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Dynamics of Social Mobility during the COVID-19 Pandemic in Canada

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ABSTRACT

Dynamics of Social Mobility during the COVID-19 Pandemic in Canada

As the number of cases increases globally, governments and authorities have continued to use mobility restrictions that were, and still are, the only effective tool to control for the viral transmission. Yet, the relationship between public orders and behavioral parameters of social distancing observed in the community is a complex process and an important policy question. The evidence shows that adherence to public orders about the social distancing is not stable and fluctuates with degree of spatial differences in information and the level of risk aversion. This study aims to uncover the behavioural parameters of change in mobility dynamics in major Canadian cities and questions the role of people's beliefs about how contagious the disease is on the level of compliancy to public orders. Our findings reveal that the degree of social distancing under strict restrictions is bound by choice, which is affected by the departure of people's beliefs from the public order about how severe the effects of disease are. Understanding the dynamics of social distancing thus helps reduce the growth rate of the number of infections, compared to that predicted by epidemiological models.

JEL Classification: I20, I26, J24

Keywords: COVID-19, mobility, transmission, viral infections

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1. Introduction

As the number of cases increases globally, governments and authorities have continued to use mobility restrictions that were, and still are, the only effective tool to control for the viral transmission. Centers for Disease Control and Prevention defines these public responses as Nonpharmaceutical Interventions (NPIs): "actions, apart from getting vaccinated and taking medicine, that people and communities can take to help slow the spread of illnesses like pandemic influenza (flu)".[4] There are recent studies (Chen and Qiu 2020, Zang et al. 2020, Fang et al. 2020) investigating how effective lockdown policies are by looking at the daily incidence of COVID19 and mobility patterns. Although the evidence unambiguously indicates that implementing NPIs with successful social distancing measures have the largest effect on curbing the pandemic, in a recent study, Askitas et al. (2020) find that restrictions on internal movement, public transport closures and international travel controls do not lead to a significant reduction of new infections. They explain that the reason of this limited impact of mobility restrictions is due to the lack of stringency in the policy implementations.

As in any democratic system, the relationship between public orders and behavioral parameters of obedience to those orders observed in a community is a complex process and an important policy question. It is vital for public authorities to understand this relationship as well as how it manifests across time and regions. Mobility patterns show how effective the lockdown policies are to control for infectious disease spread. The evidence confirms that adherence to public orders about the social distancing is not stable and fluctuates with degree of spatial and temporal differences in information and the level of risk aversion. From a policy perspective, policy makers must understand the determinants of adherence to movement restrictions to analyze the efficacy of the public health orders in any given time and region, which will also help them prepare for the possible second wave of COVID19.[5]

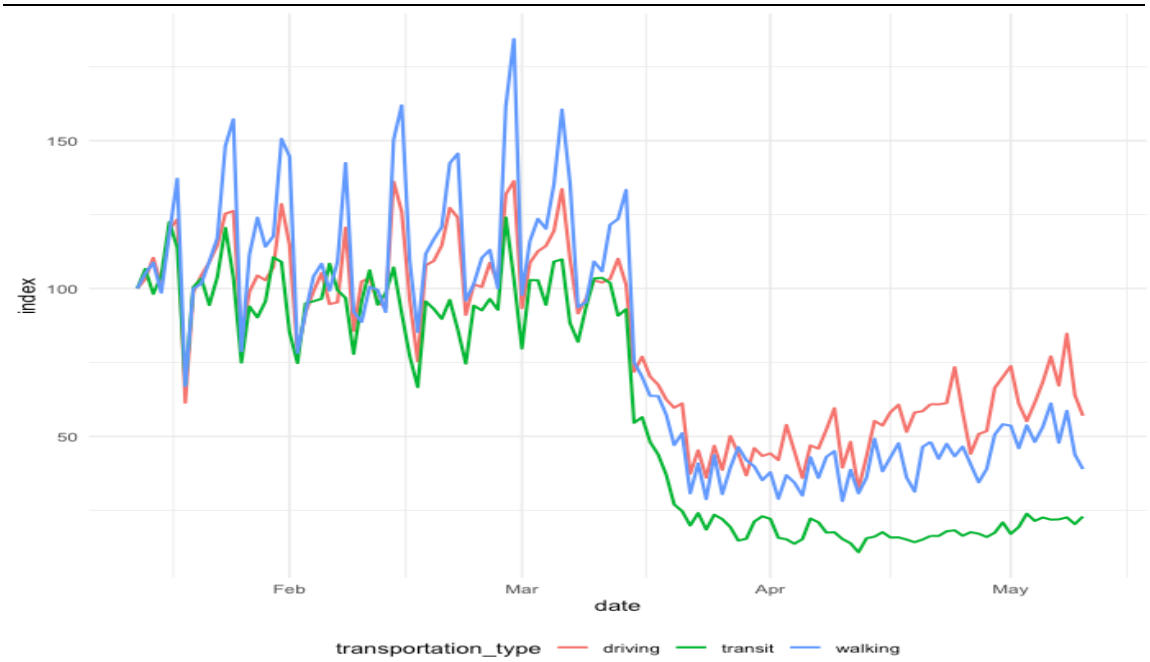
This study aims to uncover the behavioural parameters of change in mobility dynamics in major Canadian cities and questions the role of people's beliefs about

[4] https://www.cdc.gov/nonpharmaceutical-interventions/index.html

[5] Studies that have looked at a possible second wave of COVID-19 include Leung et al (2020).

how contagious the disease is on the level of compliancy to public orders. Traditionally, studies examining mobility have ignored individual-level spatial and temporal variation in where people spend time. More recently, these issues have been addressed using the concept of an individual's activity space (defined as encompassing all the locations a person interacts with over time), yielding a much more accurate picture of social mobility. In an effort to understand the COVID19 transmission due to movement, Google, Apple, and Facebook released their own interfaces to explore how much mobility has been impacted as a result of the states of emergencies that each province implemented. For instance, we show daily changes in three mobility modes before and after mobility restrictions in Halifax in Figure 1.

