SPATIOTEMPORAL SOCIODEMOGRAPHIC ANALYSIS OF COVID-19 CASE RATES AND MOBILITY IN TORONTO NEIGHBOURHOODS

by

Jack Forsyth

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Spatiotemporal socioeconomic analysis of COVID-19 case rates and mobility in Toronto neighbourhoods.

Jack Forsyth

Master of Spatial Analysis 2021

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Ryerson University

ABSTRACT

The COVID-19 pandemic has had drastic impacts on the life and livelihood of all Canadians, but research has found marginalized populations have been disproportionately impacted. To better understand the differentiating socioeconomic characteristics between neighbourhoods in Toronto, Canada that experienced excessive impacts on COVID-19 case rates, this study integrated hot spot analyses with a mobile device-derived mobility indicator measuring neighbourhood-level time away from home, demographic variables, and a marginalization index. Hot spots were in more materially deprived neighbourhood clusters where there were more essential workers and residents spent more time away from home. Short term policies to enable marginalized communities to follow government stay-at-home recommendations such as paid sick leave and improved access to testing could mitigate disproportionate impacts experienced in these neighbourhoods. These findings can be used for more equitable response in future public health crises, and support prioritization of resources to disadvantaged populations that were worst affected by COVID-19.

Keywords: mobility, COVID-19, hot spot analysis, marginalization, neighbourhood health

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1. Introduction

The unprecedented scale of health, social, and economic repercussions caused by the COVID-19 pandemic has had an extraordinary impact on global society. Canada's first documented case of the virus occurred on January 21, 2020 in Toronto, Ontario, and in the ensuing months public health officials implemented various non-pharmaceutical interventions (NPIs) to limit the strain on the healthcare system and "flatten the curve" of the epidemic ("Novel coronavirus in Canada", 2020). Although NPIs have been shown to be effective, communities' ability to adhere to these policies can range greatly due to socioeconomic realities (Kavanagh, Goel, & Venkataramani, 2020). Since the outset of the pandemic, spatial analysis techniques powered by novel data, such as device-level mobility indicators, paired with sociodemographic data have provided researchers an additional lens with which to investigate the geographic distributions of COVID-19 hotspots and social distancing (Badr et al., 2020; Huang et al., 2021a; Lou, Shen, & Niemeier, 2020). However, to date, limited research has been conducted in Canada on the spatiotemporal socioeconomic variations in how mobility reductions occurred in neighbourhood-level areas and which communities were disproportionately impacted by COVID-19.

This research project aims to develop an understanding of how COVID-19 case rates and reductions in mobility transpired in Toronto's neighbourhoods and the corresponding socioeconomic characteristics at various phases of the pandemic. To develop this understanding, the primary research question that must be addressed is: What are the similarities and differences, based on socioeconomic analysis and mobile device-derived mobility indicators, between neighbourhoods in Toronto that have been disproportionately impacted by incidence of COVID-19? The two primary research objectives for this analysis are as follows: 1) to investigate the spatial clustering pattern of physical distancing and COVID-19 cases in the city of Toronto and their relationships with marginalized populations, and 2) to identify the most relevant socioeconomic characteristics that relate to human mobility and COVID-19 case rates in Toronto's neighbourhoods during different phases of the pandemic. This research combines these methods in the Canadian context to empower policy making and provide a deeper understanding of the social determinants of health in Toronto during the COVID-19 pandemic.

2. Research context

To contextualize this research within the existing academic literature and identify the methods and data common in similar analyses, this section summarizes information into two themes: COVID-19 and device-level mobility data, and neighbourhoods and health. Each of these constitute major fields of study, so are placed only in context most relevant to the research question and objectives outlined in the introduction.

2.1 COVID-19 and device-level mobility data

During the pandemic, policy makers enacted NPIs to alter various behaviors, ultimately aimed at reducing contact rates among populations and thus reducing virus transmission (Ferguson et al., 2020). A fast-growing body of literature has developed that has investigated and quantified the impacts of NPIs, such as encouraging physical distancing, closing non-essential businesses, enacting stay-at-home orders, and regional lockdowns, by using mobile device-derived mobility indicators (Oliver et al., 2020). Physical distancing, which is keeping distance from others and reducing activities outside the home, has frequently been the focus of these studies ("Physical distancing", 2020). The primary goal of physical distancing is to reduce the number of contacts in a population, thereby reducing the reproductive number, R, which represents the expected number of secondary transmissions from an infected individual, below 1 (Ferguson et al., 2020). The ability to practice physical distancing is highly reliant on sociodemographic characteristics (Winskill et al., 2020). Low-income populations have a higher probability of death compared to their richer counterparts and are often unable to follow physical distancing policies due to employment in jobs that do not allow for proper physical distancing protocols. Individuals' perception of risk has also been found to strongly correlate with practicing physical distancing and varies greatly based on their culture, values, and prior personal exposure to the virus (Dryhurst et al., 2020). Since risk perception is rooted in culture and lived experience, there is an important spatial component to how different regions follow various NPIs.

Many physical distancing studies have used mathematical modelling to simulate the effects of reductions in contact rates in affected populations. In a historical context, the 1918 Spanish influenza pandemic has many parallels with the modern outbreak. Bootsma and Ferguson (2007) evaluated the effects of physical distancing in 16 American cities and demonstrated that the NPIs reduced peak mortality by more than 40% in most cities. More recent studies are increasingly including population-level movement data on behavioral change and are effective at modelling outbreak trajectories by incorporating data on disease characteristics, public health policies, and estimates based on census and survey data collected in previous years (Price & van Holm, 2020; Flaxman et al., 2020; Kim & Kwan, 2021a; Leung, Wu, & Leung, 2021; Maroko, Nash, & Pavilonis, 2020). Research utilizing movement data derived from mobile devices from technology companies like Apple (Apple, 2021) and Google (Google, 2021) have made it possible to quantify physical distancing in near real-time by measuring time spent away from home, routing requests, or visits to specific points of interest such as parks and grocery stores.

Recent research has made mobility data meaningful by directly comparing the effects of physical distancing on case counts. Vollmer et al. (2020) were able to embed mobility modelling into their epidemiological forecasts by using it to parameterize COVID-19's reproductive rate. These kinds of data have also been successfully applied to modelling data-driven R values for improved disease forecasting (Sharkey & Wood, 2020; Vollmer et al., 2020). The most common form of mobility data are proxies for physical distancing, but other applications such as origin-destination matrices can supplement or replace traditional commuting data that would typically be used in modelling the relationships between cities (Tizzoni et al., 2014). This form of data is particularly useful when monitoring when and how populations react to NPIs in near real-time, and to maintain a baseline understanding of connectivity despite substantial travel disruptions.

One of the primary concerns with utilizing mobility data is sampling bias and the inability to quantify that bias (Lansley, de Smith, Goodchild, & Longley, 2019). Inherently, data collection skews towards those who are better connected to mobile devices, which some private companies seek to mitigate by using a quantity over quality strategy. As an ethical and privacy rule, mobile phone data are generally aggregated to population-level indicators, and individual tracking and identification is avoided in the public health and academic fields (Oliver et al., 2020). "Blackboxing" of collection methods by commercial vendors creates issues for the academic community because it is difficult to understand which users are captured and whether that sample is representative (Dalton & Thatcher, 2015). However, even with distinct limitations, big data analysis can hold substantial value if it correlates well enough with real world phenomena and is conducted with healthy skepticism.

2.2 Neighbourhoods and health

The fundamental connection between health outcomes and the local geographic context of places or neighbourhoods is becoming increasingly well studied (Wang, 2014, Diez Roux & Mair, 2010). A neighbourhood-based understanding of health helps to explain spatial variability in health outcomes and incorporates multiple factors that can affect the health of residents, including the group characteristics of the neighbourhood, the local built and natural environmental factors, and the unique geographic contexts to which residents are exposed (Diez Roux & Mair, 2010). Due to the interconnectedness between health and the built environment, neighbourhood and health theory suggests urban planning policies can enable healthier societies through the design of physical spaces (Diez Roux & Mair, 2010). For example, wealthier neighbourhoods tend to be healthier than their more marginalized counterparts and have better access to green space and transportation, demonstrating the design of public space and transportation networks can encourage resiliency and neighbourhood health (Awuor & Melles, 2019).

In the context of COVID-19, various studies have found areas with lower socioeconomic status to have higher rates of COVID-19 (Choi et al., 2021; Sung, 2020). Neighbourhood health may be affected for a variety of reasons, including some outside the typical neighbourhoods and health framework. Physical distancing, for example, has been shown to be practiced differently between neighbourhoods (Huang et al., 2021b). Communities may (or may not) adhere to physical distancing guidelines for reasons including work, skepticism about the efficacy of physical distancing or the severity of COVID-19, or political beliefs (Lou, et al., 2020). Essential workers are often more vulnerable due to insufficient workplace safety measures and limitations in economic policies that allow workers to stay home, such as paid sick leave or unemployment benefits, suggesting further government support and greater clarity around workplace safety recommendations during the pandemic could encourage greater physical distancing.

Spatial analysis of neighbourhood variations in health can help to reveal and understand the deeply spatial manner in which health inequities arise. Detecting spatial demographic patterns is a powerful exploratory phase in analysis that can reveal underlying conditions that give rise to other phenomena (Harris, Sleight, & Webber, 2005). This form of analysis has been used in the public health realm to target public health campaigns, estimate neighbourhood-level disease burden, and describe variations in access to health services (Abbas et al., 2008; Kimura et al., 2011; Wang & Ramroop, 2018). Studying the intersection of health, geography, and socioeconomic circumstances makes it possible to generalize disease dynamics and can contribute to targeted interventions in vulnerable communities, and so long as limitations are well documented, neighbourhood-level analyses can lead to meaningful insights into health outcomes.

2.4 Conclusion

Academic research during COVID-19 has triggered a fast moving collide between novel forms of data, such as anonymized device-level indicators, and traditional epidemiological and socioeconomic methods. Local neighbourhood characteristics are also vitally important in explaining health outcomes. Limited research has been performed in Canada that connects mobility, spatial demographics, and mobile device data at neighbourhood-level study areas. The importance of incorporating the methods and approaches in these fields is evident due to the severe health, social, and economic impacts that the pandemic has caused differentially across demographic groups.

3. Data and methods

3.1 Data

This study combined COVID-19 case data (Figure 1), a mobile device-derived mobility indicator, and socioeconomic data to investigate neighbourhoods that were disproportionately impacted by COVID-19 in the city of Toronto (Table 1). Toronto is Canada's largest city, with a 2016 population of 2,731,571, and is a deeply multicultural and globally connected travel hub. It is the core of the Greater Toronto Area metropolitan area and is bordered by Lake Ontario to the south, Mississauga to the west, Vaughan and Markham in the north, and Pickering to the east, and is composed of an amalgamation of six former municipalities: Toronto, Etobicoke, York, North York, East York, and Scarborough. Toronto's 140 officially designated neighbourhoods were used as the unit of analysis for this study, which were developed by the city to support government planning by aggregating socioeconomic data to purposeful geographic zones (City of Toronto, 2021a). Neighbourhoods, each composed of approximately 20,000 residents on average but range from 6,577 to 65,913 residents as of 2016, the most recent census year, have been used in various health-based geographic studies of Toronto (Awuor & Melles, 2019; Kolpak & Wang, 2017).

