatrix} \epsilon_1^*(\omega) \\ \epsilon_2^*(\omega) \end{pmatrix}, \tag{3.5.15}$$

where $\mathbf{H}(\omega) = \mathbf{A^{-1}}(\omega)$ is called the transfer matrix, resulting in the following spectra:

$$\mathbf{S}(\omega) = \left\langle \mathbf{X}(\omega)\mathbf{X}^{\dagger}(\omega) \right\rangle = \mathbf{H}(\omega)\mathbf{\Sigma}(\omega)\mathbf{H}^{\dagger}(\omega), \tag{3.5.16}$$

where $\langle . \rangle$ is the ensemble average, $\dagger$ the transposed conjugate of the matrix, and $\mathbf{S}(\omega)$ is the spectral matrix defined as:

$$\mathbf{S}(\omega) = \begin{bmatrix} S_{11}(\omega) & S_{12}(\omega) \\ S_{21}(\omega) & S_{22}(\omega) \end{bmatrix}. \tag{3.5.17}$$

In equation 3.5.17, $S_{11}(\omega)$ and $S_{22}(\omega)$ are called the autospectra, and the elements $S_{12}(\omega)$ and $S_{21}(\omega)$ are called the cross-spectra.

We can expand the product in equation 3.5.16 to obtain $S_{11}(\omega)$ and $S_{22}(\omega)$ as:

$$\begin{aligned} S_{11}(\omega) &= \underbrace{\bar{H}_{11}(\omega)\Sigma_{11}\bar{H}_{11}^{\dagger}(\omega)}_{\text{Intrinsic}} + \underbrace{H_{12}(\omega)\left(\Sigma_{22} - \frac{\Sigma_{12}^2}{\Sigma_{11}^2}\right)H_{12}^{*}(\omega)}_{\text{Causal}} \\ S_{22}(\omega) &= \underbrace{\hat{H}_{22}(\omega)\Sigma_{22}\hat{H}_{22}^{\dagger}(\omega)}_{\text{Intrinsic}} + \underbrace{\bar{H}_{21}(\omega)\left(\Sigma_{11} - \frac{\Sigma_{21}^2}{\Sigma_{22}^2}\right)\bar{H}_{21}^{*}(\omega)}_{\text{Causal}}, \end{aligned} \tag{3.5.18}$$

where the symbols : and . âre used to differentiate the terms below from the variables H_{11}, H_{21}, and H_{22}, as follows:

$$\begin{aligned}\bar{H}_{11}(\omega) &= H_{11}(\omega) + \Sigma_{12} H_{12}(\omega) \Sigma_{11} \\ \bar{H}_{21}(\omega) &= H_{21}(\omega) + \Sigma_{12} H_{11}(\omega) \Sigma_{11} \\ \hat{H}_{22}(\omega) &= H_{22}(\omega) + \frac{\Sigma_{12}}{\Sigma_{22}} H_{21}(\omega).\end{aligned} \tag{3.5.19}$$

[3] The lag operator L is similar to the z-transform. However, z is treated as a variable, and is often used in signal processing, while L is an operator 39 . Once we have the $S_{11}(\omega)$ and $S_{22}(\omega)$ spectra as the sum of an intrinsic and a causal term, we may define indices to quantify GC in frequency domain just as we did in the time domain (chapter 3. For instance, to calculate the causal index, we divide the spectra by their respective intrinsic term in order to eliminate its influence. Thus, the causality index $I_{2\to 1}(\omega)$ is defined as:

$$I_{2\to 1}(\omega) = \log\left(\frac{S_{11}(\omega)}{\bar{H}_{11}(\omega)\Sigma_{11}\bar{H}^*_{11}(\omega)}\right), \tag{3.5.20}$$

and analogously, $I_{1\to 2}(\omega)$,

$$I_{1\to 2}(\omega) = \log\left(\frac{S_{22}(\omega)}{\hat{H}_{22}(\omega)\Sigma_{22}\hat{H}^*_{22}(\omega)}\right) \tag{3.5.21}$$

The instantaneous causality index $I_{1\leftrightarrow 2}(\omega)$ is defined as:

$$I_{1\leftrightarrow 2}(\omega) = \log\frac{\left(\bar{H}_{11}(\omega)\Sigma_{11}\bar{H}^*_{11}(\omega)\right)\left(\hat{H}_{22}(\omega)\Sigma_{22}\hat{H}^*_{22}(\omega)\right)}{\det(\mathbf{S}(\omega))}. \tag{3.5.22}$$

In equations 3.5.20 to 3.5.22 , we have one index for each value ω of the frequency. Conversely, in the time domain there was a single index for the GC between the two signals X_1 and X_2. Just as discussed in chapter 3 the indices $I_{2\to 1}(\omega), I_{1\to 2}(\omega)$ and

$I_{1\leftrightarrow 2}(\omega)$ are greater than zero if there is any relation between the time series. They are zero otherwise.

Just like in the time domain, the total GC in the frequency domain is the sum of its individual components:

$$I(\omega) = I_{2\to 1}(\omega) + I_{1\to 2}(\omega) + I_{1\leftrightarrow 2}(\omega) = \log\left(\frac{S_{11}(\omega)S_{22}(\omega)}{\det(\boldsymbol{S}(\omega))}\right). \tag{3.5.23}$$

The total GC is related to the so-called coherence $C_{12}(\omega)$ between signals (see Section C of the Appendix):

$$I(\omega) = -\log\left(1 - C_{12}(\omega)\right). \tag{3.5.24}$$

Moreover, we recover the GC in time domain through 15 . 34:

$$F_{i\to j} = \frac{1}{\omega_f - \omega_0}\int_{\omega_0}^{\omega_f} I_{i\to j}(\omega)d\omega. \tag{3.5.25}$$

3.6 Gradient Boosting

Gradient Boosting, a robust ensemble machine learning technique, as extensively detailed in the literature [**47**], emerges as a powerful solution for tackling regression problems. In the realm of regression, where the primary goal is to predict numerical values, Gradient Boosting stands out by methodically amalgamating predictions from multiple weaker regression models, typically decision trees. This sequential combination results in the creation of a resilient overarching model.

To embark on a comprehensive exploration of the principles governing gradient boosting, it is imperative to commence with an introduction to its foundational element – decision trees.

3.6.1 Decision Trees in Gradient Boosting

Decision trees, the cornerstone of Gradient Boosting, manifest as tree-like structures comprising nodes, branches, and leaves. Each node within this structure signifies a decision based on a feature, each branch denotes the outcome of that decision, and each leaf node encapsulates the final prediction or decision.

At the outset of the tree, termed the root node, the algorithm evaluates the entire dataset, strategically selecting the feature that optimally separates the data into distinct groups or values. This pivotal process is known as node splitting. Subsequent nodes in the tree encapsulate decisions based on additional features, thereby constructing a hierarchical structure.

The terminal points of the tree, designated as leaf nodes, house the conclusive predictions or decisions. The journey from the root to a specific leaf node delineates a sequence of decisions rooted in features, culminating in the ultimate outcome.

The depth of a decision tree, determined by the quantity of levels or splits, significantly influences its complexity. Shallow trees, with fewer levels, are simpler and less susceptible to overfitting, albeit they may lack predictive power. In contrast, deep trees can capture intricate patterns but are more prone to overfitting.

3.6.2 Strength in Ensemble Learning

Although individual decision trees may be perceived as weak models due to their vulnerability to overfitting, their strength magnifies when amalgamated into ensembles. Ensemble methods, exemplified by Gradient Boosting, harness the collective power of multiple decision trees to enhance predictive performance. This strategic aggregation mitigates the shortcomings of individual trees, yielding more robust and accurate predictive models.

3.6.3 Integration within Gradient Boosting

In the context of Gradient Boosting, decision trees commonly assume the role of weak learners within the ensemble. In each iteration of the boosting process, a new decision tree is meticulously crafted to rectify the errors introduced by its predecessors. This iterative refinement is pivotal for the continuous enhancement of the predictive model.

The iterative refinement process extends through subsequent rounds, with each new model addressing the residual errors of the ensemble formed by the preceding models. This iterative nature endows Gradient Boosting with the ability to adapt and augment its predictive capabilities over time. The iterative process continues until a predetermined number of iterations are achieved or until the model attains a satisfactory level of accuracy.

Boosting algorithms combine weak learners into a strong learner in an iterative way [**48**]. Given a training dataset $D = \{\mathbf{x}_i, y_i\}_1^N$, the goal of gradient boosting is to find an approximation, $\hat{F}(\mathbf{x})$, of the function $F^*(\mathbf{x})$, which maps instances $\mathbf{x}$ to their output values y, by minimizing the expected value of a given loss function, $L(y, F(\mathbf{x}))$. Gradient boosting builds an additive approximation of $F^*(\mathbf{x})$ as a weighted sum of functions

$$F_m(\mathbf{x}) = F_{m-1}(\mathbf{x}) + \rho_m h_m(\mathbf{x}),$$

where ρ_m is the weight of the m^{th} function, $h_m(\mathbf{x})$. These functions are the models of the ensemble (e.g. decision trees). The approximation is constructed iteratively. First, a constant approximation of $F^*(\mathbf{x})$ is obtained as

$$F_0(\mathbf{x}) = \arg\min_{\alpha} \sum_{i=1}^{N} L\left(y_i, \alpha\right)$$

Subsequent models are expected to minimize

$$(\rho_m, h_m(\mathbf{x})) = \arg\min_{\rho, h} \sum_{i=1}^{N} L\left(y_i, F_{m-1}\left(\mathbf{x}_i\right) + \rho h\left(\mathbf{x}_i\right)\right)$$

However, instead of solving the optimization problem directly, each h_m can be seen as a greedy step in a gradient descent optimization for F^*. For that, each model, h_m, is trained on a new dataset $D = \{\mathbf{x}_i, r_{mi}\}_{i=1}^{N}$, where the pseudo-residuals, r_{mi}, are calculated by

$$r_{mi} = \left[\frac{\partial L\left(y_i, F(\mathbf{x})\right)}{\partial F(\mathbf{x})}\right]_{F(\mathbf{x})=F_{m-1}(\mathbf{x})}$$

The value of ρ_m is subsequently computed by solving a line search optimization problem.

In the realm of gradient boosting algorithms, XGBoost, LightGBM, and CatBoost represent distinct approaches with unique strengths. XGBoost, LightGBM, and CatBoost each offer distinct advantages and drawbacks in the context of gradient boosting for numerical prediction tasks. XGBoost stands out for its widespread adoption, extensive documentation, and flexibility in parameter tuning. Its regularization techniques effectively control overfitting, promoting robust model generalization. However, XGBoost may require more preprocessing effort for handling categorical features, potentially increasing computational complexity.

In contrast, both LightGBM and CatBoost excel in handling categorical features, offering inherent support without preprocessing. LightGBM's efficiency in memory usage and scalability makes it ideal for large datasets and distributed computing environments. CatBoost's automatic handling of categorical features and robust regularization techniques provide a straightforward implementation with minimal parameter tuning.

For numerical prediction tasks, XGBoost's combination of performance, flexibility, and ease of use makes it the preferred choice. Its efficient regularization techniques and extensive community support ensure reliable model performance and troubleshooting. While LightGBM and CatBoost offer competitive performance and specialized features, they may require additional effort for users to adapt to their interfaces and parameter settings, especially in scenarios where categorical features are less prevalent or preprocessing is already established. Therefore, for the given use case of numerical prediction, XGBoost emerges as the best-suited option due to its overall effectiveness and familiarity among users.

3.6.4 XGBoost

XGBoost [**49**] is a decision tree ensemble based on gradient boosting designed to be highly scalable. Similarly to gradient boosting, XGBoost builds an additive expansion of the objective function by minimizing a loss function. Considering that XGBoost is focused only on decision trees as base classifiers, a variation of the loss function is used to control the complexity of the trees

$$L_{xgb} = \sum_{i=1}^{N} L\left(y_i, F\left(\mathbf{x}_i\right)\right) + \sum_{m=1}^{M} \Omega\left(h_m\right)$$

$$\Omega(h) = \gamma T + \frac{1}{2}\lambda\|w\|^2$$

where T is the number of leaves of the tree and w are the output scores of the leaves.

This loss function can be integrated into the split criterion of decision trees leading to a pre-pruning strategy. Higher values of γ result in simpler trees. The value of γ controls the minimum loss reduction gain needed to split an internal node. An additional regularization hyper-parameter in XGBoost is shrinkage, which reduces the step size in the additive expansion. Finally, the complexity of the trees can also be limited using other strategies as the depth of the trees, etc. A secondary benefit of tree complexity reduction is that the models are trained faster and require less storage space. Randomization techniques are also implemented in XGBoost both to reduce overfitting and to increase training speed. The randomization techniques included in XGBoost are: random subsamples to train individual trees and column subsampling at tree and tree node levels. Furthermore, XGBoost can be extended to any user-defined loss function by defining a function that outputs the gradient and the hessian (second order gradient) and passing it through the "objective" hyper-parameter.

Moreover, XGBoost proposes a sparsity-aware algorithm for finding the best split. The sparsity of an attribute can be caused by the presence of many zero valued entries and/or missing values. XGBoost automatically removes these entries from the computation of the gain for split candidates. In addition, XGBoost trees learn the default child node in which instances with missing or null values are branched. Other interesting features of XGBoost include monotonic and feature interaction constraints. These features can be specially useful when domain specific information is known. Monotonic constraints force the output of XGBoost for regression to be monotonic (increasing or decreasing) with respect to any set of given input attributes. Feature interaction constraints limit the input attributes that can be combined in the paths from the root to any leaf node. Both constraints are implemented by limiting the set of candidate splits to be considered at each node.

In addition, XGBoost implements several methods to increment the training speed of decision trees not directly related to ensemble accuracy. Specifically, XGBoost focuses on reducing the computational complexity for finding the best split, which is the most time consuming part of decision tree construction algorithms. Split finding algorithms usually enumerate all possible candidate splits and select the one with the highest gain. This requires performing a linear scan over each sorted attribute to find the best split for each node. To avoid sorting the data repeatedly in every node, XGBoost uses a specific compressed column based structure in which the data is stored pre-sorted. In this way, each attribute needs to be sorted only once. This column based storing structure allows to find the best split for each considered attributes in parallel. Furthermore, instead of scanning all possible candidate splits, XGBoost implements a method based on percentiles of the data where only a subset of candidate splits is tested and their gain is computed using aggregated statistics. This idea resembles the node level data subsampling that is already present in CART trees (Breiman et al. 1984). [**50**]

3.6.5 XG Boost Feature Importance

In the field of predictive modeling using XGBoost, measuring the feature importance plays a pivotal role in unraveling the intricate relationship between signals and their impact on predicting the target. In our research it would be the relationship between policy variables and their impact on predicting mortality rates. Here's a deeper exploration of the process and significance of feature importance gain in the context of our analysis:

As mentioned, XGBoost, as a sophisticated ensemble learning algorithm, constructs decision trees sequentially during the training process. At each node of these trees, the algorithm evaluates different features to determine optimal splits. This dynamic evaluation process aims to capture the most influential features that contribute to accurate predictions across diverse scenarios.

Central to understanding the impact of individual features is the concept of feature importance gain. This metric is calculated by summing the gains for all the splits that involve a particular feature. In essence, it quantifies how much each feature contributes to improving the model's predictive performance throughout the construction of the decision trees. The more a feature is used to make key decisions with boosted trees, the higher its score becomes.

A higher feature importance gain value (G(f)) indicates a more substantial contribution of a specific feature to the model's overall predictive capabilities. It signifies that the feature is influential in making decisions and reducing prediction errors. In various applications, these features could correspond to diverse variables or parameters that influence the predicted outcomes. As the XGBoost algorithm assigns importance scores to each feature based on their contribution to the model, this information becomes invaluable in discerning which factors have a more significant impact on the predicted outcomes. Features associated with higher importance gain values emerge as more influential in shaping the model's understanding of the relationship between input variables and predicted outcomes.

In practical terms, this analysis allows us to report and prioritize predictors with higher feature importance gain values. These predictors are deemed more effective in influencing the predicted outcomes, providing actionable insights across various domains. By focusing on the most influential predictors, informed decisions can be made, resource allocation can be optimized, and strategies can be adjusted.

3.7 Dataset

The Oxford COVID-19 Government Response Tracker (OxCGRT) [**51**] is a comprehensive tool widely utilized for assessing and comparing government responses to the COVID-19 pandemic across different countries. This tool offers a systematic way to quantify and analyze various policy interventions implemented by governments to mitigate the impact of the virus. The indicators provided by the OxCGRT cover a broad spectrum of measures, encompassing closures, economic policies, and health-related interventions. Policies:

- C1M School closing
- C2M Workplace closing
- C3M Cancel public events
- C4M Restrictions on gatherings
- C5M Close public transport
- C6M Stay at home requirements
- C7M Restrictions on internal movement
- C8EV International travel controls
- H2E Testing policy
- H3E Contact tracing
- H6M Facial Coverings
- H7E Vaccination policy
- H8M Protection of elderly people

In addition to the OxCGRT indicators, our research incorporates two additional fields related to vaccine data sourced from the Canadian Government website. These fields likely include specific information about the vaccination rollout, coverage rates, and any associated policies or strategies related to vaccine distribution and administration. Integrating vaccine data is crucial in understanding the progress of vaccination efforts and their potential impact on mitigating the spread and severity of COVID-19.

The inclusion of vaccine-related data provides a more comprehensive and nuanced perspective on our overall government response. It allows for an assessment of not only the containment measures implemented during the early stages of the pandemic but also the proactive steps taken to vaccinate the population and achieve broader immunity.