Figure 1: Apple Mobility Index - Halifax



Source: Authors' own calculations using Apple Community Mobility Report data

To the best of our knowledge, this is the first Canadian study that explores aggregated city level mobility data. We attempt to uncover how mobility modes such as daily changes in volumes of citizens using public transit have been impacted due to public sentiments that reflect the people's beliefs about how severe the effects of disease are by examining variables such as the previous day's case and death

count from COVID19. The study also controls for high-dimensional local weather conditions and removes unobserved spatial heterogeneity across cities. Our findings reveal that the degree of social distancing even under strict restrictions is bound by choice, which is affected by the departure of people's beliefs from the public order about how grim the crisis is. Understanding the dynamics of social distancing thus helps reduce the growth rate of the number of infections, compared to that predicted by epidemiological models.

The remainder of the paper is organized as follows: Section 2 introduces the data, accompanying descriptive summaries, and illustrations; Section 3 reports the estimation results and the discussions about the finding; and we provide the concluding remarks in Section 4.

2. Data

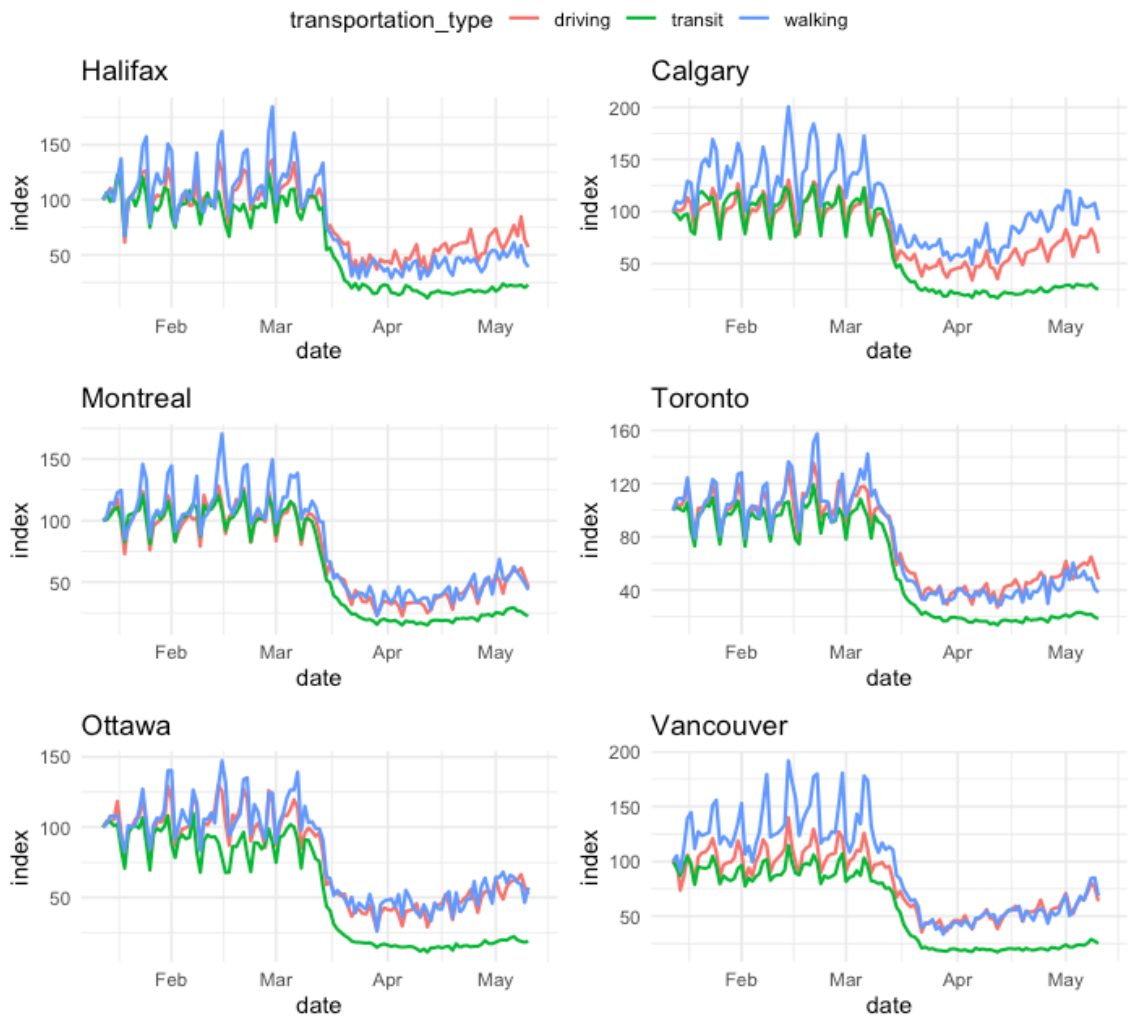
There are three types of data that are prerequisites in this study: mobility measures, local and high-dimensional weather metrics, and a proxy for a sentiment that reflects how the pandemic compromises our emotional stability and results in spatial and temporal deviance from or compliance with the public health order. All the sources represent unconventional, high-dimensional, and dynamic data structures with additional requirements for data management issues. The following subsections will give the details of these data sources and illustrate the information structures that each source offers.

