9-28-2022 1:00 PM

Understanding changes to human mobility patterns in Ontario, Canada during the COVID-19 pandemic

Ben Klar, *The University of Western Ontario*

Supervisor: Long, Jed A., *The University of Western Ontario*
Co-Supervisor: Gilliland, J, *The University of Western Ontario*
A thesis submitted in partial fulfillment of the requirements for the Master of Science degree in Geography and Environment

Abstract

Transportation research has highlighted many factors that affect human mobility patterns, but these effects have changed during the COVID-19 pandemic in accordance with changing mobility needs adapting to pandemic restrictions. We investigate COVID-19 mobility research gaps related to geographically varying associations between socio-demographic factors and mobility and the alignment of travel regions with regional pandemic restriction boundaries. Mobility indicators were modeled with socio-demographic data using a geographically weighted regression model, and flow-based travel regions were identified using the Cluster Leading Eigenvector community detection algorithm for Ontario, Canada. We find that certain associations between socio-demographics and mobility have changed due to the pandemic, and that associations vary across space. Travel regions show that travel patterns changed when pandemic restrictions were in place, and did not align with regional pandemic restriction boundaries. These findings will improve our understanding of changing mobility patterns due to the COVID-19 pandemic.

Keywords

local spatial analysis, human mobility, travel behavior, COVID-19, radius of gyration, travel time, travel regions, travel flows, community detection

Summary for Lay Audience

Mobility has a major effect on people's day-to-day lives. People need to travel to get to work, get to school, go shopping, attend appointments, and participate in leisure activities. Previous research has shown that travel patterns are different for different people. In the past, we have seen that demographic factors, such as income, age, gender, race, and job status, affects how long, how far, and what method people use to travel. When the COVID-19 pandemic started, various different restrictions on social gatherings, in-person work, and business operations were put in place across the world, changing the need for people to travel to destinations that they would normally need to travel to. Knowing that people's mobility patterns are affected by demographic factors, we look to see if changes in mobility patterns due to the COVID-19 pandemic were also dependent on demographic factors in Ontario, Canada. We found that the change in the length of time and distance people travelled after pandemic restrictions were put in place is affected by certain demographic factors, but that these effects are different depending on where in Ontario you look. The results show that patterns observed at the local level differ from patterns observed for the study area as a whole. We also identified travel regions in Ontario, which are geographic areas where a large amount of travel tends to take place within the region, and a smaller amount of travel tends to take place from one region to another. We found that these travel regions shifted over the course of the pandemic, indicating that people's travel destinations were changing along with changing pandemic restrictions. We also found that these travel regions did not align with Ontario's administrative boundaries for applying regionally targeted pandemic restrictions, which could limit the effectiveness of these regional restrictions. This research helps us to understand more about how social geography plays a role in human mobility in the context of the COVID-19 pandemic, as well as how pandemic restrictions affect overall regional travel patterns.

Co-Authorship Statement

The work presented in this thesis follows the integrated-article layout. The majority of the work, including analysis and writing of the manuscripts, was done by myself. Supervisors Dr. Jed Long and Dr. Jason Gilliland provided guidance, expertise, proofreading, and comments on the work contained in this thesis.

Chapter 2:

The co-authors of the following article which is currently under review are Dr. Long and Dr. Gilliland:

Klar, B., Long, J. & Gilliland J. Associations between socio-demographic factors and change in mobility due to COVID-19 restrictions in Ontario, Canada using Geographically Weighted Regression. The Canadian Geographer. Submitted August 2, 2022.

Chapter 3:

The following article is being prepared for publication and is co-authored by Dr. Long:

Klar, B. & Long, J. Change in functional travel regions of Ontario, Canada during the COVID-19 pandemic and their alignment with public health boundaries.

Acknowledgments

I would like to thank my primary supervisor Dr. Jed Long for the help and support he provided throughout my Master's. He was always able to offer useful and timely feedback for my thesis, course work, and other general graduate student tips. He understood my strengths and weaknesses and was able to support me in the ways that were most beneficial to my success, and he always knew the right thing to say to make me feel more confident in myself. I would not have learned as many data analysis, writing, and presentation skills as I did without Dr. Long as my supervisor.

I would also like to thank my secondary supervisor Dr. Jason Gilliland. He offered very useful feedback on my research, as well as incredibly valuable insights into the academic world, which helped me improve the quality of my research and writing.

This work was supported by the TELUS Data for Good Program. We are grateful for assistance from W. Li and J. Bettridge at TELUS who contributed to this project.

Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter 1

1 Introduction

1.1 Mobility and COVID-19

Mobility plays an important role in almost everyone's daily lives, whether it is commuting to work or school, receiving healthcare, getting groceries, going shopping, or attending entertainment or leisure activities. We also know that different people can have very different experiences with mobility due to a number of factors, most commonly the location of a person's home (Khattak et al., 2000), as well as socio-demographic factors (Axisa et al., 2012; Bai et al., 2020; Buehler, 2011; Hanson & Hanson, 1981; Larsen et al., 2009; Lenormand et al., 2015a; Manaugh et al., 2010; Pappalardo et al., 2015; Xu et al., 2018). The fact that there are so many different social factors influencing the mobility choices that people make (Buehler, 2011; X. Zhao et al., 2020), as well as the fact that certain aspects of mobility are not a choice for certain people (Khattak et al., 2000), is what makes geographers particularly interested in studying human mobility.

The COVID-19 pandemic gave transportation geographers a new perspective with which to study mobility. Many of the patterns and associations that we have long known about the interaction between people and transportation networks changed significantly due to the worldwide imposition of restrictions on non-essential in-person gatherings, making many trips that were made no longer necessary, and completely changes the way we think about mobility. From a transportation researcher's perspective, these large-scale changes were particularly interesting because they uncovered not just which trips were no longer needed, but who's. We have known for a long time that socio-economics play a large role in people's mobility needs, and the COVID-19 pandemic restrictions reinforced this, though in a different way from before. One study of mobility changes during the pandemic was particularly striking, showing that everything we had known about the amount of time and distance people in different socio-economic classes travel had completely reversed when restrictions began (Xu et al., 2018). There was a lot of discussion about so-called essential workers who were the remaining people forced to continue working in-person throughout the pandemic due to the importance of their jobs, and that the people in these positions tended to have lower socio-economic statuses (Kar et al., 2022).

In Ontario, Canada, we began to see large-scale shifts in mobility patterns in March 2020 as a result of restrictions on in-person gatherings and the closure of non-essential businesses due to the spreading of COVID-19. Over the course of the pandemic in 2020, the levels of restrictions in Ontario varied, generally in accordance with the level of risk that COVID-19 spread presented at any given time. The specific restrictions put in place also varied across regional health units at certain times (Long et al., 2021).

We have already seen an extensive amount of research in the area of human mobility during COVID-19 with various goals and approached used, but generally all coming to similar conclusions. Research has been conclusive that overall mobility decreased at the start of the pandemic (Gibbs et al., 2020; Kang et al., 2020; Santana et al., 2020; Xiong et al., 2020; You, 2022), long-distance mobility decreased the most (Dueñas et al., 2021; Kang et al., 2020; Pullano et al., 2020b; Zhang et al., 2020), and mobility changes were different for different people dependent on socio-demographic factors (Dueñas et al., 2021; Kar et al., 2022; W. D. Lee et al., 2021; Long & Ren, 2021; Pullano et al., 2020b). There were a number of limitations with these studies, such as the lack of consideration for spatially varying relationships in regression models, or data sources not being as expansive or fine-grained as they could be. This was largely due to the speed at which analysis was being performed during the early stages of the pandemic in order to quickly determine the effects of non-pharmaceutical interventions. By using a longer time range of mobility data, as well as more spatially and temporally granular data and more in-depth statistical methods, we are able to address the shortcomings of these early analyses.