Vaccine Indicators:

- V1 Vaccine Prioritisation (summary)
- V2A Vaccine Availability (summary)

By combining data from the OxCGRT tool, which covers a wide array of policy responses, with specific vaccine-related information from the Canadian Government, our research aims to offer a holistic understanding of how governmental actions have evolved over time in response to the pandemic. This multifaceted approach enables a more informed analysis of the effectiveness of various interventions and their collective impact on managing and mitigating the COVID-19 crisis in Canada.

3.8 Data Preparation

In the intricate realm of data analysis, the quality and structure of the data play a pivotal role in deriving meaningful insights. A crucial preliminary step in our investigation involves meticulous data preparation, ensuring that the information at our disposal is conducive to robust analysis and interpretation.

3.8.1 Data Splitting

In the context of our research methodology, the process of "Data Splitting" involves partitioning the dataset into distinct segments, each corresponding to a specific Canadian Province. This deliberate division serves a crucial purpose: it allows us to isolate and analyze the effects of individual provinces independently. By working with separate datasets for each province, we gain the ability to discern regional variations in the impact of policies on COVID-19 outcomes. This segmentation enables a more nuanced understanding of how different provinces respond to and are affected by various policy interventions.

3.8.2 Target Signal Selection

The "Target Signal" in our analysis refers to the variable "avgratedeaths_last7." This variable captures the average daily death rate over the last 7 days. By selecting this specific target signal, our focus is on understanding and predicting the trends in mortality rates. Daily fluctuations in death rates can be considerable, and using a 7-day average provides a more stable and representative measure. This choice allows us to investigate the relationships between policy interventions and sustained trends in mortality, providing a meaningful basis for our analysis.

3.8.3 Temporal Aggregation

To enhance the interpretability of our findings and discern more significant patterns, we employ "Temporal Aggregation" techniques. In this step, we aggregate the policy signals on a weekly time frame. Instead of focusing on daily policy changes, this approach involves summarizing policy information over weekly intervals. The aggregation process helps smooth out short-term fluctuations, offering a clearer view of long-term trends and relationships between policies and death numbers. By adopting a weekly perspective, we aim to identify more enduring impacts of policy interventions on the progression of the pandemic. This strategic temporal aggregation contributes to a more robust and insightful analysis of the interplay between policies and COVID-19 outcomes.

3.9 Data Transformation

In the context of our analysis, the first step in the data transformation process involves assessing the stationarity of signals, which encompass both policy variables and COVID-19 case data. Stationarity is a crucial concept in time series analysis, and it implies that the statistical properties of a signal, such as its mean and variance, remain constant over time.

3.9.1 Covariance Stationarity Test

To determine whether the signals exhibit covariance stationarity, we employed the Augmented Dickey–Fuller (ADF) test. This statistical test assesses the presence of a unit root in a time series, which is indicative of non-stationarity. If the ADF test suggests that the signals are not covariance stationary, it implies that the statistical properties of the signals change over time.

3.9.2 Differencing Method for Stationarity

When the ADF test indicates non-stationarity, we employ the differencing method as a means of achieving stationarity. The process involves taking the first difference of the signal, denoted as $Y(t) - Y(t-1)$. This transformation aims to remove the trend or systematic patterns in the data, making it more amenable to analysis.

Mathematically, the first difference $Y(t) - Y(t-1)$ represents the change between consecutive observations in the time series. By applying differencing, we aim to stabilize the statistical properties of the signal, transforming it into a stationary form suitable for further analysis.

This approach is particularly valuable when dealing with time series data, as it addresses issues related to non-constant mean or variance. The resulting stationary signals provide a more reliable foundation for subsequent statistical modelling and analysis, ensuring that the inherent patterns and relationships within the data are accurately captured. The choice to use differencing as a transformation method aligns with best practices in time series analysis and contributes to the robustness of our analytical approach.

3.10 Experiment

The foundation of our experiment lies in the meticulous collection of data from the COVID-19 Government Response Tracker (OxCGRT) tool. This comprehensive tool provides a rich repository of information, encompassing various policy responses and COVID-19 cases globally.

To facilitate a granular analysis, we initiated the data preprocessing phase with the segmentation of our dataset based on provinces. This segmentation allows us to isolate and scrutinize the effects of individual provinces, paving the way for a more localized examination.

Our analysis centers around the variable avgratedeaths_last7, a metric representing the average daily death rate over the last 7 days. This specific target signal serves as a key focal point in gauging the severity of the pandemic's impact.

In an effort to distill meaningful trends and patterns, we opted for temporal aggregation by aggregating policy signals on a weekly time frame. This strategic move helps to mitigate the influence of daily fluctuations, allowing us to focus on overarching trends and relationships between policies and death numbers.

We conducted an Augmented Dickey–Fuller (ADF) test to assess whether the signals, encompassing both policies and COVID-19 cases, exhibit covariance stationarity. This crucial step informs us about the stability of the time series data.

In instances where the signals are not stationary, a differencing method is employed to achieve stationarity. The first difference (Y(t) - Y(t-1)) is applied, transforming the signal into a stationary form for further analysis.

Utilizing the differenced signals, we delved into causal relationships. In the time domain, we built an Autoregressive (AR) model and conducted Fast Fourier Transform (FFT) analysis in the frequency domain. The Causality Index and conditional Granger causality were computed in both time and frequency domains, unraveling intricate dependencies.

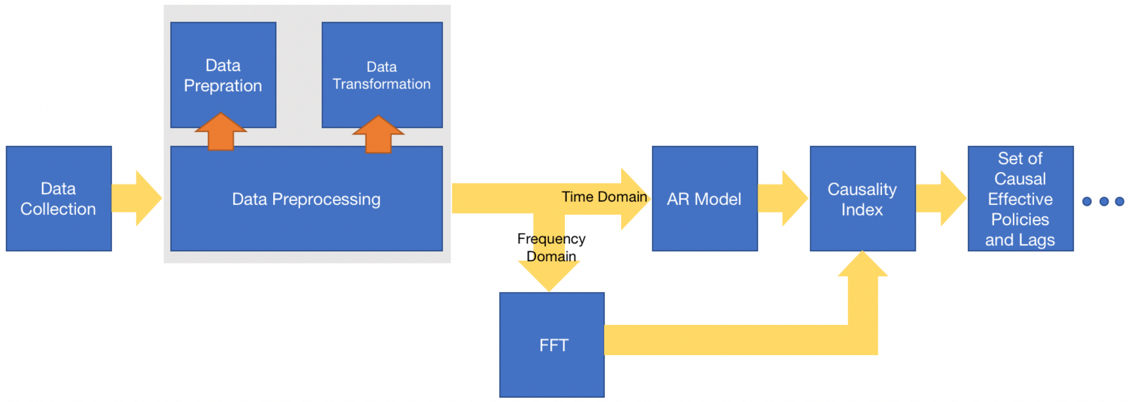
3.11 Model Building and Evaluation

The experiment culminated in the construction of two distinct models:

Utilizing the XGBoost algorithm, we trained a model to predict outcomes based on selected features. Feature importance analysis was conducted to report on the effectiveness of policies. Root Mean Squared Error (RMSE) was calculated as a measure of predictive accuracy.

The second model was Vector Autoregression (VAR) Model.Features derived from Granger causality and Conditional Granger causality analyses were employed. RMSE was calculated for this model to evaluate its accuracy.

The experiment concludes with a rigorous comparative analysis between the XGBoost and VAR models. By juxtaposing their RMSE values and assessing their respective accuracies, we aim to discern which model provides a more accurate depiction of the relationship between policies and COVID-19 outcomes. The final result, per policy, will shed light on the efficacy of these models in capturing the intricate dynamics at play during the ongoing pandemic.



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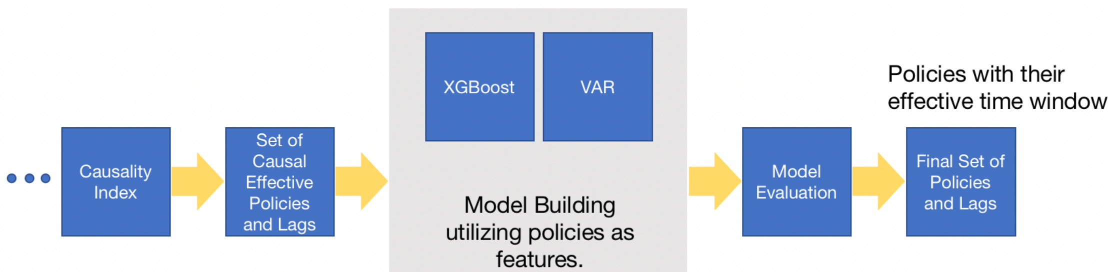


Implementation Process

Chapter 4

Findings

Feature Selection: The process of selecting pertinent features for each Canadian province involved employing advanced statistical techniques such as Granger Causality and Conditional Granger Causality. These methods facilitated the identification of policies that significantly impact mortality rates during the COVID-19 pandemic.

Model Development: The development of predictive models aimed at forecasting mortality rates necessitated the incorporation of these identified policies as key features. This integration occurred within the framework of two distinct methodologies: VAR (Vector Autoregression), a traditional linear approach, and XGBoost, a modern machine learning algorithm renowned for its predictive power and ability to capture complex relationships.

Performance Evaluation: To assess the efficacy of the constructed models, their predictive accuracy was rigorously evaluated using RMSE (Root Mean Squared Error). This metric enabled a quantitative comparison of the models' performance in forecasting mortality rates based on the selected policies, thereby providing valuable insights into the effectiveness of different modeling approaches in capturing the nuances of policy impacts on mortality outcomes during the COVID-19 pandemic in Canada.

4.1 Ontario

4.1.1 Granger Casualty

We conducted a Granger causality test on filtered data spanning from March 1, 2020, to November 1, 2021, to assess the impact of various policies on COVID-19 mortality in Ontario. Our findings reveal significant insights into the effectiveness of different interventions, as detailed below:

- Facial Coverings: This policy emerged as the most effective intervention in Ontario, with notable impacts observed at the 6th and 7th lags. The Granger Causality Index (GCI) peaked at the 7th lag, indicating a substantial reduction in mortality rates associated with widespread adoption of facial coverings. The consistent GC effects across multiple lags validate the effectiveness of this policy in curbing the spread of the virus and preventing deaths.
- Workplace Closures: Analysis shows that workplace closures were effective at mitigating COVID-19 mortality at the 4th, 6th, and 7th lags. The observed Granger causality suggests that restrictions on workplace activities played a crucial role in reducing transmission rates and ultimately lowering mortality rates in the province.
- Vaccine Prioritization: The Granger causality analysis highlights the effectiveness of vaccine prioritization strategies, particularly at the 7th lag. This finding underscores the importance of prioritizing high-risk populations for vaccination to prevent severe outcomes and reduce the burden on healthcare systems.

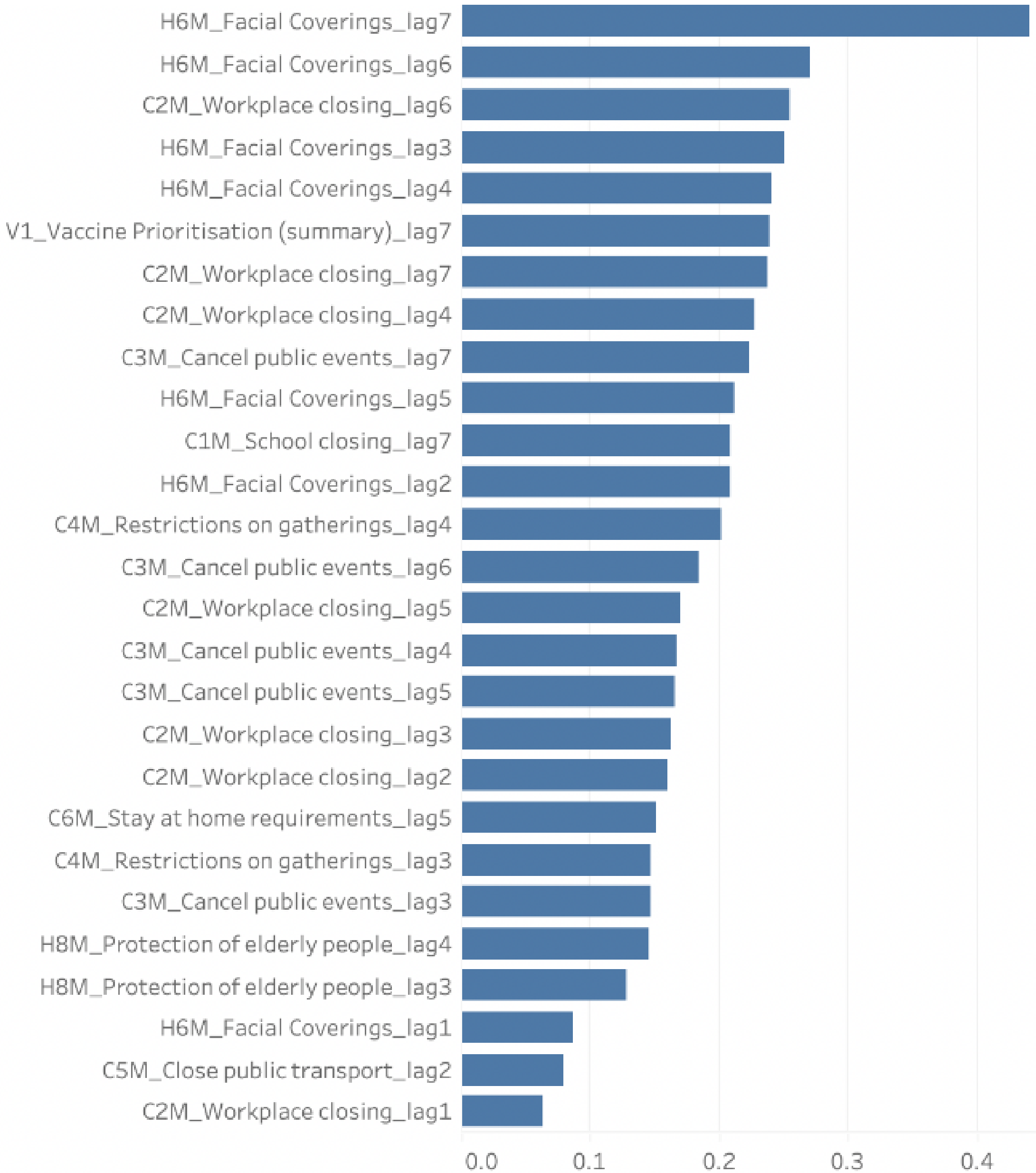
The attached table and chart provide a visual representation of the Granger causality results, illustrating the timing and magnitude of the effects of each policy on COVID-19 mortality in Ontario.

FIGURE 1. Granger Casualty Result Table for Ontario

Region	Policy	Lag	GCIxy	pGCIxy
Ontario	H6M_Facial Coverings	7	0.440408111	9.04E-05
Ontario	H6M_Facial Coverings	6	0.271166182	0.003783914
Ontario	C2M_Workplace closing	6	0.25474596	0.006056287
Ontario	H6M_Facial Coverings	3	0.250973542	0.000196033
Ontario	H6M_Facial Coverings	4	0.23990557	0.001114464
Ontario	V1_Vaccine Prioritisation (summary)	7	0.238885742	0.022142624
Ontario	C2M_Workplace closing	7	0.237208673	0.023091199
Ontario	C2M_Workplace closing	4	0.22741679	0.001706816
Ontario	C3M_Cancel public events	7	0.223181681	0.03267287
Ontario	H6M_Facial Coverings	5	0.211641812	0.00826185
Ontario	C1M_School closing	7	0.208509479	0.046612676
Ontario	H6M_Facial Coverings	2	0.208439941	0.000215658
Ontario	C4M_Restrictions on gatherings	4	0.201684954	0.004075494
Ontario	C3M_Cancel public events	6	0.184615248	0.041497581
Ontario	C2M_Workplace closing	5	0.169937933	0.028715995
Ontario	C3M_Cancel public events	4	0.167248655	0.012797242
Ontario	C3M_Cancel public events	5	0.165169808	0.032989204
Ontario	C2M_Workplace closing	3	0.163385701	0.005032551
Ontario	C2M_Workplace closing	2	0.159455004	0.001568042
Ontario	C6M_Stay at home requirements	5	0.15082786	0.049793403
Ontario	C4M_Restrictions on gatherings	3	0.147118132	0.009105546
Ontario	C3M_Cancel public events	3	0.146431752	0.009335349
Ontario	H8M_Protection of elderly people	4	0.14607525	0.025473846
Ontario	H8M_Protection of elderly people	3	0.127495602	0.018503428
Ontario	H6M_Facial Coverings	1	0.086589785	0.00716677
Ontario	C5M_Close public transport	2	0.079713554	0.039620884
Ontario	C2M_Workplace closing	1	0.063347608	0.021450841

Granger Casualty Result Table for Ontario

FIGURE 2. Granger Casualty Result Chart for Ontario



Granger Casualty Result Chart for Ontario

4.1.2 Conditional Granger Casualty

In addition to Granger causality analysis, we conducted Conditional Granger Causality (CGC) to further elucidate the effectiveness of policies in Ontario. The results of CGC reaffirm the significance of facial coverings as the most impactful intervention in reducing COVID-19 mortality. Notably, while workplace closures do not emerge as significant in CGC, this could be attributed to the complex interactions between various policies influencing their efficacy.