Table 1 summarizes the different data used in the study. Line-listed data for each COVID-19 case in Toronto was retrieved from Toronto Public Health (City of Toronto, 2021b) and filtered to include cases with episode dates (the best estimate date when the disease was acquired) until April 24, 2021 (inclusive) to align the case data with the full temporal range of mobility data. Case data contained supplemental information on age, gender, and neighbourhood of each case, although no further sociodemographic characteristics were provided. Of the 146,227 cases with episode dates between January 21, 2020 and April 24, 2021, 2,429 were removed because they did not have a known home neighbourhood. Cases were further filtered based on reported source of infection to remove those acquired in congregate settings (*n*=2,090) and healthcare settings (*n*=11,224), resulting in 130,484 cases for further analysis. Congregate and healthcare setting-acquired cases were removed from the dataset to focus analysis on cases acquired outside of physical settings that may have led to spatially concentrated outbreaks.

Table 1. Data table

Dataset	Data source	Key metrics	Temporal range	Last updated	Spatial resolution
COVID-19 case counts	Toronto Public Health	Cases, cases per 1,000 population	Daily, Jan 21, 2020 to Apr 24, 2021	Jun 2, 2021	Toronto neighbourhood
Census data	City of Toronto	Average income, household size, population density, essential workers	Static, 2016	2016	Toronto neighbourhood
Ontario Marginalization Index	Ministry of Health Ontario	Material deprivation, ethnic concentration, dependency, residential instability	Static, 2016	2018	Toronto neighbourhood
Mobility indicator	BlueDot	"Time away" indicator	Daily, Jan 1, 2020 to Apr 24, 2021	Apr 24, 2021	Toronto neighbourhood

COVID-19 case rates in Toronto neighbourhoods were calculated independently for each of six time periods to link case data with census data at the neighbourhood-level and to better emphasize within-period spatial distribution of cases regardless of their prior or subsequent caseloads at various segments of the pandemic. The first time period covered the entirety of the study period, from January 21, 2020 to April 24, 2021, and the remaining five were discrete subsets of the study period that were determined based on major changes in public health recommendations by the government of Ontario (Table 2). To aggregate from line-listed case data to neighbourhood-level, each case was assigned to a neighbourhood based on episode date, then converted to a rate using the neighbourhood population. This aggregation resulted in a single COVID-19 case rate per neighbourhood for each time period based on the count of cases acquired within the time period.

Table 2. Study time periods for COVID-19 incidence and mobility indicator groupings

Time period	Time period start and end	Rationale	# cases	% total cases
1	January 21, 2020 – March 16, 2020	First case in Toronto, early pandemic	440	0.3
2	March 17, 2020 – June 21, 2020	Initial lockdown, first wave	8,070	6.2
3	June 22, 2020 – October 9, 2020	Reduced restrictions, summer	8,524	6.5
4	October 10, 2020 – December 25, 2020	Rising second wave	34,021	26.1
5	December 26, 2020 – April 24, 2021	Beginning of province-wide shelter-in-place, 3rd wave	79,429	60.9

This study integrated an anonymized, aggregated device-level movement indicator provided by BlueDot, a Toronto-based health technology company that has partnered with mobile location data providers (Veraset, 2021). Aggregated mobile phone data has been used to investigate measures of mobility throughout the COVID-19 pandemic (Badr et al., 2020; Sharkey & Wood, 2020; Watts et al., 2020). The movement indicator, which approximates each neighbourhood's amount of time spent away from home, was provided at the neighbourhood level and powered by GPS location data from a mobility panel of roughly 85,000 monthly active users within the city during the study period. To determine how each neighbourhood in Toronto followed government NPI recommendations, the time away indicator was calculated by first determining each device's home location based on where it spent the majority of its time between midnight and 9 AM each day. Next, the proportion of time that each device was observed more than 200 meters from its respective assigned home was calculated. Device-level data were aggregated to daily neighbourhood-level indicator values by calculating the mean proportion of time away across all devices that spent the previous night in a neighbourhood. All data provided for this research were only available as daily indicator values at the neighbourhood level and no device-level data was accessible. To assign a single mobility data to each neighbourhood per time period, the mean daily time away from home was used for the days within the time period. Due to the nature of how the indicator was calculated, the underlying location data can only be captured when devices are powered on and reporting data, which can vary by device and day. For this reason, the values should not be interpreted literally, but rather as relative proxies of movement.

Toronto-wide publicly available mobility data made available by Apple and Google (Apple, 2021; Google, 2021) were used for a correlation analysis to validate BlueDot's mobility indicator. Both companies have released mobility data to the public to support COVID-19 research and mitigation efforts, but only at higher level geographic units, such as cities or counties. Google's Community Mobility Reports are based on aggregated, anonymized data that measure movement over time to point of interest categories and are available as a daily index relative to the corresponding day of week median value from the period between January 3rd and February 6th, 2020 (Google, 2021). Apple's Mobility Trends Report data is derived from the quantity of routing requests via its Apple Maps service, bucketed into three categories, "walking", "driving", and "transit", and is calculated as an index against a baseline from January 13th, 2020 (Apple, 2021).

Since Apple and Google data are only available at the Toronto-wide level, daily BlueDot mobility data were analyzed at the city-wide spatial level rather than neighbourhood-by-neighbourhood by aggregating the neighbourhood level data into a single daily population-weighted value. A Pearson correlation analysis was conducted on Google's residential index and Apple's driving index on the 321 days communally available in all three datasets, ranging from February 15, 2020, to December 31, 2020. Although the Apple and Google data are indices with different baselines, their general approximation of overall mobility was deemed appropriate for use without further processing. Statistically significant correlations between each mobility data provider were found. Apple and BlueDot mobility data were most strongly correlated (r=.76, *p*<.001), followed by BlueDot and Google (r=-.47, p <0.001), then Apple and Google (r=-.45, *p*<.001). The negative correlation between Apple and BlueDot data with Google is expected because Google's residential index measures an increase in time at home, whereas the other are proxies for time spent away from home. Overall, the correlation analysis demonstrated that BlueDot data was equally or more aligned with other data sets commonly used in the literature (Huang et al., 2021a). Considerations around the usage of mobility data are explored in detail in section 5.6.

Socioeconomic data were sourced from the Ontario Marginalization Index (ON-Marg) and Toronto's Neighbourhood Profiles. ON-Marg is a validated census-based composite index that includes several measures of marginalization based on demographic indicators (Matheson & van Ingen, 2016). The relationship between marginalization and COVID-19 has been well documented (Strully, Yang, & Liu, 2021; Hawkins, Charles, & Mehaffey, 2020) and the ON-Marg, which measures multifaceted data in an interpretable way, has been used to investigate the effects of marginalization on health outcomes in the past (Moin, Moineddin, & Upshur, 2018; Zygmunt et al., 2020). ON-Marg dimensions include residential instability, which measures community-level concentrations of people experiencing high rates of housing or family instability; material deprivation, linked to poverty and attributed to a community's or individual's inability to access essential material needs; dependency, a measure of residents lacking income from employment; and ethnic concentration, a measure of recent immigrants and/or members of a "visible minority" (Matheson & van Ingen, 2016). The ethnic concentration variable is of interest due to its inclusion of new immigrants, a group that are often in more vulnerable socioeconomic situations. When used nationally, ON-Marg factor scores have a mean of 0 and standard deviation of 1, with higher values demonstrating increased marginalization.

Other census variables were selected from Toronto's 2016 Neighbourhood Profiles, which are derived from the 2016 Canadian census, the most recent census available to the study (City of Toronto, 2021a). These variables included average household size, population density, income, and proportion of the workforce considered essential workers. The essential workers variable was calculated as the percentage of the workforce over 15 in "essential" employment sectors as defined by National Occupation Classification categories following the same grouping as Rao et al. (2021): health, sales, service, trades, transportation, natural resources, agriculture, manufacturing, and utilities. Each census variable has an established relationship with COVID-19 incidence and is individually important enough to include in the study regardless of confounding in ON-Marg (Jing et al., 2020; Kavanagh et al., 2020, Lou, et al., 2020; Maroko, et al., 2020; Strully et al., 2021).

3.2 Analysis methods

Pearson correlation analyses were conducted to identify the relationship between variables and validate their usage in the study. The first analysis compared the sociodemographic variables described in section 3.1 to demonstrate the direction and strength of their relationships with one another, as well as with mobility and COVID-19 incidence. A stepwise multiple linear regression model was explored during preliminary analysis, but high multicollinearity and overfitting made the resulting model difficult to interpret, and all sociodemographic variables in the study were preferred to be kept due to their interpretability and relative importance in other studies (Jing et al., 2020; Niedzwiedz et al., 2020; Tammes, 2020).

Next, the spatial patterns of neighbourhood-level mobility and incidence were analyzed via hot spot analysis using the Python Spatial Analysis Library (PySAL) (Rey & Anselin, 2007). Hot spots and cold spots were determined independently for the two cluster variables (COVID-19 incidence and time away) using the Getis Ord Gi* statistic using contiguity to define neighbours (i.e. where any two neighbourhoods shared a boundary) (Maroko et al., 2020). The Getis Ord Gi* statistic analyzes each feature in the context of itself and its neighbours to identify regions that have statistically significant spatial groupings of the input variable (Getis & Ord, 1992). It is a useful tool for analyzing the spatial patterns of COVID-19 in urban areas (Maroko et al., 2020). The resulting hot and cold spots were deemed significant only if they exceeded a 95% confidence level. These clusters demonstrated areas of Toronto where rates of COVID-19, and, independently, time away from home, were disproportionately concentrated.

Finally, Wilcoxon two-sample tests were conducted in R to determine whether the distribution of demographic characteristics between the two neighbourhood groups (i.e. the neighbourhoods in hot spots and the neighbourhoods in cold spots) were different, for each time period for mobility and COVID-19 clusters. Due to small sample size and non-normally distributed cluster variables (Chen-Shapiro, $p < 0.01$), a Wilcoxon two-sample test was deemed most appropriate for testing whether socioeconomic composition between groups was different (Brzezinski, 2012; Maroko et al., 2020). For summary purposes, group medians for ON-Marg and other census variables were calculated to present a single representative value for each hot and cold spot per variable and time period for comparative analysis between the two cluster groups of disproportionately affected neighbourhoods. Statistical results for the analysis variables were then summarized and compared across variables and time periods and mapped using PySAL and QGIS.

