The role of population mobility and non-pharmaceutical interventions on COVID-19 infection: A Canadian case study of Granger-causal relationships

Boxi Lin, Thai-Son Tang, Lehang Zhong

Division of Biostatistics, Dalla Lana School of Public Health, University of Toronto, Canada.

ABSTRACT

Introduction: The COVID-19 disease has been the cause of more than 13,350 deaths in Canada. As a result, nonpharmaceutical interventions (NPIs) have been adopted by government officials to mitigate dissemination of the disease. Quantifying NPI effectiveness is challenging due to variability in their implementation between geographic regions. Mobility data can help understand the role of NPIs in reducing COVID-19 cases.

Methods: We used aggregate-level data to compare COVID-19 daily cases per 100 000 population, timing and level of NPI implementation, and mobility trends in six Canadian provinces. Using the Granger test, we assessed bi-directional predictive causality between NPIs, mobility and daily cases.

Results: We found that implementations of NPI and daily COVID-19 cases causally influence population mobility in all provinces, while the relationship between daily cases and NPIs remains unclear.

Conclusion: This study shows that NPIs and daily cases contribute to minimizing population mobility in Canada, but suggests that NPIs may have to be implemented and enforced more promptly to significantly influence COVID-19 cases.

INTRODUCTION

The COVID-19 disease, first recognized in 2019 and caused by the SARS CoV-2 virus[1], was identified as a global pandemic by the World Health Organization (WHO) in March 2020[2]. As of December 2020, nearly 71 million COVID-19 cases have been confirmed globally, including more than 13 million deaths[3]. In Canada alone, almost half a million COVID-19 cases have been confirmed, with 13,350 deaths attributed to the disease as of December 14th, 2020[3].

After the WHO issued a statement calling for action to stop, contain, control, delay and reduce the impact of the virus, governments around the world adopted nonpharmaceutical interventions (NPIs) to mitigate dissemination of the disease. In Canada, country-wide measures such as border closing and limiting of international travel were promptly enforced. Provincial, territorial and municipal governments additionally adopted control mechanisms, including closure of non-essential businesses, cancellation of public transport services, and school closures[4]. Although these measures have proven to be effective in slowing the spread of COVID-19 in other countries[5,6], their effectiveness in Canada remains unclear. Understanding the effectiveness of NPIs is crucial for decision-makers to maintain effective public health responses against unprecedented crises such as the COVID-19 pandemic[7].

Quantifying the impact of NPIs is challenging due to variability in their type, timing, and duration of implementation between regions, as well as the levels of implementation within said regions. Previous studies had estimated the effect of NPIs as the correlation between COVID-19 transmission and state-responses[7], however, such effect estimation may be biased by underlying factors hidden in the complicated causal pathway between NPIs implementation and COVID-19 transmission.

Mobility data can help understand the extent to which NPIs intervene in the control of communicable diseases[8], especially for NPIs implemented as recommendations. A study on mobility and control measures in China revealed that the magnitude of the early epidemic outside of Wuhan was well predicted by the volume of human movement out of Wuhan alone[9]. Another study in the US found that mobility patterns were strongly correlated to decreased COVID-19 case growth, but these effects were not perceptible until 9-12 days after mobility reduction[10]. These and other studies focusing on COVID-19 and mobility trends are limited by unidimensional metrics of overall mobility[10–13], and fail to account for mobility linked to specific activities in their analyses, such as traveling to parks vs workplaces.

This study aims to jointly analyze the temporal directionality and correlation between non-pharmaceutical interventions, population mobility trends and COVID-19 cases in six Canadian provinces: Alberta (AB), British Columbia (BC), Manitoba (MB), Ontario (ON), Quebec (QC) and Saskatchewan (SK).

METHODS

Data collection

1. COVID-19 cases and percent positive tests

Individual-level time-series data on confirmed and presumptive positive COVID-19 daily cases in Canada was obtained from the "COVID-19 Canada Open Data Working Group". To mitigate reporting issues such as under-reporting of daily cases during weekends, a seven-day rolling average was applied to daily cases, using confirmed cases on each date and the previous and subsequent 3 days.

Confirmed cases were used to calculate daily cases per 100,000 population. Provincial population data was obtained from the 2016 Canada Census[14]. Daily percent positive tests were calculated as 7-day averaged daily confirmed cases over 7-day averaged daily total tests.

2. Mobility data

Aggregated community mobility reports were obtained from official open-source databases made available by Google LLC and Apple Inc.[15,16]

Google mobility data was measured by cellular phone tracking to specific categories of location, namely grocery and pharmacy, parks and outdoor recreation, transit, retail and indoor recreation, places of residence, and workplaces (details in the Appendix). Mobility was quantified as an aggregated score accounting for visit frequency and length of stay at a point in time compared to baseline. The baseline period was defined as the 5-week period between January 3rd and February 6th, 2020. All aggregated data was accessed with permission of users that opted-in to Location History for their Google Account[15].

Apple mobility data was defined and aggregated as walking, driving and public transport use, and was measured by cellular phone tracking as the relative volume of directions requests compared to a baseline volume on January 13th, 2020[16].

3. Non-pharmaceutical interventions

Nonpharmaceutical intervention data was independently gathered and curated as part of the Oxford COVID-19 Government response Tracker (OxCGRT) project. The data consists of a standardized series of cross-temporal indicators that measure policies on a numerical scale of severity/intensity. All data was collected from publicly available sources and is available under the Creative Commons Attribution CC BY standard. Details on definitions and collection of these NPIs can be found elsewhere[17].