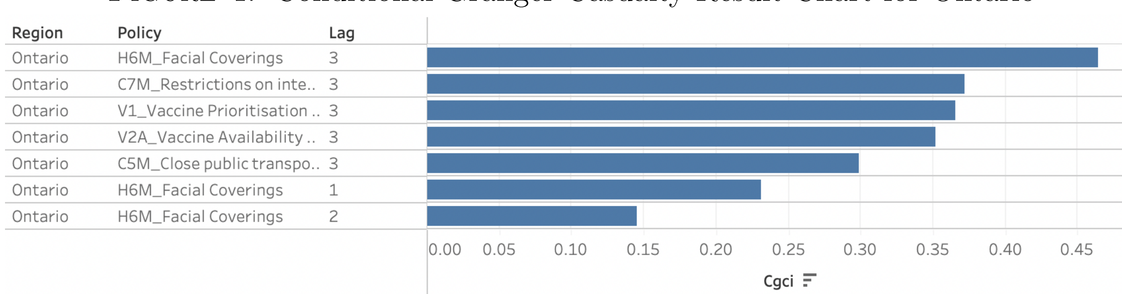
The attached table and chart present the CGC results, highlighting the policies with the most significant conditional causal effects on COVID-19 mortality in Ontario.

FIGURE 3. Conditional Granger Casualty Result Table for Ontario

Region	Policy	Lag	CGCI	CGCIP
Ontario	H6M_Facial Coverings	3	0.463820354	0.001417994
Ontario	C7M_Restrictions on internal movement	3	0.372003068	0.005979146
Ontario	V1_Vaccine Prioritisation (summary)	3	0.365565768	0.006608874
Ontario	V2A_Vaccine Availability (summary)	3	0.351570942	0.008212897
Ontario	C5M_Close public transport	3	0.298674992	0.018565758
Ontario	H6M_Facial Coverings	1	0.230967379	6.95E-05
Ontario	H6M_Facial Coverings	2	0.145725524	0.024331077

Conditional Granger Casualty Result Table for Ontario

FIGURE 4. Conditional Granger Casualty Result Chart for Ontario



Conditional Granger Casualty Result Chart for Ontario

4.1.3 Granger Casualty in Frequency Domain

Further analysis in the frequency domain using the Granger causality formula highlights consistent findings with the time domain analysis. The following policies have been identified as significant contributors to reducing COVID-19 mortality in Ontario:

- H6M_Facial Coverings
- C1M_School closing
- C2M_Workplace closing
- C5M_Close public transport
- V1_Vaccine Prioritisation (summary)
- V2A_Vaccine Availability (summary)

The attached table illustrates the frequency domain Granger causality results, reaffirming the importance of these policies in mitigating the impact of the pandemic in Ontario.

FIGURE 5. Granger Casualty in Frequency Chart for Ontario

Region	PolicyName	GrangerCausality	Frequency
Ontario	H6M_Facial Coverings	5.73E-98	0.060810811
Ontario	H6M_Facial Coverings	5.73E-98	0.25
Ontario	H6M_Facial Coverings	5.73E-98	0.371621622
Ontario	C1M_School closing	1.43E-98	0.25
Ontario	C1M_School closing	1.43E-98	0.263513514
Ontario	C2M_Workplace closing	1.43E-98	0.067567568
Ontario	C2M_Workplace closing	1.43E-98	0.087837838
Ontario	C2M_Workplace closing	1.43E-98	0.148648649
Ontario	C2M_Workplace closing	1.43E-98	0.256756757
Ontario	C2M_Workplace closing	1.43E-98	0.277027027
Ontario	C2M_Workplace closing	1.43E-98	0.317567568
Ontario	C5M_Close public transport	1.43E-98	0.006756757
Ontario	H6M_Facial Coverings	1.43E-98	0.054054054
Ontario	H6M_Facial Coverings	1.43E-98	0.094594595
Ontario	H6M_Facial Coverings	1.43E-98	0.114864865
Ontario	H6M_Facial Coverings	1.43E-98	0.162162162
Ontario	H6M_Facial Coverings	1.43E-98	0.168918919
Ontario	H6M_Facial Coverings	1.43E-98	0.182432432
Ontario	H6M_Facial Coverings	1.43E-98	0.277027027
Ontario	H6M_Facial Coverings	1.43E-98	0.344594595
Ontario	H6M_Facial Coverings	1.43E-98	0.385135135
Ontario	V1_Vaccine Prioritisation (summary)	1.43E-98	0.195945946
Ontario	V2A_Vaccine Availability (summary)	1.43E-98	0.486486486

Granger Casualty in Frequency Chart for Ontario

4.1.4 Model Performance Evaluation

XGboost performs better when allowing the algorithm to select features.

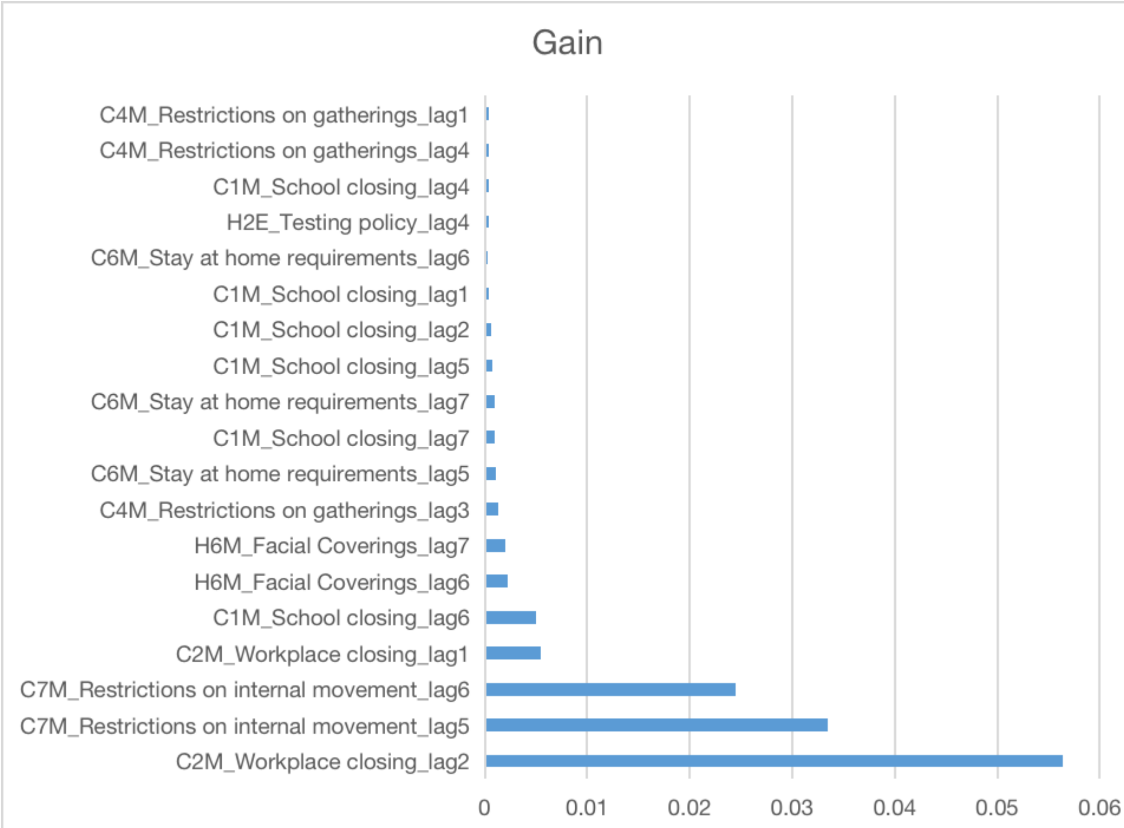
Figure 6. Model Performance Evaluation for Ontario

Region	Features	Method	RMSE
Ontario	All Features	XGBoost	0.0352916
Ontario	20 Top Features by GC index	XGB	0.0421976
Ontario	5 Top Features by GC index	VAR	0.075328
Ontario	10 Top Features by GC index	VAR	0.075328
Ontario	20 Top Features by GC index	VAR	0.075328
Ontario	5 Top Features by CGC index	VAR	0.075328
Ontario	10 Top Features by CGC index	VAR	0.075328
Ontario	20 Top Features by CGC index	VAR	0.075328
Ontario	5 Top Features by GC index	XGB	0.0761463
Ontario	10 Top Features by CGC index	XGB	0.0846824
Ontario	20 Top Features by CGC index	XGB	0.0846824
Ontario	5 Top Features by CGC index	XGB	0.087087
Ontario	10 Top Features by GC index	XGB	0.095537

Model Performance Evaluation for Ontario

Since XGboost has the lowest RMSE when selecting all features then the policies with higher gain of this model will be reported for Ontario. These policies are as below:

FIGURE 7. XGBoost Feature Importance Gain for Ontario's Policies



XGBoost Feature Importance Gain for Ontario's Policies

4.2 Alberta

4.2.1 Granger Casaulity

We conducted a Granger causality test on filtered data spanning from March 1, 2020, to November 1, 2021, to assess the impact of various policies. Our findings reveal the following noteworthy results, detailed in the attached table.

The analysis of policy effectiveness and their associated time lags provides valuable insights into the dynamics of COVID-19 mitigation strategies.

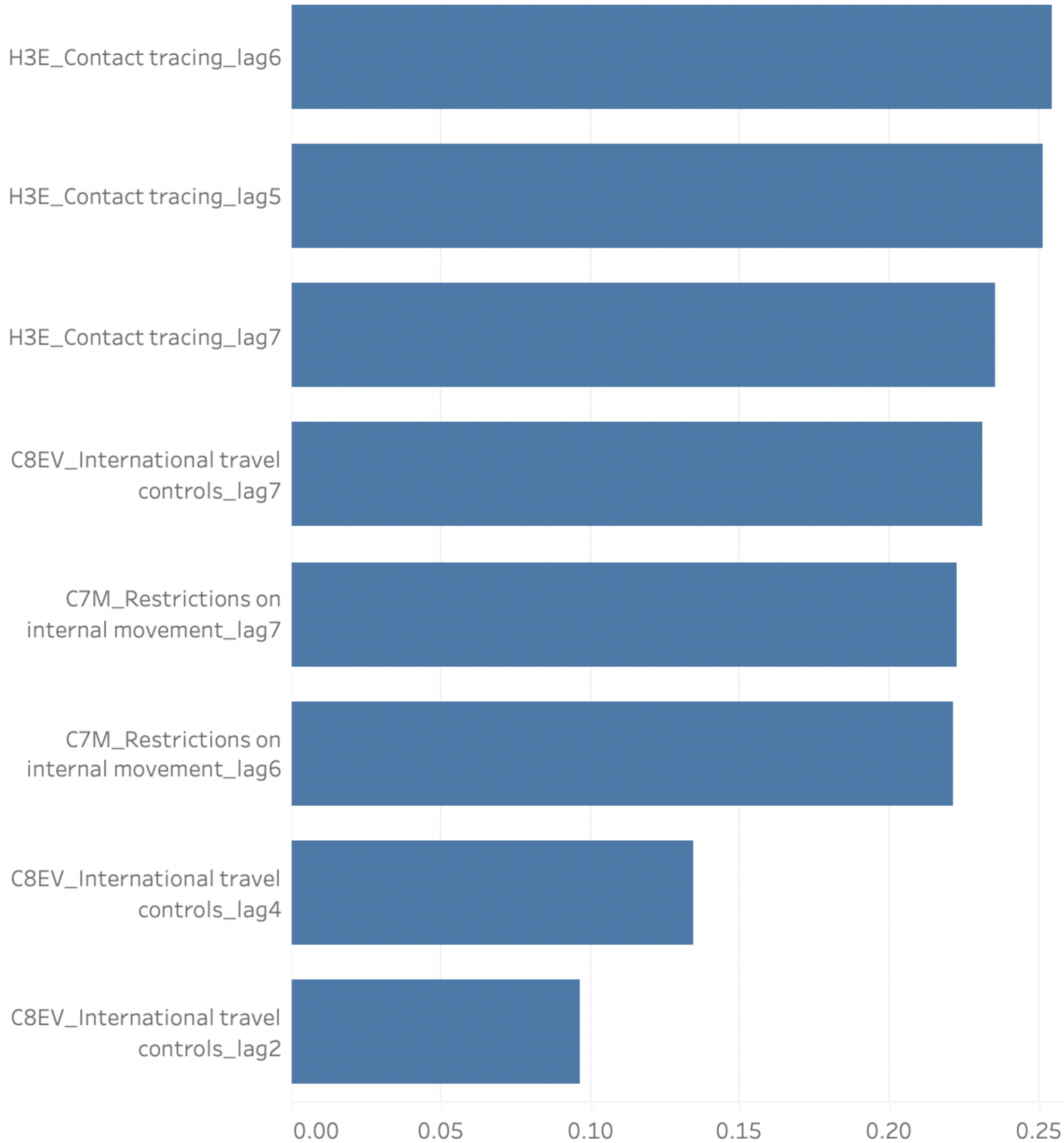
- The policy of contact tracing demonstrated its most significant impact during the 5th to 7th lags in Alberta. This indicates that it took approximately one month for contact tracing measures to exhibit tangible effects on the weekly death toll in the province. This delay suggests the importance of sustained efforts and comprehensive implementation of contact tracing protocols to realize their full potential in reducing mortality rates.

- In conjunction with contact tracing, restrictions on internal movement emerged as a relevant factor in Alberta during the identified lag periods. This highlights the interplay between policies aimed at minimizing interpersonal interactions and controlling the spread of the virus within the community. The correlation between contact tracing effectiveness and internal movement restrictions underscores the importance of a multifaceted approach in containing the pandemic's impact.

- The maximum GCI observed among all policies in Alberta is 0.25, indicating a relatively low level compared to GCIs associated with policies in other provinces. This suggests a weaker causal relationship between implemented policies and the weekly death count in Alberta compared to other regions. While this finding may reflect the complexity of factors influencing mortality rates, it also underscores the need for further investigation into the efficacy of specific policies and their interactions within the provincial context.

Overall, the comprehensive analysis of policy effectiveness and Granger causality provides a nuanced understanding of the dynamics shaping COVID-19 mortality outcomes in Alberta. These findings contribute to ongoing discussions surrounding the optimization of public health interventions and the development of evidence-based strategies for pandemic management within the province.

FIGURE 8. Granger Casualty Result Chart for Alberta

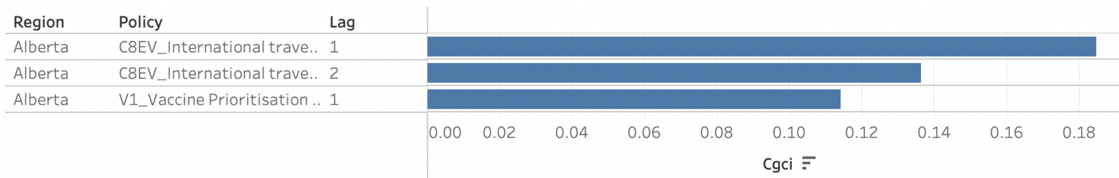


Granger Casualty Result Chart for Alberta

4.2.2 Conditional Granger Casualty

In addition to Granger Causality (GC) analysis, Conditional Granger Causality (CGC) further highlights the significance of International Travel as one of the most effective policies in mitigating the impact of COVID-19. While CGC does not explicitly identify the Contact Tracing policy, this absence may be attributed to the intricate interplay of various policies that indirectly influence its efficacy.

FIGURE 9. Conditional Granger Casualty Result Chart for Alberta



Conditional Granger Casualty Result Chart for Alberta

4.2.3 Granger Casualty in Frequency Domain

In the frequency domain analysis using the Granger causality formula, we see similar behaviour. The convergence of findings between Frequency analysis and time domain analysis underscores the robustness of the identified top policy. Specifically, Workplace Closing emerged as a key policy consistently reported across both analyses, indicating its substantial impact on mortality outcomes during the pandemic.

Moreover, it is noteworthy that Workplace Closing exhibits discernible GC effects in the frequency domain, reinforcing its significance as a pivotal intervention in controlling the spread of COVID-19. This multifaceted analysis provides a comprehensive understanding of policy dynamics, shedding light on the interconnectedness of interventions and their collective impact on public health outcomes.

FIGURE 10. Granger Casualty in Frequency Chart for Alberta

Region	PolicyName	GrangerCausality	Frequency
Alberta	C7M_Restrictions on internal movement	7.98E-97	0.135135135
Alberta	C7M_Restrictions on internal movement	7.98E-97	0.459459459
Alberta	C2M_Workplace closing	2.00E-97	0.337837838
Alberta	C2M_Workplace closing	2.00E-97	0.47972973
Alberta	C7M_Restrictions on internal movement	2.00E-97	0.033783784
Alberta	C7M_Restrictions on internal movement	2.00E-97	0.108108108
Alberta	C7M_Restrictions on internal movement	2.00E-97	0.310810811
Alberta	C7M_Restrictions on internal movement	2.00E-97	0.351351351
Alberta	C7M_Restrictions on internal movement	2.00E-97	0.358108108
Alberta	C7M_Restrictions on internal movement	2.00E-97	0.378378378
Alberta	C7M_Restrictions on internal movement	2.00E-97	0.466216216

Granger Casualty in Frequency Chart for Alberta

4.2.4 Model Performance Evaluation

VAR performs better when using the Policies from GC analysis.

Figure 11. Model Performance Evaluation for Alberta

Region	Features	Method	RMSE
Alberta	5 Top Features by GC index	VAR	0.0431701
Alberta	10 Top Features by GC index	VAR	0.0431701
Alberta	20 Top Features by GC index	VAR	0.0431701
Alberta	5 Top Features by CGC index	VAR	0.0431701
Alberta	10 Top Features by CGC index	VAR	0.0431701
Alberta	20 Top Features by CGC index	VAR	0.0431701
Alberta	All Features	XGBoost	0.0707753
Alberta	5 Top Features by GC index	XGB	0.0961991
Alberta	10 Top Features by GC index	XGB	0.1113368
Alberta	20 Top Features by GC index	XGB	0.1113368
Alberta	5 Top Features by CGC index	XGB	0.1546068
Alberta	10 Top Features by CGC index	XGB	0.1546068
Alberta	20 Top Features by CGC index	XGB	0.1546068

Model Performance Evaluation for Alberta

Since VAR has the lowest RMSE when selecting GC policies, the most effective policies for Alberta are policies reported under GC.