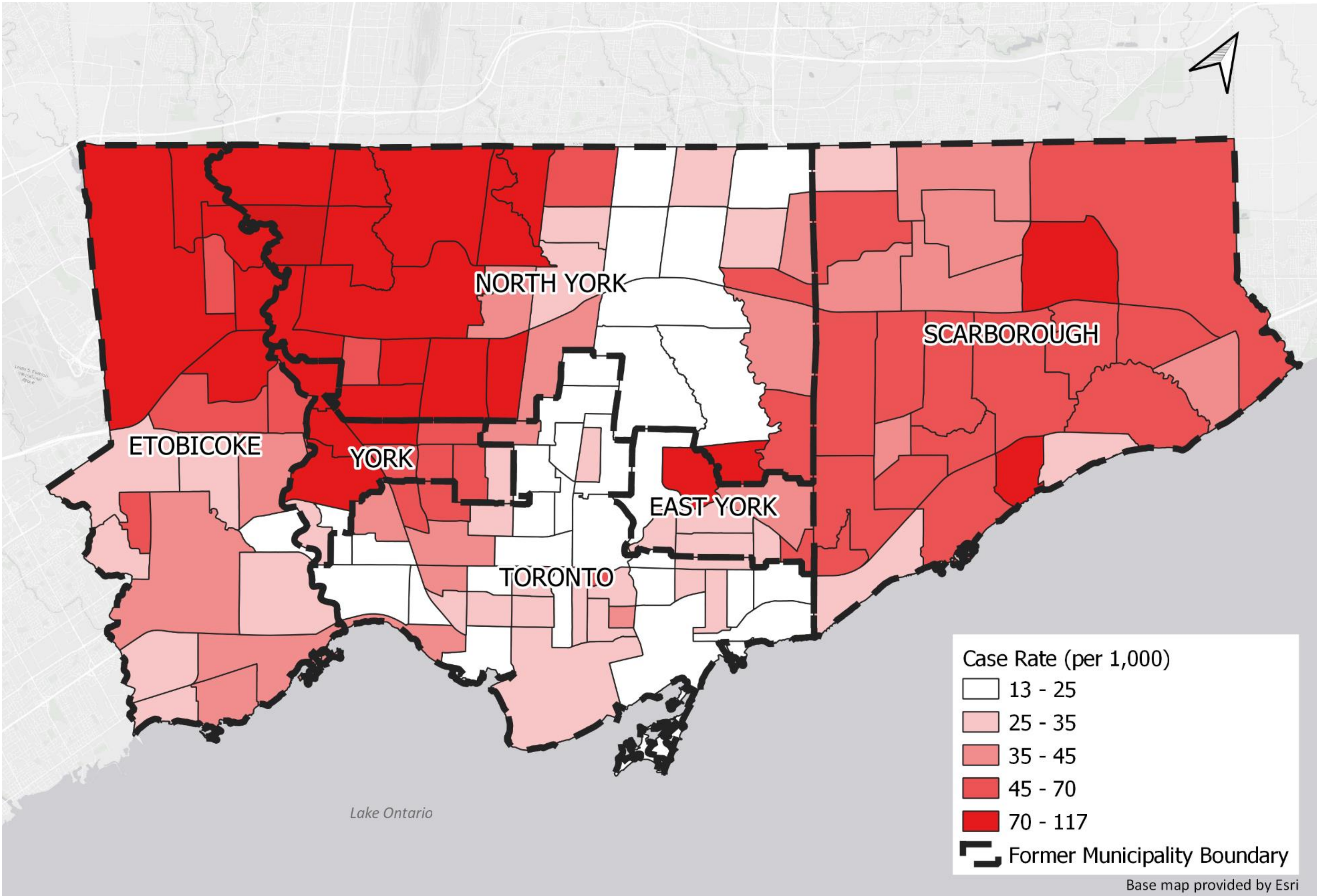


Figure 1. COVID-19 rates (per 1,000) in Toronto neighbourhoods over full study period.

4. Results

4.1 Correlation analysis

The Pearson correlation analysis results on socioeconomic variables, COVID-19, and time away can be found in Table 3. COVID-19 rates were most positively correlated with essential workers, material deprivation, and ethnic concentration. Time away had a moderate positive correlation with incidence and essential workers, but low correlation with other variables. Two of the ON-Marg factors had strong individual relationships with non-ON-Marg variables – material deprivation with income, and residential instability with household size, suggesting the two non-composite variables have high collinearity with their respective ON-Marg factor. However, their strong correlation with cases and relative importance in explaining COVID-19 cases in other studies suggests they are important to include for further analysis.

Table 3. Pearson correlation results on analysis variables with means and standard deviations (SD) (n=140)

	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. Case rate (per 1000)	47.8	25.4	1.00									
2. Time away	17.2%	1.9%	.35*	1.00								
3. Household size	2.5	0.4	.56*	.09	1.00							
4. Population density	6,374	4,840	-.15	-.26*	-.53*	1.00						
5. Residential instability	0.76	0.78	-.23*	-.07	-.84*	.66*	1.00					
6. Material deprivation	0.26	0.89	.77*	.07	.50*	-.05	-.19*	1.00				
7. Dependency	-0.23	0.39	.09	.03	.41*	-.41*	-.46*	.10	1.00			
8. Ethnic concentration	1.04	0.84	.62*	-.02	.51*	.02	-.04	.65*	.17*	1.00		
9. Income	51,882	38,738	-.50*	.08	-.24*	-.08	-.02	-.61*	.00	-.50*	1.00	
10. Essential workers	43%	12%	.87*	.27*	.67*	-.20*	-.34*	.89*	.23*	.64*	-.63*	1.00

* denotes $p < .05$

4.2 Spatial clusters of COVID-19 and mobility

Over the entire study period, neighbourhoods in COVID-19 hot spots (*n*=23) were in the city's northwest, whereas cold spot neighbourhoods (*n*=27) aligned closely with the city's downtown core and extended north towards the city's geographic center (Figure 4). Neighbourhoods in hot spots of mobility (*n*=25) were also in the city's northwest, although they included five additional neighbourhoods to the south and east that were not identified as COVID-19 hot spots and excluded three neighbourhoods to the west. Mobility cold spots neighbourhoods (*n*=14) were primarily located in Toronto's downtown and extended east along the lakeshore, with one pocket of three neighbourhoods on the northern border between North York and Scarborough. Clusters of mobility and COVID-19 incidence aligned closely in hot spots (91% of COVID-19 hot spot neighbourhoods were also mobility hot spots) but had considerably different spatial distribution in cold spots (25% of COVID-19 cold spot neighbourhoods coincided with mobility cold spots). There were no cases where a hot or cold spot of either variable aligned with the opposite cluster of the other variable. Lack of classification as a hot spot does not imply that a neighbourhood fared well, but rather that it and its neighbours were not significantly above the citywide average since many neighbourhoods that were not in hot spots experienced considerable caseloads.

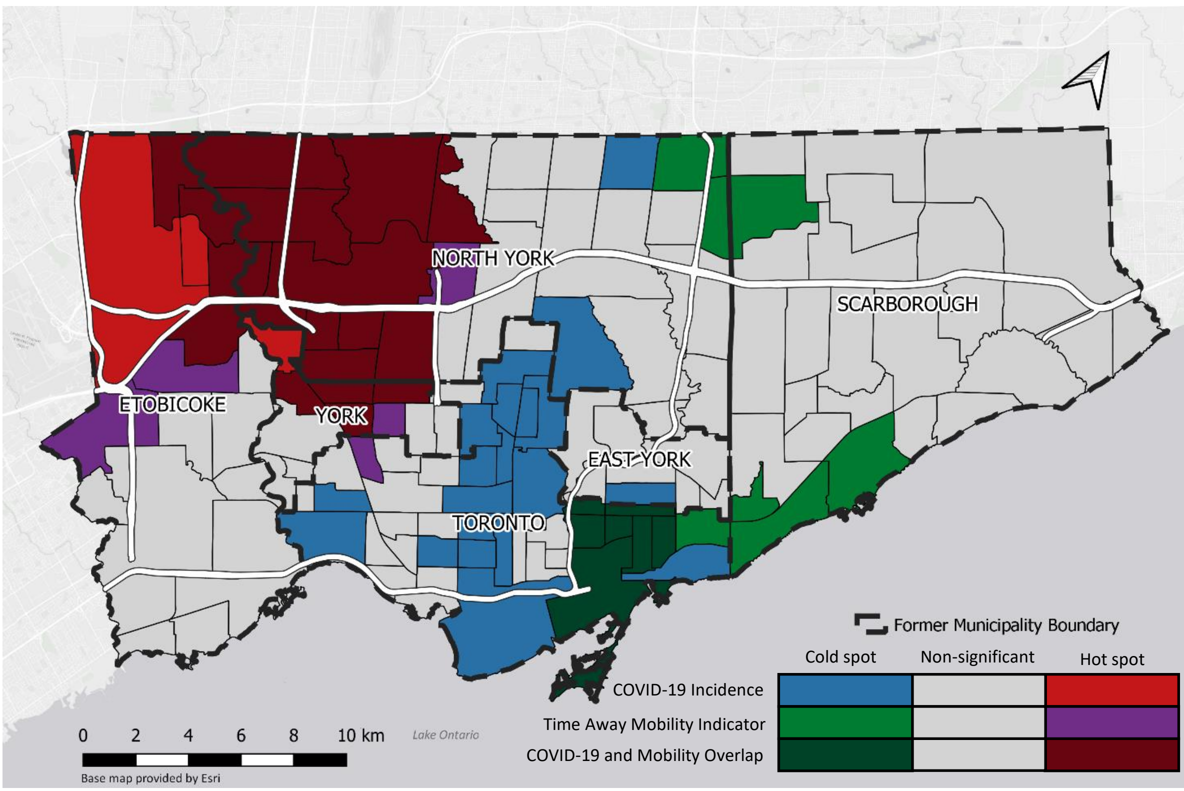


Figure 2. Cluster analysis overlay of COVID-19 case rate and time away mobility indicator in Toronto during full study period.

The dynamic spatiotemporal distribution of COVID-19 and mobility are demonstrated in Figure 5. In the earliest phase of the pandemic, hot spots for each cluster variable were primarily in the center of Toronto on a north-south axis. After this initial phase, hot spots consistently aligned in Toronto's northwest for both mobility and COVID-19. Relative to hot spots, there was greater spatial variance in cold spot distribution in both cluster variables over time. COVID-19 cold spots were frequently in the city's center after the first time period, but mobility cold spots stretched along the lakeshore eastward from downtown and included sections of Scarborough in the first three time periods prior to aligning downtown in the latter two time periods. Interpretation of the temporal hot spot analysis results must be conducted carefully, as earlier phases of the pandemic had considerably fewer cases than later phases and increased chance of under-detection due to limited testing capacity. Figure 5 is best interpreted as showing spatial patterning rather than COVID-19 severity across phases.

The hot and cold spot locations in the first time period are particularly distinctive relative to the other time periods for both mobility and COVID-19. Many of the neighbourhoods that experienced the earliest concentration of COVID-19 subsequently became those with the lowest incidence in the fourth and fifth time periods, when the citywide number of cases was the highest. In a similar but reversed pattern, the two groups of COVID-19 cold spots in in Toronto's northwest at the outset of the pandemic transitioned to hot spots for subsequent time periods. Mobility hot spots followed a similar pattern, where clusters of greater time spent away from home were initially concentrated in central downtown areas and a subset of these neighbourhoods that had greater pre-restriction movement characteristics later became cold spots in the final two time periods.