2.1 Mobility Data

In April, regional mobility trends were made available for public use by Apple, Google, and Facebook to aid COVID19 efforts. This is the first time in history that one can publicly access the data covering different modes and levels of people's mobility in daily frequency for more than 131 countries and major cities. All three providers commented on their websites that the availability of their data is temporary for a limited time during the COVID19 pandemic. Apple's Mobility Trends Report was released on April 14th by Apple, which is the main data source used in this paper. Apple provides a csv file (wide form) directly downloadable

from their dedicated website starting from January 13, 2020.[6] This anonymized data captures daily movement patterns across cities globally. The data provides the daily changes in volumes for driving, walking, and transit compared to the baseline volume indexed to 100 on the first date of observation (January 13) for a given mode of transport. The following six graphs shows the mobility trends for six cities.

Figure 2: Apple Mobility Index – All Six Cities



Source: Authors' own calculations based on Apple Community Mobility data

[6] https://www.apple.com/covid19/mobility

Google also provides regional Community Mobility Reports mobility trends to *help researchers look into predicting epidemics, plan urban and transit infrastructure, and understand people's mobility and responses to conflict and natural disasters.*[7] Although the data provide more detailed modes of mobility including retail, grocery, parks, transit, workplaces and residential, Google does not provide disaggregated city-level data for Canada. This level of aggregation at the provincial level masks important geotemporal differences specially for larger provinces.

Figure 3: Google and Facebook – Nova Scotia

Source: Authors' own calculations based on Google and Facebook mobility data

[7] https://www.google.com/covid19/mobility/

Finally, Facebook's Movements Range Data is released in their website[8] stating that the data *inform researchers and public health experts about how populations are responding to physical distancing measures.* The Facebook data is the only data in finer spatial scales, at the county-level. Hence. the size of the data is big without any level of aggregation at the provincial level. These datasets have two different metrics: Change in Movement and Stay Put. The Change in Movement metric looks at how much people are moving around and compares it to a baseline period that predates most social distancing measures. The Stay Put metric looks at the fraction of the population that appears to stay within a small area surrounding their home for an entire day. We provide an illustration in Figure 3 to give a better idea how Google and Facebook (Change in Movement) data look like.

As it appears in these three mobility datasets, there is a trade-off between the level of information on mobility details and the level of spatial aggregation. Therefore, the ideal data for our work would be the Apple data with a city-level aggregation and just-enough details in mobility modes.

2.2 Weather Data

Although the historical climate data can be obtained from multiple sources, it requires a substantial amount of time and effort to select the right one. These sources compile the information based on physical weather stations located in different sections in the region. The most reliable data with minimum missing values are from stations that are located at the airports and many studies use their values for the cities. We have tried multiple data sources such as **Climate Data Extraction Tool** from the Government of Canada's website[9], and **Air Quality Open Data Platform**[10], which provides a worldwide weather and air quality dataset specially organized for researches on the COVID-19 pandemic. Data collection is based on the physical weather stations located in different sections in the city. Because the most reliable data with minimum missing values are from stations that are located at the airports, we use their values for the cities. The

[8] https://data.humdata.org/dataset/movement-range-maps

[9] https://climate-change.canada.ca/climate-data/#/daily-climate-data

[10] https://aqicn.org/data-platform/covid19/verify/a1e436e6-5829-4b50-bfb3-82d2f4865d7c

most reliable weather data, however, is provided at **WeatherStats.ca**.[11] Their **Weather Data Dashboard** reports high-dimensional high-frequency data based on their own forecasting algorithms. Their data are collected over time from Environment and Climate Change Canada as well as Citizen Weather Observer Program (CWOP). The data contains 70 unique meteorological metrics for each city. The details are provided in Appendix.

2.3 COVID-19 Data

The data on COVID-19 for Canada was taken from the R package **CanCovidData** written by Von Bergmann (2020)[12]. We used the provincial data as a proxy for COVID-19 sentiment in major Canadian cities. Their data lines up with the official updates from the Public Health Agency of Canada. Table 1 below provides the most updated numbers for each province:

Table 1: COVID-19 pandemic in Canada by province (June 13)

Province	Population	Tests	Cases	Recov.	Deaths	Active
British Columbia	5,110,917	165,256	2,709	2,354	168	187
Alberta	4,413,146	325,149	7,346	6,811	159	346
Saskatchewan	1,181,666	54,508	663	627	13	23
Manitoba	1,377,517	55,255	301	289	7	5
Ontario	14,711,827	953,015	31,726	26,187	2,498	3,041
Quebec	8,537,674	515,673	53,666	20,823	5,148	27,695
New Brunswick	779,993	36,125	154	125	1	28
Prince Edward Island	158,158	8,463	27	27	0	0
Nova Scotia	977,457	48,787	1,061	995	62	4
Newfoundland and Lab.	521,365	14,256	261	256	3	2
Canada	**37,894,799**	**2,178,345**	**97,943**	**58,513**	**8,049**	**31,371**

Source: https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Canada

We are aware that a sentiment analysis at diverse temporal and spatial scales is not a simple task and the use of cases or deaths as a proxy for the local sentiment on COVID19 pandemic would be problematic. One of the essential issues is that