4.3 Quebec

4.3.1 Granger Casualty

Our Granger causality analysis on data from March 1, 2020, to November 1, 2021, sheds light on the effectiveness of various policies in mitigating COVID-19 mortality in Quebec. Noteworthy findings are detailed below:

Facial Coverings: Implemented with a lag of 7 weeks, facial coverings emerged as a significant policy in reducing COVID-19 mortality rates. The substantial Granger Causality Index (GCI) values of 0.7 and 0.9 indicate a robust causal relationship between the adoption of facial coverings and the decrease in weekly death rates. This underscores the importance of widespread mask usage in preventing virus transmission and saving lives.

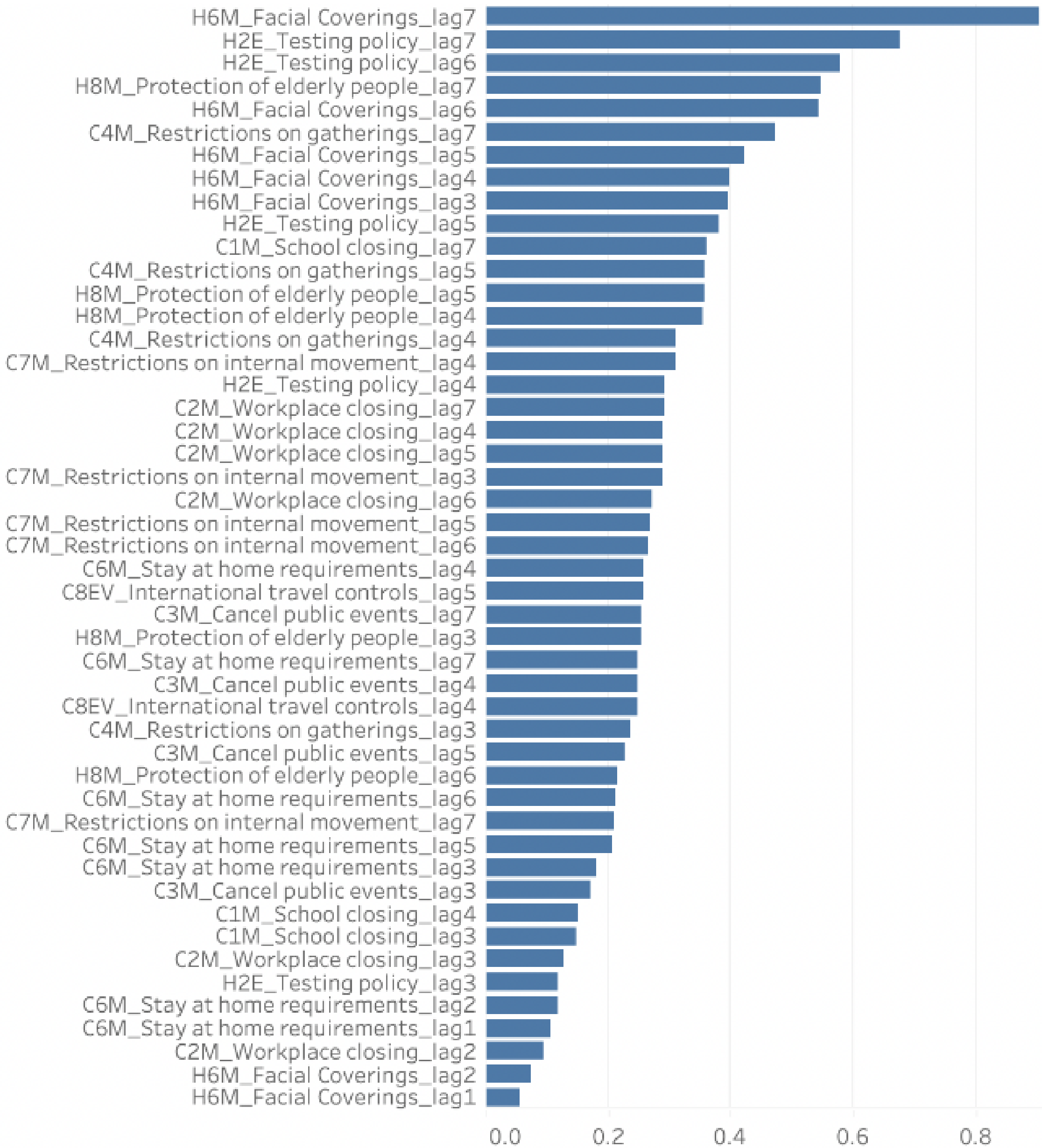
Testing Policy: Similarly, the testing policy, implemented with lags of both 6th and 7th weeks, demonstrated significant effectiveness in controlling mortality rates. The observed GCIs of 0.7 and 0.9 signify a strong causal link between testing measures and mortality outcomes. Timely and widespread testing helps identify and isolate cases, preventing further spread and reducing the burden on healthcare systems.

Protection of Elderly: Implemented with a lag of 7 weeks, the policy aimed at protecting the elderly population also exhibited notable effectiveness in reducing mortality rates in Quebec. Shielding vulnerable populations through targeted interventions such as prioritized vaccination and care measures plays a crucial role in preventing severe outcomes and reducing mortality.

Furthermore, the synergistic effects of stay-at-home orders, workplace closures, and facial coverings policies highlight the importance of a comprehensive and integrated approach to public health interventions. These policies collectively contribute to mitigating the impact of the pandemic, emphasizing the need for multi-dimensional strategies in pandemic management.

The attached chart provides a visual representation of the Granger causality results, illustrating the timing and magnitude of the effects of each policy on COVID-19 mortality in Quebec.

Figure 12. Granger Casualty Result Chart for Quebec



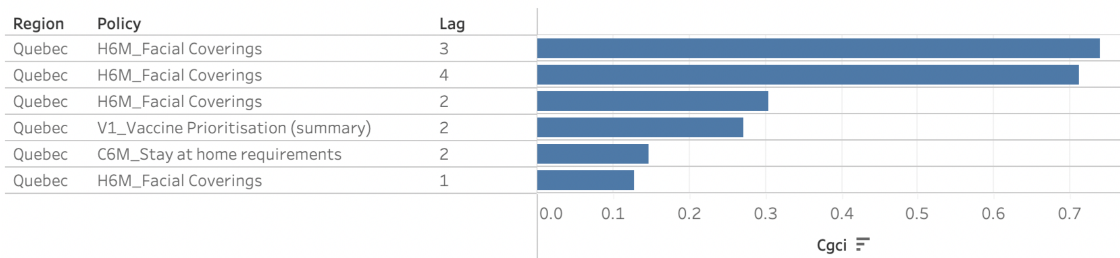
Granger Casualty Result Chart for Quebec

4.3.2 Conditional Granger Casualty

In addition to Granger Causality (GC) analysis, Conditional Granger Causality (CGC) also underscores the effectiveness of Facial Coverings as one of the most impactful policies in mitigating the impact of COVID-19. However, the absence of Protection of Elderly in CGC results suggests that its efficacy might be influenced by other implemented policies, thereby necessitating a more nuanced exploration of its causal relationships.

The attached chart presents the CGC results, highlighting the policies with significant conditional causal effects on COVID-19 mortality in Quebec.

FIGURE 13. Conditional Granger Casualty Result Chart for Quebec



Conditional Granger Casualty Result Chart for Quebec

4.3.3 Granger Casualty in Frequency Domain

The Frequency Domain analysis has identified Contact Tracing, Vaccination Policy, and Vaccine Availability as key factors contributing to the management of the pandemic. These findings highlight the multifaceted nature of policy interventions and emphasize the importance of considering various domains of analysis to comprehensively evaluate their effectiveness in addressing public health challenges such as COVID-19.

Figure 14. Granger Casualty in Frequency Chart for Quebec

Region	PolicyName	GrangerCausality	Frequency
Quebec	H3E_Contact tracing	2.30E-98	0.486486486
Quebec	H7E_Vaccination policy	2.30E-98	0.006756757
Quebec	H7E_Vaccination policy	2.30E-98	0.013513514
Quebec	H7E_Vaccination policy	2.30E-98	0.493243243
Quebec	V2A_Vaccine Availability (summary)	2.30E-98	0.006756757

Granger Casualty in Frequency Chart for Quebec

4.3.4 Model Performance Evaluation

Since XGBoost has the lowest RMSE when selecting GC and CGC policies, the most effective policies for Alberta are policies reported under GC and CGC.

Figure 15. Model Performance Evaluation for Quebec

Region	Features	Method	RMSE
Quebec	20 Top Features by GC index	XGB	0.0828989
Quebec	5 Top Features by CGC index	XGB	0.0992856
Quebec	10 Top Features by CGC index	XGB	0.0993209
Quebec	20 Top Features by CGC index	XGB	0.0993209
Quebec	5 Top Features by GC index	VAR	0.1165472
Quebec	10 Top Features by GC index	VAR	0.1165472
Quebec	20 Top Features by GC index	VAR	0.1165472
Quebec	5 Top Features by CGC index	VAR	0.1165472
Quebec	10 Top Features by CGC index	VAR	0.1165472
Quebec	20 Top Features by CGC index	VAR	0.1165472
Quebec	All Features	XGBoost	0.1224066
Quebec	5 Top Features by GC index	XGB	0.1273446
Quebec	10 Top Features by GC index	XGB	0.1273835

Model Performance Evaluation for Quebec

4.4 British Columbia

4.4.1 Granger Casualty

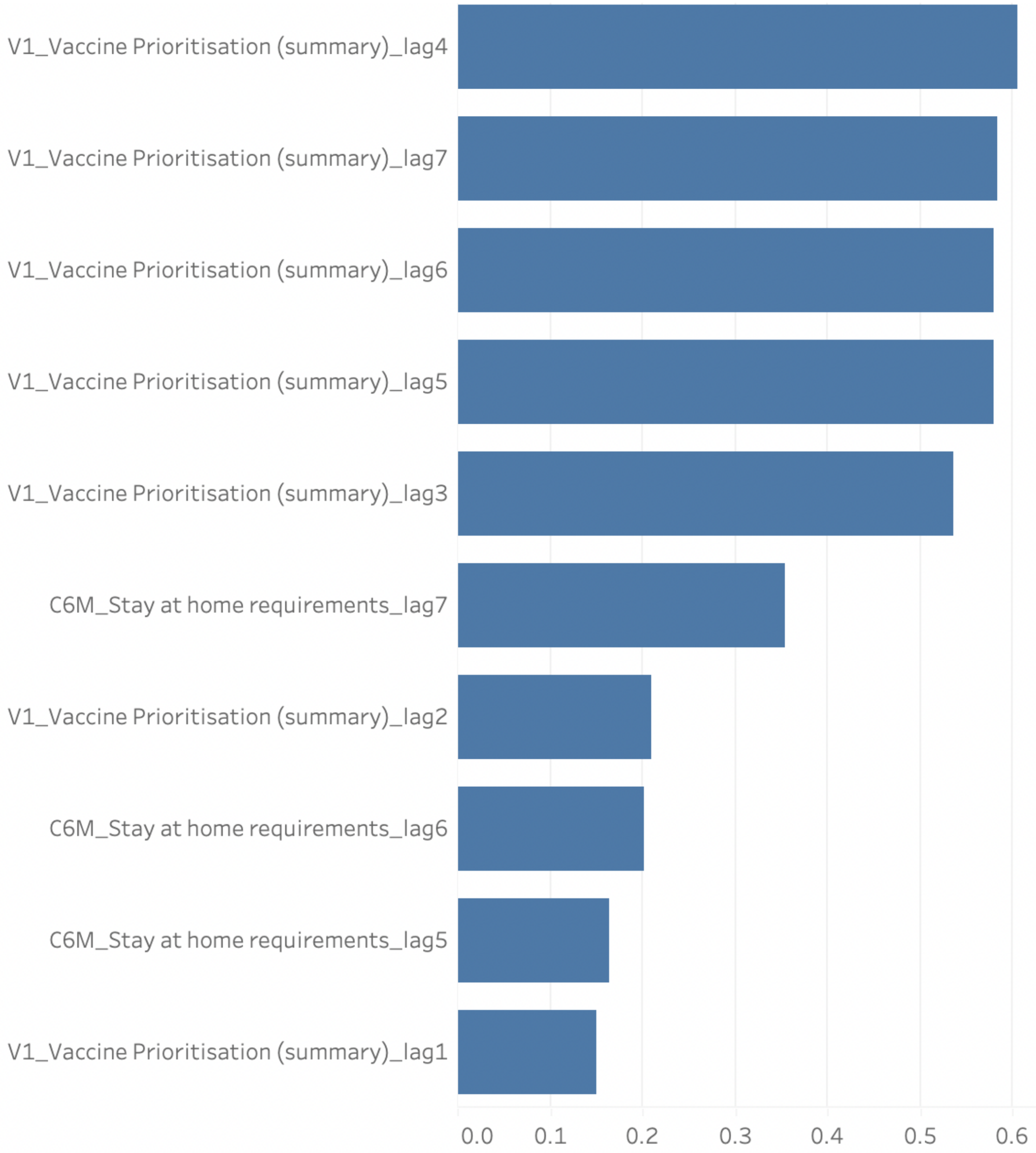
In the context of British Columbia, the analysis of effective policies and their associated lags reveals noteworthy findings:

Vaccine Prioritisation: Implemented with lags ranging from the 3rd to 7th week, the vaccine prioritisation policy exhibited a substantial effect on the weekly death count, particularly in the week immediately following implementation. This effect persisted for the subsequent two months, indicating a sustained impact on mortality outcomes. The observed strong causal relationship between vaccine prioritisation and the number of weekly deaths over the next 1 and 2 months underscores the efficacy of this policy in mitigating the impact of COVID-19 in British Columbia.

Stay-at-Home Policy: Implemented with a lag of 7 weeks, the stay-at-home policy demonstrated a notable long-term causal effect on mortality rates in British Columbia. However, unlike vaccine prioritisation, which showed both immediate and sustained effects, the impact of the stay-at-home policy was primarily observed over an extended period, highlighting its role in reducing mortality rates over time rather than immediately following implementation.

These findings underscore the nuanced dynamics of policy effectiveness in mitigating the impact of the COVID-19 pandemic in British Columbia. The differential temporal effects of vaccine prioritisation and the stay-at-home policy provide valuable insights for evidence-based decision-making and strategic planning in public health crisis management within the province.

FIGURE 16. Granger Casualty Result Chart for British Columbia

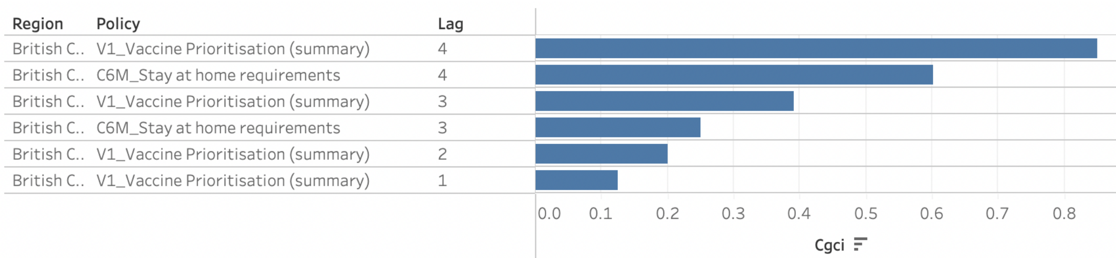


Granger Casualty Result Chart for British Columbia

4.4.2 Conditional Granger Casualty

In addition to the analysis conducted through Granger Causality (GC), Conditional Granger Causality (CGC) analysis also underscores the effectiveness of Vaccine Prioritization as one of the most impactful policies in mitigating the impact of COVID-19. This further reinforces the significance of prioritizing vaccination efforts in combating the pandemic in British Columbia.

FIGURE 17. Conditional Granger Casualty Result Chart for British Columbia



Conditional Granger Casualty Result Chart for British Columbia

4.4.3 Granger Casualty in Frequency Domain

The analysis conducted in the Frequency Domain has identified additional policies that contribute to the management of the pandemic. Unlike the time domain analysis, which primarily focuses on establishing causal links between policies and their effects on mortality rates, the Frequency Domain analysis provides a broader perspective by capturing a wider range of factors influencing the dynamics of the pandemic. This comprehensive approach ensures a more holistic understanding of the intricate relationships between policies and their impacts on public health outcomes.

FIGURE 18. Granger Casualty in Frequency Chart for British Columbia

Region	PolicyName	GrangerCausality	Frequency
British Columbia	H7E_Vaccination policy	2.02E-98	0.486486486
British Columbia	C8EV_International travel controls	5.04E-99	0.006756757
British Columbia	C8EV_International travel controls	5.04E-99	0.493243243
British Columbia	V2A_Vaccine Availability (summary)	5.04E-99	0.493243243

Granger Casualty in Frequency Chart for British Columbia

4.4.4 Model Performance Evaluation

XGBoost performs better when using all features (policies).