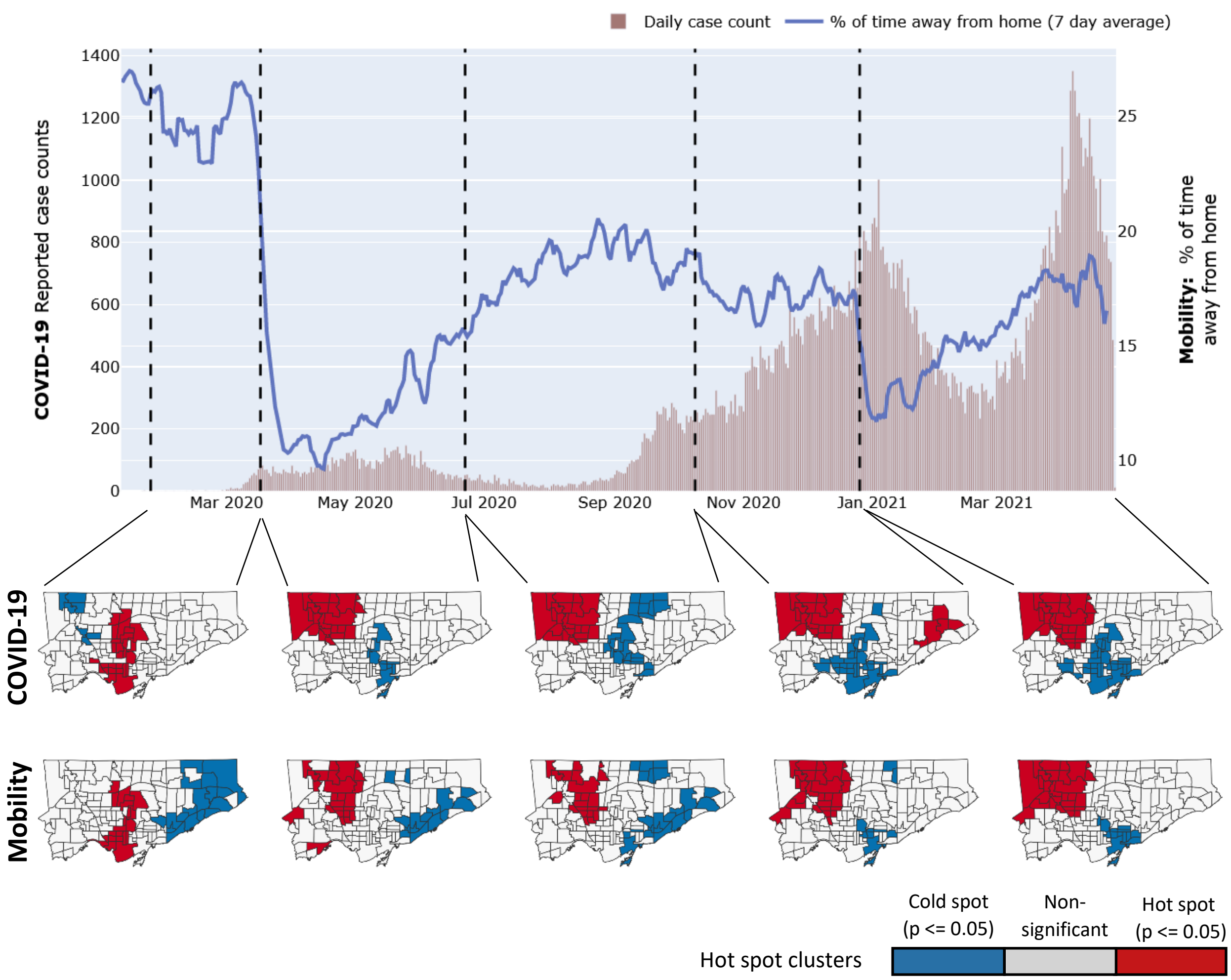


Figure 3. Epidemic curve of COVID-19 cases in Toronto with Toronto-wide time away mobility indicator and corresponding clusters of COVID-19 case rates and mobility.

4.3 Demographic characteristics of COVID-19 and mobility clusters

Over the full study period, Toronto's COVID-19 hot spot neighbourhoods had statistically significant higher material deprivation, ethnic concentration, spent more time away from home, had a greater proportion of essential workers, and had larger household sizes than their counterparts in cold spots (Table 4). Complete time period-specific results are available in Appendix A. Hot spots also had less residential instability and lower population density than cold spots. Notably, two of the four ON-Marg dimensions, residential instability and dependency, were not significantly different between the two groups. Hot spots were also found to have much lower population density and lower income than cold spots. The non-clustered "other" neighbourhoods' group average for every variable except dependency and time away was consistently between that of the hot and cold spots, demonstrating the relatively consistent demographic traits not only between clusters, but also with neighbourhoods that did not fall into either category.

Table 4. Wilcoxon two sample significance test results between hot and cold spots of COVID-19 incidence and time away from full study period with median group values

Cluster variable	Variable	Hot spots	Cold spots	Other	Hot vs. cold p value
COVID-19		n=23	n=27	n=90	
	COVID-19: Case rate (per 1000)	84.7	21.4	37.6	**<.001**
	Mobility: Time away (%)	18.9	16.6	16.5	**.010**
	ON-Marg: Material deprivation	1.28	-0.68	0.15	**<.001**
	ON-Marg: Ethnic concentration	1.45	0.05	0.81	**<.001**
	ON-Marg: Residential instability	0.39	0.97	0.61	.103
	ON-Marg: Dependency	-0.26	-0.48	-0.22	.415
	Census: Average income ($)	32,815	70,600	44,139	**<.001**
	Census: Household size (individuals)	2.7	2.2	2.6	**<.001**
	Census: Population density (per km^2)	4,012	7,838	4,931	**.019**
	Census: Essential workers (%)	60.1	28.7	43.5	**<.001**
Time away		n=25	n=14	n=101	
	COVID-19: Case rate (per 1000)	78.1	26.8	34.5	**.008**
	Mobility: Time away (%)	18.4	15.6	16.7	**.009**
	ON-Marg: Material deprivation	1.25	0.08	-0.05	**.022**
	ON-Marg: Ethnic concentration	1.28	0.37	0.59	.131
	ON-Marg: Residential instability	0.34	0.54	0.73	.955
	ON-Marg: Dependency	-0.27	-0.37	-0.27	.955
	Census: Average income ($)	33,528	51,157	47,384	**.022**
	Census: Household size (individuals)	2.7	2.4	2.4	.198
	Census: Population density (per km^2)	4,007	7,107	5,395	.065
	Census: Essential workers (%)	60.0	34.5	39.3	**<.001**

Geographic concentrations of high and low levels of mobility had fewer defining demographic characteristics than the COVID-19 cluster analysis (Table 4). Neighbourhoods in mobility hot spots had significantly higher rates of COVID-19, material deprivation, and household sizes than mobility cold spots, as well as lower income and a greater share of essential workers, but no other variables were found to be statistically significant. However, as a group, mobility hot spots had lower residential instability, lower population density, and higher ethnic concentration than cold spots. The “other” neighbourhoods were occasionally higher or lower than both hot and cold spots for some variables, suggesting nuanced relationships between the time away mobility indicator and the demographic characteristics selected for this analysis.

While the spatial pattern of clusters of COVID-19 cases and mobility shifted slightly over time, the group sociodemographic characteristics that clusters shared remained similar in all but the first time period (Figure 6). In this initial phase, COVID-19 clusters occurred in neighbourhoods that were well below the citywide averages for material deprivation and essential workers, the variables that were most consistently a significant measure of between-group differences, and cold spots were in areas that were above the city average (Figure 6). This initial period of decreased material deprivation in hot spots is inverse to the findings from the four subsequent time periods and demonstrates that the locations that were most severely affected in the early pandemic were much less materially deprived than their counterparts. Ethnic concentration followed a similar but less pronounced pattern, and instability had an inverse pattern, where greater instability was associated with hot spots in the first time period, and then fell to a consistent rate afterwards. Time away from home was not significantly different between COVID-19 clusters in the first time period, although this period took place before Toronto’s earliest mobility restrictions.

Later in the study period, neighbourhoods in COVID-19 hot spots in time periods two through five consistently had significantly more material deprivation and essential workers, higher ethnic concentration, larger household sizes, lower income, and spent more time away from home. In mobility hot spots, material deprivation and percentage of essential workers were again consistently significant between groups, except for over the summertime period, with greater deprivation associated with an increase in time spent away from home. In periods four and five, which accounted for the bulk of the cases in the study period, lower income and higher ethnic concentration were strongly associated with clusters of increased mobility.

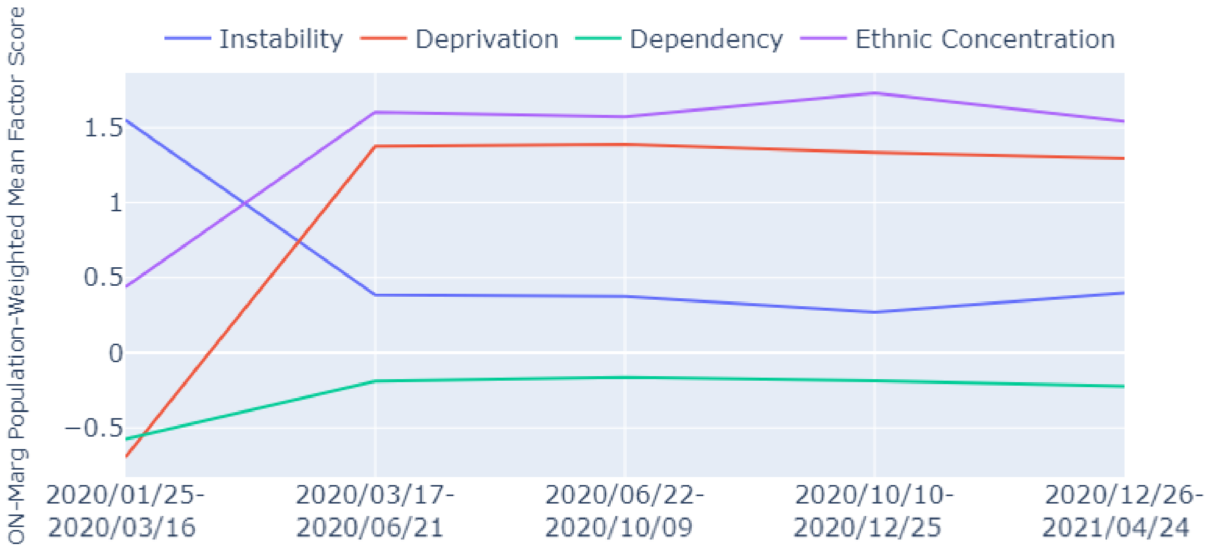


Figure 4. ON-Marg factor scores in hot spots of COVID-19 incidence during each time period.

5. Discussion

The way individuals interact with the physical and social constructs of neighbourhoods can cause profound impacts on human health (Awuor & Melles, 2019). Inequitable access to social programs, services, and facilities often negatively affects neighbourhood health and can lead to neighbourhood segregation by various sociodemographic strata, such as income or race. Place plays a central role in understanding social determinants of health due to the wide-ranging spatial nature of accessibility to services, local environmental factors, and the socioeconomic composition of residents. The findings in this study demonstrate Toronto's neighbourhoods have experienced the COVID-19 pandemic in significantly different ways, with hot spots of COVID-19 cases occurring in more materially and racially marginalized communities that disproportionately experienced the impacts of the virus. Further, these same marginalized neighbourhoods tended to be less likely to reduce their mobility relative to more advantaged communities within the city.