1.2 Background

1.2.1 Mobility and Big Data

Historically, human mobility research has been carried out using travel surveys, where study participants are asked to report the locations and purposes of trips that they make during a specified time period. This gave researchers detailed information about what types of trips they were making, the purpose of the trips, the travel mode, the time and duration, and any other variable that the researcher felt was important for their specific study. It also allowed these mobility attributes to be tied to other information such as socio-demographic factors. However, this can only be done on a limited number of people. A successor to travel surveys was GPS-based surveys, where participants would carry GPS trackers during any trips they make during the study period. This gives the benefits of the travel surveys, but with higher spatial and temporal resolution.

More recently, the prevalence of mobile devices has allowed for the collection of big data, which is generated as a by-product of location tracking equipped mobile devices that people carry regularly with them. While not specifically intended for mobility research purposes, these big datasets have become a common way to perform mobility research. This allows for a large sample size of location data, and a high spatial and temporal resolution, but has a trade-off of not having information about socio-demographic variables. There are two main types of passively collected mobile phone data: call detail records (CDR) and sightings data. CDR data contains data points for when an event took place on the device that requires a connection to a cell tower, such as a call or text. Sightings data contains points for every time a phone is positioned. Sightings typically occur at a much higher frequency than CDRs, therefore offering a much higher spatial and temporal resolution (C. Chen et al., 2016a).

Because of the importance of large-scale data sources to analyze mass mobility across a large study area, researchers have to look to sources of automated large-scale data collection. Using location data from cell towers offers a relatively large and random sample and is temporally dense, but trajectories are not always perfect due to the nature of cell tower layouts (C. Chen et al., 2016a). Other methods include app-based data sources from Google (Huang et al., 2021; Stevens et al., 2022), Facebook (Shepherd et al., 2021; Spyratos et al., 2019), and Apple Maps (Huang et al., 2021). These app-based data sources may have more spatial and temporal gaps if location is only measured when the app is being used, but might have more potential to connect the data to socio-demographic information. There are also data aggregation and location intelligence companies like SafeGraph and Descartes Labs (Gao et al., 2020; Liang et al., 2021). These companies have may datasets that mobility data can be compared with to gain a deeper understanding into the social factors behind mobility patterns.

The three historic methods of collecting mobility data – travel surveys, GPS, and mobile phone – each have their own benefits and limitations that must be considered to determine which data source to use for a study. The oldest method, travel surveys, have a number of limitations as they were mainly used at a time of limited technological options. Collecting these datasets are costly and time-consuming, with a limited sample depending on the resources available as it requires a limited number of individuals to manually fill out a questionnaire indicating details of the trips they made (Xu et al., 2015). However, due to the limited number of participants and the manual process, non-spatial attributes about individuals being surveyed can also be collected, which can help for studying how mobility relates to socio-demographic factors (Xu et al., 2015). It also guarantees an accurate representation of the data since there is no need to infer when a trip was taken from passively collected data. As an example of the data that a travel survey can provide, Hanson and Hanson (1981) use a dataset that samples 97 random households in Sweden for a five-week period. Each member of the household details the trips they made for each time they left their home, including each stop they made on their trip, the time of arrival and departure, the means of transportation, the street address, the type of location visited, activities pursued, and the expenditure at the location.

When GPS technology became widely available for use by the public in the late 1990s, it became a tool for tracking movement patterns more accurately and without the need for individuals to fill out a survey (Xu et al., 2015). This had the benefit of giving more accurate trajectories and trip timings through an automated process, but still required individual participants to be used for the study who must carry the GPS device with them as they travel, therefore limiting the sample size to the resources available. GPS could be used in combination with travel surveys, allowing for participants to give any additional information that the researchers are looking for not captured by GPS (C. Chen et al., 2016a). In many instances, GPS devices were used on their own, introducing the new problem where details such as trip destinations or stop points must be derived from the

GPS trajectories (Shen et al., 2013). GPS devices also have the limitations of signal loss and battery life.

With mobile devices, location information can be generated passively as the mobile device communicates with the cellular network. The temporal resolution of cellular location data can vary based on which events that determine when a location is tracked are used. Call Detail Records (CDR) data tracks the mobile phone's position each time a call or text is sent by or delivered to the device. Sightings data tracks the location of the mobile device more frequently, offering a more fine-grained trajectory. App-based location tracking tracks the device's location only when the app is being used. Figure 1-1 outlines the difference in trajectories among the technology-based location tracking methods.

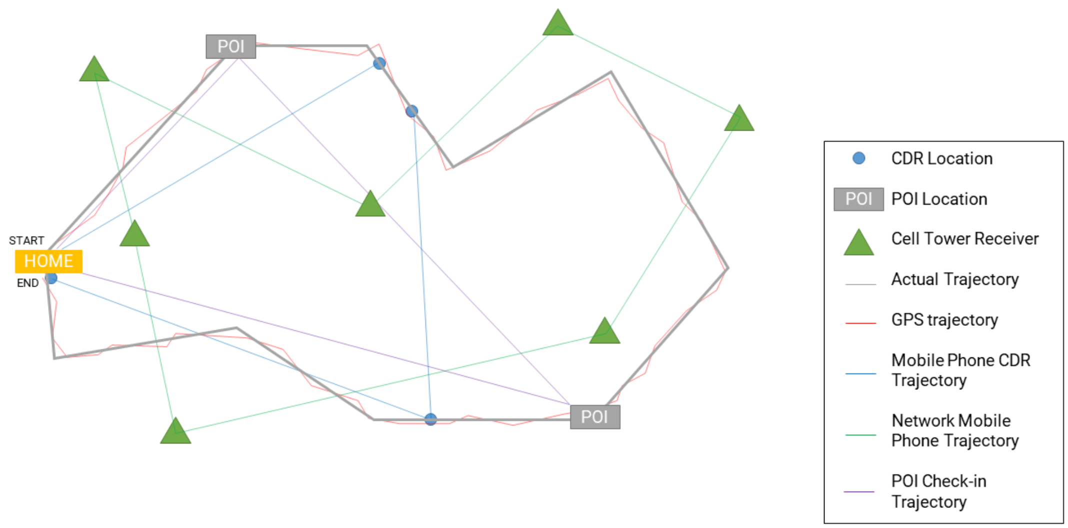


Figure 1-1: Hypothetical trajectory demonstrating the difference between GPS, Mobile Phone CDR, Mobile Phone Network, and POI Check-In trajectories

1.2.2 Quantifying Mobility

Mobility is a very broad topic, and therefore has many different ways of being measured. In transportation research, human mobility is often measured or described using activity locations, origin-destination matrices, individual trip making, and commuting patterns (Xu et al., 2018). Studies often focus on identifying and modelling travel to and from common activity locations such as home and work. The specific methods used to measure human mobility vary across disciplines (i.e. geography, planning, transportation engineering, and network science), and there are common overlapping approaches that exist, such as quantifying the spatial extent of individual activity space (González et al., 2008), understanding travel between ‘anchor’ points, and understanding regularities in human mobility.

Different measures of mobility are meant to capture different characteristics, such as space, time, movement, and location/travel attributes (Fillekes et al., 2019). These different aspects of mobility are particularly important in the context of the COVID-19 pandemic, where restrictions may have influenced different aspects of mobility in different ways. For example, just because someone spends less time moving does not necessarily mean that their activity space has decreased, or that they spend less time outside of the home. Similarly, just because someone is at home more often does not necessarily mean that they visit less destinations. To capture different elements of mobility, different measures must be used. Within this thesis, three different measures of mobility are used: movement time, radius of gyration, and flows. Movement time captures the temporal aspect of mobility, measuring time in motion. Radius of gyration captures the distance aspect of mobility, measuring the approximate distance travelled to each destination. Flows capture the geographic context of mobility patterns with the number of trips made and their destination location, which can be used to create an Origin-Destination (O-D) Matrix (C. Chen et al., 2016).