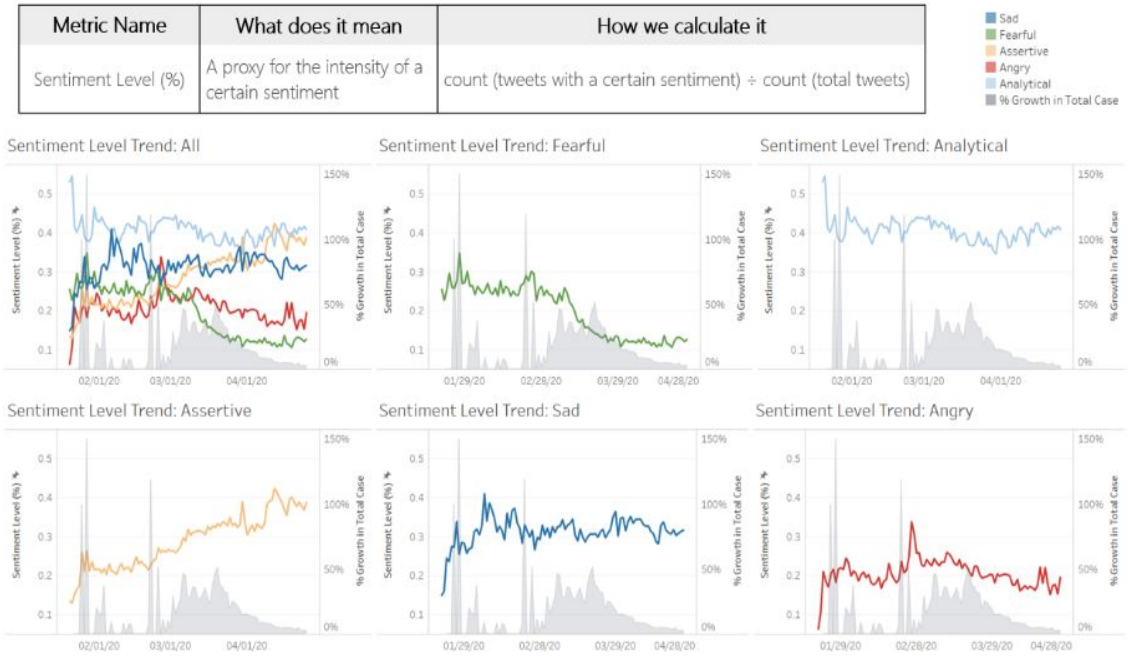
[11] https://www.weatherstats.ca

[12] https://mountainmath.github.io/CanCovidData/

even if the number of cases or deaths rises, it would be possible to observe that the people's feeling become positive. In a recent work, Yu et al.[13] mine the Twitter data for the content of COVID-19 related tweets to see how people's feelings and expressions changed over time during the pandemic in the U.S. Figure 4 below shows five segments of sentiment, one of which is fearfulness. As it is clear from the figure, even though the number of cases rises, people feel less fearful. In our estimations in the next section, we will comment on this fact.

Figure 4: Segments of Sentiment in the U.S due to COVID19 Pandemic

Metric Name	What does it mean	How we calculate it
Sentiment Level (%)	A proxy for the intensity of a certain sentiment	count (tweets with a certain sentiment) ÷ count (total tweets)



Source: https://public.tableau.com/profile/nanluo#!/vizhome/Book2_v2_15887433980520/SentimentLevel

3. Empirical framework and estimation results

3.1 Framework

Our empirical objective is to explore the sensitivity of the social mobility to local weather conditions and sentiment that reflects the people's feeling about beliefs on how contagious the disease is. Since the state of emergency rules do not change day by day, any significant effect of the weather conditions as well as the sentiment

[13] https://github.com/xxz-jessica/COVID-19_UCD_Challenge

that is captured by the lag values of pervious COVID19 cases (or deaths) on the local social mobility demonstrate the degree to which people's choice departs from the public order.

After merging all three data sources, we obtain an unbalanced long panel with six cities and about 420 observations between March 1 and May 10. Due to time dimension of the data, we applied several panel unit root tests (Breitung and Pesaran, 2008), and none of them indicated the existence of a unit root.

We start our analysis by estimating the determinants of the mobility discussed in data section. In these estimations, we utilize the pooled OLS, fixed effect and random effect models. These estimates further help us to calculate the weather elasticity of mobility, and sentiment elasticities of mobility. More specifically, we first estimate the following regression using pooled OLS for city i in a given day t:

$$Mobility_{it} = \alpha + \beta_1 sentiments_{it-1} + \beta_2 weather_{it} + \delta_i + dow_t + \varepsilon_{it} \qquad (1)$$

where $weather$ is a vector of seventy different measures of weather conditions listed in Appendix. We define our outcome variable, $Mobility_{it}$, separately in specification as transit, driving, and walking from the Apple data. In order to capture an overall mobility index, we also use two average values. First, since driving and transit indices generally move in opposite directions, they may cancel out each other. Therefore, the average of driving and transit may capture the overall daily mobility within the city. Second, we also use the total mobility, which is defined as the average of three modes of mobility. As for sentiments towards COVID19 in each city and day, we use the daily numbers of new deaths and new cases from the previous day, which is denoted by $sentiments_{it-1}$.Using the values from the previous day allows for the potential delays in announcements by health and provincial authorities. We control for city dummies, δ_i to account for the unobserved heterogeneity across cities. Finally, as illustrated in the graphs, all mobility measures exhibit cyclical daily trends. Hence, we control for these trends by adding day of the week dummies, dow_t.[14]

[14] We also tested time fixed effects for each day. Their addition does not improve the results, which are also rejected by a simple F-test.