In the earliest phase of the COVID-19 pandemic (January 21, 2020 – March 16, 2020), Toronto's less materially deprived neighbourhoods experienced the earliest clusters of cases. However, as the pandemic developed, hot spots of COVID-19 occurred in neighbourhoods that were more materially deprived, more ethnically concentrated, spent more time away from home, and had a greater concentration of essential workers. The strong correlation between material deprivation and essential workers with hot spots in all but the earliest phase of the pandemic aligns with other research findings that COVID-19 has frequently affected more marginalized communities (Chang et al., 2021; Choi et al., 2021; Dasgupta et al., 2020;). Further, the spatial overlap between COVID-19 and time away hot spots, with 95% of COVID-19 hot spot neighbourhoods coinciding with mobility hot spots in the full study period, suggests that neighbourhoods with higher levels of poverty had increased exposure to the virus, likely due to more frontline workers in jobs that cannot be done remotely (Huang et al., 2021b). The spatiotemporal alignment between the two sets of hot spots demonstrates that there were uniquely affected areas of Toronto that extended to a region larger than city-designed neighbourhood boundaries, indicating that targeted policy efforts in awareness, testing, and vaccination could be effective in broad areas and need not be precisely determined neighbourhood by neighbourhood.

5.1 Spatial distribution of clusters

The spatial patterning of COVID-19 hot and cold spots was generally consistent over the study period, with one important exception. In the first time period, 47% of cases had travel-related sources of infection (Appendix B), resulting in a spatial pattern where hot spot neighbourhoods were more strongly associated with higher income, densely populated neighbourhoods, indicating that individuals with the means to travel were more affected in the earliest days of the pandemic. In stark contrast to the later time periods, cold spots were in Toronto's more materially deprived and ethnically concentrated northwest, where neighbourhoods likely avoided the earliest cases due to lower international travel at a time when COVID-19 was primarily imported from other countries. The spatial concentration of cases when travel-related sources of infection were most common suggests disease surveillance measures early in the pandemic would be most prudent in neighbourhoods with the propensity for travel and at border crossings. However, unseen nuances in the distribution of cases likely exists due to the greater surveillance efforts applied towards testing international travelers at a time when testing capacity was more limited.

Although the first time period cluster analysis had a unique pattern, hot spots of COVID-19 and mobility otherwise shared a consistent spatial relationship for the remainder of the study period. However, cold spots of the two cluster variables shared a more nuanced relationship. The lack of alignment between cold spots (25% of COVID-19 cold spot neighbourhoods were also mobility cold spots in the full study period) shows that the spatial correlation between low mobility as indicated by the time away indicator and infection are complex. The correlation analysis (Table 3) revealed a moderate positive relationship between time away and COVID-19, but the Wilcoxon results comparing hot and cold spots of COVID-19 show that neighbourhoods that were not part of a cluster had the lowest average mobility. This relationship is explored further in section 5.3.

5.2 Socioeconomic characteristics of COVID-19 clusters

The link between poverty, crowded housing, and social vulnerability during public health events is well documented (Dasgupta et al., 2020; Huang et al., 2021b). Higher population density can act as a catalyst for the spread of COVID-19 because it makes it difficult to reduce contact rates (Tammes, 2020). However, at an intracity level, this study found the most densely populated neighbourhoods were not those that experienced the most severe COVID-19 case burden in Toronto, aligning with findings in Chicago and New York (Maroko et al., 2020). In fact, over the full study period some of the most densely populated neighbourhoods in Toronto were in COVID-19 cold spots (7,838 people per km^2), and outlying, lower density neighbourhoods were associated with hot spots (4,012 people per km^2). However, neighbourhoods in hot spots had an average 0.5 more individuals per household (2.7 people), indicating that within-household contact rates contributed more to clusters of COVID-19 than neighbourhood-wide population density. While household size can be considered an element of marginalization, the risk of COVID-19 infection has been found to increase tenfold for those living in a household with a diagnosed case (Jing et al., 2020), showing its utility for understanding the spatial distribution of COVID-19 incidence.

Higher material deprivation and ethnic concentration had strong relationships with hot spots. Ethnic concentration was positively correlated with both COVID-19 hot spots and increased mobility, although only statistically significant between groups in the COVID-19 analysis. Recent immigrants and materially deprived individuals are often at higher risk of exposure due to crowded housing, lower-wage employment, and residency in low-income neighbourhoods (Strully et al., 2021). Further, correlations have been found between minority status and increased COVID-19 risk that is not fully explained by socioeconomic status (Niedzwiedz et al., 2020). Race-based social determinants of health like structural racism and xenophobia can act as a barrier to healthcare and negatively affect communities. Racially marginalized communities in Toronto also face increased exposure to negative environmental determinants of health such as air pollution (Awuor & Melles, 2019), which has been correlated with cases of severe COVID-19 and other respiratory diseases (Sundaram et al., 2020). The deep connection between ethnic concentration and COVID-19 hot spots in Toronto suggests efforts towards community outreach for new immigrants and continued robust offerings in as many languages as possible to share information accessibly could support some of the city's most affected neighbourhoods.

The hot spot analysis reveals that clusters of COVID-19 were most strongly associated with economic and racial measures of marginalization but had a weaker relationship with marginalization in the form of residential instability and dependency. The lack of significance in the dependency measure may in part be due to the removal of institutional outbreaks, as Ontario had severe outbreaks in long term care homes earlier in the pandemic. However, dependency was significantly lower in hot spots in the final two time periods, showing neighbourhoods with a greater proportion of population engaged in the work force had higher case rates, potentially spurred on by a proportional increase in younger, working Torontonians acquiring the disease ("1 in 3 new COVID-19 cases", 2021).

5.3 Socioeconomic characteristics of mobility clusters

The socioeconomic characteristics of mobility clusters shared similar traits with those of COVID-19, although there are important distinctions between the two cluster analyses. Unlike COVID-19, mobility cold spots in Toronto were often not in the city's most affluent neighbourhoods but rather in Scarborough and along the city's eastern lakeshore. Although reductions in mobility have been found to be closely associated with a reduction in COVID-19 caseloads (Huang et al., 2021a; Leung et al., 2021), the spatial mismatch and corresponding neighbourhood characteristics between mobility and COVID-19 cold spots show higher income and lower economic and racial marginalization were stronger spatial indicators of reduced COVID-19 rates than reductions in time away from home. While reducing overall mobility is important, long-term investment in community health and provision of short-term mitigation strategies is vitally important for continued resiliency in the face of future public health crises.

Compared to COVID-19 clusters, fewer variables in the mobility cluster analysis had statistically significant differences between hot and cold spots of mobility, demonstrating there were complex relationships in the demographics of mobility. Although material deprivation was significantly lower in cold spots it was lower still in the non-clustered group of "other" neighbourhoods. Many studies that investigated the relationship between mobility, marginalization, and COVID-19 have been conducted at larger spatial scales (such as US counties) and have highlighted the disproportionate impact between marginalized communities relative to those that are less marginalized, but less research has been conducted on the differences between middling and well-off areas in terms of mobility at finer spatial resolutions. Further research may be warranted to clarify the relationship between economically advantaged communities and their relative movement in contrast with average neighbourhoods to improve how we understand mitigation strategies outside of the economic extremes.

The complicated relationship between mobility, COVID-19 cases, and social determinants of health is exemplified via a case study of neighbourhoods. Toronto's third-most mobile neighbourhood, Bridle Path-Sunnybrook-York Mills, had the city's highest average income and a relatively low COVID-19 case rate, ranking 19th overall in the city over the study period. Alternatively, Regent Park, North St. James Town, Taylor Massey, and Oakridge neighbourhoods were 4 of the 7 least mobile neighbourhoods in Toronto, but each were above the 50th percentile of case rates. The four neighbourhoods in the low mobility group had high material deprivation and ethnic concentration, as well as high residential instability and population density, with the latter two variables more frequently associated with cold spots. It is likely their low mobility and socioeconomic status, but relatively high urbanness represents a group of neighbourhoods that had more urban housing characteristics than hot spot averages but were still negatively affected for the same underlying demographic reasons.

5.4 Comparison with Public Health Ontario hot spots

Public Health Ontario delineated a set of COVID-19 hot spots to prioritize vaccine distribution based on forward sortation areas (the first three digits of a postal code) (Wilson, 2021). At the time of writing, the government had not released their methodology, although the Ontario premier's office claims these hot spots were determined based on the “number of cases, the number of hospitalizations, and the illness burden” (Wilson, 2021). They also looked at “sociodemographic data” to determine the degree of racialization in each community. Public Health Ontario’s hot spots provide an informative contrast with the hot spots found in this study, despite the two studies’ incompatible geographic scopes. The hot spots found in this study were a subset of Public Health Ontario’s, and cold spots and their adjacent neighbourhoods were generally the only areas in Toronto that were not considered hot spots at the provincial scale (Figure 7). Toronto has suffered disproportionate impacts of COVID-19 relative to other areas of the province, so it is reasonable that much of Toronto would be identified as a hot spot given a larger study area because many of the province’s hardest hit areas were within the city. In this study, the study area was constrained to within Toronto to accentuate intracity differences between communities. Both methods are useful in developing an understanding of sociodemographic contributors to COVID-19 incidence, but Ontario’s methods are less geographically targeted, resulting in a coarser understanding of the spatial distribution of COVID-19 and corresponding sociodemographic characteristics of disproportionately affected neighbourhoods within Toronto.

