**Quantifying the relationship between lockdowns, mobility, and effective reproduction number (Rt) during the COVID-19 pandemic in Ontario, Canada**

**Abstract**

**Background**: The COVID-19 pandemic and subsequent lockdown measures have led to increasing mental health issues in the general population.

**Objective**: We aimed to compare the effect of various lockdown interventions on mobility and the spread of COVID-19 in the public health units in Ontario, as measured by Rt (effective viral replication number over time).

**Methods**: Weekly effective reproduction number (Rt) was calculated based on daily cases in each of the designated public health units. A combined mobility score for Ontario was calculated using Google Mobility data. Segmented regressions were used to determine changes in the behaviour of Rt.

**Results**:

**Conclusions**:

Keywords: COVID-19, lockdown, pandemic, psychiatric emergency

**Introduction**

During the COVID-19 pandemic, public health mandated lockdown measures have imposed lengthy restrictions on movement and social gatherings. The scope and intensity of such lockdowns have been heterogenous and varied widely between jurisdictions worldwide (Thomas 2021). Unsurprisingly, such restrictions have generated unprecedented controversy as their effects on the spread of infection are necessarily weighed against impositions on civil liberties (Wilder-Smith). Quantitative evaluations of the effectiveness of such measures in attenuating pandemic peaks are rapidly emerging (Islam 2020, Fong 2020, Brauner 2020, Flaxman, 2020).

Many lockdown studies lack a true counterfactual and merely suggest correlation between lockdown measures and temporally associated reductions in case counts (Edelstein 2020). The use of pre-intervention growth rates to define the success of interventions is limited by the recognition that epidemic curves are time varying and that slowing occurs through natural dynamics even in the absence of intervention (Bendavid 2020). Likewise, ecological studies suffer from confounding by both known and unknown factors, and enough comparisons exist to favour nearly any hypothesis. Furthermore, it remains unclear how pandemic curves might look based on social distancing recommendations alone rather than legal mandate. As a direct result, there has been intense public debate over whether lockdown measures should be more restrictive or rely on voluntary compliance.

Policy considerations, however, must balance the potential benefits of lockdowns against direct and indirect harms. In particular, extraordinary evidence of efficacy is required to justify restrictions on movement and assembly in liberal democratic societies (Fong 2020; Bensimon 2007; Kass 2001). In addition, mandatory restrictions may further isolate the marginalized, elderly, and those living alone.

A previous study in Australia (Wang 2020) compared mobility and effective viral reproductive number (Rt) before and after lockdown measures, in order to assess their relationship. We conducted a similar analysis, with the intention of using anonymized and aggregated regional Google mobility reports, which use a GPS-linked index of visits and length of stay compared to the pre-pandemic baseline January 3 to March 1, 2020. This quasi-natural experiment compares the effect of lockdown interventions on mobility and the spread of COVID-19 in public health units within the Greater Toronto Area (GTA), a densely populated urban area within Ontario, Canada as measured by Rt.

**Methods**

Ontario is divided into 36 public health units (PHUs) that administer public health services, and of those, Peel (PEL), Toronto (TOR), York (YRK), Halton (HAL), and Durham (DUR) compose the Greater Toronto Area (GTA), the most densely populated contiguous region in Canada with 6.4 million total inhabitants (548,430 in Halton, 645 862 in Durham, 1,381,744 in Peel, 1,109,909 in York, 2,731,571 in Toronto) (StatsCan). After November 7, 2020, Ontario imposed a variable colour-coded approach to regional public health restrictions (**Table 1**), allowing direct comparison of their effectiveness in reducing Rt.

Table

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**Table 1**. Lockdown restrictions as described by the colour-coded five-stage COVID-19 framework implemented in Ontario on November 7, 2020. Prior to November 7, provincial stage 1, stage 2, and stage 3 restrictions were treated as red, orange, and yellow, respectively.

Official COVID-19 data (daily PCR-confirmed cases) from March 1, 2020 to March 8, 2021 (14 days following the return to Ontario’s colour-coded restriction framework) were obtained at the level of the five PHUs from https://covid-19.ontario.ca/data run by Public Health Ontario. Estimates of the effective reproduction number (Rt) at the PHU level were calculated using the EpiEstim R package calculator, found at https://github.com/alechay/covid19-rt/tree/master.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Toronto | Peel | York | Durham | Halton |
| 14-Mar |  |  |  |  |  |
| 14-May |  |  |  |  |  |
| 15-Jun |  |  |  |  |  |
| 22-Jun |  |  |  |  |  |
| 12-Aug |  |  |  |  |  |
| 10-Oct |  |  |  |  |  |
| 19-Oct |  |  |  |  |  |
| 07-Nov |  |  |  |  |  |
| 16-Nov |  |  |  |  |  |
| 23-Nov |  |  |  |  |  |
| 14-Dec |  |  |  |  |  |
| 26-Dec |  |  |  |  |  |
| 16-Feb |  |  |  |  |  |
| 22-Feb |  |  |  |  |  |
| 19-Mar |  |  |  |  |  |

**Figure 1**: Graph of PCR-confirmed cases in the five public health units in the Greater Toronto Area during the first and second pandemic wave. The shaded areas indicates the colour coded levels of lockdown.