For the purpose of this analysis, eleven NPI indicators reported at the provincial level, pertaining to containment and closure, economic response, and health systems were used (Appendix, Table A1). All NPI values were encoded using an ordinal scale, with the lower values (zero) representing no measures in place and larger values indicating ubiquitous implementation of these policies.

Table 1. List of nonpharmaceutical interventions (NPI) included in analysis.

Code	Name
Containment and Closure	
C1	School Closing
C2	Workplace Closing
C3	Cancel Public Events
C4	Restrictions in gathering size
C6	Stay at home requirements
C7	Internal movement restrictions

Code	Name
Economic Measures	
E2	Debt/contract relief for households
Health Measures	
H1	Public information campaign
H2	Testing policy
H3	Contact tracing
H6	Facial coverings

Statistical analysis

All analyses were stratified by province and included mobility trends, NPIs, and daily cases per 100,000 population, observed between February 15th and December 28th, 2020. Analyses were limited to provinces with more than 10,000 cumulative cases as of December 28th, 2020, namely Ontario, Quebec, Alberta, British Columbia, Manitoba and Saskatchewan.

Temporal correlation was assessed using the Granger causality test, a method for establishing, via a hypothesis testing paradigm, whether movements in one time series are useful in forecasting movements in another[18]. The test uses an autoregressive model for the outcome, adjusted for lagged values of a factor and outcome and assesses whether the lagged factors are retained in the model through an F-test[18]. A significant Granger test was interpreted as "predictive causality", indicating the leader-follower relationship between the two time series, but we note its difference from conventional causal inference methods that utilize structural equation models or counterfactual outcomes[19].

Granger causality was analyzed bi-directionally between 1) Daily cases per 100,000 population and NPIs, 2) Daily cases per 100,000 population and mobility scores, and 3) mobility scores and NPIs. Lags of 1 to 30 days were used in the causality test for each set of variables, with the reported optimal lag chosen based on the Akaike Information Criteria. P-values obtained from Granger tests were adjusted for multiple correlated comparisons using the Bonferroni correction. As non-stationarity would violate the asymptotic distributional assumption, the integrated time series were made stationary before entering the hypothesis testing procedure.

Directionality of dependency for each causal association was reported as the median value of the cross-correlation (ρ; CC) function between each set of factor-outcome time-series. The cross-correlations were calculated across a lag range of [-20, 20] days. All analyses were performed using the statistical software, R version 3.6.1[20].

RESULTS

Description of cases, mobility and NPIs

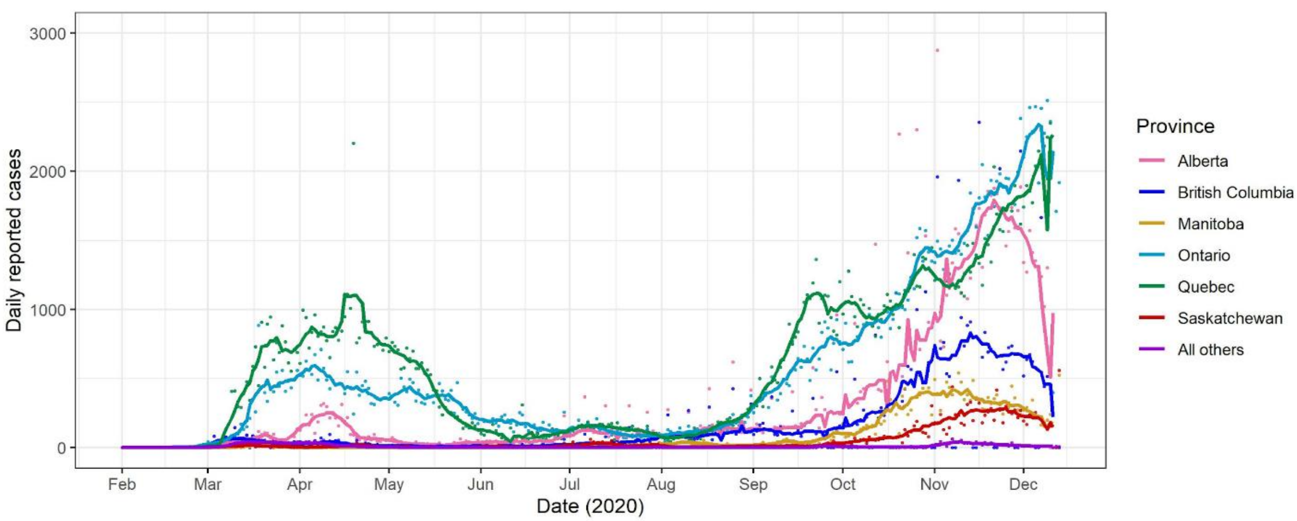

Figure 1. Time series of provincial daily confirmed COVID-19 cases (dots) with 7-day moving average (lines).

Trends of COVID-19 daily cases were available for all Canadian provinces from February 15th to December 28th, 2020 (Figure 1). The time series of the six provinces of interest were asynchronous and presented varying magnitude of daily cases. Cases in Ontario and Quebec reached a maximum peak (first wave) between April and May, followed by a rapid decrease around June. A second steep increase (second wave) for these two provinces was observed in September, which fluctuated but continued to increase steadily for the remainder of the year, reaching more than 2000 daily cases per 100,000 population by December. In Alberta, British Columbia and Manitoba, a similar upsurge was observed in mid-September, although at a much lower magnitude and with a somewhat rapid decline by the end of the year; for these provinces (excluding Alberta) only a first wave was observed. Saskatchewan and all other provinces (combined) presented fewer than 500 daily cases per 100,000 population for the entire time period.