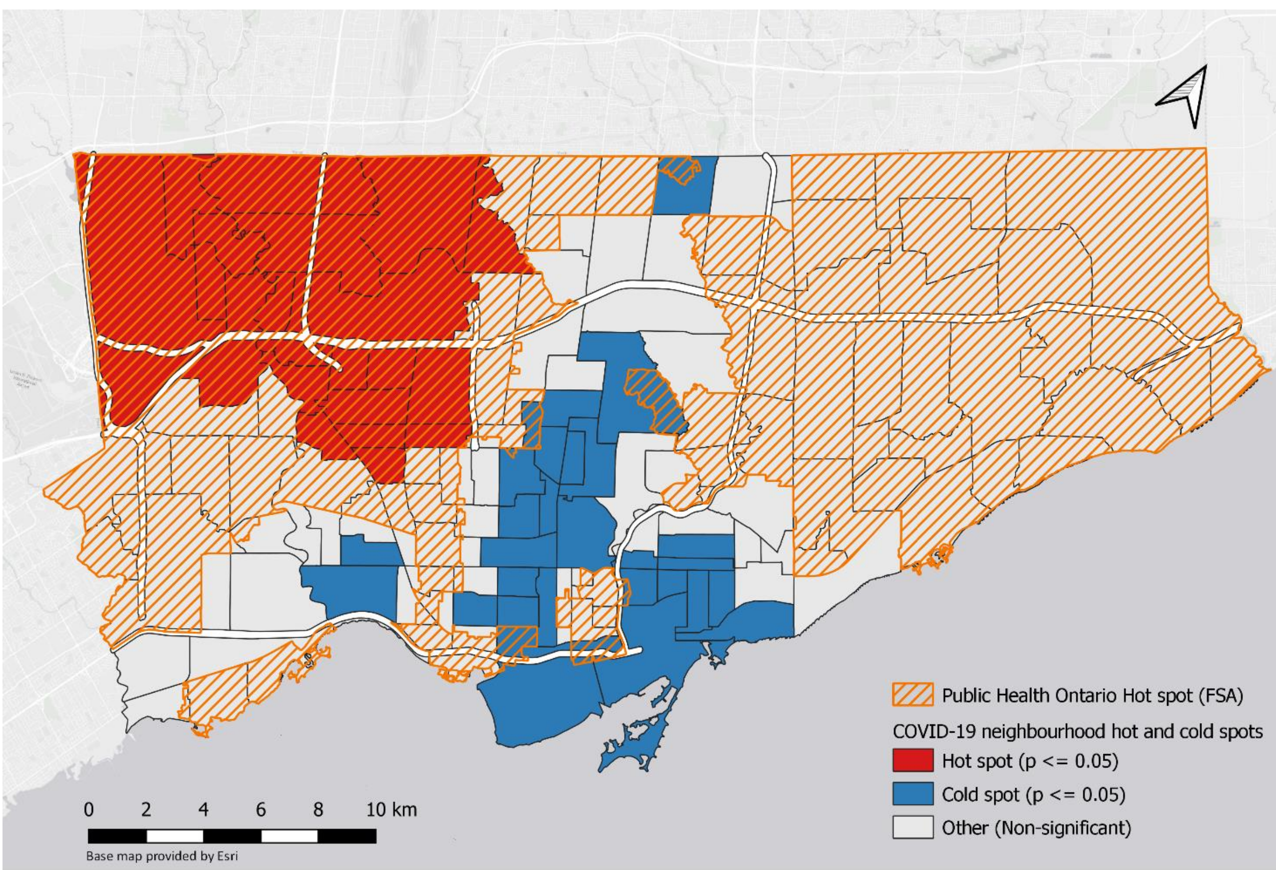


Figure 5. Comparison of Public Health Ontario’s hot spots with within-Toronto neighbourhood-level hot spots.

5.5 Policy and implications

The spatial clustering techniques applied in this study identified where clusters of COVID-19 and mobility did, and did not, coincidence in Toronto during the pandemic and their sociodemographic characteristics. The findings support an increasingly growing body of literature that shows that marginalized communities have disproportionately suffered the effects of COVID-19 (Dasgupta et al., 2020; Strully et al., 2021; Sundaram et al., 2020; Hawkins et al., 2020). The spatiotemporal consistency in hot spots in all but the earliest phase of the pandemic shows that the underlying conditions contributing to high rates of COVID-19 remained in place throughout the pandemic in more materially deprived and racially concentrated neighbourhoods, but the earliest affected, wealthier, neighbourhoods were able to better mitigate their risk of infection.

The association between larger household sizes and COVID-19 hot spots has relevant implications for policymakers during future infectious disease-related events. Providing increased access to voluntary isolation (Sundaram et al., 2020) and wraparound services, like grocery and prescription drug delivery (Madad, Nuzzo, & Bourdeaux, 2020), may reduce chains of transmission that disproportionately affect more vulnerable households. For frontline workers with increased occupational risk of COVID-19 exposure, paid sick leave and workplace testing could reduce their personal and, by extension, household exposure (Sundaram et al., 2020). Increased economic support for individuals and businesses deemed essential through greater focus on workplace safety and increased public transportation frequency would allow safer practices to be followed by those who do not have the financial means to strictly adhere to stay-at-home orders and could limit chains of household transmission.

Policy makers can use findings to manage spatially targeted public awareness and testing campaigns, coordinate healthcare resources, and boost communities' ability to observe government recommendations in future outbreaks, especially in lower income neighbourhoods in Toronto's northwest. Increased focus on the neighbourhoods identified in hot spot analyses is particularly important because they not only experienced disproportionate case rates, but by extension also have the highest risk of exposure. Due to the spatial alignment in mobility and COVID-19 hot spots and efficacy of physical distancing in mitigating COVID-19 infection, short term policies to reduce contact rates are not necessarily fraught with engrained determinants of health. In future public health crises, policies can immediately seek to address inequities by creating the support structures for individuals to protect themselves and their communities.

This research does not imply causation between mobility and COVID-19 incidence, as there are many factors that contribute to disease incidence. Further, the ecological study design does not include individual-level characteristics. However, the spatial correlation between time away and COVID-19 rates in hot spot neighbourhoods suggests mobility may exacerbate preexisting disparities resulting from marginalization and that the luxury of physical distancing was not affordable by Toronto's vulnerable populations. These findings can be used for more equitable response in future public health crises, and support decision making and prioritization of resources to the disadvantaged populations that are most likely to be worst affected by COVID-19.

5.6 Limitations and future research

There are several limitations to this study. First, using neighbourhoods as the unit of analysis poses challenges due to the modifiable areal unit problem and the ecological fallacy. These issues arise from applying arbitrary spatial bounds on a dataset that can result in different findings if the data were delineated into different spatial units (Hennerdal & Nielsen, 2017). Neighbourhood-level metrics can also mischaracterize the individuals that live there, as applying a single value to a group of people can lead to false conclusions (Dalton & Thatcher, 2015). Similarly, the modifiable temporal unit problem could lead to different findings if time periods were selected based on different criteria. Further, the neighbourhood effect averaging problem (NEAP) specifies that individuals' exposure to environmental factors regress towards the mean of the study area, failing to fully capture the health impact that comes from residence-based exposures (Kim & Kwan, 2021b). Within Toronto neighbourhoods, the NEAP suggests there were likely population cohorts with distinct vulnerability to COVID-19 due to differences in residence-based exposure that were not identified due to neighbourhood averaging.

Further, the uncertain geographic context problem (UGCoP) arises due to uncertainty around the geographic areas that influence individuals. Residents of Toronto neighbourhoods have unique behaviors and experiences from the varying physical and social impacts of their surroundings and their places of work and leisure. The UGCoP is distinct from the MAUP, because addressing it requires estimating the true geographic context for an individual, rather than identifying the most useful areal division for a given study to mitigate the MAUP (Kwan, 2012).

Additionally, identification of COVID-19 case data is strongly tied to testing, which is voluntary and not universally accessible to all groups. While an Ontario-wide study found that likelihood of testing is largely consistent across socioeconomic groups (Sundaram et al., 2020), targeted testing of individuals who travelled internationally may have led to a detection bias earlier in the pandemic. This analysis could be extended by investigating case outcomes (hospitalizations and deaths) rather than just cases to provide an even deeper understanding in the health inequities experienced during the pandemic.

Mobility data does not capture the type of activity undertaken out of home, may underestimate out of home movement in the downtown core, and the daily sample of the population may not be consistent. Time spent away from home, which has frequently been used as a proxy for measuring lockdowns, may not sufficiently measure the range of activities taken during lockdowns. This finding aligns with other research that found mobile device-derived indicators after the first few months of the pandemic had less predictive power in estimating COVID-19 case rates (Gatalo et al., 2021). Future research directions could continue this investigation into neighbourhood health, physical distancing, and associated demographics by incorporating more specialized mobility data to measure visits to specific point of interest categories and quantifying the number of devices exhibiting typical “work” behavior to associate the degree of physical distancing more strongly with the kinds of activities undertaken while away from home to provide greater clarity around the policy implications that enable physical distancing. A merger of these data with census-derived tapestry data could create meaningful and impactful interpretations of findings when presenting findings to policy makers.

Lastly, mobility data are drawn from an unknown population sample and may be skewed by demographic characteristics such as income, age, or race, although they have been demonstrated to be reasonably consistent across various socioeconomic groups (Squire, 2019). One comparative analysis between other mobility providers found general agreement, but notable differences between four open source datasets with moderate to high Pearson correlations ranging from 0.33 to 0.60 between different providers (Huang et al., 2021a). The similarity in their findings with those in the mobility data comparison in this study shows that mobility data source correlations tend to have moderate variability, and the underlying population sample between sources is inconsistent. Evidently, no single dataset is a perfect proxy for human mobility regardless of data provider, but this should not invalidate a novel form of data that has provided valuable insights into the complicated dynamics of COVID-19.

Future research directions that incorporate alternative quantitative and qualitative data would help to create an improved understanding of local contexts and support policy making decisions. Additional forms of quantitative data that could be incorporated into a similar, neighbourhood-level study could include industry of employment, transit usage during the pandemic, and a risk perception index derived from qualitative surveys. This index could be derived from surveys with questions pertaining to risk perception and individuals’ interest in adopting various policy options, such as voluntary self-isolation or wraparound services broken down by various demographic and geographic strata. Separately, surveys could also be designed to include questions around motivating factors behind following or disregarding government policy to refine future messaging. Additionally, industry-specific data points could provide researchers with additional information on how to reduce workplace exposure risk by pinpointing where best practices were not followed to provide clear recommendations to workplaces for improved safety.

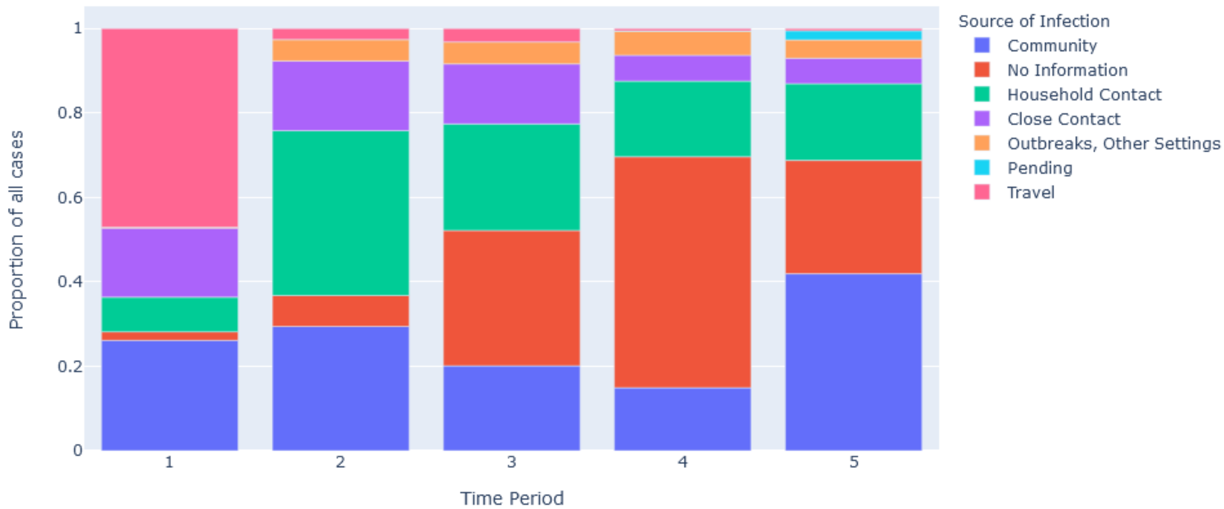
6. Conclusion

This research investigated spatiotemporal trends in COVID-19, mobility, and social determinants of health at a neighbourhood level in Toronto. Neighbourhoods in the city's northwest suffered disproportionate impacts of COVID-19 and tended to have more essential workers, increased material deprivation, ethnic concentration, and lower reductions in mobility. In contrast, the clusters of neighbourhoods with the lowest rates of COVID-19 were in the city's more advantaged neighbourhoods, which had higher incomes and smaller household sizes. The strong spatial alignment between hot spots of mobility and COVID-19 cases aligns with other findings around the efficacy of reducing overall mobility and time spent away from home, or lack of, while the misalignment between cold spots suggests there may be deeper interactions at play in communities that had low COVID-19 incidence but also less reduction in mobility. The temporal trends explained in this paper also highlight the changing demographic dynamics of the pandemic, as wealthier neighbourhoods were most affected at the outset of the pandemic and neighbourhoods with higher levels of material deprivation quickly became hot spot locations for COVID-19 once the disease became widespread in Toronto.