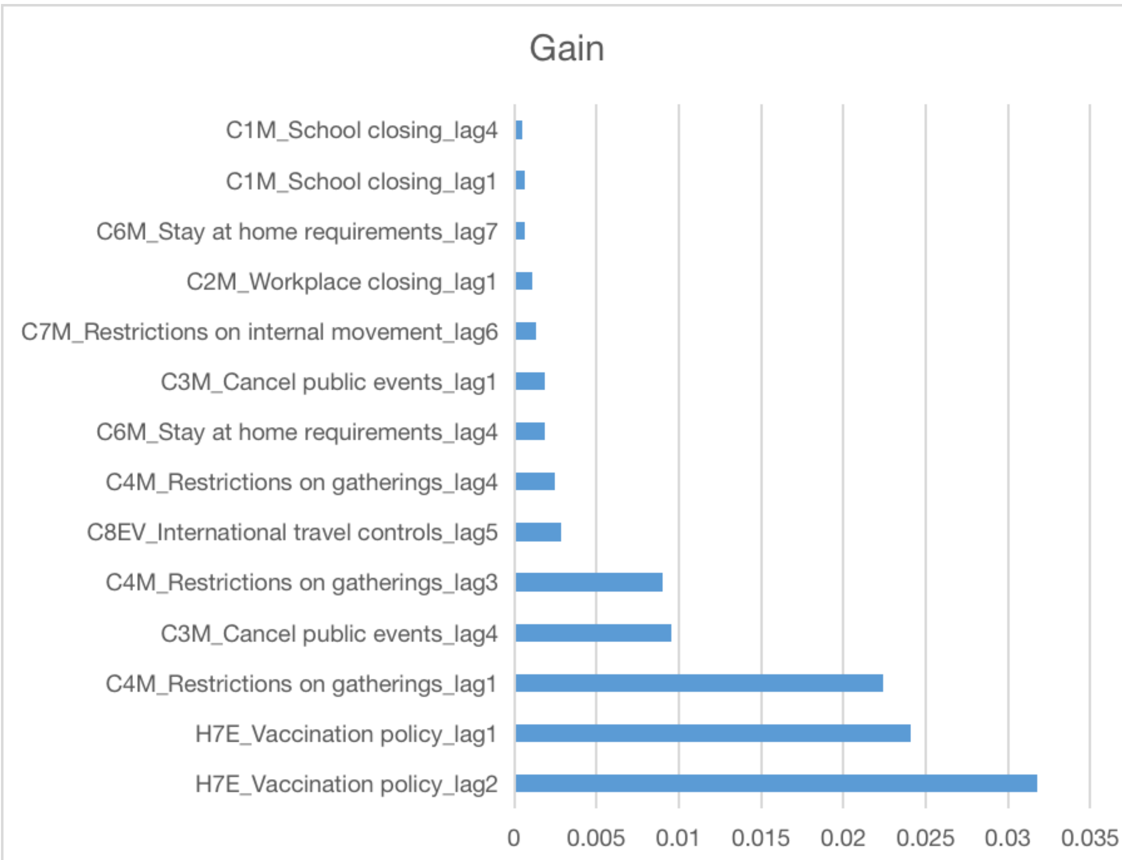
FIGURE 19. XGBoost Feature Importance Gain for Ontario's Policies

Region	Features	Method	RMSE
British Columbia	All Features	XGBoost	0.0141591
British Columbia	5 Top Features by CGC index	XGB	0.0837918
British Columbia	10 Top Features by CGC index	XGB	0.0837918
British Columbia	20 Top Features by CGC index	XGB	0.0837918
British Columbia	5 Top Features by GC index	VAR	0.0891031
British Columbia	10 Top Features by GC index	VAR	0.0891031
British Columbia	20 Top Features by GC index	VAR	0.0891031
British Columbia	5 Top Features by CGC index	VAR	0.0891031
British Columbia	10 Top Features by CGC index	VAR	0.0891031
British Columbia	20 Top Features by CGC index	VAR	0.0891031
British Columbia	5 Top Features by GC index	XGB	0.1003569
British Columbia	10 Top Features by GC index	XGB	0.1044581
British Columbia	20 Top Features by GC index	XGB	0.1044581

Model Performance Evaluation for British Columbia

Since XGboost has the lowest RMSE when selecting all features then the policies with higher gain of this model will be reported for British Columbia. These policies are as below:

FIGURE 20. XGBoost Feature Importance Gain for British Columbia's Policies



XGBoost Feature Importance Gain for British Columbia's Policies

4.5 Nova Scotia

4.5.1 Granger Casualty

The examination of the most effective policies and their associated lags has revealed noteworthy insights:

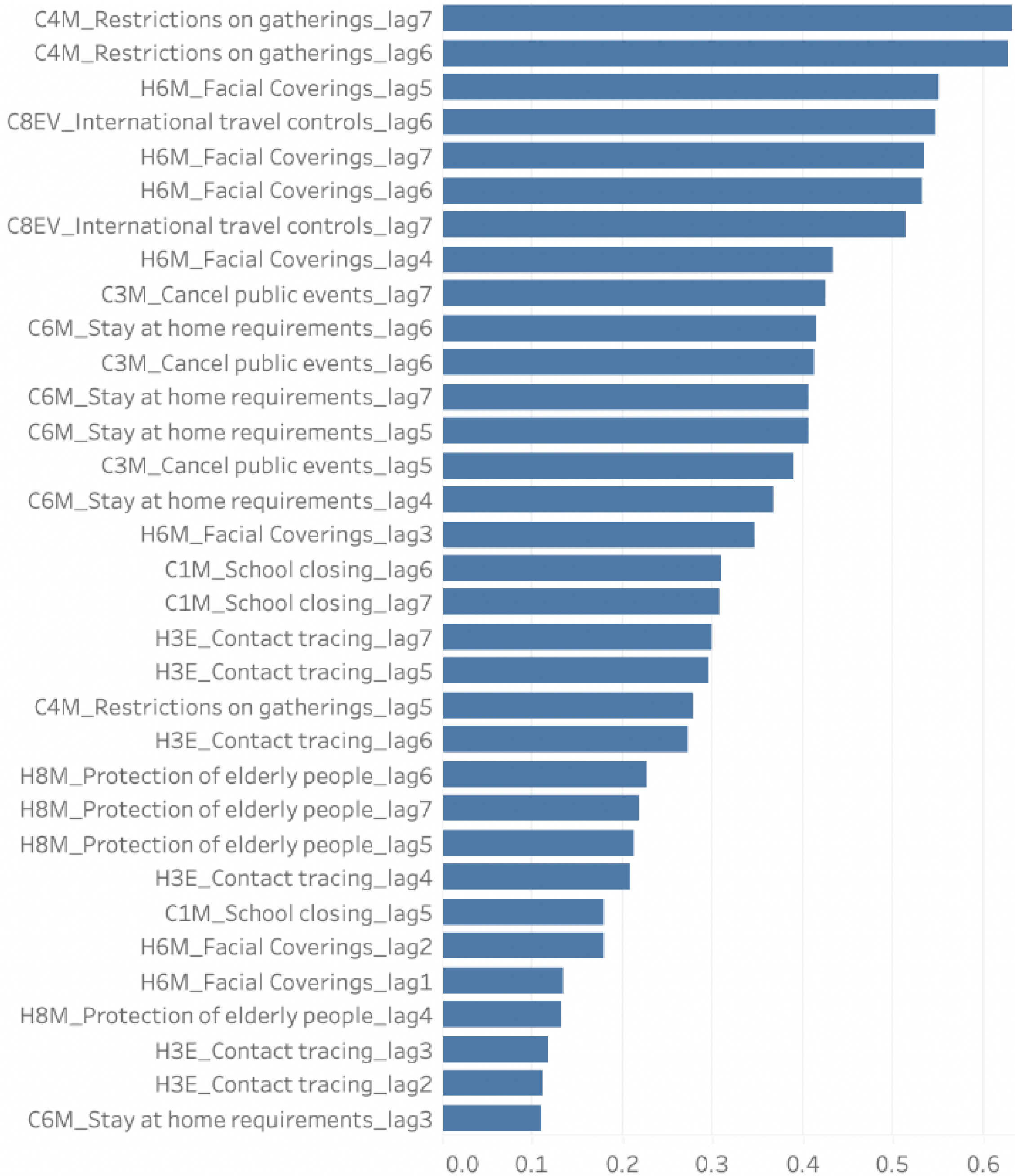
Restrictions on Gatherings: Implemented with lags in the 6th and 7th weeks, restrictions on gatherings emerged as the most impactful policy, displaying a Granger Causality Index (GCI) of 0.63. This substantial GCI signifies a robust and long-term causal relationship, emphasizing the enduring effectiveness of gathering restrictions in mitigating the number of weekly deaths.

International Travel Controls: Also implemented with lags in the 6th and 7th weeks, international travel controls demonstrated a significant causal effect on mortality rates, contributing to the comprehensive policy landscape.

Facial Coverings: Implemented with lags in the 5th, 6th, and 7th weeks, facial coverings were identified as another highly effective policy. The varying lags indicate both short-term and sustained impacts on the number of weekly deaths, showcasing the versatility of facial coverings in curbing the spread of COVID-19.

In total, eight significant policies exhibited a causality effect on the number of weekly deaths. Notably, the restrictions on gatherings stand out as the most influential, underscoring its prolonged impact on mortality outcomes. Interestingly, facial coverings and contact tracing policies demonstrated specific short-term effects, providing a nuanced understanding of the diverse temporal dynamics associated with different policies. This comprehensive analysis contributes valuable insights to the intricate relationship between policy interventions and their effectiveness in managing the ongoing COVID-19 pandemic.

FIGURE 21. Granger Casualty Result Chart for Nova Scotia



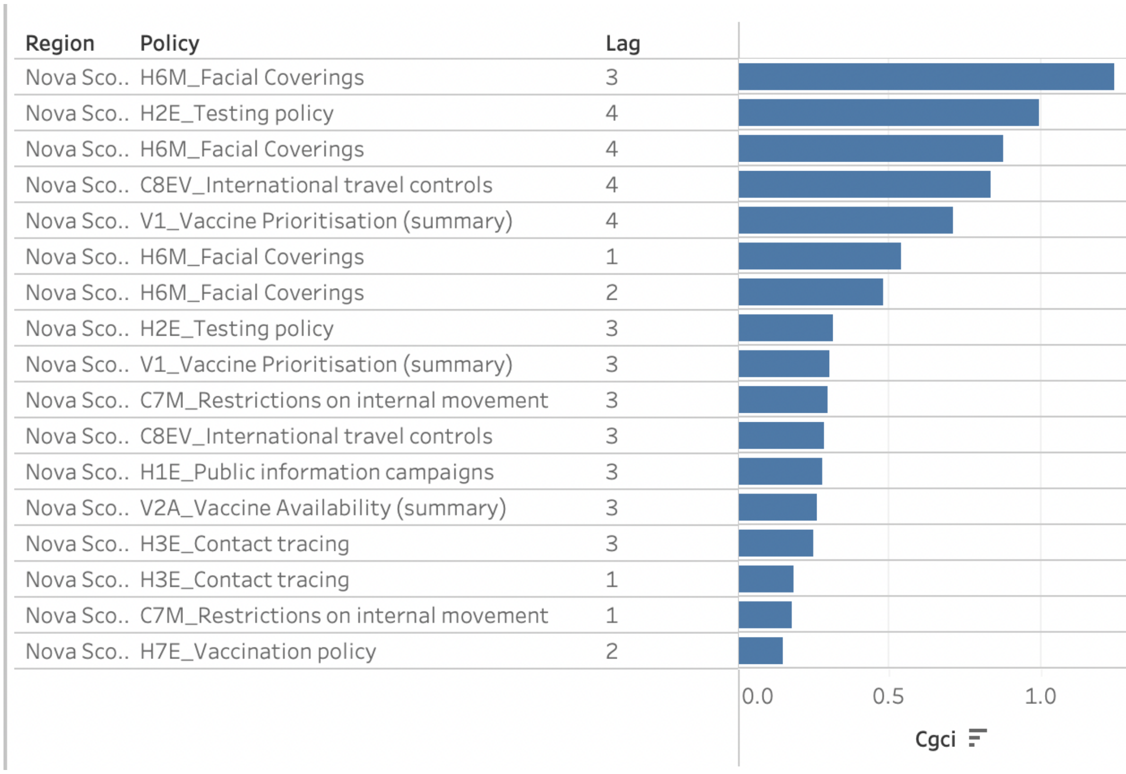
Granger Casualty Result Chart for Nova Scotia

4.5.2 Conditional Granger Casualty

Furthermore, the analysis of Conditional Granger Causality (CGC) reveals that International Travel Controls and Facial Coverings are also identified as effective policies in mitigating the impact of COVID-19. This corroborates and extends the findings obtained through previous Granger Causality (GC) analyses, providing additional evidence of the effectiveness of these policies in controlling the spread of the virus and reducing mortality rates.

Comparing these results to previous GC analyses, which may have focused on other aspects or subsets of data, demonstrates the robustness and consistency of the findings across different analytical approaches. The convergence of results from both GC and CGC analyses underscores the reliability and significance of International Travel Controls and Facial Coverings as pivotal interventions in combating the COVID-19 pandemic. This multi-dimensional analysis enhances our understanding of the effectiveness of various policy interventions and informs evidence-based decision-making in public health crisis management efforts.

FIGURE 22. Conditional Granger Casualty Result Chart for Nova Scotia



Conditional Granger Casualty Result Chart for Nova Scotia

4.5.3 Granger Casualty in Frequency Domain

In the Frequency Domain analysis, the H7E vaccination policy has been identified with the highest Granger Causality (GC) in the frequency domain. This aligns with findings from the time domain analysis, further reinforcing the significance of the H7E vaccination policy in influencing mortality outcomes during the COVID-19 pandemic.

FIGURE 23. Granger Casualty in Frequency Chart for Nova Scotia

Region	PolicyName	GrangerCausality	Frequency
Nova Scotia	H7E_Vaccination policy	6.52E-98	0.006756757
Nova Scotia	H7E_Vaccination policy	6.52E-98	0.060810811
Nova Scotia	H7E_Vaccination policy	1.63E-98	0.074324324

Granger Casualty in Frequency Chart for Nova Scotia

4.5.4 Model Performance Evaluation

XGBoost performs better when using the Policies from GC analysis.

FIGURE 24. Model Performance Evaluation for Nova Scotia

Region	Features	Method	RMSE
Nova Scotia	10 Top Features by GC index	XGB	0.0126987
Nova Scotia	5 Top Features by CGC index	XGB	0.0159094
Nova Scotia	20 Top Features by GC index	XGB	0.0161358
Nova Scotia	20 Top Features by CGC index	XGB	0.0161575
Nova Scotia	5 Top Features by GC index	XGB	0.0167918
Nova Scotia	10 Top Features by CGC index	XGB	0.0172982
Nova Scotia	All Features	XGBoost	0.017326
Nova Scotia	5 Top Features by GC index	VAR	0.0472125
Nova Scotia	10 Top Features by GC index	VAR	0.0472125
Nova Scotia	20 Top Features by GC index	VAR	0.0472125
Nova Scotia	5 Top Features by CGC index	VAR	0.0472125
Nova Scotia	10 Top Features by CGC index	VAR	0.0472125
Nova Scotia	20 Top Features by CGC index	VAR	0.0472125

Model Performance Evaluation for Nova Scotia

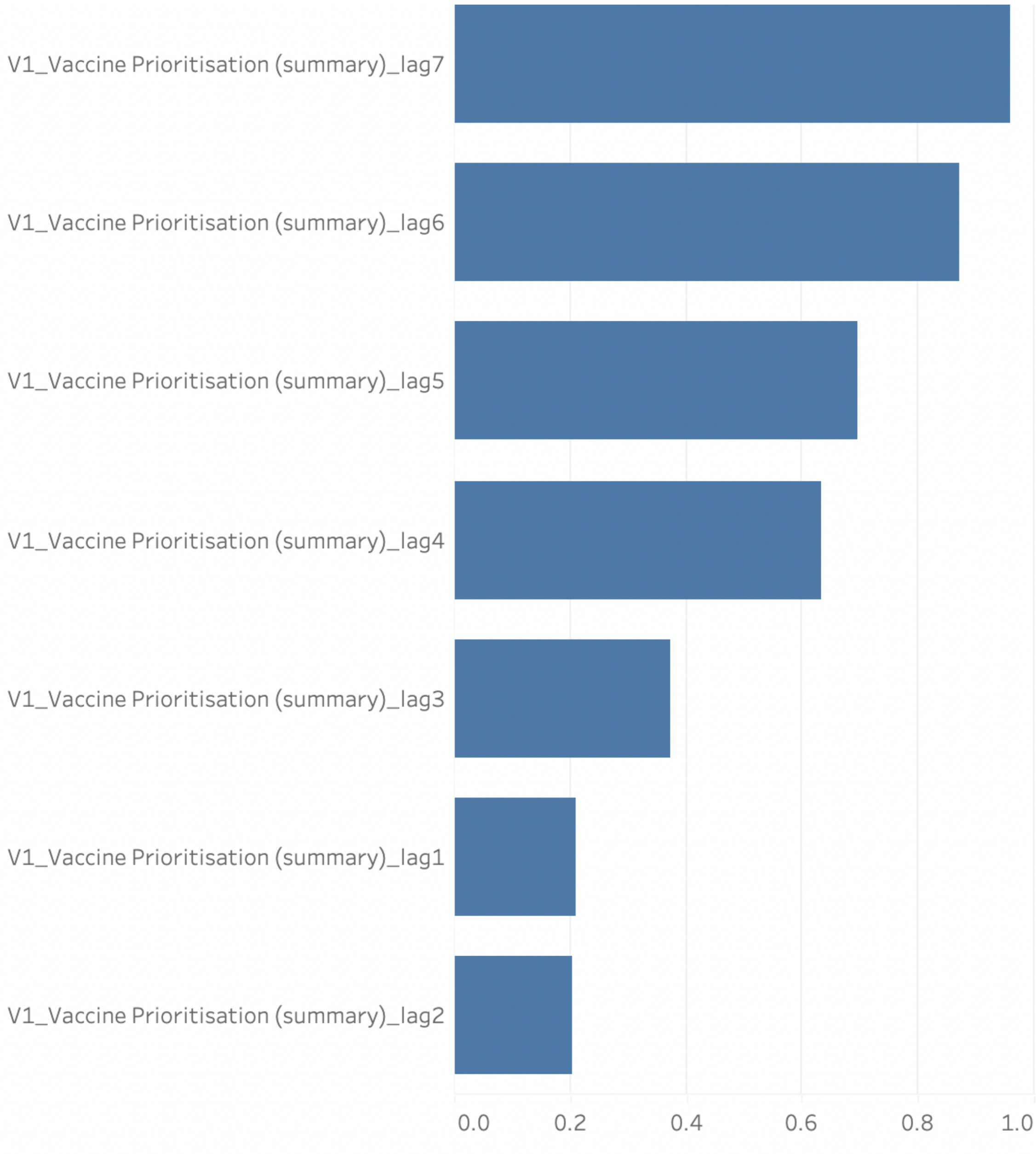
Considering that XGBoost yields the lowest Root Mean Squared Error (RMSE) when predicting the impact of policies identified through Granger Causality (GC) analysis, it suggests that these policies are particularly effective in mitigating the effects of COVID-19 in Nova Scotia. Therefore, policies identified by GC analysis in the time domain emerge as the most influential interventions for addressing the pandemic within the province. This highlights the importance of leveraging GC analysis to identify and prioritize effective policies tailored to the specific context of Nova Scotia's public health needs.