Percent change in mobility was available for the entire time period in all six provinces. Mobility related to grocery and pharmacy remained constant for the majority of the time period. All provinces presented similar mobility patterns with respect to driving, retail and recreation, grocery and pharmacy, transit stations and workplaces (Figure 2). In these five factors, mobility plummeted more than 50% at the third week of March (when a State of Emergency was declared in most provinces and territories), whereas residential mobility increased more than 20%. Most mobility factors leaned toward baseline levels at the start of summer, and others - such as workplace - remained constant until the holiday season. In contrast to the above mobility factors, walking, driving and parks and outdoor recreation increased drastically during the summer months and slowly decreased at the onset of the second wave. Higher increase in percent mobility in Ontario compared to other provinces was consistently observed.

The implementation date and enforcement level of NPIs varied widely both between and within provinces. For the purposes of this report, we illustrate longitudinal changes in five out of the eleven NPIs analyzed (Figure 3). Quebec and Saskatchewan were the only provinces to not enforce contact tracing systems at the beginning of the pandemic. Alberta imposed more relaxed interventions related to people agglomerations (public events cancellations, gathering sizes, school closures).

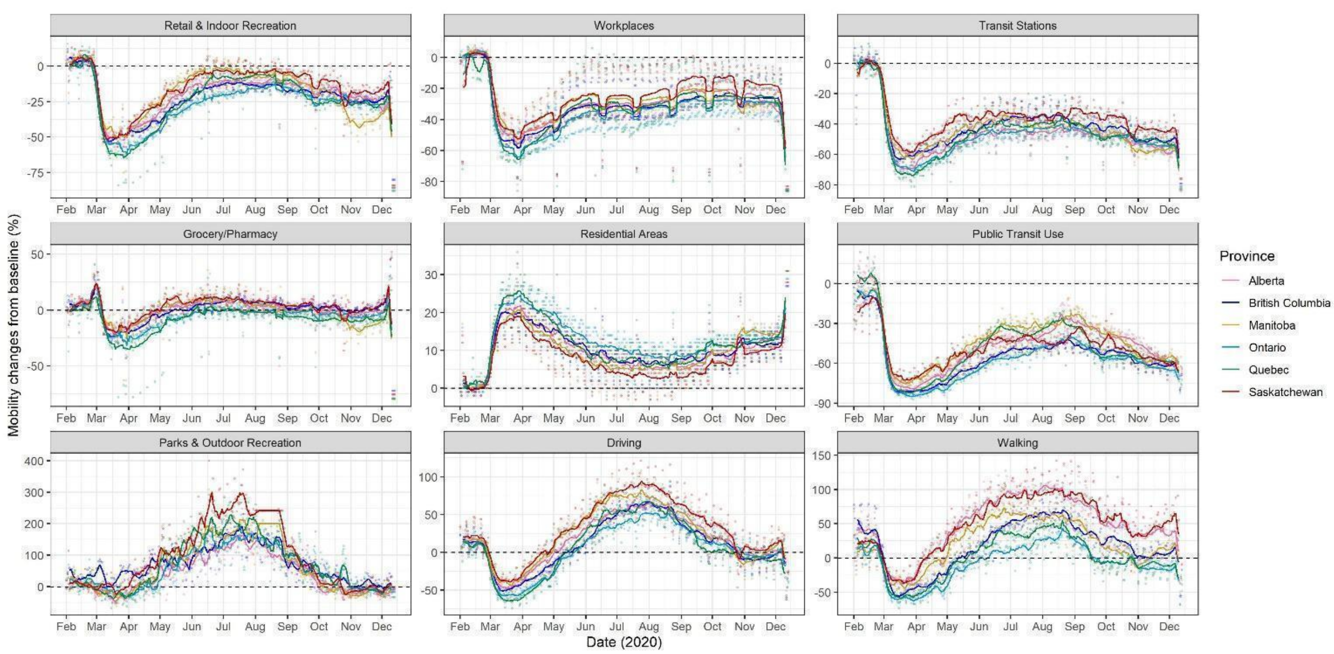

Figure 2. Google and Apple mobility time-series at provincial level: Mobility percent change from baseline (dots) with 7-day moving average (lines).