As it is an ad-hoc empirical model, Specification (1) can be extended by the choice of variables and the introduction of nonlinearity with different levels of polynomials and interactions. In order to find the most explanatory weather variables among seventy different metrics, we applied penalized regression methods (LASSO) to reduce the high dimensionality in Specification (1). At the end of the process, very few weather variables are chosen as significant predictors. We used these variables as our base set and expanded it with different specifications. As for the nonlinearity, we applied several different non-parametric models (mostly ensemble learning algorithms and TensorFlow applications) and compared their predictive powers with the base and extended models. The results indicate that linear models with the selected weather variables can capture the essence of relationship between mobility metrics and the selected covariates.[15]

After these estimations, we calculated the average marginal effect of weather and sentiments at the means of other variables. Using these average marginal effects, we calculated the elasticity of daily cases of transit, driving, and walking. In a similar way, we calculated elasticity of temperature, and precipitation of mobility, and each city as well. Moreover, we calculated marginal elasticities at different level of sentiments, and weather conditions.

3.2 Results

We begin by estimating a fixed-effect model given in Equation (1) by using a dummy variable least square method. The objective of this estimation to investigate the association between the factors abstracted in the previous sections and the mobility of the local population within a city. The estimation results for each mobility mode are summarized in Table 2. For each mobility model, we define three specifications starting from a base model with maximum temperature and add precipitation amount and the minimum wind speed in the second and third specifications, respectively.

[15] The results of LASSO and nonparametric estimations and their scripts can be provided upon request.

Table 2. Estimations of transportation modes within city

Variables	Transit			Driving			Walking		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cases	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Temperature	-1.03**	-1.02**	-1.05**	-0.18	-0.18	-0.20	0.04	0.06	0.02
	(0.21)	(0.20)	(0.21)	(0.18)	(0.17)	(0.18)	(0.24)	(0.23)	(0.24)
Precipitation		-0.49*	-0.44		-0.55**	-0.50*		-0.92**	-0.84**
		(0.20)	(0.23)		(0.17)	(0.19)		(0.22)	(0.25)
Wind speed			-0.18			-0.18			-0.27
			(0.29)			(0.26)			(0.34)
Observations	420	420	420	420	420	420	420	420	420
R-squared	0.28	0.29	0.29	0.26	0.27	0.27	0.29	0.31	0.31

Robust standard errors clustered at the city-level are in parenthesis. Significance levels are (**) is $p < 0.01$ and (*) is $p < 0.05$. All specifications include city and day-of-week fixed effects. Cases represents the number of previous day's new COVID19 cases. Temperature measures the daily maximum temperature. Wind speed represents the daily minimum wind speed value. Precipitation is the daily total precipitation level.

The findings in columns (1-3) in Table 2 are consistent with expectations that the use of public transportation decreases when the number of COVID19 cases rises. Our results also indicate that the transit usage decreases when daily temperature increases. Similarly, an increase in precipitation also leads to a decline in the utilization of transit. However, wind does not have any statistical effect on transit usage.

In the following columns of Table 2, we further analyze the effect of the same factors on driving. We again find that a rise in COVID19 cases and more precipitation decreases the likelihood of driving. However, our results indicate that temperature does not have any effect on driving within a city. Similarly, in Columns (6-9), we show that cases and precipitation decrease walking, while temperature does not seem to be affecting the individual's decision to walk.

We next turn to investigate whether the combination of indexes, which could be a better measure of overall mobility, will yield different findings. The results are summarized in Table 3. In Columns (1-3), our main outcome for mobility is the average of transit and driving indices. A strong negative correlation between driving and transit during the pandemic indicates that people switch their mode of transportation without necessarily cutting back their overall mobility. Therefore,

averaging these two modes would provide a better index to measure the variation in social mobility. Following the same reasoning, in Columns (4-6), the main outcome is the average of three modes we used in our analyzes. Mainly, we are interested in capturing whether these modes of mobility act as substitutes or the changes in the local weather and sentiment affect people's overall mobility. Our results reveal that the number of cases, temperature, and precipitation lead to a decline in overall driving and transit use within a city. However, the effect of temperature becomes less robust when we include all transportation modes, which may indicate that people substitute using transit and cars with walking when the temperature increases.

Table 3. Estimations of mobility index within city

Variables	Average of Driving + Transit			Average of all modes		
	(1)	(2)	(3)	(4)	(5)	(6)
Cases	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Temperature	-0.61**	-0.60**	-0.62**	-0.39	-0.38	-0.41*
	(0.19)	(0.19)	(0.19)	(0.20)	(0.20)	(0.20)
Precipitation		-0.52**	-0.47*		-0.65**	-0.59**
		(0.18)	(0.21)		(0.19)	(0.22)
Wind speed			-0.18			-0.21
			(0.27)			(0.29)
Observations	420	420	420	420	420	420
R-squared	0.26	0.27	0.27	0.25	0.27	0.27

Robust standard errors clustered at the city-level are in parenthesis. Significance levels are (**) is $p < 0.01$ and (*) is $p < 0.05$. All specifications include city and day-of-week fixed effects. Cases denotes the number of previous day's new COVID19 cases. Temperature measures the daily maximum temperature. Wind speed represents the daily minimum wind speed value. Precipitation is the daily total precipitation level.