4.6 Manitoba

4.6.1 Granger Casualty

In the analysis of the most effective policies and their associated lags in Manitoba, Vaccine Prioritization emerges as the sole significant intervention. Specifically, the lags numbered 6th and 7th exhibit notable Granger Causality Index (GCI) values, reaffirming the policy's importance and effectiveness in reducing the number of weekly deaths. This finding underscores the critical role of Vaccine Prioritization in mitigating the impact of COVID-19 within Manitoba, highlighting its significance for evidence-based policy-making and strategic public health interventions in the province.

Figure 25. Granger Casualty Result Chart for Manitoba

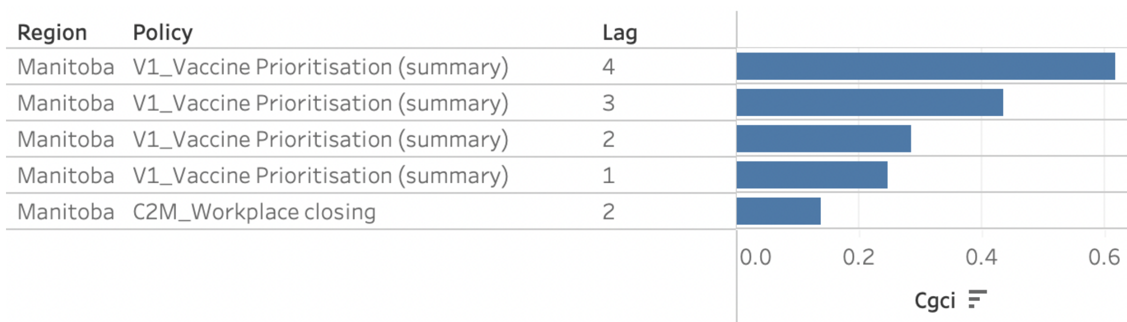


Granger Casualty Result Chart for Manitoba

4.6.2 Conditional Granger Casualty

Furthermore, the analysis of Conditional Granger Causality (CGC) also corroborates the effectiveness of Vaccine Prioritization as the most impactful policy in Manitoba. This additional analysis provides further validation of the significant causal relationship between the implementation of Vaccine Prioritization and the reduction in the number of weekly deaths within the province. The consistency of findings between Granger Causality and Conditional Granger Causality analyses underscores the robustness of the evidence supporting the pivotal role of Vaccine Prioritization in combating the COVID-19 pandemic in Manitoba.

FIGURE 26. Conditional Granger Casualty Result Chart for Manitoba



Conditional Granger Casualty Result Chart for Manitoba

4.6.3 Granger Casualty in Frequency Domain

The Frequency Domain analysis has yielded additional insights compared to the time domain analysis, identifying multiple policies that play crucial roles in mitigating the impact of COVID-19 in Manitoba. These policies include:

1. C1M School Closing: The closure of schools emerges as a significant policy intervention in Manitoba, contributing to the management of the pandemic by reducing opportunities for viral transmission among students and staff.

2. C4M Restrictions on Gatherings: Restrictions on gatherings are identified as another impactful policy, aiming to limit social interactions and thereby mitigate the spread of the virus within the community.

3. V1 Vaccine Prioritization (Summary): Vaccine prioritization is reaffirmed as a critical intervention in Manitoba, highlighting the importance of allocating vaccines strategically to those most at risk to maximize the effectiveness of vaccination efforts.

4. C8EV International Travel Controls: Implementing controls on international travel is recognized as a key policy in Manitoba, aiming to prevent the importation of new cases and variants of the virus from other regions.

The identification of these policies in the Frequency Domain analysis provides valuable insights for policymakers and public health officials in Manitoba, informing evidence-based decision-making and strategic planning efforts to effectively manage the COVID-19 pandemic within the province.

FIGURE 27. Granger Casualty in Frequency Chart for Manitoba

Region	PolicyName	GrangerCausality	Frequency
Manitoba	C1M_School closing	2.77E-95	0.182432432
Manitoba	C4M_Restrictions on gatherings	2.77E-95	0.189189189
Manitoba	C4M_Restrictions on gatherings	2.77E-95	0.358108108
Manitoba	V1_Vaccine Prioritisation (summary)	2.77E-95	0.27027027
Manitoba	C1M_School closing	6.92E-96	0.087837838
Manitoba	C1M_School closing	6.92E-96	0.141891892
Manitoba	C1M_School closing	6.92E-96	0.459459459
Manitoba	C4M_Restrictions on gatherings	6.92E-96	0.290540541
Manitoba	C8EV_International travel controls	6.92E-96	0.236486486
Manitoba	C8EV_International travel controls	6.92E-96	0.445945946
Manitoba	V1_Vaccine Prioritisation (summary)	6.92E-96	0.445945946

Granger Casualty in Frequency Chart for Manitoba

4.6.4 Model Performance Evaluation

XGBoost performs better when using all features (policies).

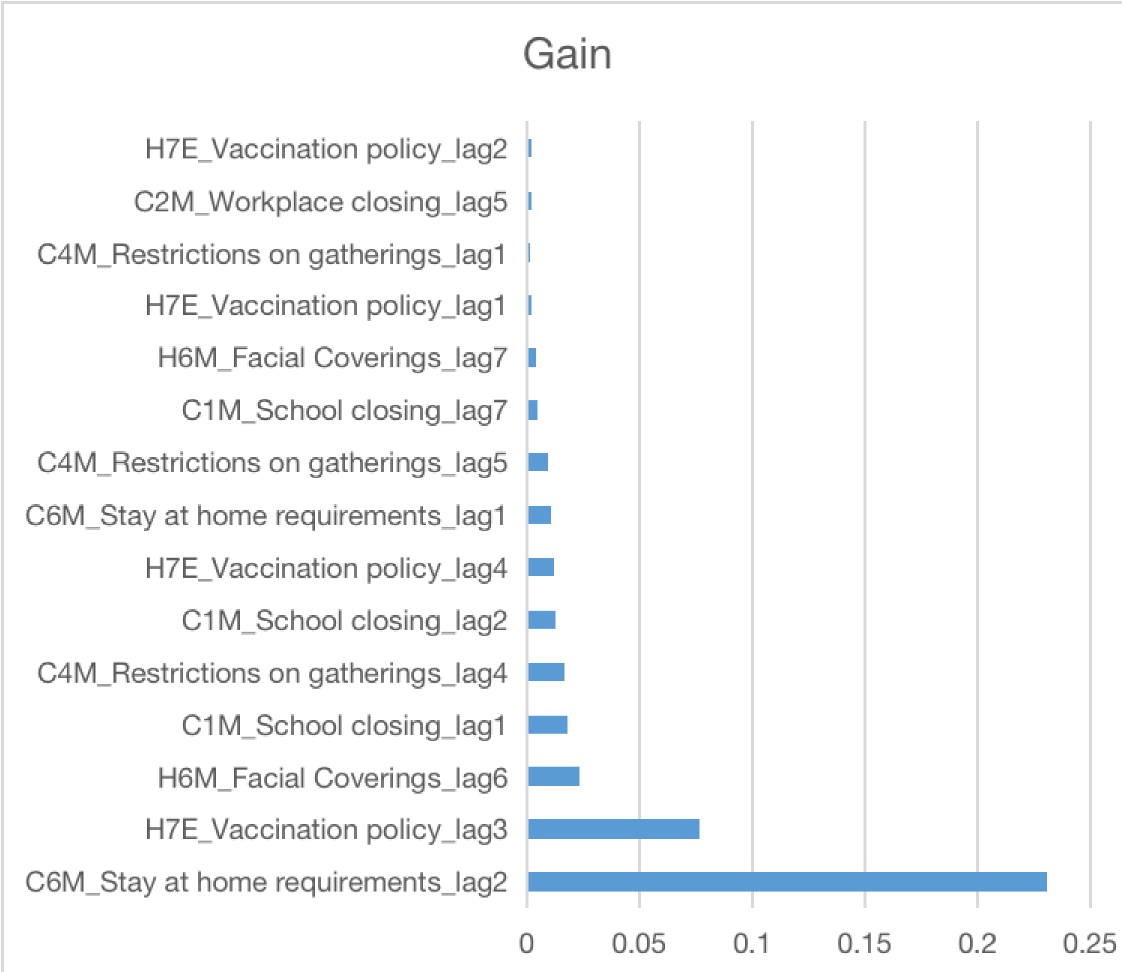
FIGURE 28. Model Performance Evaluation for Manitoba

Region	Features	Method	RMSE
Manitoba	All Features	XGBoost	0.0394611
Manitoba	5 Top Features by GC index	VAR	0.1203445
Manitoba	10 Top Features by GC index	VAR	0.1203445
Manitoba	20 Top Features by GC index	VAR	0.1203445
Manitoba	5 Top Features by CGC index	VAR	0.1203445
Manitoba	10 Top Features by CGC index	VAR	0.1203445
Manitoba	20 Top Features by CGC index	VAR	0.1203445
Manitoba	5 Top Features by CGC index	XGB	0.2980367
Manitoba	10 Top Features by CGC index	XGB	0.2980367
Manitoba	20 Top Features by CGC index	XGB	0.2980367
Manitoba	10 Top Features by GC index	XGB	0.337098
Manitoba	20 Top Features by GC index	XGB	0.337098
Manitoba	5 Top Features by GC index	XGB	0.3505707

Model Performance Evaluation for Manitoba

Since XGboost has the lowest RMSE when selecting all features then the policies with higher gain of this model will be reported for Manitoba. These policies are as below:

FIGURE 29. XGBoost Feature Importance Gain for Manitoba's Policies



XGBoost Feature Importance Gain for Manitoba's Policies

4.7 New Brunswick

4.7.1 Granger Casualty

In New Brunswick, an analysis of the most effective policies and their associated lags has identified several key interventions:

- Restrictions on Gatherings: Implemented with lags in the 6th and 7th weeks, restrictions on gatherings have emerged as a significant policy in mitigating the impact of COVID-19. These measures aim to limit social interactions and reduce opportunities for viral transmission within the community.

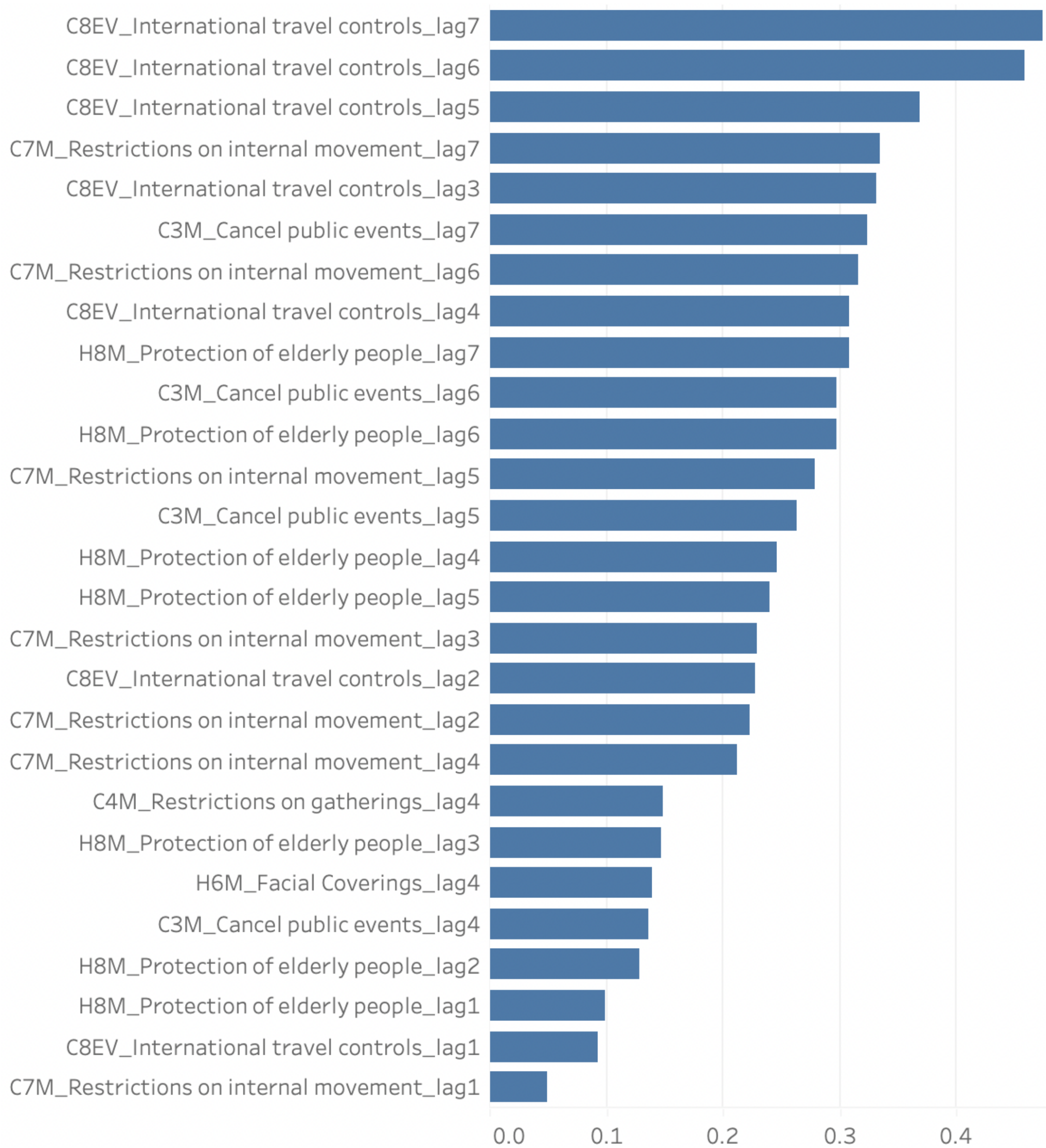
- Restriction on Internal Movement: Similarly, restrictions on internal movement, implemented with lags in the 6th and 7th weeks, have been recognized as an effective policy in controlling the spread of the virus within New Brunswick.

- Protection of Elderly: Implemented with lags in the 6th and 7th weeks, policies aimed at protecting the elderly population have shown effectiveness in reducing mortality rates and protecting vulnerable individuals from severe illness.

- Cancel Public Events: Implemented with lags in the 5th, 6th, and 7th weeks, the cancellation of public events has also emerged as a significant intervention in mitigating the impact of COVID-19 in New Brunswick.