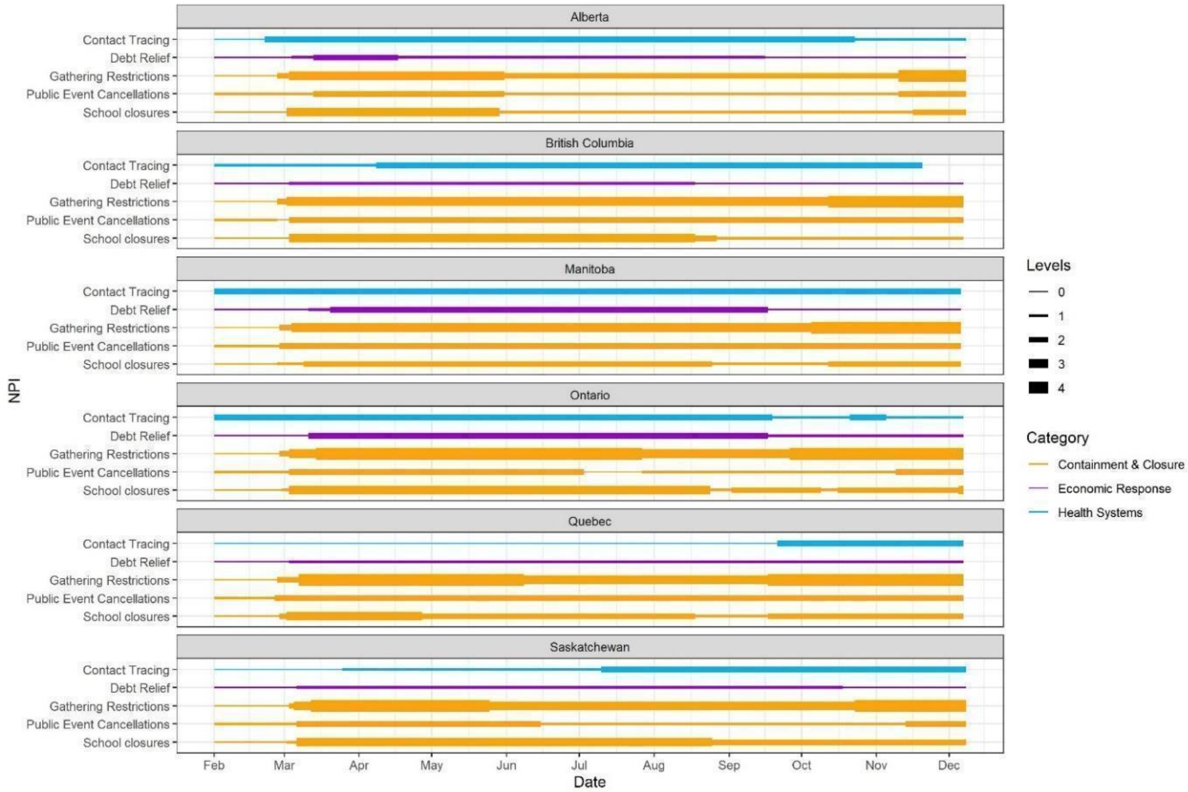

Figure 3. Levels of NPI implementation in each province across time for five of the eleven NPIs examined.

Restrictions on gathering size policies varied widely between provinces. In Ontario for instance, a limit on gatherings of 101-1000 people was enforced in March, which quickly increased to a maximum of 10 people by the end of the month. Restrictions were later relaxed allowing gatherings of 11-100 people by the end of summer, only to return to more stringent measures in early October. Similar trends were observed in Quebec and Saskatchewan. In contrast, Alberta allowed gatherings of up to 1000 people for most of the calendar year. Testing policies, public information campaign, and stay-at-home orders were constantly in place and were implemented similarly in all provinces.

Relationship between Daily Cases and NPIs, Mobility

The majority of NPIs were positively correlated with daily cases per 100 000 population (Figure 4). Public event cancellations exhibited strongest positive correlations with daily cases in Quebec (ρ = 0.43) and weaker correlations in Ontario (ρ = 0.11) and Manitoba (ρ = 0.11). Similarly, school closures were positively correlated in Quebec (ρ = 0.28), but were negatively correlated in British Columbia (ρ = -0.25) and showed weak correlations in the remaining provinces. Quebec was the only province observed to have a positive correlation between debt relief and daily cases (ρ = 0.43). Contact tracing was negatively correlated with daily cases in Ontario (ρ = -0.31) and Alberta (ρ = -0.13), contrasting the strong positive correlation observed in Quebec (ρ = 0.69).