After examining what factors are significantly associated with the modes of mobility, we also quantify their impact. One convenient way to understand the magnitude of their effects is the elasticity of different modes of mobility with respect to weather and sentiment. More specifically, we show the percentage change of mobility when each factor changes by 1 percent.

In Table 4, we present the overall factor elasticities of different modes of mobility. All these elasticities are calculated using the most comprehensive specifications, which are the last columns of each modes of mobilities, presented in Table 2 and Table 3. Moreover, all these elasticities are calculated at the mean values of each control variable. In Column (1), we show that the elasticity of daily cases is -0.31, and the elasticity of the temperature is -0.25, and the elasticity of the precipitation is -0.03. Taken together, these elasticities demonstrate that each 1% increase in the number of cases in the previous day leads to a decline in the transit usage by 0.3%. To capture sentiments, we also use an alternative measure, the number of deaths in the previous deaths. The results are very similar as expected as cases and deaths are highly correlated. The correlation between these two measures are 0.86 and cannot be used in the same estimation. We present these results in appendix table 1 and 2.

Table 4. Elasticity of mobility modes

Variables	Transit	Driving	Walking	Mobility1	Mobility2
	(1)	(2)	(3)	(4)	(5)
Cases	-0.32**	-0.14**	-0.17**	-0.21**	-0.19**
	(-0.04)	(-0.02)	(0.02)	(0.03)	(0.02)
Temperature	-0.26**	-0.03	0	-0.11**	-0.07*
	(-0.05)	(0.03)	(0.01)	(0.04)	(0.01)
Precipitation	-0.03	-0.02*	-0.03**	-0.02*	-0.03
	(-0.01)	(0.00)	(0.00)	(0.03)	(0.03)

Robust standard errors are in parenthesis. **p<0.01, *p<0.05. Elasticities are calculated for previous day's cases, daily maximum temperature, and daily precipitation levels. Mobility1 is the average of 2 mobility modes (transit and driving). Mobility2 is the average of 3 mobility modes (transit, driving and walking).

The descriptive statistics illustrate that the average minimum transit index is 31 in Ottawa, while maximum is 37 in Calgary during the closure period compared to the baseline of 100. On the other hand, the average minimum driving index is 53 also in Ottawa, and maximum is 65 in Halifax. These indexes show a clear drop both in driving and transit usage after closures. Moreover, the average minimum of walking index is 54 in Toronto, and maximum is 88 in Calgary. These figures also demonstrate that there is a clear drop in walking in Toronto. However,

the extent of walking has not decreased too much in Calgary as it was not that high to begin with. All these indexes averages are around 100 before closures, and we present a detailed information on each index by city in Figure 2 above. Meanwhile, during the same period, the average number of cases was 320, temperature was 8.5 Celsius and precipitation was 2.2mm on average.

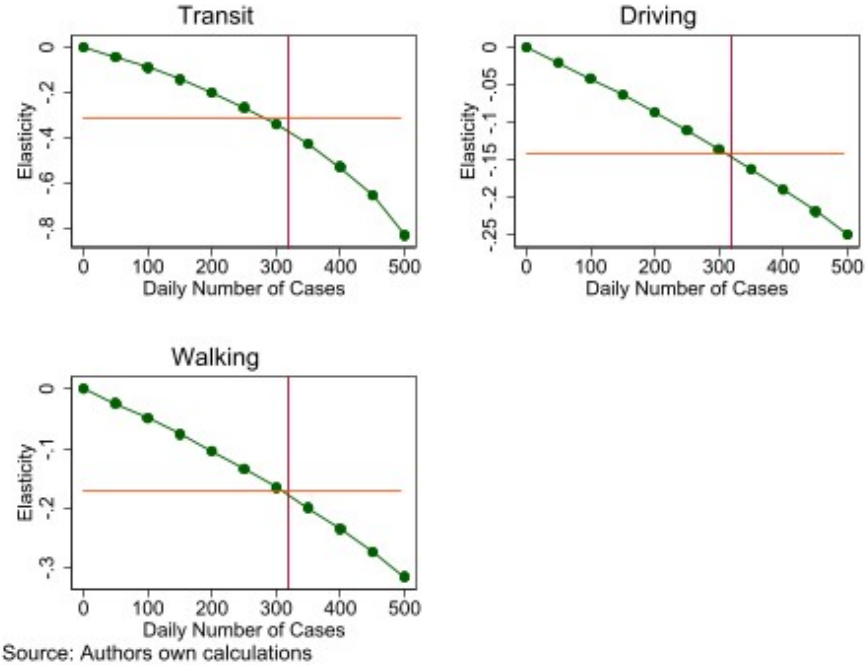
Using these values and elasticities presented in Column (1) of Table 4, we calculate the magnitudes in a more useful way for policy makers. When a given city has 10 more cases than average, transit usage decreases approximately by 1%. When temperature increases by 1Celsius than its average,8.5C, the transit decreases by 3%. When precipitation increases by 1mm, then transit decreases 1.4%.

In Figure 5, we present the daily number of previous cases' elasticity of different modes of transport. The horizontal lines represent the elasticity at the average value of variables, which are the coefficients in Table 4, while the vertical lines illustrate the average number of cases, which is used to calculate the aforementioned elasticities. As known, elasticities could be different over the varying number of cases. Alluding to this, we find in Figure 5 that the elasticity for each type of mobility significantly decreases when there is an upsurge in the number of cases.