Measures of space include the number of visited locations, the extent of the space covered (also referred to as ‘activity-space’ (González et al., 2008)), and the shape or distribution of location data. Counts of places visited is useful for giving an indication of how many activities a person participates in, irrespective of the geographic context of the activity location and its proximity to a person. This is useful in some cases where we may be interested in the social factors that affect a person’s ability to participate in activities (Fransen et al., 2018; Hanson & Hanson, 1981), but it does not consider the geographic context of long versus short trips. The extent of space can cover several different meaningful aspects of a person’s life. Life-space refers to the geographic area that a person travels within over a specified period of time, which could be calculated with the convex hull or the standard deviational ellipse (Hirsch et al., 2014), indicating the size of the space that a person covers. A combination of count and extent can be calculated using radius of gyration, which is a measure of the distance from the geographic midpoint of all of a person's destinations to each of these destinations (Pepe et al., 2020; Xu et al., 2018). The shape and distribution of a person's mobility patterns indicates whether their life-spaces are mono- or poly-centric, which shows whether someone has one main place they travel to regularly (typically a home), or if there are several common destination points (Hasanzadeh, 2019). In Chapter 2 of this thesis, a measure of extent is used, specifically radius of gyration, in order to capture the geographic differences in the distance travelled across Ontario due to variation of densities.

Measures of time include the duration, the timing, and temporal distribution of time spent at different locations. The duration of time actively completing one's journey can often indicate something about a person's social disadvantage in a city, as areas with more socially-disadvantaged groups often have lower-quality transportation infrastructure, or rely on slower modes of transportation (Khattak et al., 2000). The timing of a trip does not have much of a social equity implication, but it is useful for understanding overall travel patterns and how to build transportation infrastructure or provide public transit service in a way that best meets demand. Temporal distribution can be expressed by an indicator such as entropy, where a low entropy indicates spending more time in few locations, and high entropy indicates spending less time in a greater variety of places (Fillekes et al., 2019). Chapter 2 of this thesis uses duration of time spent moving as an indicator for time, as it is likely to best reflect changing travel patterns during the pandemic and is easy to calculate using our dataset.

The movement scope categorizes different components of a trajectory into 'stops' and 'moves' and is the prerequisite for being able to compute mobility metrics from GPS or cell tower data. Stops are usually defined as a minimum time duration that the movement track was detected in a certain radius, often between 5 and 15 minutes to avoid short stops along someone's movement trajectory as being detected as a stop at a destination. For our calculation in Chapter 2, we use 10 minutes as the cutoff for a stop versus a movement, but this also compensates for the fact that mobile phone devices locations are not fluid in our data and jump between cell tower receivers. To be detected as being in motion, a cellular device much travel from one cell tower receiver's reception zone to another's, and cell tower receivers are not uniform distances apart across our study area. The attributes of a movement trajectory indicate other characteristics of the movement trajectory, such as the mode that a person used to complete a trip. This may only be available in data gained from travel surveys where a participant indicates their travel mode, but the use of machine learning could be used to predict the mode of a trip based on various attributes of the trip (X. Zhao et al., 2020).

Mobility measures can be either individual or aggregate. Individual measures include some of the person-specific measures discussed, such as duration and distance travelled. Individual measures allow for analysis of specific people's travel patterns, which can be easily compared with characteristics of the person, such as socio-demographic data. These individual measures of mobility can be aggregated together based on common characteristics of individuals. Often, it is useful to aggregate measures based on a representation of the person's home location, such as a postal code or an estimated home location based on their trajectory. This geographic aggregation of individual mobility measures is useful for being able to predict characteristics of individuals using census data. Aggregate measures of mobility are used to represent sample-wide travel patterns. For example, an origin-destination flows matrix tells us how many trips are made by a sample between each pair of geographic units. This helps to not only understand how far people are travelling, but where they are travelling and how common certain types of trips are. With this information, we can tell how many trips are made between specific neighbourhoods, or where trips to urban or suburban employment centres are originating. This gives us a much more detailed understanding of how people use the travel network across a region. It can also be used to create functional travel regions using community detection algorithms, as we do in Chapter 3.

It is useful to look at three of the most common mobility measures – travel time, travel distance, and number of trips – to understand what each measure is useful for. Travel time is a more important factor in understanding the social costs of mobility, since the time spent travelling is the measure that best reflects the time that is taken away from engaging in activities. We may expect overall travel times to be longer or shorter based on geographic context, for example denser versus less dense areas, but a given travel time has the same impact on a person’s life no matter the geographic context. Travel distance is important for understanding the proximity of important destinations, for example, how far away the nearest grocery store is. Distance is particularly useful if a study is focusing on active transportation, where someone travels the same speed no matter what road they are using. However, there is a large discrepancy among the distance between activity locations in urban areas, suburban areas and rural areas. In urban areas, you may be able to cross the street to reach a grocery store, while in rural areas it could be a 30-minute drive on a highway. This discrepancy is especially apparent for trips that take the same amount of time but area very different distances. A 15-minute drive on a 100 km/h highway is 25 kilometres, whereas a 25 minute trip in an urban area during a peak travelling period could only take you 5 to 10 kilometres. Therefore, it is important to be careful and acknowledge the context for which you are using distance-based metrics. Total number of trips is useful for understanding the social determinants of how many activities a person has to (or is able to) participate in during a specified period of time, irrespective of the time or distance to reach the activities. This could distinguish between someone who works from home, someone who simply commutes to work and back, and someone who performs several chores throughout the day. Each of these measures are useful for particular circumstances, and it must be understood what each measure is responding to.

Table 1-1: Characteristics of travel time, travel distance, and number of trips mobility measures

	Variability based on geographic context	**Captures participation in activities**	**Captures social cost of travel**	**Varies based on travel mode**
Travel Time	No	No	Yes	Yes
Travel Distance	Yes	No	No	No
Number of Trips	No	Yes	No	No

1.2.3 Rapid Analysis of Mobility Patterns during COVID-19

Early on in the pandemic, there was a rush to provide data on the impacts of non-pharmaceutical interventions (M. Lee et al., 2020; Warren & Skillman, 2020; Xiong et al., 2020). Due to the rapidly changing nature of pandemic responses, there was an urgency to get data to the public as soon as possible to assess the impacts of these interventions and decide the best way to move forward. Due to the nature of these fast-paced responses, the findings were somewhat limited in the depth of their analysis and their scientific rigor. The early call for the publishing of data on the effectiveness of non-pharmaceutical interventions led to papers like Oliver et al. (2020), which looked to provide real-time up-to-date datasets outlining the current state of the pandemic, and how to move forward with different intervention options. Many of these early papers rely on some form of passively collected data, such as mobile phone tracking data, as this data is rapidly available. However, many of these studies were not necessarily scientifically rigorous in their analysis and were mainly meant to provide mobility data to the public as quickly as possible. While this information was useful at the time, it is now even more useful for us to go back and perform more in-depth analysis of mobility data for a longer range of time to better understand the different aspects of mobility during the pandemic.

Lee et al. (2020) provide national mobility trends across the Unites States during the early stages of the pandemic, and their relation to confirmed COVID-19 cases in each state. This study performed analysis on the differing effects on different socio-economic groups. However, the study had the limitations of being early in the pandemic offering a limited range of results of how mobility was affected, and it did not use a rigorous model approach to determine associations between mobility and socio-economic factors. Similarly, Warren and Skillman (2020) used mobility from Descartes Labs to show mobility changes during the first month of pandemic restrictions in the United States, but there were no geographic models, no connection to COVID-19 cases or socio-economic factors, and only includes a very small range of time. Xiong et al. (2020) were able to go a bit farther and use a model that captures the time-varying relationship between COVID-19 infections and inflow for a relatively large range of time, but is still limited in its consideration of geographic variability and social factors. By analyzing data further into the pandemic, by using rigorous spatial modeling techniques, and by connecting mobility data with socio-economic data, we were able to address the shortcomings of these early studies to provide a more comprehensive analysis on the effects of COVID-19 on mobility.