In total, six significant policies have been identified in New Brunswick. Among these, international travel controls exhibit the highest Granger Causality Index (GCI) of 0.47, indicating a strong causal relationship with the reduction in mortality rates. Additionally, all significant policies mentioned in the analysis have demonstrated effects within one month or less, highlighting their immediate impact on addressing the challenges posed by the pandemic in New Brunswick. These findings provide valuable insights for policymakers and public health officials in designing evidence-based strategies for effective pandemic management within the province. Granger Casualty Result Chart for New Brunswick

FIGURE 30. Granger Casualty Result Chart for New Brunswick

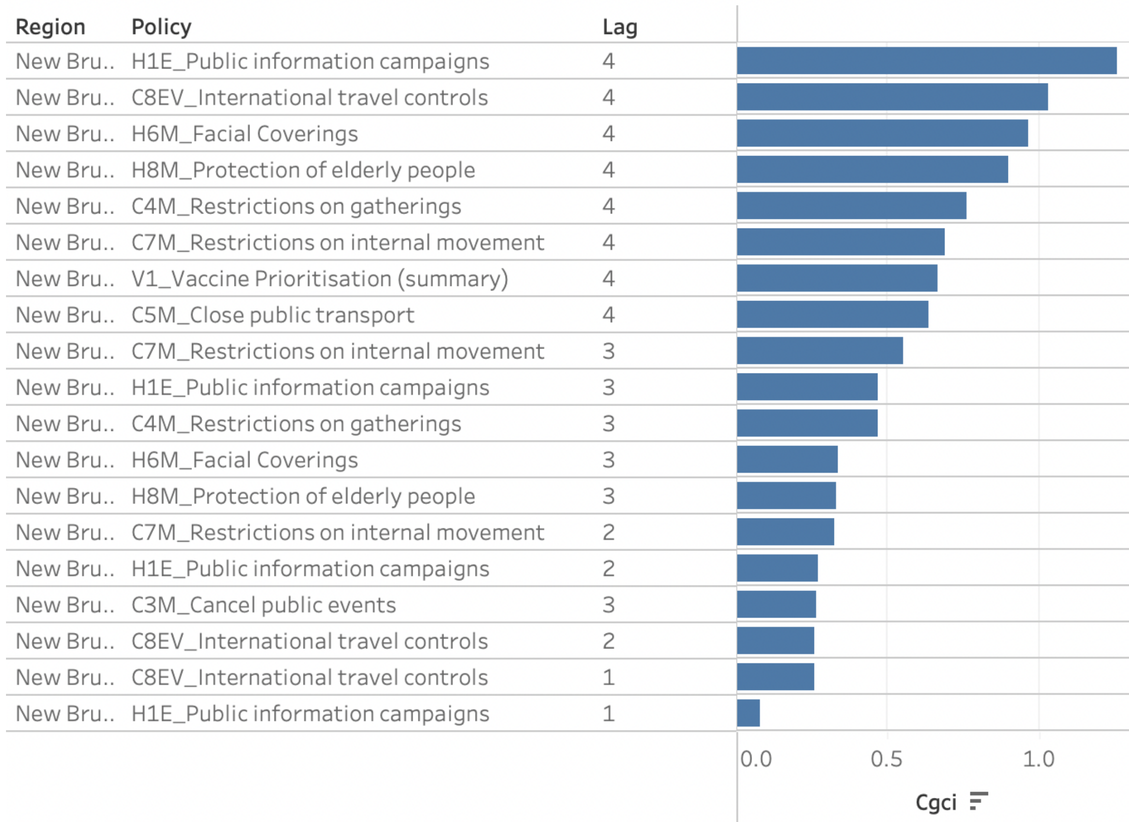


Granger Casualty Result Chart for New Brunswick

4.7.2 Conditional Granger Casualty

In addition to the analysis conducted through Granger Causality (GC), Conditional Granger Causality (CGC) also identifies international travel controls and protection of the elderly as among the most effective policies in New Brunswick for mitigating the impact of COVID-19. Furthermore, CGC analysis has highlighted the importance of additional interventions, such as facial coverings and public information campaigns, in contributing to the management of the pandemic within the province. These findings provide comprehensive insights into the effectiveness of various policy interventions in addressing the challenges posed by COVID-19 in New Brunswick, thereby informing evidence-based decision-making and strategic planning efforts for public health crisis management.

FIGURE 31. Conditional Granger Casualty Result Chart for New Brunswick



Conditional Granger Casualty Result Chart for New Brunswick

4.7.3 Granger Casualty in Frequency Domain

In New Brunswick, the Frequency Domain analysis has identified H8M as having the highest Granger Causality (GC) in the frequency domain, consistent with findings from the time domain analysis. This underscores the significance of H8M as a pivotal factor influencing mortality outcomes during the COVID-19 pandemic in the province. The convergence of results between the frequency and time domain analyses reaffirms the robustness of the evidence supporting the crucial role of H8M in shaping the dynamics of the pandemic in New Brunswick.

FIGURE 32. Granger Casualty in Frequency Chart for New Brunswick

Region	PolicyName	GrangerCausality	Frequency
New Brunswick	H8M_Protection of elderly people	2.66E-97	0.317567568
New Brunswick	H8M_Protection of elderly people	6.66E-98	0.128378378
New Brunswick	H8M_Protection of elderly people	6.66E-98	0.148648649
New Brunswick	H8M_Protection of elderly people	6.66E-98	0.216216216
New Brunswick	H8M_Protection of elderly people	1.66E-98	0.466216216

Granger Casualty in Frequency Chart for New Brunswick

4.7.4 Model Performance Evaluation

XGBoost performs better when using the Policies from CGC analysis.

FIGURE 33. Model Performance Evaluation for New Brunswick

Region	Features	Method	RMSE
New Brunswick	20 Top Features by CGC index	XGB	0.0133361
New Brunswick	5 Top Features by GC index	XGB	0.0158175
New Brunswick	10 Top Features by CGC index	XGB	0.0185794
New Brunswick	5 Top Features by CGC index	XGB	0.0208358
New Brunswick	10 Top Features by GC index	XGB	0.0314218
New Brunswick	20 Top Features by GC index	XGB	0.0333349
New Brunswick	5 Top Features by GC index	VAR	0.0350027
New Brunswick	10 Top Features by GC index	VAR	0.0350027
New Brunswick	20 Top Features by GC index	VAR	0.0350027
New Brunswick	5 Top Features by CGC index	VAR	0.0350027
New Brunswick	10 Top Features by CGC index	VAR	0.0350027
New Brunswick	20 Top Features by CGC index	VAR	0.0350027
New Brunswick	All Features	XGBoost	0.066881

Model Performance Evaluation for New Brunswick

In New Brunswick, the effectiveness of policies identified through Conditional Granger Causality (CGC) analysis is further supported by XGBoost, which yields the lowest Root Mean Squared Error (RMSE) when predicting their impact. This indicates that these policies are particularly effective in mitigating the effects of COVID-19 within the province. Therefore, policies identified by CGC analysis in the time domain are deemed the most influential interventions for addressing the pandemic in New Brunswick. This underscores the importance of utilizing CGC analysis to identify and prioritize effective policies tailored to the specific public health needs of New Brunswick.

4.8 Newfoundland and Labrador

4.8.1 Granger Casualty

In Newfoundland and Labrador, an analysis of the most effective policies and their associated lags has identified several key interventions:

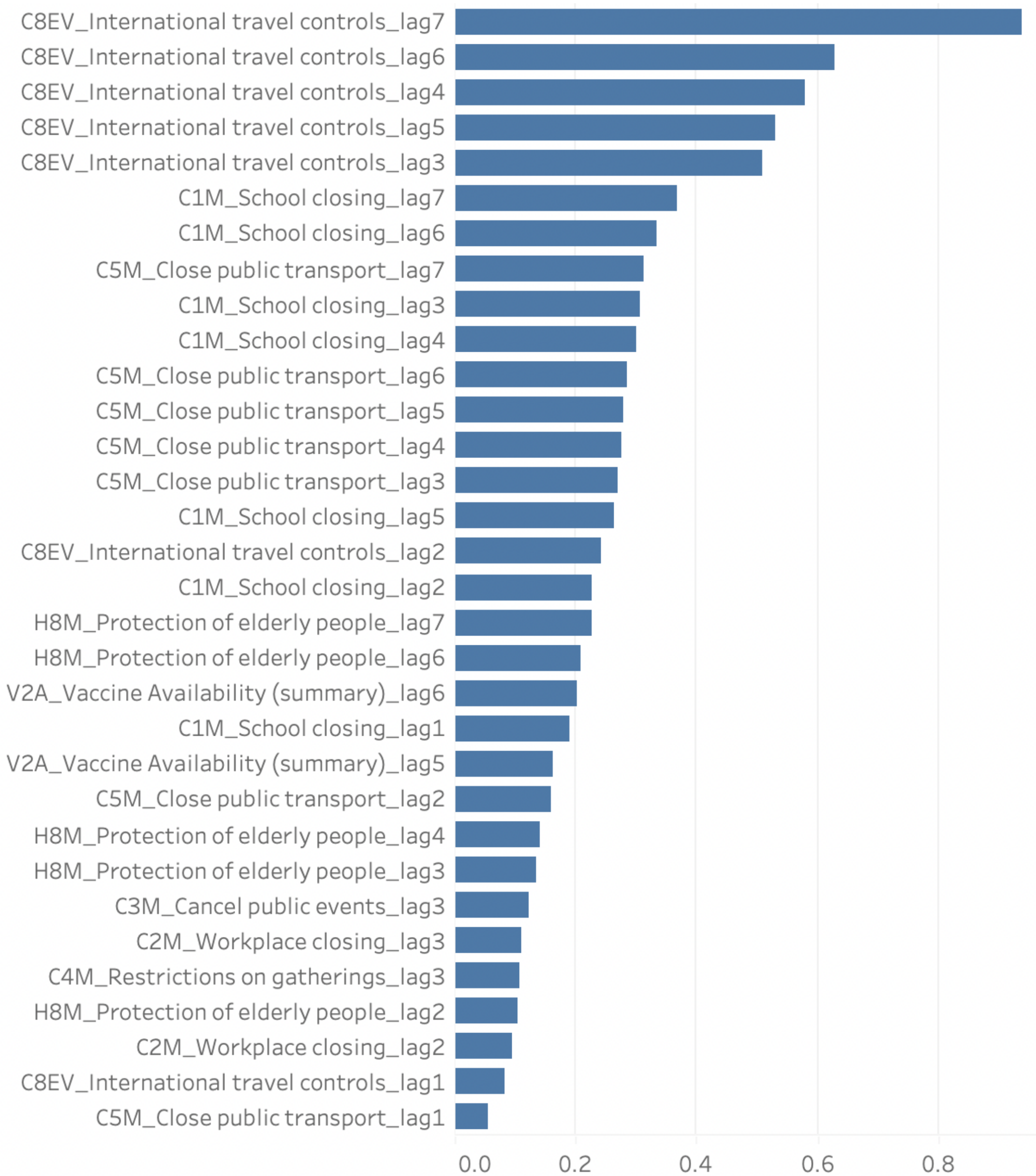
- International Travel Controls: Implemented with lags ranging from the 3rd to 7th weeks, international travel controls emerged as a significant policy in mitigating the impact of COVID-19. This policy demonstrated a strong causal relationship with the number of weekly deaths, exhibiting both short-term and long-term effects in reducing mortality rates.

- School Closing: Similarly, the school closing policy, implemented with lags ranging from the 3rd to 7th weeks, demonstrated effectiveness in the first week itself. This intervention played a crucial role in reducing transmission rates and protecting vulnerable populations, highlighting its importance in controlling the spread of the virus.

- Close Public Transport: Implemented with lags ranging from the 3rd to 7th weeks, the closure of public transport also emerged as a significant policy in Newfoundland and Labrador. This intervention contributed to reducing mobility and interpersonal contact, thereby mitigating the spread of COVID-19 within the province.

In total, eight significant policies have been identified in Newfoundland and Labrador. Among these, international travel controls exhibited a particularly strong causal relationship with the number of weekly deaths, demonstrating both short-term and long-term effects. Additionally, the school closing policy showed immediate effectiveness in reducing transmission rates, underscoring its importance in controlling the pandemic. These findings provide valuable insights for evidence-based decision-making and strategic planning in public health crisis management efforts within Newfoundland and Labrador.

Figure 34. Granger Casualty Result Chart for Newfoundland and Labrador

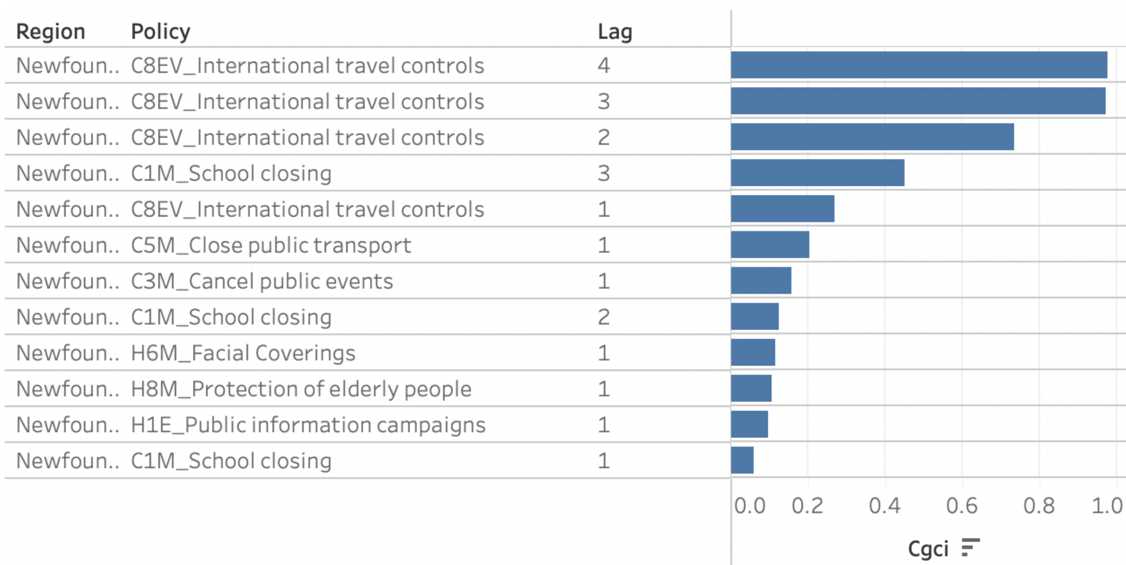


Granger Casualty Result Chart for Newfoundland and Labrador

4.8.2 Conditional Granger Casualty

Furthermore, the analysis of Conditional Granger Causality (CGC) in Newfoundland and Labrador corroborates the effectiveness of international travel controls and school closing as among the most impactful policies in mitigating the impact of COVID-19. This additional analysis provides further validation of the significant causal relationship between the implementation of these policies and the reduction in the number of weekly deaths within the province. Additionally, CGC analysis has identified facial coverings and public information campaigns as important interventions contributing to the management of the pandemic in Newfoundland and Labrador. These findings offer comprehensive insights into the effectiveness of various policy interventions in addressing the challenges posed by COVID-19 in the province, thereby informing evidence-based decision-making and strategic planning efforts for public health crisis management.

FIGURE 35. Conditional Granger Casualty Result Chart for Newfoundland and Labrador



Conditional Granger Casualty Result Chart for Newfoundland and Labrador

4.8.3 Granger Casualty in Frequency Domain

In Newfoundland and Labrador, the Frequency Domain analysis has further validated the significance of international travel controls, consistent with findings from both Conditional Granger Causality (CGC) and Granger Causality (GC) analyses in the time domain. This convergence of results across different analytical approaches underscores the robustness of the evidence supporting the pivotal role of international travel controls in mitigating the impact of COVID-19 within the province. The consistency of findings from Frequency Domain analysis with those from CGC and GC analyses enhances our understanding of the effectiveness of this policy intervention in addressing the challenges posed by the pandemic in Newfoundland and Labrador.

FIGURE 36. Granger Casualty in Frequency Chart for Newfoundland and Labrador

Region	PolicyName	GrangerCausality	Frequency
Newfoundland and Labrador	C8EV_International travel controls	2.76E-96	0.486486486
Newfoundland and Labrador	C8EV_International travel controls	1.73E-97	0.47972973

Granger Casualty in Frequency Chart for Newfoundland and Labrador

4.8.4 Model Performance Evaluation

XGBoost performs better when using the Policies from GC analysis.

FIGURE 37. Model Performance Evaluation for Newfoundland and Labrador

Region	Features	Method	RMSE
Newfoundland and Labrador	20 Top Features by GC index	XGB	0.0033679
Newfoundland and Labrador	5 Top Features by GC index	XGB	0.0048679
Newfoundland and Labrador	20 Top Features by CGC index	XGB	0.0050476
Newfoundland and Labrador	10 Top Features by CGC index	XGB	0.0050944
Newfoundland and Labrador	10 Top Features by GC index	XGB	0.0053353
Newfoundland and Labrador	5 Top Features by CGC index	XGB	0.0054689
Newfoundland and Labrador	5 Top Features by GC index	VAR	0.0126391
Newfoundland and Labrador	10 Top Features by GC index	VAR	0.0126391
Newfoundland and Labrador	20 Top Features by GC index	VAR	0.0126391
Newfoundland and Labrador	5 Top Features by CGC index	VAR	0.0126391
Newfoundland and Labrador	10 Top Features by CGC index	VAR	0.0126391
Newfoundland and Labrador	20 Top Features by CGC index	VAR	0.0126391
Newfoundland and Labrador	All Features	XGBoost	0.0132147

Model Performance Evaluation for Newfoundland and Labrador

In Newfoundland and Labrador, the optimal performance in XGBoost modeling is attained by incorporating the top 20 policies identified through Granger analysis in the time domain. This approach leverages the insights gleaned from rigorous temporal analyses, ensuring that the selected policies are not only influential but also well-aligned with the dynamic patterns of the COVID-19 pandemic within the province. By prioritizing these policies in the modeling process, we can effectively capture the nuanced interplay between policy interventions and their impacts on mortality outcomes, thereby enhancing the accuracy and relevance of our predictive models for informing evidence-based decision-making in public health crisis management.