In a similar way, Figure 6 demonstrates the temperature elasticities of transit, driving and walking at different level of temperatures. We find in Figure 6 that the elasticity of transit usage and driving is very conducive to the changes in temperature, where the intensity of both modes of transportation plunge with rising temperatures. Interestingly, the elasticity of walking is increasing with higher levels of temperature, and it turns to be positive when temperature is above 5 Celsius. Moreover, from figure 6, we clearly observe that when weather gets warmer people's tendency for walking also significantly rises as well.

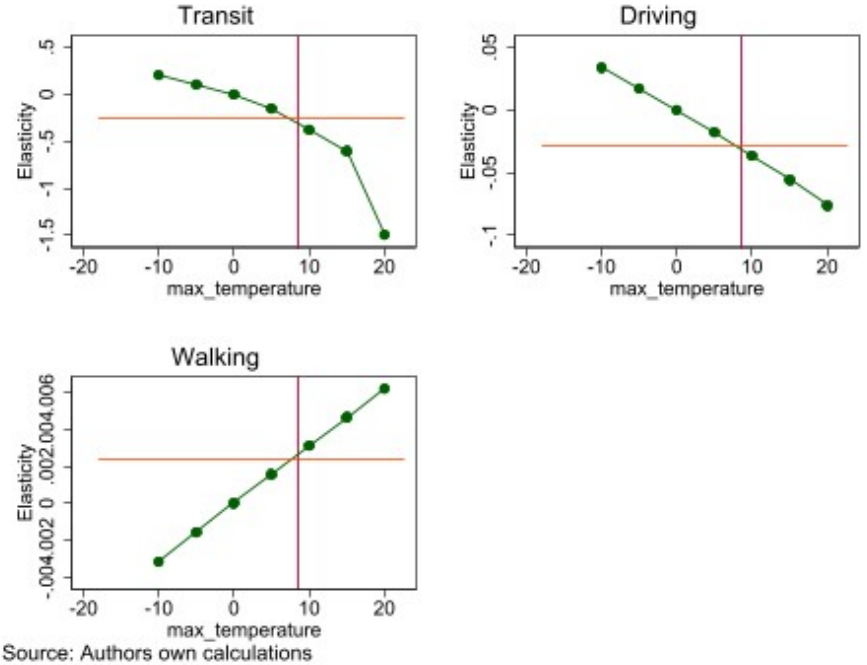
Finally, the precipitation elasticity of mobility is illustrated in Figure 7. As evident from the figure, these elasticities are negative and very small in magnitude when there is a light precipitation, less than 4mm. However, we also see in Figure 7 that all different types of mobility were affected negatively and substantially when precipitation amount exceeds 5mm.

Figure 5: Average Marginal Elasticities by Cases



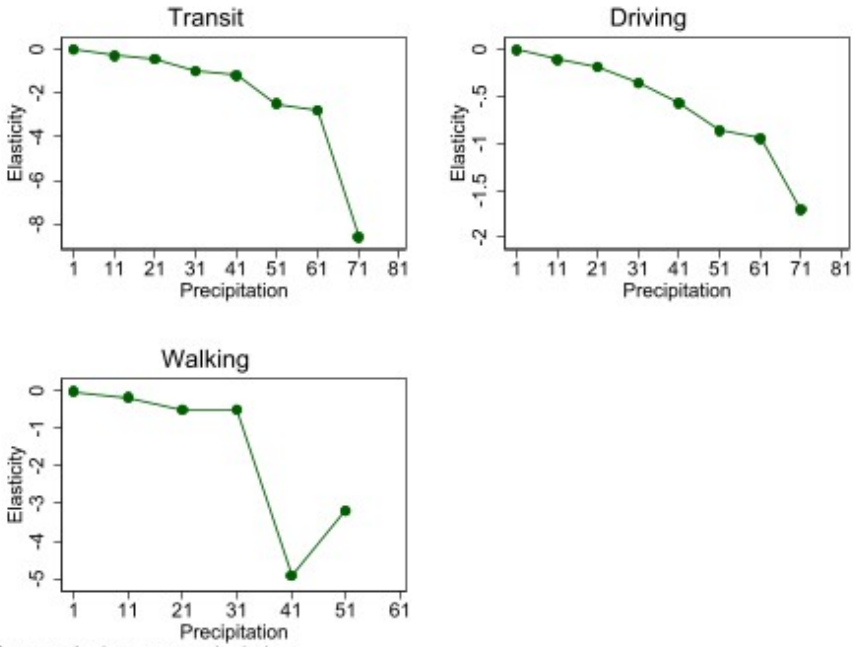
Source: Authors own calculations

Figure 6: Average Marginal Elasticities by Temperature



Source: Authors own calculations

Figure 7: Average Marginal Elasticities by Precipitation



Source: Authors own calculations

4. Conclusion

The COVID19 outbreak has been recorded in more than 200 countries with several millions of confirmed cases and around seven percent mortality rate. In the later stages of the epidemic, after failing to "trace" each infection back to its origin, nonpharmaceutical interventions - commonly referred as "social distancing" or "lockdown" policies - were undertaken. The aim of these interventions was to slow down the pandemic by limiting the level of mobility and to keep health system capacities serviceable. Mobility restrictions were, and still are, the only effective tool to control for the viral transmission.