1.3 Research Objectives and Questions

The study of human mobility is useful for understanding what factors cause people to move the way they do as individuals, and to understand the geographic contexts that influence trip patterns of the population from a regional and inter-regional perspective. The overall research question for this thesis is: How did human mobility patterns in Ontario change during the COVID-19 pandemic relative to pre-pandemic, and do mobility patterns we have observed in previous transportation research still apply during the pandemic? The two following research chapters in this thesis are guided by these general objectives of the study of mobility, and are applied to the context of Ontario, Canada during the COVID-19 pandemic.

The overall objective of Chapter 2 is to study how changes in mobility during COVID-19 relate to socio-demographic factors. Specifically, Chapter 2 seeks to answer the following questions:

1. Do relationships between socio-demographic variables and mobility vary across Ontario?
2. Did people with lower socio-economic status have higher relative mobility during COVID-19?

The objective of Chapter 3 is to identify and analyze functional regions from flow patterns at different times of the pandemic. Chapter 3 demonstrates how functional regions are representations of flow patterns, and seeks to answer the following questions:

3. Do functional regions in Southern Ontario change over the course of the COVID-19 pandemic?
4. Do functional regions in Southern Ontario align with Ontario’s Public Health Unit boundaries, to which regionally targeted pandemic restrictions were applied?

1.4 References

Axisa, J. J., Scott, D. M., & Bruce Newbold, K. (2012). Factors influencing commute distance: A case study of Toronto's commuter shed. Journal of Transport Geography, 24, 123–129. https://doi.org/10.1016/j.jtrangeo.2011.10.005

Bai, X., Zhai, W., Steiner, R. L., & He, Z. (2020). Exploring extreme commuting and its relationship to land use and socioeconomics in the central Puget Sound. Transportation Research Part D: Transport and Environment, 88, 102574. https://doi.org/10.1016/j.trd.2020.102574

Buehler, R. (2011). Determinants of transport mode choice: A comparison of Germany and the USA. Journal of Transport Geography, 19(4), 644–657. https://doi.org/10.1016/j.jtrangeo.2010.07.005

Chen, C., Ma, J., Susilo, Y., Liu, Y., & Wang, M. (2016a). The promises of big data and small data for travel behavior (aka human mobility) analysis. Transportation Research Part C: Emerging Technologies, 68, 285–299. https://doi.org/10.1016/j.trc.2016.04.005

Chen, C., Ma, J., Susilo, Y., Liu, Y., & Wang, M. (2016b). The promises of big data and small data for travel behavior (aka human mobility) analysis. Transportation Research Part C: Emerging Technologies, 68, 285–299. https://doi.org/10.1016/j.trc.2016.04.005

Dueñas, M., Campi, M., & Olmos, L. E. (2021). Changes in mobility and socioeconomic conditions during the COVID-19 outbreak. Humanities and Social Sciences Communications, 8(1), 1–10. https://doi.org/10.1057/s41599-021-00775-0

Fillekes, M. P., Giannouli, E., Kim, E.-K., Zijlstra, W., & Weibel, R. (2019). Towards a comprehensive set of GPS-based indicators reflecting the multidimensional nature of daily mobility for applications in health and aging research. International Journal of Health Geographics, 18(1), 17. https://doi.org/10.1186/s12942-019-0181-0

Fransen, K., Farber, S., Deruyter, G., & De Maeyer, P. (2018). A spatio-temporal accessibility measure for modelling activity participation in discretionary activities. Travel Behaviour and Society, 10, 10–20. https://doi.org/10.1016/j.tbs.2017.09.002

Gao, S., Rao, J., Kang, Y., Liang, Y., & Kruse, J. (2020). Mapping county-level mobility pattern changes in the United States in response to COVID-19. SIGSPATIAL Special, 12(1), 16–26. https://doi.org/10.1145/3404820.3404824

Gibbs, H., Liu, Y., Pearson, C. A. B., Jarvis, C. I., Grundy, C., Quilty, B. J., Diamond, C., & Eggo, R. M. (2020). Changing travel patterns in China during the early stages of the COVID-19 pandemic. Nature Communications, 11(1), 5012. https://doi.org/10.1038/s41467-020-18783-0

González, M. C., Hidalgo, C. A., & Barabási, A.-L. (2008). Understanding individual human mobility patterns. Nature, 453(7196), 779–782. https://doi.org/10.1038/nature06958

Hanson, S., & Hanson, P. (1981). The Travel-Activity Patterns of Urban Residents: Dimensions and Relationships to Sociodemographic Characteristics. Economic Geography, 57(4), 332–347. https://doi.org/10.2307/144213

Hasanzadeh, K. (2019). Exploring centricity of activity spaces: From measurement to the identification of personal and environmental factors. Travel Behaviour and Society, 14, 57–65. https://doi.org/10.1016/j.tbs.2018.10.001

Hirsch, J. A., Winters, M., Clarke, P., & McKay, H. (2014). Generating GPS activity spaces that shed light upon the mobility habits of older adults: A descriptive analysis. International Journal of Health Geographics, 13(1), 51. https://doi.org/10.1186/1476-072X-13-51

Huang, X., Li, Z., Jiang, Y., Ye, X., Deng, C., Zhang, J., & Li, X. (2021). The characteristics of multi-source mobility datasets and how they reveal the luxury nature of social distancing in the U.S. during the COVID-19 pandemic. International Journal of Digital Earth, 14(4), 424–442. https://doi.org/10.1080/17538947.2021.1886358

Kang, Y., Gao, S., Liang, Y., Li, M., Rao, J., & Kruse, J. (2020). Multiscale dynamic human mobility flow dataset in the U.S. during the COVID-19 epidemic. Scientific Data, 7(1), 390. https://doi.org/10.1038/s41597-020-00734-5

Kar, A., Le, H. T. K., & Miller, H. J. (2022). What Is Essential Travel? Socioeconomic Differences in Travel Demand in Columbus, Ohio, during the COVID-19 Lockdown. Annals of the American Association of Geographers, 112(4), 1023–1046. https://doi.org/10.1080/24694452.2021.1956876

Khattak, A. J., Amerlynck, V. J., & Quercia, R. G. (2000). Are Travel Times and Distances to Work Greater for Residents of Poor Urban Neighborhoods? Transportation Research Record, 1718(1), 73–82. https://doi.org/10.3141/1718-10

Larsen, K., Gilliland, J., Hess, P., Tucker, P., Irwin, J., & He, M. (2009). The Influence of the Physical Environment and Sociodemographic Characteristics on Children's Mode of Travel to and From School. American Journal of Public Health, 99(3), 520–526. https://doi.org/10.2105/AJPH.2008.135319

Lee, M., Zhao, J., Sun, Q., Pan, Y., Zhou, W., Xiong, C., & Zhang, L. (2020). Human mobility trends during the early stage of the COVID-19 pandemic in the United States. PLOS ONE, 15(11), e0241468. https://doi.org/10.1371/journal.pone.0241468

Lee, W. D., Qian, M., & Schwanen, T. (2021). The association between socioeconomic status and mobility reductions in the early stage of England's COVID-19 epidemic. Health & Place, 69, 102563. https://doi.org/10.1016/j.healthplace.2021.102563

Lenormand, M., Louail, T., Cantú-Ros, O. G., Picornell, M., Herranz, R., Arias, J. M., Barthelemy, M., Miguel, M. S., & Ramasco, J. J. (2015). Influence of sociodemographic characteristics on human mobility. Scientific Reports, 5(1), 10075. https://doi.org/10.1038/srep10075

Liang, Y., Yin, J., Pan, B., Lin, M., & Chi, G. (2021). Assessing the validity of SafeGraph data for visitor monitoring in Yellowstone National Park. Travel and Tourism Research Association: Advancing Tourism Research Globally. https://scholarworks.umass.edu/ttra/2021/research_papers/1