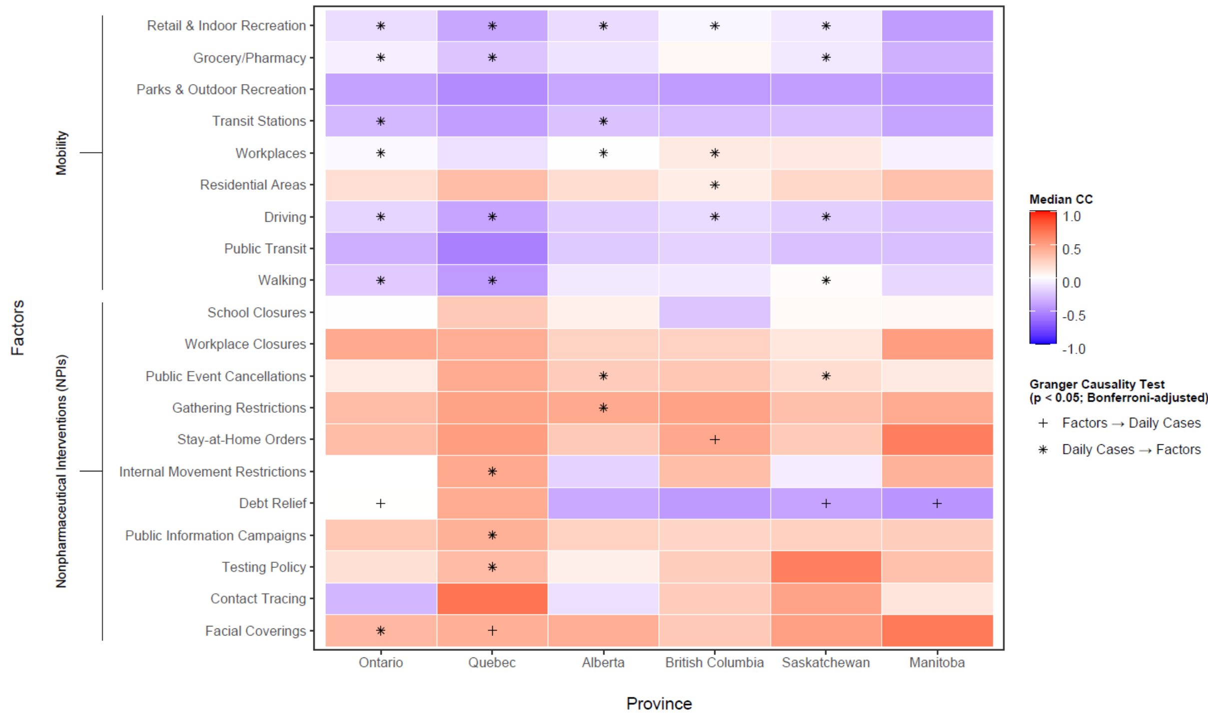

Figure 4. Median cross correlations (CC) between daily cases per 100 000 population and mobility (top half) and NPIs (bottom half). Significant causal relationships (Bonferroni-adjusted p-values < 0.05) are highlighted for factors on daily cases (+) and the direction of daily cases on factors (*).

While Granger causality tests revealed that most median CCs did not infer causal relationships between NPIs and daily cases, the increase in daily cases in Quebec were shown to causally influence implementation of stricter internal movement restrictions ($\rho = 0.44$; $p < 0.001$), public information campaigns ($\rho = 0.41$; $p < 0.001$), and new testing policies ($\rho = 0.35$; $p < 0.001$). Public event cancellations (AB: $\rho = 0.27$, $p = 0.004$; SK: $\rho = 0.18$, $p = 0.007$) and gathering restrictions (AB: $\rho = 0.44$, $p = 0.001$) were also attributed to daily cases per 100 000 population. On the other hand, implementation of debt relief policies caused a reduction in daily cases in Saskatchewan ($\rho = -0.40$; $p < 0.001$) and Manitoba ($\rho = -0.46$; $p < 0.001$).

With respect to mobility, daily cases were positively correlated with movement towards residential areas and negatively correlated with non-residential mobility (retail, indoor & outdoor areas, grocery stores, pharmacies, parks, transit stations), as well as overall outdoor mobility measures (walking, driving, public transit use) (Figure 5). Most Granger tests further suggested that daily cases causally influence reduction in mobility to non-residential areas (excluding parks, outdoor recreation, and public transportation) across all provinces aside from Manitoba. Furthermore, daily cases were attributed to an increase in mobility towards residential areas in British Columbia ($\rho = 0.10$; $p < 0.001$).

On average across all provinces, the selected optimal lags for the underlying autoregressive models were larger for Granger tests involving mobility scores (mean=21.8 days) than those with NPIs (mean=16.3 days) (Figure A1). As NPI and mobility factors were highly correlated amongst themselves, little variation in lags was observed; Saskatchewan averaged the highest lags at 30 days and 21.7 days in mobility and NPIs, respectively, and Quebec saw the smallest lags, averaging 16.73 days (mobility) and 13.56 days (NPIs).

Relationship between NPIs and Mobility

The majority of NPIs were positively correlated with mobility to residential areas (Figure 5a) and negatively correlated with all other mobility factors, including essential movement to grocery and pharmacy (Figure 5b).

Stricter restrictions on gatherings causally influenced a decrease in mobility across all provinces (Figure 5). School closures led to causal increases in residential mobility in Ontario ($\rho = 0.31$; $p < 0.001$), Quebec ($\rho = 0.35$; $p < 0.001$), Alberta ($\rho = 0.50$; $p < 0.001$), and Manitoba ($\rho = 0.19$; $p = 0.005$), while public event cancellations led to increases only in Ontario ($\rho = 0.49$; $p = 0.006$) and Quebec ($\rho = 0.38$; $p < 0.001$). Note that an increase in residential areas represents decreases in all other mobility types.

Debt relief and public information campaigns were shown to causally influence residential mobility in Quebec (debt relief: $\rho = 0.19$, $p < 0.001$; info campaigns: $\rho = 0.14$, $p < 0.001$), Saskatchewan (debt relief: $\rho = 0.01$, $p < 0.001$; info campaigns: $\rho = 0.11$, $p = 0.002$) and Manitoba (debt relief: $\rho = -0.04$, $p = 0.02$; info campaigns: $\rho = 0.13$, $p < 0.001$). Weak correlations were observed for testing policy, contact tracing and facial coverings.

Increase in non-residential mobility factors were also attributed to implementation of health systems such as testing (QC: $\rho = 0.07$, $p = 0.025$; AB: $\rho = 0.18$; $p = 0.048$) and facial covering (ON: $\rho = 0.07$, $p < 0.001$; QC: $\rho = 0.16$, $p = 0.007$; SK: $\rho = 0.13$, $p < 0.001$).