Google Daily Mobility Reports (Google 2020) were collected for each PHU for workplaces, residential, parks, grocery and pharmacy, retail and recreation, and transit stations. A global mobility index (GMI) similar to that used in a previous Australian study (Wang 2020) was calculated to represent global mobility change, as the mean of each type of mobility *i*in a day *t*:

GMI(t)=∑6i=1Mobilityi/6.

Segmented regressions were used to identify breakpoints in the behavior of Rt over time (and shifts in COVID-19 transmission trends) for each of the PHUs. Regressions were based on zero to eight breakpoints, using discrete regression segments with at least five data points per segment. Intercepts and slopes were calculated for the best model, using separate intercepts at each different segment, allowing for separate identification of increases or decreases in Rt, and sudden jumps or plunges in daily values.

Median incubation period is 5.8 days, and 97.5% of COVID-19 patients develop symptoms within 11.7 days of infection (McAloon 2020). Therefore, we selected three scenarios to account for reporting delays from illness onset, testing, and incubation—immediately following policy change, 7 days following policy change, and 14 days following policy change—to relate policy change and mobility change to Rt. We calculated correlation between GMI (and each of the 6 types of mobility) and Rt for each PHU via ordinary least squares regression, accounting for time lag:

COVs,t=αS+βiMobi, s,t−n+γt+εs,t (n = 0, 1,…, t − 1)

COV is Rt on date t. Mobi denotes each type i (i=1, 2…6) of mobility; and Mobi, s,t−n is the mobility index in PHU s on the date (t − n). n equals 0, 7, and 14. βi is the standardised coefficient for each type of mobility; ε is the standardised error; αS denotes the fixed place effect of state s and γt denotes the fixed date effect for a transmission period after date t.

We calculated magnitude and significance of each coefficient, indicating association between COVID-19 spread and mobility. We also calculated fixed place effect and fixed date effect, to denote variations in unobserved confounders on viral spread. Calculations were made using *R*, with code available on GitHub.

Temporal autocorrelation (caused by dependence of measuring units, confounding factors) could bias estimates and standard errors. To assess its effect, we calculated standardized residuals and used them to create plots relating the autocorrelation factor– against lag) up to 20 days.

If autocorrelation was detected at certain lag values, effect corrected on model parameters and significance levels by refitting the model incorporating the residuals into the linear predictor. If autocorrelation was detected at more than one lag, we refitted all models with one, two or three lags, and chose the one for which no improvement in model fit was obtained.

**Results**

**Figure 2** indicates the changes in the rate of spread (Rt) in each PHU based on increasing or decreasing lockdown restrictions. The most rapid decline in Rt occurred just prior to initiation of the first province-wide lockdown, and the decline continued during the first lockdown period. Rt increased in the selected PHUs during the summer months as restrictions were decreased. During the red restrictions, Rt decreased in Peel, and paradoxically increased in Toronto and York. During the grey lockdown period, transmission decreased in the province and in all five PHUs tracked.

The GMI in all PHUs in the GTA decreased with the first lockdown (**Figure 3A**) and showed weekly cycles with outliers on public holidays. GMI did not decrease further with increased restrictions and began to increase even before restrictions were loosened. This trend to increased mobility continued into the summer, then remained stable between July and September. The increase in GMI was largely the result of increased mobility to recreational spaces. GMI decreased after September and continued to decrease at the same rate when restrictions were reintroduced.

The greatest mobility decreases (**Figure 3B**) were seen to retail, transit stations, and workspaces, while mobility to residence increased. Mobility to groceries and pharmacies were largely unchanged throughout the observation period.

**Chart

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**Figure 2**. Segmented regressions and effective reproduction number (Rt) of the COVID19 pandemic in five public health units in the Greater Toronto Are. Breakpoints are indicated as dotted lines. Blue and red lines are segments with significant increases and decreases in Rt. Global mobility index (GMI) by Greater Toronto Area public health unit (PHU), with public health interventions indicated

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**Figure 3**. Six types of mobility for five public health units in the GTA, with colour-coded public health interventions indicated.