Long, J. A., Malekzadeh, M., Klar, B., & Martin, G. (2021). Do regionally targeted lockdowns alter movement to non-lockdown regions? Evidence from Ontario, Canada. Health & Place, 102668. https://doi.org/10.1016/j.healthplace.2021.102668

Long, J., & Ren, C. (2021). Associations between mobility and socio-economic indicators vary across the timeline of the Covid-19 pandemic. SocArXiv. https://doi.org/10.31235/osf.io/tca34

Manaugh, K., Miranda-Moreno, L. F., & El-Geneidy, A. M. (2010). The effect of neighbourhood characteristics, accessibility, home–work location, and demographics on commuting distances. Transportation, 37(4), 627–646. https://doi.org/10.1007/s11116-010-9275-z

Oliver, N., Lepri, B., Sterly, H., Lambiotte, R., Deletaille, S., De Nadai, M., Letouzé, E., Salah, A. A., Benjamins, R., Cattuto, C., Colizza, V., de Cordes, N., Fraiberger, S. P., Koebe, T., Lehmann, S., Murillo, J., Pentland, A., Pham, P. N., Pivetta, F., … Vinck, P. (2020). Mobile phone data for informing public health actions across the COVID-19 pandemic life cycle. Science Advances, 6(23), eabc0764. https://doi.org/10.1126/sciadv.abc0764

Pappalardo, L., Pedreschi, D., Smoreda, Z., & Giannotti, F. (2015). Using big data to study the link between human mobility and socio-economic development. 2015 IEEE International Conference on Big Data (Big Data), 871–878. https://doi.org/10.1109/BigData.2015.7363835

Pepe, E., Bajardi, P., Gauvin, L., Privitera, F., Lake, B., Cattuto, C., & Tizzoni, M. (2020). COVID-19 outbreak response, a dataset to assess mobility changes in Italy following national lockdown. Scientific Data, 7(1), 230. https://doi.org/10.1038/s41597-020-00575-2

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020). Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: A population-based study. The Lancet Digital Health, 2(12), e638–e649. https://doi.org/10.1016/S2589-7500(20)30243-0

Santana, C., Botta, F., Barbosa, H., Privitera, F., Menezes, R., & Di Clemente, R. (2020). Analysis of human mobility in the UK during the COVID-19 pandemic. https://doi.org/10.13140/RG.2.2.33207.14240

Shen, Y., Kwan, M.-P., & Chai, Y. (2013). Investigating commuting flexibility with GPS data and 3D geovisualization: A case study of Beijing, China. Journal of Transport Geography, 32, 1–11. https://doi.org/10.1016/j.jtrangeo.2013.07.007

Shepherd, H. E. R., Atherden, F. S., Chan, H. M. T., Loveridge, A., & Tatem, A. J. (2021). Domestic and international mobility trends in the United Kingdom during the COVID-19 pandemic: An analysis of facebook data. International Journal of Health Geographics, 20(1), 46. https://doi.org/10.1186/s12942-021-00299-5

Spyratos, S., Vespe, M., Natale, F., Weber, I., Zagheni, E., & Rango, M. (2019). Quantifying international human mobility patterns using Facebook Network data. PLOS ONE, 14(10), e0224134. https://doi.org/10.1371/journal.pone.0224134

Stevens, N. T., Sen, A., Kiwon, F., Morita, P. P., Steiner, S. H., & Zhang, Q. (2022). Estimating the Effects of Non-Pharmaceutical Interventions and Population Mobility on Daily COVID-19 Cases: Evidence from Ontario. Canadian Public Policy, 48(1), 144–161. https://doi.org/10.3138/cpp.2021-022

Warren, M. S., & Skillman, S. W. (2020). Mobility Changes in Response to COVID-19 (arXiv:2003.14228). arXiv. https://doi.org/10.48550/arXiv.2003.14228

Xiong, C., Hu, S., Yang, M., Luo, W., & Zhang, L. (2020). Mobile device data reveal the dynamics in a positive relationship between human mobility and COVID-19 infections. Proceedings of the National Academy of Sciences, 117(44), 27087–27089. https://doi.org/10.1073/pnas.2010836117

Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). Human mobility and socioeconomic status: Analysis of Singapore and Boston. Computers, Environment and Urban Systems, 72, 51–67. https://doi.org/10.1016/j.compenvurbsys.2018.04.001

Xu, Y., Shaw, S.-L., Zhao, Z., Yin, L., Fang, Z., & Li, Q. (2015). Understanding aggregate human mobility patterns using passive mobile phone location data: A home-based approach. Transportation, 42(4), 625–646. https://doi.org/10.1007/s11116-015-9597-y

You, G. (2022). The disturbance of urban mobility in the context of COVID-19 pandemic. Cities, 128, 103821. https://doi.org/10.1016/j.cities.2022.103821

Zhang, W., Chong, Z., Li, X., & Nie, G. (2020). Spatial patterns and determinant factors of population flow networks in China: Analysis on Tencent Location Big Data. Cities, 99, 102640. https://doi.org/10.1016/j.cities.2020.102640

Zhao, X., Yan, X., Yu, A., & Van Hentenryck, P. (2020). Prediction and behavioral analysis of travel mode choice: A comparison of machine learning and logit models. Travel Behaviour and Society, 20, 22–35. https://doi.org/10.1016/j.tbs.2020.02.003

Chapter 2

2 Associations between socio-demographic factors and change in mobility due to COVID-19 restrictions in Ontario, Canada using Geographically Weighted Regression

2.1 Introduction

Starting in March 2020, we began to see large-scale shifts in mobility patterns across Ontario, Canada as a result of restrictions on in-person gatherings and the closure of non-essential businesses due to the spreading of COVID-19. Over the course of the pandemic in 2020, the levels of restrictions in Ontario varied, generally in accordance with the level of risk that COVID-19 spread presented at any given time. The specific restrictions put in place also varied across regional health units at certain times (Long & Ren, 2021).

We know from previous transportation and human mobility research that people's mobility patterns are often dictated by socio-demographic factors. For example, previous research has shown that socio-economic status tends to have an influence on mobility, and we usually find that higher socio-economic status associated with higher rates of mobility (Fransen et al., 2018; Khattak et al., 2000; Manaugh et al., 2010; Morency et al., 2011; Pappalardo et al., 2015; Xu et al., 2018), with a few exceptions showing the inverse relationship (Xu et al., 2018). We know that urban form tends to influence the distance factor of mobility, where people in denser, urban areas tend to travel shorter distances and have a smaller activity spaces (Manaugh et al., 2010; Morency et al., 2011; Xu et al., 2018). However, with widespread changes in mobility during the COVID-19 pandemic, we seek to understand how changes in these base-mobility levels were associated with a variety of socio-economic factors, and whether these relationships vary across space.

The major shift in mobility patterns that we saw in Ontario over the course of 2020 gives us the opportunity to investigate to what extent these associations still exist the same way during the pandemic as they did pre-pandemic. Additionally, building on analysis that shows how the interaction between socio-demographics and mobility exhibited temporal variation over the course of 2020 in our study area of Ontario, Canada (Long & Ren, 2021) and how higher socio-economic status was generally associated with a greater ability to reduce one's mobility (Bonaccorsi et al., 2020a; Jay et al., 2020; W. D. Lee et al., 2021; Pullano et al., 2020b; Weill et al., 2020), this analysis reveals spatial variation in these interactions in Ontario, revealing that different socio-economic indicators affect mobility differently in different parts of Ontario.

Our analysis uses two key mobility metrics, Movement Time and a modified Radius of Gyration, and compares these to five socio-demographic variables at three time periods in 2020 using a linear regression model and a geographically weighted regression (GWR) model. Movement time and radius of gyration are measured using mobile phone positioning data and aggregated by home neighbourhood Aggregate Dissemination Area (ADA). The ADAs are then linked to socio-demographic attributes based on the 2016 Canadian Census to be used as covariates in our model. Associations between the socio-demographic covariates and the mobility metrics are fitted both globally using the linear regression model, and locally with the GWR model, to identify how socio-demographic variables are associated with mobility, and how these associations vary across space.