4.9 Saskatchewan

4.9.1 Granger Casualty

In Saskatchewan, an in-depth examination of the most effective policies and their corresponding lags reveals notable insights:

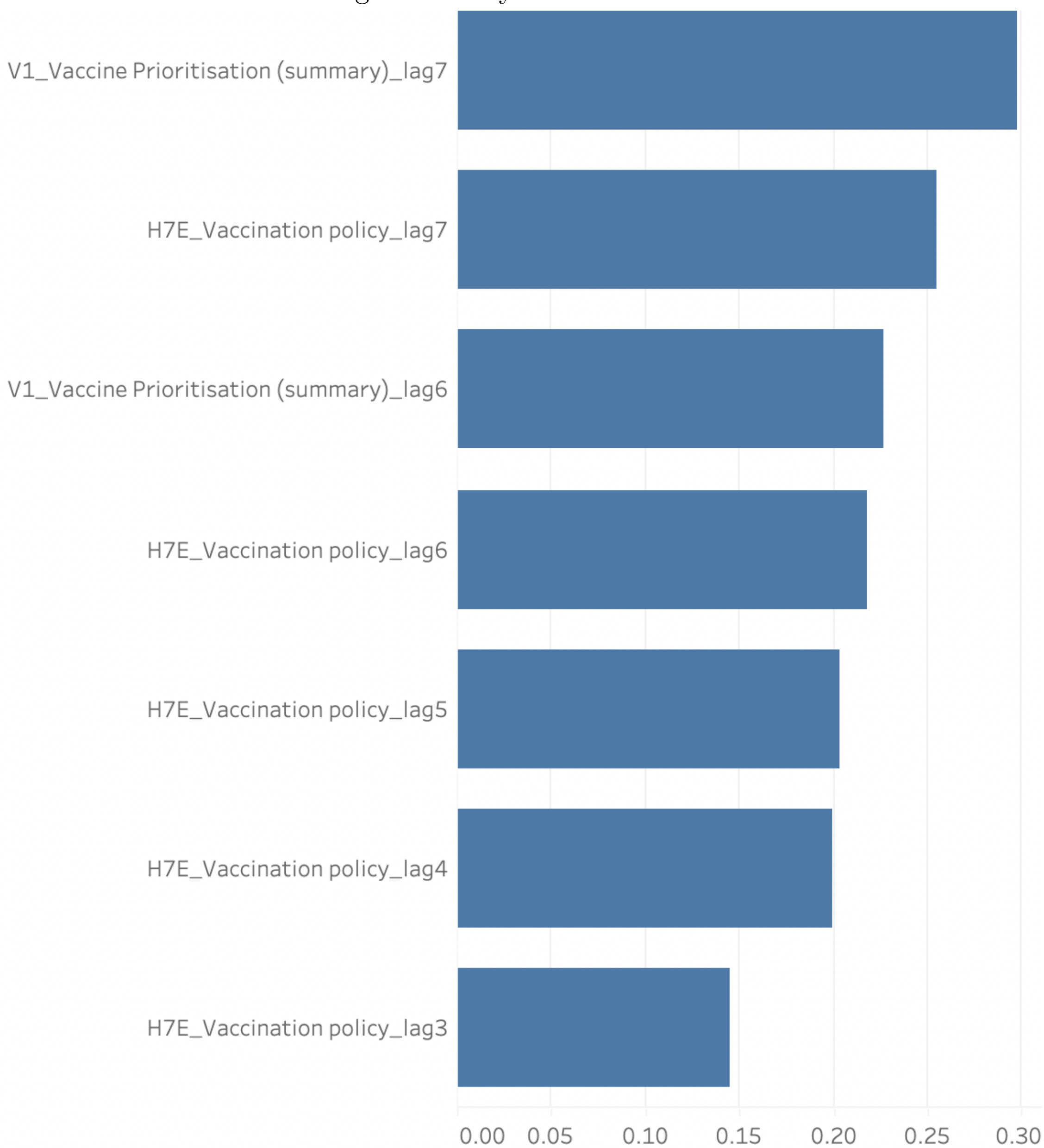
- Vaccine Prioritization: Implemented with lags in the 6th and 7th weeks, the vaccination prioritization policy has emerged as one of the most impactful interventions in mitigating the number of weekly deaths. This policy prioritizes the distribution of vaccines to specific demographic groups or regions based on predetermined criteria, ensuring that those most vulnerable to severe illness or exposure are protected first.

- Vaccine Policy: Implemented with lags ranging from the 3rd to 7th weeks, the vaccination policy encompasses a broader framework that governs the distribution, administration, and monitoring of vaccines across the province. This comprehensive policy approach ensures efficient vaccine deployment and adherence to established guidelines and protocols, contributing to the overall effectiveness of the vaccination strategy in Saskatchewan.

The analysis indicates that both vaccination prioritization and vaccination policies exert significant influence on the number of weekly deaths in Saskatchewan, particularly in the subsequent 6 to 7 weeks following implementation. This underscores the critical role of proactive vaccination measures in reducing mortality rates and mitigating the impact of COVID-19 within the province.

These findings provide valuable insights for policymakers and public health officials in Saskatchewan, highlighting the importance of prioritizing and optimizing vaccination efforts as a cornerstone of effective pandemic management strategies. By focusing on these key policies and their respective lags, stakeholders can tailor interventions to address the specific needs and challenges of Saskatchewan's population, ultimately contributing to improved public health outcomes in the face of the ongoing pandemic.

Figure 38. Granger Casualty Result Chart for Saskatchewan

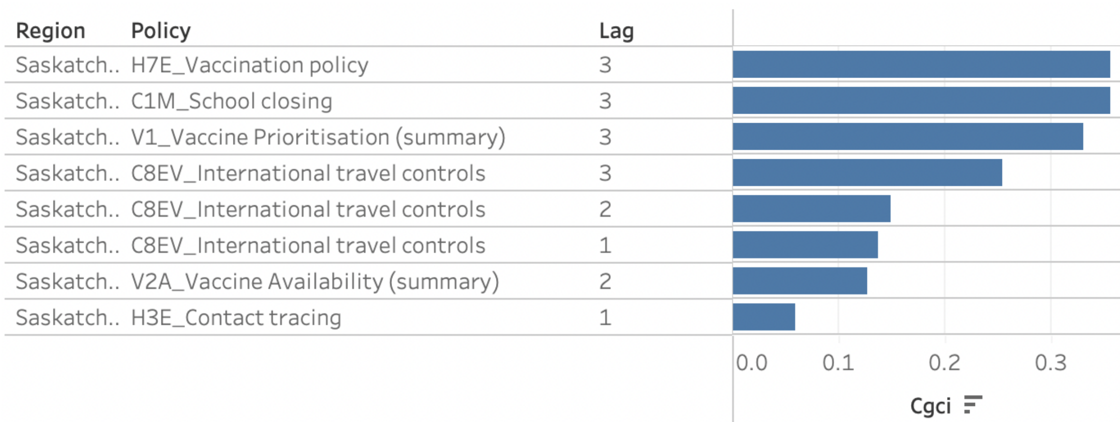


Granger Casualty Result Chart for Saskatchewan

4.9.2 Conditional Granger Casualty

Furthermore, the analysis of Conditional Granger Causality (CGC) also underscores the effectiveness of the vaccination policy as one of the most impactful interventions in Saskatchewan. This additional analysis provides further validation of the significant causal relationship between the implementation of the vaccination policy and the reduction in the number of weekly deaths within the province. The consistency of findings from CGC analysis reinforces the importance of prioritizing and optimizing vaccination efforts as a critical component of Saskatchewan's pandemic management strategy.

FIGURE 39. Conditional Granger Casualty Result Chart for Saskatchewan



Conditional Granger Casualty Result Chart for Saskatchewan

4.9.3 Granger Casualty in Frequency Domain

In Saskatchewan, the Frequency Domain analysis has identified H7E as a significant factor, aligning with the findings from the time domain analysis. This convergence of results underscores the robustness and consistency of the evidence supporting the pivotal role of H7E in influencing mortality outcomes during the COVID-19 pandemic within the province. The consistency between Frequency Domain and time domain analyses enhances our understanding of the effectiveness of this policy intervention and reinforces its importance in informing evidence-based decision-making for public health crisis management in Saskatchewan.

FIGURE 40. Granger Casualty in Frequency Chart for Saskatchewan

Region	PolicyName	GrangerCausality	Frequency
Saskatchewan	H7E_Vaccination policy	6.55E-98	0.067567568
Saskatchewan	H7E_Vaccination policy	6.55E-98	0.222972973
Saskatchewan	H7E_Vaccination policy	1.64E-98	0.006756757
Saskatchewan	H7E_Vaccination policy	1.64E-98	0.013513514
Saskatchewan	H7E_Vaccination policy	1.64E-98	0.027027027
Saskatchewan	H7E_Vaccination policy	1.64E-98	0.121621622
Saskatchewan	H7E_Vaccination policy	1.64E-98	0.128378378
Saskatchewan	H7E_Vaccination policy	1.64E-98	0.236486486
Saskatchewan	H7E_Vaccination policy	1.64E-98	0.283783784
Saskatchewan	H7E_Vaccination policy	1.64E-98	0.412162162

Granger Casualty in Frequency Chart for Saskatchewan

4.9.4 Model Performance Evaluation

XGBoost performs better when using all policies.

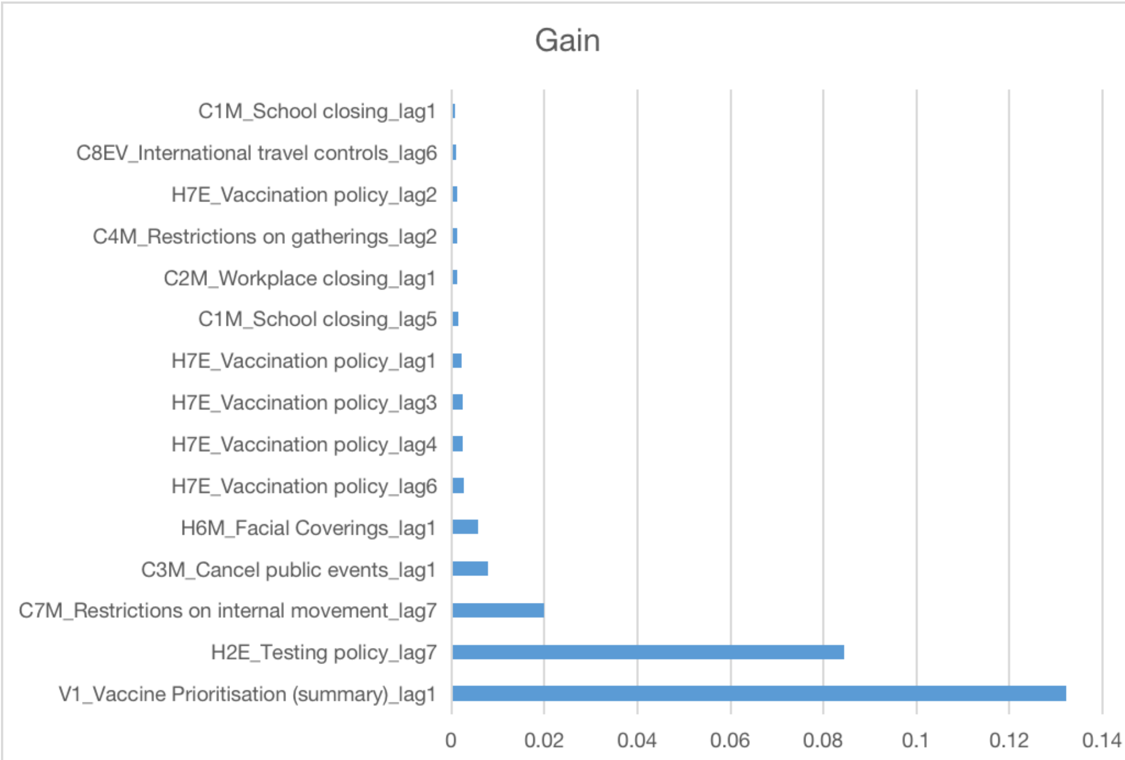
Figure 41. Model Performance Evaluation for Saskatchewan

Region	Features	Method	RMSE
Saskatchewan	All Features	XGBoost	0.0519107
Saskatchewan	10 Top Features by CGC index	XGB	0.0928051
Saskatchewan	20 Top Features by CGC index	XGB	0.0928051
Saskatchewan	5 Top Features by CGC index	XGB	0.0949773
Saskatchewan	5 Top Features by GC index	XGB	0.1241309
Saskatchewan	10 Top Features by GC index	XGB	0.1269235
Saskatchewan	20 Top Features by GC index	XGB	0.1269235
Saskatchewan	5 Top Features by GC index	VAR	0.2298064
Saskatchewan	10 Top Features by GC index	VAR	0.2298064
Saskatchewan	20 Top Features by GC index	VAR	0.2298064
Saskatchewan	5 Top Features by CGC index	VAR	0.2298064
Saskatchewan	10 Top Features by CGC index	VAR	0.2298064
Saskatchewan	20 Top Features by CGC index	VAR	0.2298064

Model Performance Evaluation for Saskatchewan

As XGBoost yields the lowest Root Mean Squared Error (RMSE) when considering all features, the policies exhibiting higher gains in this model will be highlighted for reporting in Saskatchewan. These policies are outlined below:

FIGURE 42. XGBoost Feature Importance Gain for Saskatchewan's Policies



XGBoost Feature Importance Gain for Saskatchewan's Policies

Chapter 5

Conclusion

In conclusion, this research has undertaken a comprehensive exploration of the impact of COVID-19-related public policies on death rates at the provincial level in Canada. The study acknowledges the diverse responses shaped by geographical, cultural, economic, and healthcare factors. The dual methodology, incorporating both traditional linear approaches and modern machine learning techniques, has provided a nuanced understanding of the complex dynamics governing the relationship between public policies and mortality outcomes.

The findings underscore the importance of considering the temporal aspects of policy effectiveness, going beyond binary evaluations. The identification of specific policies with varying impacts on death rates emphasizes the need for targeted and adaptive strategies. The comparative analysis between linear and machine learning approaches has shed light on the strengths and limitations of each method, contributing to evidence-based decision-making.

The significance of this study lies in its provincial-level analysis, offering insights tailored to the unique contexts of different regions within Canada. The knowledge gained is instrumental not only for immediate policy decisions but also for future pandemic preparedness. By delving into the details of policy effectiveness and temporal dynamics, this research equips Canadian policymakers and public health professionals with critical knowledge for crafting informed and adaptive strategies.

As we navigate the ongoing challenges of the COVID-19 pandemic and prepare for future health crises, the collective insights derived from this research lay the groundwork for a more resilient and responsive healthcare system in Canada. The study contributes to the evolving understanding of pandemic response strategies, emphasizing the importance of evidence-based decision-making in mitigating the impact of global health crises.

In examining the efficacy of various COVID-19 mitigation policies implemented across provinces, it becomes evident that nuanced approaches tailored to each region yield the most impactful outcomes.

Ontario, for instance, demonstrated significant success with policies identified through the XGboost algorithm. This encompassed strategies such as implementing workplace closures with a lag of 2, imposing restrictions on internal movement with lags of 5 and 6, mandating school closures with a lag of 6, and enforcing facial covering mandates with lags of 6 and 7.

In Alberta, VAR model demonstrated significant success through the implementation of policies identified by the Granger Causality algorithm. This includes such as contact tracing with lags of 5, 6, and 7, controlling international travel with a lag of 7, and implementing restrictions on internal movement with a lag of 7, were found to be most effective in curtailing the spread of the virus.

Quebec echoed this pattern, with Granger Causality algorithm-identified policies proving most effective. These included the widespread adoption of facial coverings with lags of 7, 6, 5, and 4, rigorous testing policies with lags of 7 and 6, prioritizing the protection of elderly populations with lags of 7 and 5, and implementing restrictions on gatherings and school closures with lags of 7.

British Columbia, however, deviated slightly from this trend, showcasing optimal results with policies identified through the XGboost algorithm. Noteworthy measures included prompt vaccination policies with lags of 1 and 2, early restrictions on gatherings with a lag of 1, cancellation of public events with a lag of 4, and subsequent restrictions on gatherings with a lag of 3, alongside stringent controls on international travel with a lag of 5.

Nova Scotia mirrored the effectiveness of Granger Causality algorithm-identified policies, particularly emphasizing restrictions on gatherings with lags of 7 and 6, mandating facial coverings with lags of 5, 7, and 6, and controlling international travel with a lag of 6 and 7.

Manitoba's success stemmed from the utilization of policies identified by the XG-boost algorithm, highlighting the significance of stay-at-home requirements with a lag of 2, vaccination policies with a lag of 3, facial covering mandates with a lag of 6, and timely closures of schools and restrictions on gatherings with lags of 1, 2, and 4, respectively.

New Brunswick's strategy, as determined by the Conditional Granger causality algorithm, underscored the importance of comprehensive public information campaigns with a lag of 4, stringent controls on international travel with a lag of 4, widespread adoption of facial coverings with a lag of 4, prioritizing the protection of elderly populations with a lag of 4, implementing restrictions on gatherings and internal movement with a lag of 4.

Newfoundland and Labrador's approach, guided by the Granger causality algorithm, showcased the effectiveness of strict controls on international travel with lags ranging from 7 to 3, timely school closures with lags of 7, 6, 3, and 4, and the suspension of public transportation with lags of 7, 6, 5, and 4.

Finally in Saskatchewan, the efficacy of COVID-19 mitigation strategies rested on a proactive approach guided by the XGBoost algorithm, showcased the effectiveness of strict controls on Vaccination Prioritization, Cancel public events and Facial covering with lag of 1 and restrictions on internal movement and Testing Policy with lag of 7 .

Overall, this multi-provincial analysis underscores the importance of leveraging data-driven algorithms to identify and implement contextually relevant policies, thus optimizing the effectiveness of COVID-19 mitigation strategies across diverse regional landscapes.

Upon analyzing the various COVID-19 mitigation strategies across provinces, a notable finding emerges: the widespread adoption of facial covering mandates. This policy emerges as the most common thread woven throughout the provinces' approaches to curbing the spread of the virus. From Ontario to Nova Scotia, from Alberta to Newfoundland and Labrador, the consistent enforcement of facial covering mandates underscores its universality and recognition as a fundamental tool in combating the pandemic.

This ubiquitous policy is often complemented by other measures tailored to each province's unique circumstances and informed by data-driven algorithms. While facial covering mandates serve as a common denominator, provinces also deploy a range of additional strategies, such as restrictions on gatherings, school closures, vaccination campaigns, and controls on international travel, each adapted to the specific needs and epidemiological contexts of their respective regions.

By recognizing the prominence of facial covering mandates alongside other targeted interventions, policymakers can draw insights from this shared approach while also tailoring strategies to address the nuanced challenges presented by the pandemic in their jurisdictions. This collective emphasis on facial coverings highlights not only their effectiveness but also the collaborative spirit driving the collective response to the public health crisis across provincial boundaries.

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