The strong spatial and socioeconomic relationships between COVID-19 and mobility have important policy implications for future pandemics. Short term policies to enable marginalized communities and essential workers to effectively follow government guidelines through paid sick leave, wraparound services, voluntary self-isolation, and improved access to testing could mitigate the disproportionate impacts experienced in these neighbourhoods. Providing the necessary short and long term supports to encourage healthier communities and limit healthcare inequities will reduce the economic and social impact of future pandemics. The location of the neighbourhood in which one lives does not necessarily need to define their risk of contracting COVID-19 or a future disease if proactive measures are taken to support marginalized residents before and during the next pandemic.

7. Appendices

Appendix A. COVID-19 cases source of infection as proportion of all cases, per time period.

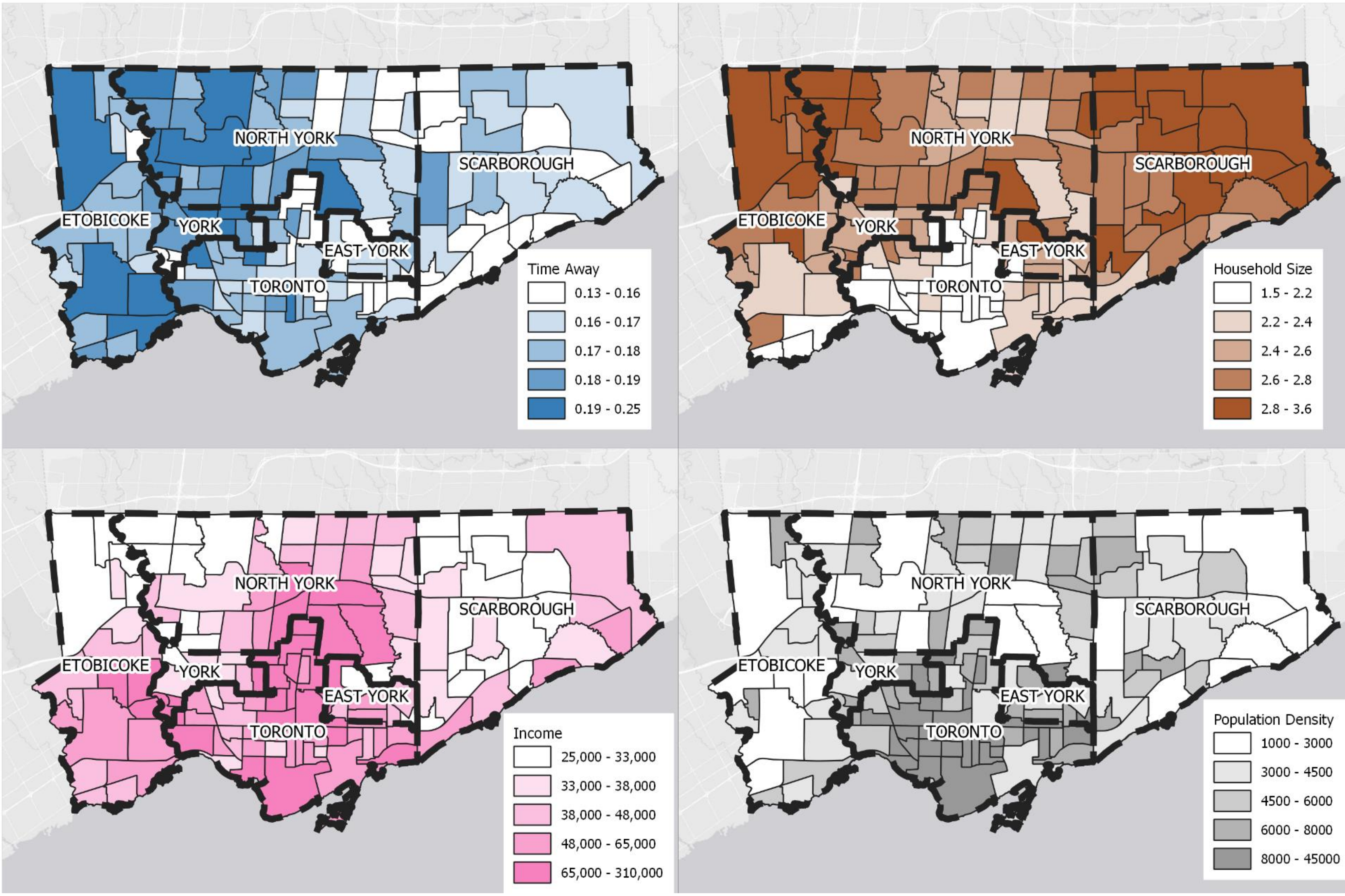


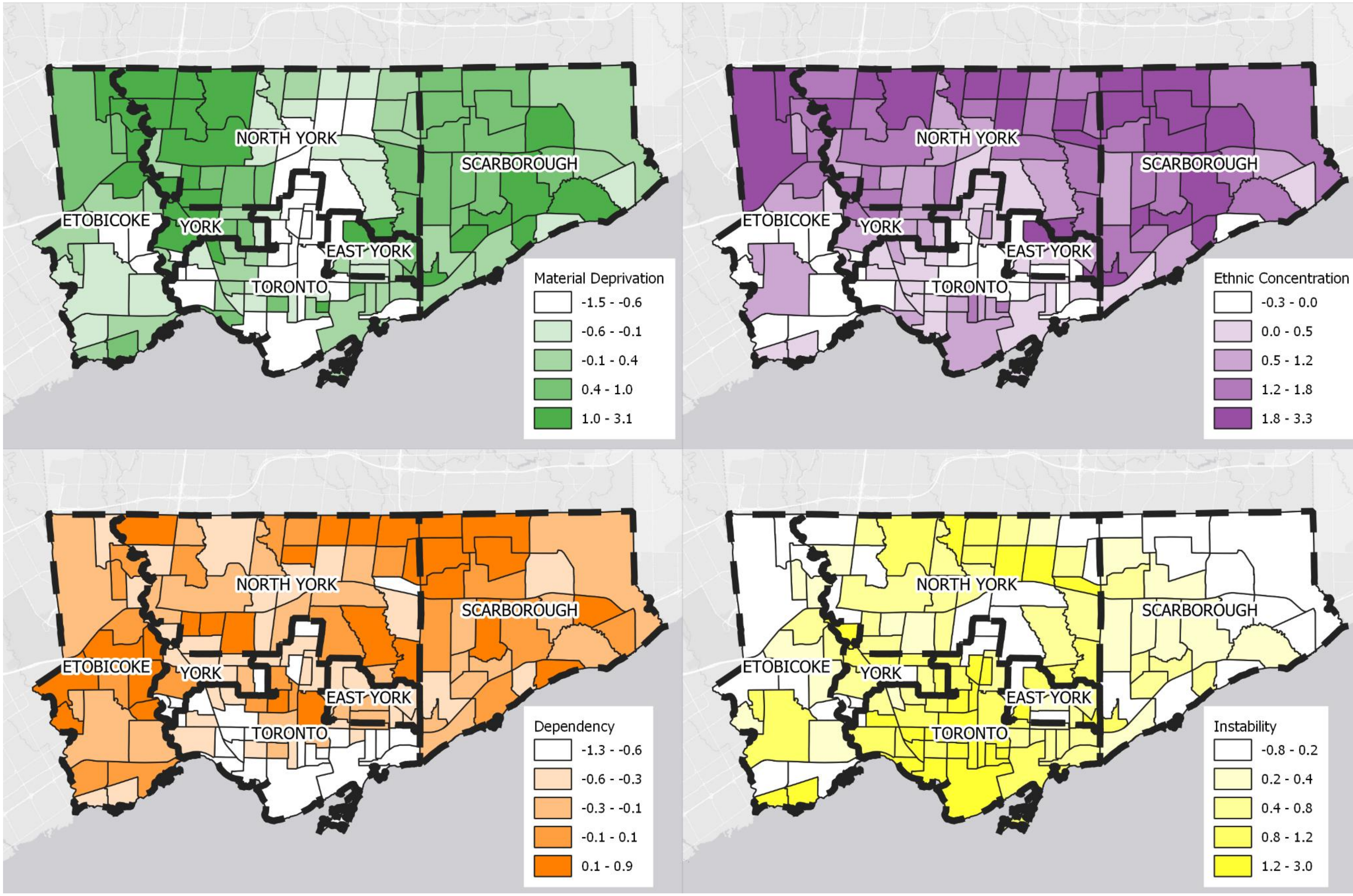
Appendix B. Complete Wilcoxon two sample significant test results for by time period and cluster variable.