We hypothesize that non-uniform changes in mobility patterns during the pandemic in Ontario can be explained by social inequities, as we have seen elsewhere in the world during the pandemic (Bonaccorsi et al., 2020a; Chang et al., 2021; Dorn et al., 2020; Gibbs et al., 2020; W. D. Lee et al., 2021; Pepe et al., 2020; Pullano et al., 2020b), and similar in nature to mobility inequities we have observed pre-pandemic (Fransen et al., 2018; Kwan, 1999; Lenormand et al., 2015b; Manaugh et al., 2010; Morency et al., 2011; Páez et al., 2009; Xu et al., 2018). Further, we predict that in addition to the temporal variability of association that we have seen (Long & Ren, 2021), we will also see spatial variation in these associations. These results will give us a more in-depth understanding of how social factors affect mobility, guiding us on how social inequities in transportation can be addressed, both during and after the pandemic. For example, understanding how much time (or distance) people in different communities spend travelling to important destinations such as work, grocery, school and healthcare will highlight the need for investment of better transportation access to these destinations, or investment of more of these destinations in communities where they are needed most.

2.2 Background

2.2.1 Social Factors and mobility

The social factors associated with mobility have been examined pre-pandemic, with focus on higher and lower socio-economic status neighbourhoods (Khattak et al., 2000; Xu et al., 2018), race and visible minority communities (Khattak et al., 2000), employment type (Long & Reuschke, 2021), and gender (Kwan, 1999). One of the main themes we see in this research pre-pandemic is that in general, a higher socio-economic status allows for a greater degree of mobility, often translating to a higher ability to participate in activities (Fransen et al., 2018) or a greater level of diversification of mobility (Pappalardo et al., 2015). From this perspective, we often view these aspects of mobility as a privilege that those with a higher socio-economic status are able to enjoy. There are also cases where this was reversed – where higher income earners tend to have lower overall mobility. This is usually the case in large metropolitan areas (Khattak et al., 2000; Manaugh et al., 2010; Morency et al., 2011), such as Singapore (Xu et al., 2018), where people with a higher socio-economic status tend to live in more urban areas and require less time and distance to reach important destinations. There are several other factors that have been shown in transportation literature to have an effect on people's mobility, including age (Fransen et al., 2018; Manaugh et al., 2010; Morency et al., 2011) and belonging to visible minority groups (Fransen et al., 2018; Khattak et al., 2000).

2.2.2 Mobility during COVID-19

During COVID, we have seen several shifts in the way we have previously understood how social factors affect mobility patterns, most notably the swapping of higher-income earners and lower-income earners and their relative amounts of mobility. Specifically, we have seen that wealthier people are more likely to be able to stay home, and therefore travel for shorter amounts of time and distance than those with lower incomes, who are more likely to have to continue working at places of employment; revealing the so-called 'luxury of social distancing' (Huang et al., 2021). This pattern was observed in many places across the world including the United States (Jay et al., 2020; Weill et al., 2020), France (Pullano et al., 2020), Italy (Bonaccorsi et al., 2020), England (W. D. Lee et al., 2021), and Canada

(Long & Ren, 2021). Interestingly, prior to the pandemic there have been different findings on the effect that working from home would have on reducing mobility, with the earlier consensus being that homeworking decreases overall travel (Mokhtarian, 1991), but more recent studies indicating that there may be a null or even opposite effect (Kim, 2016; Lachapelle et al., 2018; J. Long & Reuschke, 2021; Rietveld, 2011). This could be because home-based workers tend to offset their shorter commutes with a greater level of non-work travel (Shin, 2019). However, this is under the assumption that a wide range of social and recreational activities are available, which was not always the case during the COVID-19 pandemic.

We have seen that relationships between mobility and socio-economic factors have varied throughout the timeline of the pandemic. In particular, previous work has shown that the relationship between changes in mobility and socio-demographic factors was temporally-varying in Ontario, Canada (Long & Ren, 2021). For example, this research found that areas with higher population density were associated with lower radius of gyration during the first and second waves, but a higher geographical range of mobility in the summer of 2020. Conversely, economic dependency – a composite measure of elements related to age, workforce participation, and dependency on social assistance programs – was positively related to geographical range of mobility throughout most of the timeline, but the magnitude of the coefficient changed over time with its highest value in the summer. Varying associations were also seen in the US (Jay et al., 2020), with a growing gap in mobility between low- and high-income households in the first 20 days after emergency declarations. Results from England looking at how socio-economic factors impacted mobility reduction (W. D. Lee et al., 2021), while over a shorter time range, suggest that there was some variation of these associations at different time points with slightly different model coefficients for the four weeks after the beginning of restrictions being put in place.

In addition to observed temporal variability, relationships between mobility and socio-demographic factors may vary across geographic space as well. Such, spatially varying relationships are indicative of processes that may be functionally different in different regions, and therefore exhibit different statistical relationships at different locations in space (Fotheringham et al., 2003). Previous work has shown, at broad scales, a spatially varying relationship between COVID-19 related changes in mobility and socio-demographic factors in England (W. D. Lee et al., 2021). In this work, the authors find that relationships between mobility changes during COVID-19 and socio-economic indicators vary greatly across England, and that a simple linear regression is not appropriate for capturing the inherent spatial heterogeneity of these relationships (W. D. Lee et al., 2021). Therefore, here we propose to extend this work in three key ways. First, our analysis looks at multiple time periods throughout the pandemic to study spatially varying relationships over time. Second, we employ a finer level of aggregation than this previous study, exploring mobility levels at the neighbourhood-level, which allows us to better capture the relationship between mobility levels and socio-demographic factors. Third, we also examine two different measures of mobility, as numerous studies have suggested that the way in which mobility is measured can result in different inferences about the relationships with socio-demographic factors (Long & Ren, 2021; Long & Reuschke, 2021).

2.3 Methods

2.3.1 Data and Variables

2.3.1.1 Network Mobility Data

The de-identified data used for this research was obtained from TELUS Communications Inc. as part of their Data for Good program. These data are accessed via the TELUS Insights platform, which is a privacy-protecting system for analysing aggregated and mass mobility patterns in Canada. The data comprise connections between mobile devices and cell tower receivers over time. As a device moves through space, it changes connections from receiver to receiver, generally connecting to the closest receiver. Cell tower receivers are distributed across space with a higher concentration in areas with higher population density and a lower concentration in areas with lower population density. For each connection, the data contain the start and end time of the connection, as well as geographic coordinates associated with the receiver. The data consists of an aggregate of approximately 3.5 million cellular devices in Ontario during the year 2020.

2.3.1.1.1 Estimating Home Neighbourhood Aggregate Dissemination Area

To estimate the home neighbourhood of each mobile device, clusters of receivers were identified based on a focal receiver and the surrounding receivers that the focal receiver directly connects to, termed handovers. The cluster of receivers with the greatest total dwell time of the device was labelled as the home cluster. A weighted average (by dwell time at each receiver) of the receivers that make up the home cluster was used to estimate the home neighbourhood of the device. We then identified the Aggregate Dissemination Area (ADA) census unit associated with the home neighbourhood estimate for each device using a spatial intersection. An ADA is an aggregated form of smaller census units, roughly representing 5000 to 15,000 people. The home neighbourhood estimate for each device is recomputed for each calendar month. There are a total of 1685 ADAs in Ontario, however only ADAs that included a minimum of 20 devices were used in subsequent analysis. In total, a subset of 1540 ADAs were included in the analysis here.