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**Figure 4**. Correlation between global mobility index (GMI) and Rt over three periods of time with increasing public health restrictions.

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**Figure 5**. Regression coefficients of each type of mobility in each of five public health units in the Greater Toronto Area over three periods of time (right after, 7 days after the lockdown date, and 14 days after the lockdown date).

The correlation coefficients between global mobility and Rt in the second wave are positive in all PHU (**Figure 4**), indicating that higher mobility is associated with higher growth rates. The magnitude of correlation coefficients increases after lockdown and was significant (p<0.05) in all PHUs fourteen days after lockdown, reflecting that the incubation period brings in a time-lag effect of human mobility on growth rates. There was no substantial change in the magnitude of correlation over time. The relationship between growth rates and mobility varied.

**Figure 5** compares the regression coefficients of each type of mobility in the province and each PHU over three periods of time (immediately after, 7 days after lockdown, and 14 days after lockdown). Rt has a significant negative association (p < 0.01) with mobility to retail/recreation immediately after lockdown and with mobility to workspaces from seven to 14 days after lockdown; while mobility to transit stations is positively (p < 0.01) associated with Rt across three periods of time, indicating that higher transit usage is linked to higher growth rates. The link is stronger after seven-days and 14-days, reflecting the time lag effect of mobility on spread and the delay of policy intervention.

**Discussion**

Using COVID-19 data and Google mobility data, our study relates human mobility, social restriction policies, and COVID-19 spread in Ontario. Our analysis was nearly identical to that performed in an Australian study (Wang) but had contrary results. Due to the differences in transmission dynamics and confounders, however, we interpret our findings with caution and link them to the empirical experiences in other countries.

Visual inspection of cases and mobility level alongside the timeline of policy interventions suggests that the lockdown policies as implemented were ineffective in decreasing spread, and the observed decline in human mobility was not accompanied by a corresponding drop in Rt. This challenges the fundamental association between lockdown orders and virus transmission. Overall mobility remained low even after restrictions were lifted. There were imperfect correspondences between restrictions and spread, with mobility declining prior to restrictions, similar to observations in the Sweden, South Korea, Australia, and the United States (Gupta 2020; Tran 2020).

Mobility has a 7 to 14-day time lag effect on spread, reflecting the relationship with viral incubation. The results suggest a dynamic association between mobility and COVID-19 spread, which varies across space and time. Similar local findings have been reported in New York City (Kissler 2020), where decreased commuting movements between boroughs as measured by Facebook mobility data was negatively correlated with prevalence. Preliminary suggests the same is true internationally, where a suggestive but inconsistent relationship between mobility and virus spread may also be affected by individual preventative behaviours such as social distancing, hygiene, and mask wearing (Bergman 2020). Changes in weather conditions could also weaken the association between mobility and virus spread. There were more mixed patterns of mobility-spread correlation after the initial lockdowns, which might reflect diminishing effects due to lockdown fatigue.

*Limitations*

First, Google data uses 3 January to 6 February 2010 as baseline, resulting in biases in contexts where human mobility declined as early reaction to the appearance of COVID-19 in media reports. Second, it is possible that GMI should be weighted to account for the inherent risk level of each mobility type. If workspace mobility is higher risk than mobility to parks, it would be reasonable to assign a higher weight to the former. There are several types of delays to consider that might bias these results: 1) delay between the mobility measure and the date of confirmed cases, 2) the reporting delay from the illness onset date, and 3) delay introduced by incubation and testing. Google data is also a coarse proxy for mobility and social distancing and relies on the movement of those who have a smart device (Gupta 2020).

estimated growth rate from the incidence date should account for the delay period to better quantify the impact of lockdown on the transmission dynamics.

The effects of lockdowns may also be confounded by simultaneous media messaging and voluntary changes in behaviour. Finally, the effects of such lockdowns can be positioned within the context of previous studies indicating a frequently paradoxical effect of more restrictive lockdowns in increasing transmission (Bendavid 2021, Santamaria 2020), which may ultimately depend on population density, household density, political climate, travel and border closures, as well as whether sectors of the economy closed by lockdowns are in fact major drivers of spread.

Our findings should be interpreted with caution, since they may not indicate causal direction between mobility control and virus spread. The dynamics of individual behavioural changes reflect the importance of government level supervision and policy implementation should last for a longer period of time to maintain its efficacy. Governments should consider the 14-day relationship between mobility and virus spread when reducing restrictions.

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