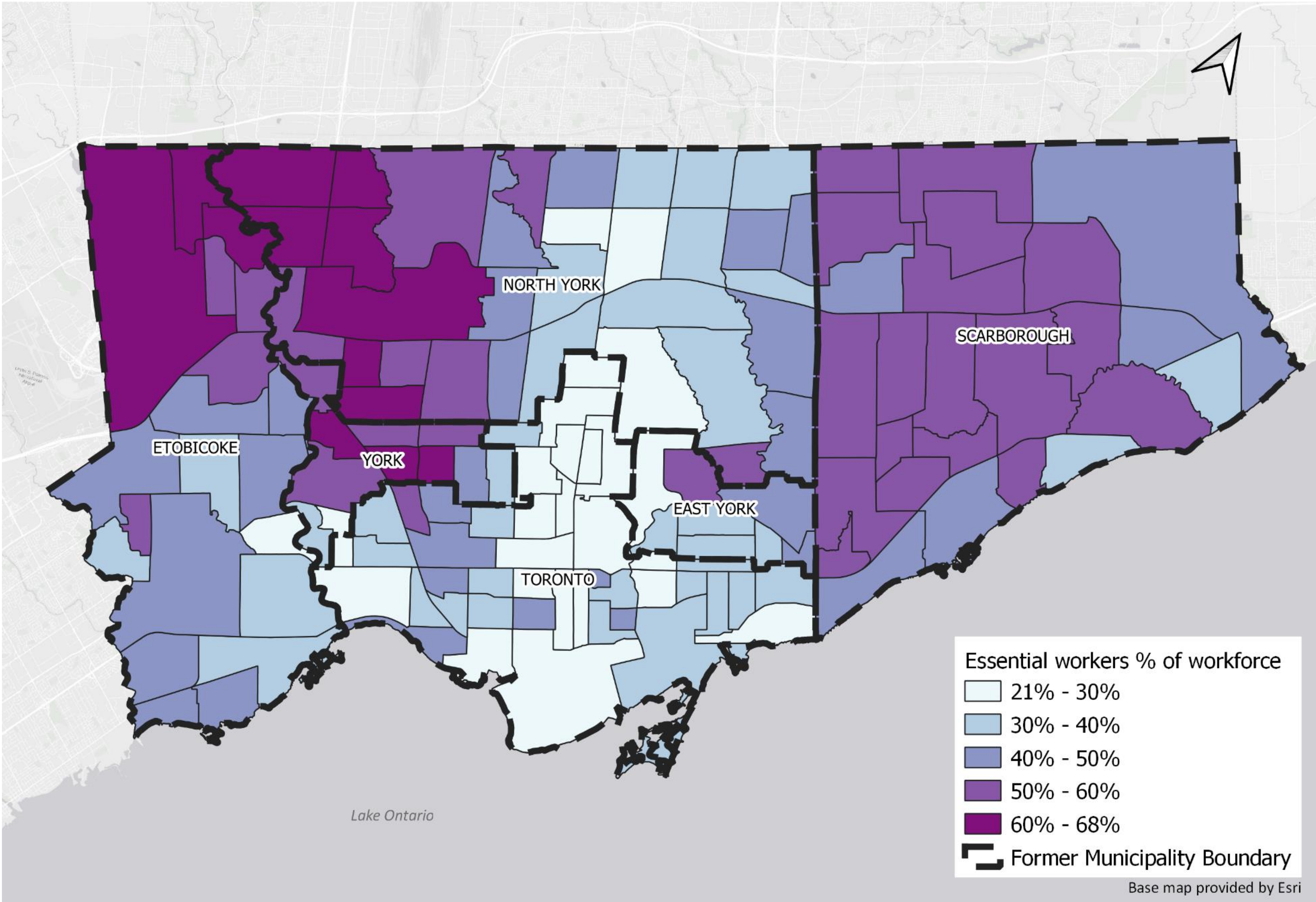
Variable	Time Period	Incidence: Hot spots	Incidence: Cold spots	Incidence: Other	Incidence: Hot vs. cold p value	Incidence: significance
ON-Marg: Material deprivation	1	-0.69	1.678	0.442	0.024	*
ON-Marg: Material deprivation	2	1.374	-0.489	0.115	0.009	**
ON-Marg: Material deprivation	3	1.387	-0.258	0.146	0.000	***
ON-Marg: Material deprivation	4	1.334	-0.617	0.236	0.000	***
ON-Marg: Material deprivation	5	1.362	-0.608	0.277	0.000	***
ON-Marg: Ethnic concentration	1	0.445	1.531	1.162	0.031	*
ON-Marg: Ethnic concentration	2	1.603	0.096	1.002	0.007	**
ON-Marg: Ethnic concentration	3	1.572	0.869	0.969	0.003	**
ON-Marg: Ethnic concentration	4	1.73	0.313	1.078	0.000	***
ON-Marg: Ethnic concentration	5	1.568	0.282	1.156	0.000	***
ON-Marg: Residential Instability	1	-0.572	-0.505	-0.152	1.000	
ON-Marg: Residential Instability	2	-0.19	-0.325	-0.235	0.097	
ON-Marg: Residential Instability	3	-0.163	-0.025	-0.296	0.944	
ON-Marg: Residential Instability	4	-0.187	-0.505	-0.158	0.096	
ON-Marg: Residential Instability	5	-0.213	-0.503	-0.153	0.041	*
ON-Marg: Dependency	1	1.558	0.86	0.576	0.582	
ON-Marg: Dependency	2	0.385	0.773	0.821	0.295	
ON-Marg: Dependency	3	0.376	0.55	0.885	0.645	
ON-Marg: Dependency	4	0.27	1.551	0.639	0.000	***
ON-Marg: Dependency	5	0.39	1.613	0.573	0.002	**
Mobility: Time away (%)	1	27.7	24.3	24.5	0.098	
Mobility: Time away (%)	2	15.3	13.2	13	0.029	*
Mobility: Time away (%)	3	20.2	17.1	18	0.001	***
Mobility: Time away (%)	4	18.9	17	17.1	0.011	*
Mobility: Time away (%)	5	18.5	14.4	15.4	0.000	***
Census: Average income ($)	1	85863	32214	44710	0.024	*
Census: Average income ($)	2	32689	104870	51880	0.007	**
Census: Average income ($)	3	32820	79173	49584	0.000	***
Census: Average income ($)	4	31626	81617	48028	0.000	***
Census: Average income ($)	5	32512	82275	46809	0.000	***
Census: Household size (individuals)	1	2.1	2.5	2.6	0.176	
Census: Household size (individuals)	2	2.9	2.3	2.5	0.009	**
Census: Household size (individuals)	3	2.8	2.5	2.4	0.001	**
Census: Household size (individuals)	4	2.9	2.0	2.5	0.000	***
Census: Household size (individuals)	5	2.8	2.0	2.6	0.000	***
Population density (per km2)	1	8996	6215	5791	0.726	
Population density (per km2)	2	4088	6002	6795	0.023	*
Population density (per km2)	3	4104	5400	7072	0.257	
Population density (per km2)	4	4209	8919	6171	0.002	**
Population density (per km2)	5	4331	9592	5836	0.004	**
Census: Essential workers (%)	1	30.0	62.7	46.1	0.044	*
Census: Essential workers (%)	2	60.1	27.8	40.9	0.007	***
Census: Essential workers (%)	3	60.1	32.8	41.8	0.000	***
Census: Essential workers (%)	4	59.0	28.9	43.2	0.000	***
Census: Essential workers (%)	5	60.4	28.9	43.5	0.000	***

Variable	Time Period	Incidence: Hot spots	Incidence: Cold spots	Incidence: Other	Incidence: Hot vs. cold p value	Incidence: significance
ON-Marg: Material deprivation	1	-0.692	0.838	0.368	0.001	***
ON-Marg: Material deprivation	2	1.14	0.777	-0.009	0.565	
ON-Marg: Material deprivation	3	1.334	0.647	-0.033	0.006	**
ON-Marg: Material deprivation	4	1.224	-0.283	0.105	0.000	***
ON-Marg: Material deprivation	5	1.228	-0.334	0.1	0.000	***
ON-Marg: Ethnic concentration	1	0.467	1.521	1.074	0.008	**
ON-Marg: Ethnic concentration	2	1.248	1.423	0.934	0.832	
ON-Marg: Ethnic concentration	3	1.402	1.382	0.888	0.768	
ON-Marg: Ethnic concentration	4	1.385	0.407	1.013	0.024	*
ON-Marg: Ethnic concentration	5	1.434	0.039	1.047	0.000	***
ON-Marg: Residential Instability	1	-0.569	-0.12	-0.176	0.002	**
ON-Marg: Residential Instability	2	-0.211	-0.202	-0.243	0.832	
ON-Marg: Residential Instability	3	-0.216	-0.064	-0.279	0.431	
ON-Marg: Residential Instability	4	-0.171	-0.145	-0.252	0.589	
ON-Marg: Residential Instability	5	-0.154	-0.408	-0.235	0.001	**
ON-Marg: Dependency	1	1.797	0.101	0.647	0.021	*
ON-Marg: Dependency	2	0.392	0.495	0.878	0.414	
ON-Marg: Dependency	3	0.443	0.418	0.9	0.731	
ON-Marg: Dependency	4	0.377	0.763	0.833	0.464	
ON-Marg: Dependency	5	0.368	0.837	0.838	0.022	*
Mobility: Time away (%)	1	27.9	23	24.8	0.000	***
Mobility: Time away (%)	2	15	11.6	13.3	0.000	***
Mobility: Time away (%)	3	19.8	16.4	18.3	0.000	***
Mobility: Time away (%)	4	19.4	16.1	17.1	0.001	***
Mobility: Time away (%)	5	18.2	13.3	15.3	0.000	***
Census: Average income ($)	1	83538	35269	47775	0.001	***
Census: Average income ($)	2	36001	38077	57497	0.694	
Census: Average income ($)	3	35339	38995	58154	0.085	
Census: Average income ($)	4	34513	76158	53734	0.001	***
Census: Average income ($)	5	33953	79906	53248	0.000	***
Census: Household size (individuals)	1	2.0	2.9	2.5	0.001	***
Census: Household size (individuals)	2	2.7	2.7	2.4	0.694	
Census: Household size (individuals)	3	2.8	2.7	2.4	0.313	
Census: Household size (individuals)	4	2.8	2.3	2.5	0.013	*
Census: Household size (individuals)	5	2.8	2.2	2.5	0.000	***
Population density (per km2)	1	10303	3770	5987	0.004	**
Population density (per km2)	2	4979	5135	6872	0.650	
Population density (per km2)	3	5526	5231	6817	0.806	
Population density (per km2)	4	4421	5684	6811	0.215	
Population density (per km2)	5	4221	6931	6806	0.002	**
ON-Marg: Material deprivation	1	-0.692	0.838	0.368	0.001	***
ON-Marg: Material deprivation	2	1.14	0.777	-0.009	0.565	
ON-Marg: Material deprivation	3	1.334	0.647	-0.033	0.006	**
ON-Marg: Material deprivation	4	1.224	-0.283	0.105	0.000	***
ON-Marg: Material deprivation	5	1.228	-0.334	0.1	0.000	***
Census: Essential workers (%)	1	28.1	52.8	43.5	0.001	***
Census: Essential workers (%)	2	59.8	49.4	37.0	0.03	*
Census: Essential workers (%)	3	60.1	45.2	37.4	0.000	***
Census: Essential workers (%)	4	59.8	32.5	39.4	0.000	***
Census: Essential workers (%)	5	60.0	32.0	40.3	0.000	***

Appendix C. Neighbourhood maps for analysis variables.




NORTH YORK
SCARBOROUGH
ETOBICOKE
YORK
EAST YORK
TORONTO
Material Deprivation
-1.5 - -0.6
-0.6 - -0.1
-0.1 - 0.4
0.4 - 1.0
1.0 - 3.1
Ethnic Concentration
-0.3 - 0.0
0.0 - 0.5
0.5 - 1.2
1.2 - 1.8
1.8 - 3.3
Dependency
-1.3 - -0.6
-0.6 - -0.3
-0.3 - -0.1
-0.1 - 0.1
0.1 - 0.9
Instability
-0.8 - 0.2
0.2 - 0.4
0.4 - 0.8
0.8 - 1.2
1.2 - 3.0


NORTH YORK
SCARBOROUGH
ETOBICOKE
YORK
EAST YORK
TORONTO
Lake Ontario
Essential workers % of workforce
21% - 30%
30% - 40%
40% - 50%
50% - 60%
60% - 68%
Former Municipality Boundary
Base map provided by Esri

8. Reference List

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