2.3.1.2 Mobility Measures

Two different mobility measures were used as response variables to analyze the temporal and geographical components of local mobility. Movement Time measures the total amount of time per day that a mobile device was deemed to be 'in motion' and is used to represent the temporal component of mobility. Previous studies have used similar measures of travel time, such as commute time, to capture the cumulative travel demand experienced by an individual in a given day (Khattak et al., 2000). To calculate the Movement Time metric, we separated the network mobility data into two subsets: stops and motion. Stops were identified as any instance where a device was at the same network tower receiver for a period of 10 minutes or longer. Motion was then identified as any instance that was not deemed a stop. We calculated the sum of the motion time for every day as a measure of the movement time of a device. An example of how movement time was calculated for a particular mobile device is shown in Table 2-1.

$$MT = \sum_i \sum_t D_{i,t} \quad \text{where} \quad D_{i,t} < 10 \qquad (2\text{-}1)$$

$D_{i,t}$ = dwell time at tower i and time t

Table 2-1: Example of the movement time calculation for a hypothetical scenario

Device ID	Cell Tower	Start Time	End Time	Duration (min)	In Motion?	Movement Time (min)
XYZ123	A	9:00:00	9:15:00	15	No	0
XYZ123	B	9:15:00	9:19:00	4	Yes	4
XYZ123	C	9:19:00	9:26:00	7	Yes	7
XYZ123	D	9:26:00	9:38:00	12	No	0
TOTAL				**38**		**11**

Radius of Gyration is a common measure of the geographical range of mobility that is used on cell-phone based studies of mobility and is used to represent the geographical distance component of mobility, particularly when working with big data (González et al., 2008; Lee et al., 2021; Long & Ren, 2021; Lu et al., 2013; Pepe et al., 2020; Xu et al., 2018; Zhao et al., 2019). Here, we used a modified version of the classical *Radius of Gyration* statistic, to measure a device's geographical range of movement. The classical Radius of Gyration calculation (González et al., 2008) is the square root of the sum of the squared distances, d, between each of the n different observed locations, i, and the mean centre of all the observed locations, μ.

$$ROG_{classical} = \sqrt{\frac{\sum_i^n (d_{i,\mu})^2}{n}} \tag{2-2}$$

Our modified version replaces the mean centre value with the home neighbourhood location estimate, h. We also only included those locations that were identified as Stops in the movement time measure (having a dwell time of greater than 10 minutes) as the geographical locations used in the radius of gyration measure. Further, we excluded all stops that occurred within the devices home neighbourhood cluster from the calculation.

$$ROG = \sqrt{\frac{\sum_i^n (d_{i,h})^2}{n}} \tag{2-3}$$

2.3.1.2.1 Comparing to Baseline Levels

The Movement Time (MT) and Radius of Gyration (ROG) measures for each mobile device were aggregated by taking the mean daily values for each Aggregate Dissemination Area (ADA) containing the home neighbourhood of each device. The mean daily values for each ADA region were then adjusted relative to the baseline (pre-pandemic) values. The baseline values were the average daily values for the month of February, 2020, accounting for day of the week. Aggregated values were divided by the baseline values to create the relative to baseline values with a value of 100 representing baseline mobility levels and below 100 relatively lower mobility and above 100 relatively higher mobility. All analysis will be performed on these relative measures of the mobility metrics.

$$x_{relative} = \frac{x}{b} \times 100 \qquad (2\text{-}4)$$

$x_{relative} =$ mobility metric (Movement Time or Radius of Gyration) relative to baseline
$x =$ actual mobility metric (Movement Time or Radius of Gyration)
$b =$ baseline value for mobility metric

Pearson's r correlation is calculated in our results to show the difference between these two measures, and to confirm that modelling each metric separately provides sufficiently different information.

In Section 2.4.1 we calculate the correlation between our movement time and radius of gyration values for each of the three time periods to ensure that using each of the two metrics capture a different aspect of mobility and provide us with different information.

2.3.1.3 Covariates

Covariates for the statistical analysis were selected from the 2016 Canadian Census that reflect a range of socio-demographic indicators, including age, economic, race, education, and urban form (Table 2-2). *Average Age* indicates the general age of the area, *Median Income* indicates the general economic status of people in an area, *Percent Visible Minority* indicates the amount to which racialized groups make up an area, *Percent Post-Secondary*

Educated represents the level of education generally received in the area, and *Percent Detached Home* is an indicator of the degree of 'urbanness' of the area.

These covariates are similar to ones that have been used in previous transportation research exploring effects of socio-demographic factors on mobility patterns. For example, Lee et al. (2021) use the share of households in the top income quintile as their variable representing income. They also use share of non-English speakers and share of lower middle class to represent education and occupation type, similar to our post-secondary educated variable. Similarly, Morency et al. (2011) use specific age categories, an average income variable, family size, availability of public transit nearby or a driver's license, and employment or student status. Pullano et al also used age and standard of living indicators – measured as a ratio of income to household size. In another example, Xu et al. (2018) use housing price and monthly income. In a previous study in Ontario, Canada, Long and Ren (2021) use three indicators from the Canadian index of Multiple Deprivation, representing economic dependency, ethno-cultural composition, and residential instability.

Based on this past research, we can demonstrate other examples of studies that use common socio-demographic indicators such as age, income. Visible Minority, while less commonly included in transportation research, has been analyzed in previously with its relation to social class in urban areas (Khattak et al., 2000). Importantly for our research, we know race and ethnicity played a role in COVID-19 outcomes (Dorn et al., 2020; Pareek et al., 2020), and we believe that this may have been associated with people's mobility patterns during the pandemic. Post-secondary education, while a bit different from other variables that have been used in previous research, is a well-defined variable in the Canadian Census that generally represents education and skill level. Proportion of detached homes is also different from other indicators of urban form and density, but here we use it as an indicator of urban form since it presents a proxy measure of density and housing structure.

Table 2-2: Summary statistics and definitions of the five covariates from the 2016 Canadian Census

Covariate	Paraphrased Census Canada definition	Mean	Median	St. Dev.

Average Age (years)	The average age of residents living in the ADA	40.91	41.20	4.34
Median Income ($)	The median pre-tax income among households living in the ADA	34077.61	33711.00	8570.97
Percentage Visible Minority (%)	The percentage of people living in the ADA who belong to a visible minority group defined by the Employment Equity Act	26.62	16.70	27.05
Percentage Post-Secondary Educated (%)	The percentage of people living in the ADA who have earned a 'Postsecondary certificate, diploma or degree', including an apprenticeship or trades certificate or diploma, college, CEGEP, or other non-university certificate or diploma, and university certificates, diplomas and degrees	63.25	63.00	12.33
Percentage Detached Home (%)	Number of private dwellings that fall in the structural type category of 'single-detached'	59.01	62.99	26.05

2.3.2 Spatial-Statistical Analysis

To determine the effect of independent variables on a continuous variable, we first use a multivariate linear regression model. This initial analysis provides us with a global-level model to examine the relationship of each predictor variable in the model. Subsequently, the residuals of the prediction for each observation give an idea of how well the model predicts the response variable. When we are working with geographic data and our observations are geographic units, we can map the residuals and use a Moran's I test for global spatial autocorrelation to test whether the residuals are spatially autocorrelated (Brunsdon et al., 1996). If they exhibit positive spatial autocorrelation, a simple linear regression model may yield biased parameter estimates, warranting a model that can incorporate spatial effects.

In cases where the nature of a relationship between variables is not fixed over space, a Geographically Weighted Regression (GWR) model can be used to account for such spatial heterogeneity (Brunsdon et al., 1996). GWR estimates regression coefficients of the model for each location through the use of a spatially local kernel function (Fotheringham et al., 2017). The GWR regression model can be expressed as:

$$y_i = \sum_{j=0}^{m} \beta_j(u_i, v_i) x_{ij} + \varepsilon_i \tag{2-5}$$

where y_i is the estimated response variable for location i, x_{ij} is the jth predictor variable out of m variables for location i, $\beta_j(u_i, v_i)$ is the jth coefficient for location i, the set of locations are (u_i, v_i), and ε_i is the error term for location i (Fotheringham et al., 2017).