(a)

(b)

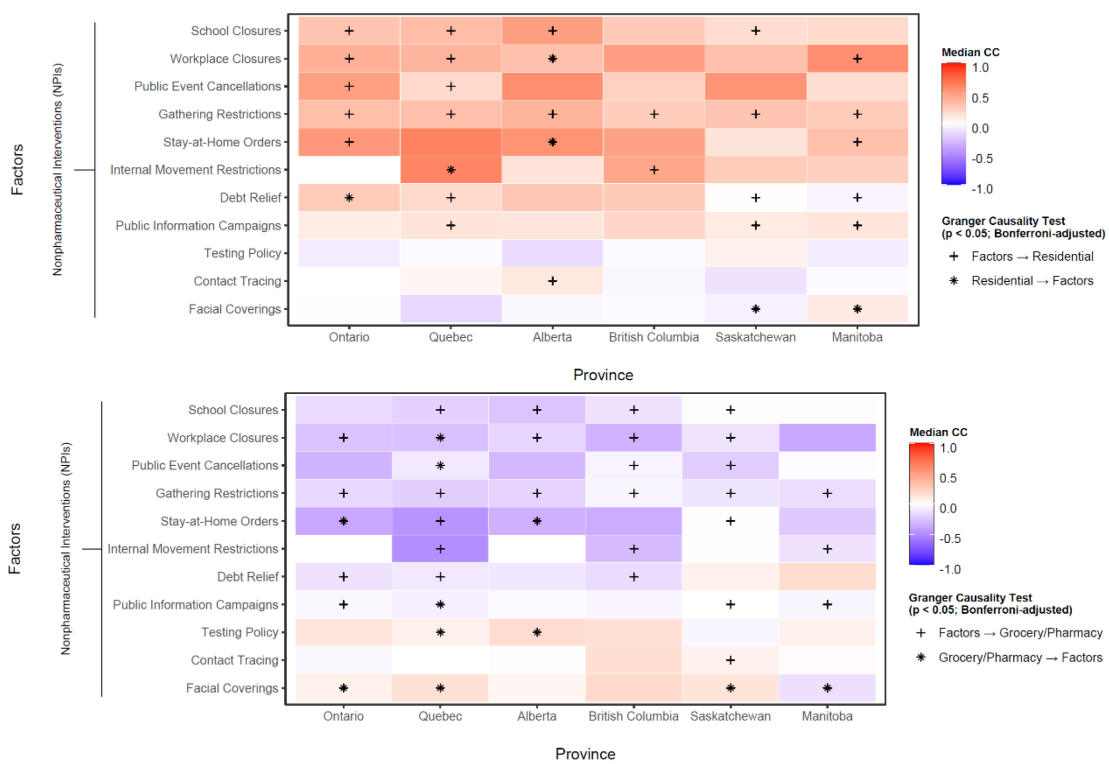

Figure 5. Median cross correlations between (a) Mobility towards residential areas and NPIs, and (b) Mobility towards grocery stores and pharmacies and NPIs. Significant causal relationships (Bonferroni-adjusted p-values < 0.05) are highlighted for the direction of NPIs on mobility (+) and the direction of mobility on NPIs (*).

Optimal lags were similar in both residential and non-residential mobility, averaging 10.67 and 11.61 days, respectively (Figure A1). On average, the largest lags were observed in Quebec (residential: 17.64 days; grocery/pharmacy: 13.91 days) and the smallest in Saskatchewan (residential: 7.10 days; grocery/pharmacy: 8.54 days).

DISCUSSION

In this study, we used aggregate-level data to compare COVID-19 daily cases, timing and level of NPI implementation, and mobility trends in six Canadian provinces. Using Granger methodology, we tested bi-directional predictive causality between NPIs, mobility and daily cases.

As summarized in Figure 6, we found that in Canada, NPI implementations and daily COVID-19 cases causally influence population mobility, while the relationship between daily cases and NPIs remain unclear.

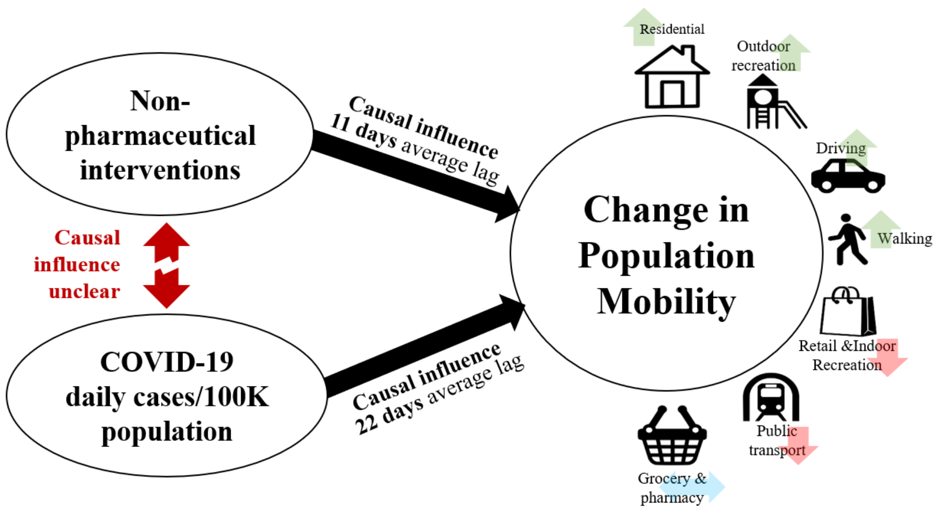

Figure 6. Granger causal relationships between NPIs, mobility factors, and COVID-19 daily cases per 100 000 population.