Although the evidence unambiguously indicates that implementing NPI's with successful social distancing measures have the largest effect on curbing the pandemic, they do not lead to a significant reduction of new infections due to the lack of stringency in the policy implementations. The adherence to public orders about the social distancing is not stable and fluctuates with degree of spatial differences in information and the level of risk aversion. Understanding the dynamics of social distancing thus helps reduce the growth rate of the number of infections, compared to that predicted by epidemiological models.

This study aims to uncover the behavioural parameters of change in mobility dynamics in major Canadian cities and questions the role of people's beliefs about how contagious the disease is on the level of compliancy to public orders. We attempted to uncover how mobility modes have been impacted due to public sentiments as well as

weather conditions. The panel structure of the data allowed us to remove unobserved spatial heterogeneity across cities so that our findings reveal how the degree of social distancing measured by three modes of mobility are associated with their major determinants.

All results indicate that the sentiment proxied by the number of daily COVID19 cases has a strong impact on all modes of mobility. Among the seventy different weather metrics, we find only three variables, temperature, precipitation, and wing speed, have significant effects on the level of local mobility. Moreover, we document sizable elasticities of mobility modes with respect to case numbers, temperature and precipitation suggesting that individual's mobility decision indeed is conducive to these factors. Thereby, the future public health interventions could potentially incorporate such responses in the design of their policies. Our results further allude to varying elasticities between modes of transportation and factors contributing these decisions depending on their levels. More specifically, we find that elasticities for each mode of transportation increases by an increasing COVID19 cases, temperature, and precipitation.

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Appendix

Table A.1 Effect of different factors on modes of transportation within city

Variables	Transit			Driving			Walking		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deaths	-0.18**	-0.18**	-0.18**	-0.09**	-0.10**	-0.10**	-0.15**	-0.16**	-0.16**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Temperature	-1.25**	-1.23**	-1.27**	-0.43*	-0.41*	-0.45*	-0.22	-0.19	-0.24
	(0.21)	(0.21)	(0.22)	(0.18)	(0.18)	(0.19)	(0.25)	(0.24)	(0.25)
Precipitation		-0.47*	-0.40		-0.52**	-0.45*		-0.90**	-0.80**
		(0.21)	(0.24)		(0.17)	(0.20)		(0.22)	(0.26)
Wind speed			-0.24			-0.24			-0.33
			(0.32)			(0.28)			(0.36)
Observations	414	414	414	414	414	414	414	414	414
R-squared	0.17	0.17	0.18	0.15	0.16	0.16	0.20	0.22	0.22

Robust standard errors are in parenthesis. **p<0.01, *p<0.05. All columns are controlled for city and day of the week fixed effects. Temperature represents the daily maximum temperature. Wind speed represents the daily minimum wind speed value. Precipitation represents the daily total precipitation level.

Table A.2 Effect of different factors on alternative measures of transportation within city

Variables	Average of 2 mobility modes			Average of 3 mobility modes		
	(1)	(2)	(3)	(4)	(5)	(6)
Deaths	-0.13**	-0.14**	-0.14**	-0.14**	-0.15**	-0.15**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Temperature	-0.84**	-0.82**	-0.86**	-0.63**	-0.61**	-0.65**
	(0.20)	(0.20)	(0.20)	(0.21)	(0.21)	(0.22)
Precipitation		-0.49**	-0.43*		-0.63**	-0.55*
		(0.19)	(0.22)		(0.19)	(0.23)
Wind speed			-0.24			-0.27
			(0.30)			(0.32)
Observations	414	414	414	414	414	414
R-squared	0.14	0.15	0.15	0.14	0.15	0.15

Robust standard errors are in parenthesis. **p<0.01, *p<0.05. All columns are controlled for city and day of the week fixed effects. Deaths represent number of previous day's new deaths. Temperature represents the daily maximum temperature. Wind speed represents the daily minimum wind speed value. Precipitation represents the daily total precipitation level.

Table A.3 : List of Weather Variables

maximum temperature	heating degree days
average hourly temperature	cooling degree days
average temperature	growing degree days base 5
minimum temperature	growing degree days base 7
maximum humidex	growing degree days base 10
minimum windchill	precipitation
maximum relative humidity	rain
average hourly relative humidity	snow
average relative humidity	snow amount on ground (cm)
minimum relative humidity	time of sunrise
maximum dew point	time of sunset
average hourly dew point	amount of daylight
average dew point	sunrise forecast
minimum dew point	sunset forecast
maximum wind speed	minimum UV forecast
average hourly wind speed	maximum UV forecast
average wind speed	minimum high temperature forecast
minimum wind speed	maximum high temperature forecast
maximum wind gust	minimum low temperature forecast
wind gust direction speed	maximum low temperature forecast
maximum sea pressure	solar radiation
average hourly sea pressure	maximum cloud cover 4 oktas
average sea pressure	average hourly cloud cover 4 oktas
minimum sea pressure	average cloud cover 4
maximum station pressure	minimum cloud cover 4
average hourly station pressure	maximum cloud cover 8 oktas
average station pressure	average hourly cloud cover 8 oktas
minimum station pressure	average cloud cover 8
maximum visibility	minimum cloud cover 8
average hourly visibility	maximum cloud cover 10 oktas
average visibility	average hourly cloud cover 10 oktas
minimum visibility	average cloud cover 10
maximum health index	minimum cloud cover 10
average hourly health index	
average health index	
minimum health index	

Source: https://www.weatherstats.ca/