Daily cases were shown to cause an increase in mobility to residential areas and a decrease to non-residential areas, excluding parks and outdoor recreation. We found that the average optimal lag between daily cases and mobility reduction was of 2-3 weeks, which is consistent with findings from a recently published study[10]. This, as reported in other studies[21], may indicate that communities are taking necessary precautions and changing their mobility patterns based on reports from news and social media outlets, prior to receiving official orders from public health authorities.

The causal direction of influence between NPIs and daily cases differed across provinces. We found that daily cases influenced the implementation of public event cancellations, gathering restrictions, internal movement restrictions, public information campaign, testing and facial covering policies. This suggests that health officials may be enforcing NPIs in a reactive – rather than proactive – manner, perhaps based on the number of observed cases rather than on forecasted information. In particular, the implementation of internal movement restrictions, public information campaigns and more testing policies in Quebec were in response to increasing daily cases per capita, as suggested by Granger tests (Figure 4). Debt relief was the only NPI found to attenuate rising daily COVID cases in Saskatchewan and Manitoba and should be further investigated.

NPIs related to containment and closure were shown to influence decreased mobility towards non-residential areas, and consequently, increased residential mobility. This, supported by the 11-day average optimal lags found in causality comparisons, may be regarded as an indicator that communities across Canada are adhering to government policies, but require time to react to these policy changes. Surprisingly, we found that NPIs directed to health systems, such as facial coverings, and testing policies did not have a causal link with daily cases per 100 000 population. Given that these NPIs are not directly targeted towards limiting mobility, we acknowledge that their effect in reduction of infection may be masked by other factors not accounted for in this study.

Our study has limitations, for instance COVID-19 mobility reports from Google LCC were obtained from a sample of individuals with enabled in-location tracking. These data can present potential bias by excluding non-Google users. Nonetheless, a study of COVID-19 cases and mobility in Italy showed that the estimated mobility trends from Google LCC were consistent with those obtained from an estimation based on data from the Italian Transport Ministry[11]. Furthermore, with the aim of increasing the representativeness of usage against the overall population, we opted to include Apple mobility data in all our analyses. Findings between the two data sources were consistent.

Additionally, Granger causality tests are limited in their ability to infer the magnitude of dependences. In this sense, median CC was reported as means to increase interpretability of p-values. The median CC is robust to the direction of the test given symmetric intervals for time-lags. However, careful interpretation should be considered in cases where opposite cross-correlation values are observed over time, suggesting a median CC of zero does not necessarily imply no correlation. In particular, we observed this phenomenon when testing the effect of debt relief on daily cases in Ontario, where we observed significant Granger causality despite a correlation close to zero (Figure 4).

In comparison to published literature on mobility and COVID-19 cases, this study benefits from incorporating NPIs in the form of time series data, including the time, duration and levels of enforcement. Additionally, we take heterogeneities into account by examining relationships at provincial level. Such heterogeneities were mostly ignored by previous studies where effects of NPIs and population mobility were reported as overall correlations with COVID-19 transmission[7,10,22]. Compared with these cross-sectional effect estimation, our results from time series analysis utilize the variation of NPI implementation and dynamics of population mobility within each province, and is less likely to be biased by demographic differences among provinces. Nonetheless, we recognize that we may still be overlooking causal links specific to highly populated cities, or regions with higher testing capacity. In future iterations of this study, we intend to analyze differences in NPIs effectiveness at both city and provincial level.

Our results strongly support that NPIs are an effective way of minimizing population mobility in Canada, particularly those pertaining to gathering restrictions, public event cancellations and debt relief. Further studies are needed to explore these associations in detail. Based on these findings, and in light of a surge in new cases in the first weeks of 2021, the population may benefit from government officials focusing their resources in prompt enforcement of these interventions.

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Appendix.

METHODS

1. Google mobility data.

Google mobility data was measured by cellular phone tracking to the following specific categories of location:

- Grocery and pharmacy (grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies)
- Parks and outdoor recreation (local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens)
- Transit stations (public transport hubs such as subway, bus, and train stations)
- Retail and indoor recreation (restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters)
- Places of residence
- Workplaces

2. Details on Nonpharmaceutical interventions

Code, name and level description of all nonpharmaceutical interventions included in this study are presented in Table A1.

3. Software for statistical analysis

All analyses were performed using the statistical software, R version 3.6.1[20]. The Granger causality test was performed using the *causality.test* function in the NlinTS package, optimal lags were selected using the *VARselect* function in the vars package and median cross-correlations were calculated with the *ccf* function in the stats package.

Table A1. Non pharmaceutical interventions code, name and level description.

Code	Name	Levels
Containment and Closure		
C1	School Closing (schools and universities)	0 - No measures 1 – Recommend closing, or all schools open with alterations 2 - Require closing (only some levels or categories) 3 - Require closing all levels
C2	Workplace Closing	0 - No measures 1 - recommend closing (or work from home) 2 - require closing (or work from home) for some sectors 3 - require closing (or work from home) all-but-essential workplaces (e.g. grocery stores, doctors)
C3	Cancel Public Events	0- No measures 1 - Recommend cancelling 2 - Require cancelling
C4	Restrictions in gathering size	0 - No restrictions 1 - Restrictions on very large gatherings (above 1000 people) 2 - Restrictions on gatherings between 101-1000 people 3 - Restrictions on gatherings between 11-100 people 4 - Restrictions on gatherings of 10 people or less
C6	Stay at home requirements	0 - No measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips 3 - Require not leaving house with minimal exceptions (e.g. allowed to leave only once a week)
C7	Internal movement restrictions	0 - No measures 1 - Recommend not to travel between regions/cities 2 – internal movement restrictions in place
Economic Measures		
E2	Debt/contract relief for households	0 - No 1 - Narrow relief, specific to one kind of contract 2 - broad debt/contract relief
Health Measures		
H1	Public information campaign	0 - No COVID-19 public information campaign 1 - Public officials urging caution about COVID-19 2 - Coordinated public information campaign
H2	Testing policy	0 – No testing policy 1 – Only those who have symptoms AND meet specific criteria 2 – testing of anyone showing COVID-19 symptoms 3 – open public testing
H3	Contact tracing	0 - No contact tracing 1 - Limited contact tracing - not done for all cases 2 - Comprehensive contact tracing - done for all identified cases
H6	Facial coverings	0 - No policy 1 - Recommended 2 - Required in some specified shared/public spaces outside the home with other people present 3- Required in all shared/public spaces outside the home 4- Required outside the home at all times

RESULTS

Additional Figures

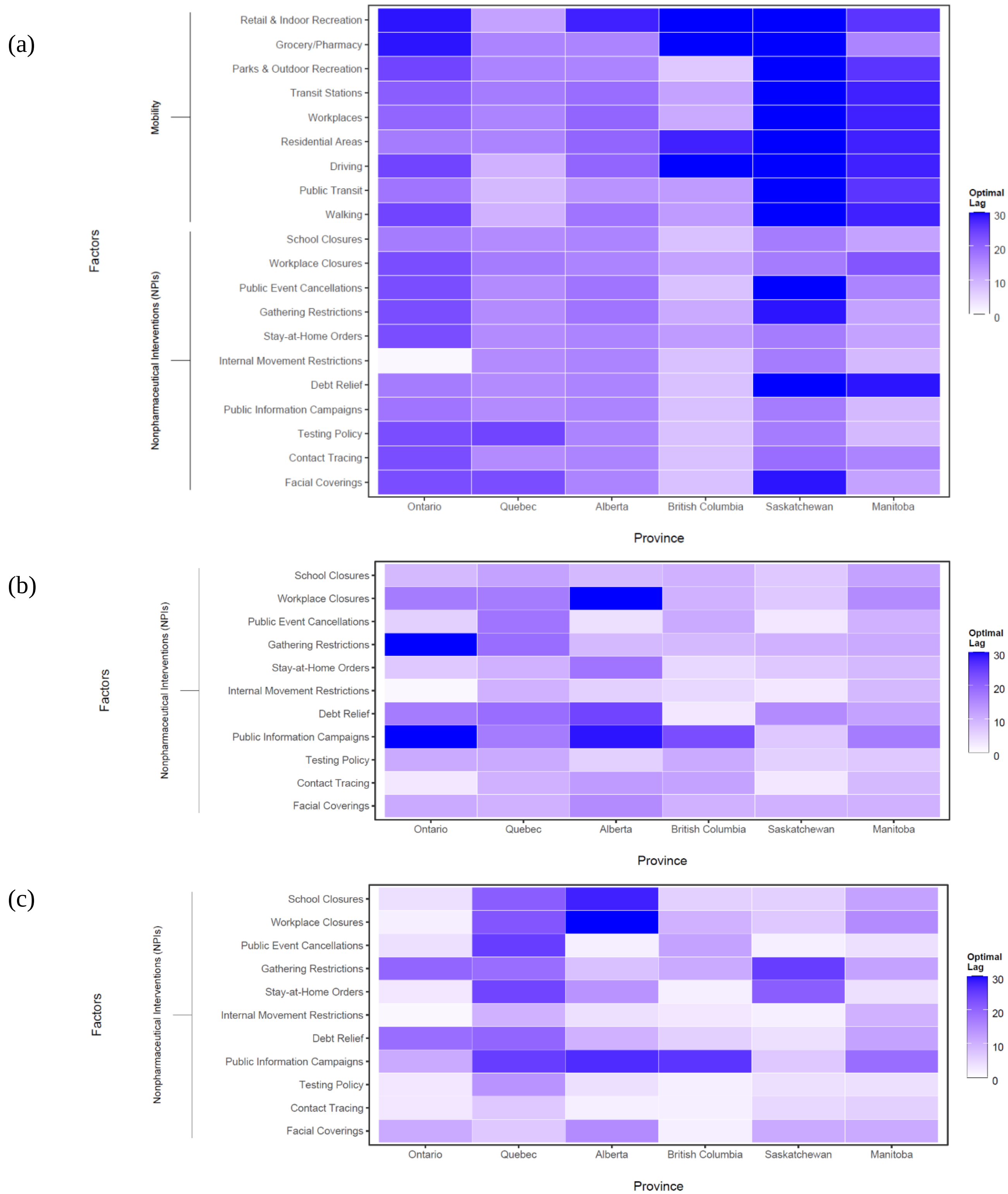

Figure A1. Selected optimal lags for Granger causality tests between (a) Daily cases and Mobility, NPIs, (b) Mobility towards residential areas and NPIs, and (c) Mobility towards grocery stores and pharmacies and NPIs.