A spatial weight matrix quantifies the spatial relationship between each pair of observations. The weight between two observations is calculated based on their distance and a distance kernel function, which generally decreases the weight between two observations as their distance from each other increases, usually with either a Gaussian or negative exponential curve. The spatial weight matrix is used to calculate localized parameter estimates $\beta_k(u_j, v_j)$ for each regressor, x_{jk}, and the matrix is constructed from the weights to define the spatial neighbourhood that provides the best model fit. The GWR function requires a kernel function and bandwidth for W as input which controls the definition of a spatially local neighbourhood (Brunsdon et al., 1996). Here we used an adaptive kernel based on a nearest neighbour conceptualization of spatial relationships (Gollini et al., 2014). The kernel shape (distance decay effect) was modelled using a bi-square function, and the bandwidth is computed adaptively based on the number of nearest neighbours to optimize the model fit following the optimization routine outlined in Gollini et al. (2014). This process interactively selects different bandwidth sizes until the model is optimized in terms of the Akaike Information Criterion (AIC) (Akaike, 1998). Through this process, we identify the optimal bandwidth for a given model representing the localness of the spatial relationship being explored – that is smaller bandwidths are associated with a stronger local relationship while larger bandwidths are indication of a broader, more global relationship. As the bandwidth approaches the size of the study area (n) the GWR model becomes equivalent to the classical regression model. All analysis was performed in R and GWR models were fit using the 'GWmodel' package (Gollini et al., 2014).

2.3.3 Time Periods

Movement time and radius of gyration measures were calculated for each day in 2020. However, the focus of this analysis was on the geographical variation in the relationship between mobility and socioeconomic variables. Therefore, to implement the spatial statistical modelling approach, we selected three five-day (weekdays) periods in 2020 representing three different levels of restrictions during the pandemic in Ontario, Canada. The week of April 6^{th} to April 10^{th} (the April time period) represents the beginning of the pandemic when there were severe restrictions in place and overall mobility levels were very low. The week of August 10^{th} to August 14^{th} (the August time period) represents an inter-wave period during the summer of 2020 when restrictions were relatively low and mobility had begun to increase (Long & Ren, 2021). The week of September 21 to September 25 (the September time period) was after most elementary and high school students had returned to in-person learning, but before the next wave of restrictions were put in place. Each of these three time periods represent different time periods during the pandemic with varying mobility patterns among different types of people.

The goal of this analysis is to determine the impacts of five key socio-demographic variables on two mobility metrics at three different times during the COVID-19 pandemic in Ontario. Six different models are tested, one for each combination of response variable (movement time and radius of gyration) and time period, and each having the same five covariates (Table 2-2).

2.4 Results

2.4.1 Data / Descriptive Statistics

In general, Average Daily Movement Time (Figure 2-1) had a very large decrease at the time of the first lockdown in Ontario in March, and then gradually started increasing again over the course of the summer, reaching a local peak in September, and then gradually started decreasing again after this point. These changes generally relate to the times at which government restrictions were applied or removed. Radius of Gyration (Figure 2-2) had a similar pattern, but the peak took place around August rather than September, and was noticeably higher than the rest of the year. Figure 2-1 and Figure 2-2 show the raw movement time and radius of gyration values, rather than the values relative to the baseline levels which is used for the analysis.

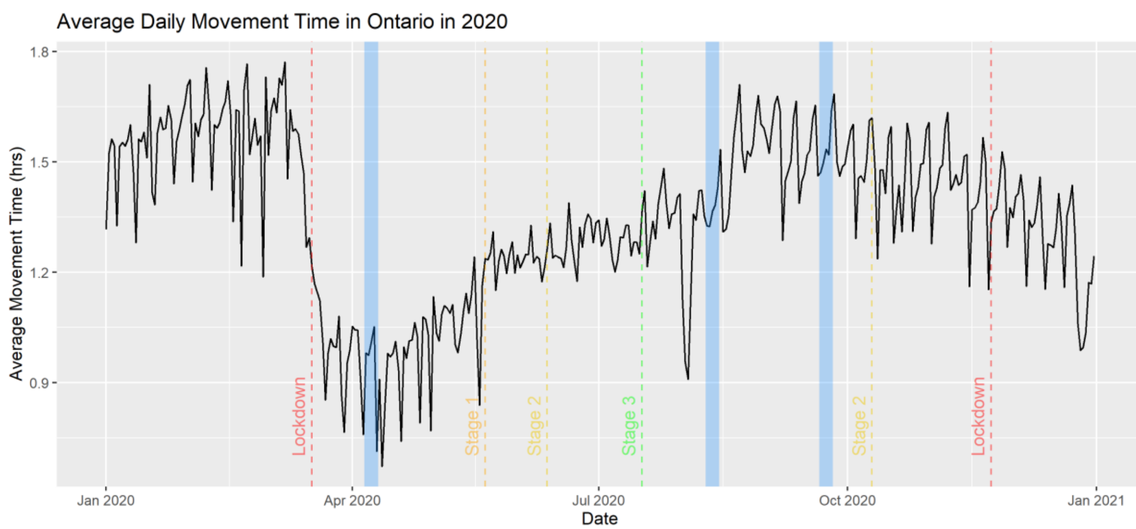


Figure 2-1: Time series plot of average daily movement time over the course of 2020 with the study periods highlighted in blue

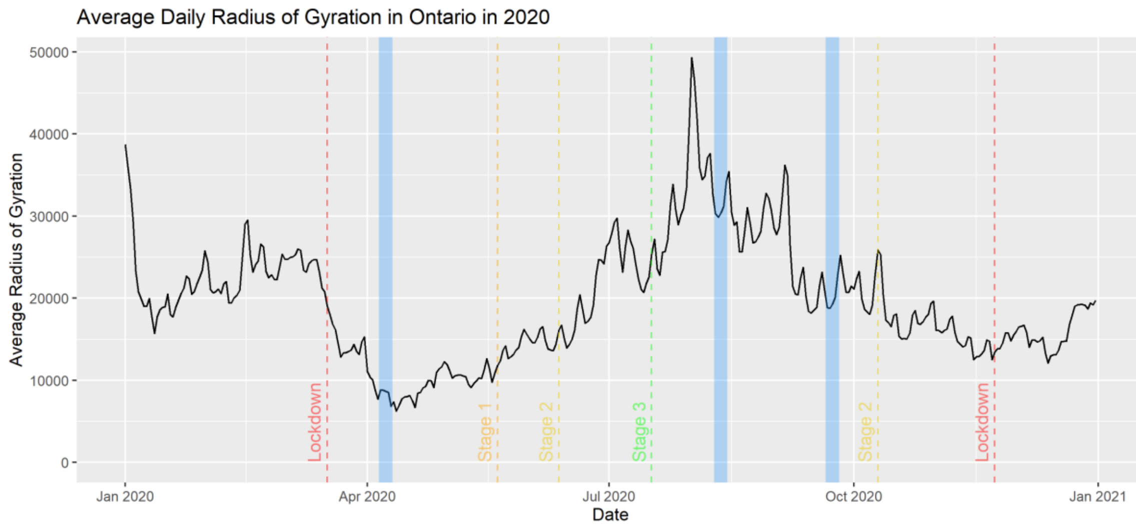


Figure 2-2: Time series plot of average daily radius of gyration over the course of 2020 with the study periods highlighted in blue

Changes in mobility were greatest in April where the mean movement time was 61.2% of the baseline, and Radius of Gyration was at 38% of the baseline. The average movement time remained below the baseline in the August and September time periods, but radius of gyration increased to 140.4% of the baseline in August. The spread of both metrics were lowest in April based on standard deviation, were the greatest in August, and then decreased again in September but remaining above April.

Table 2-3: Summary statistics for the two mobility metrics during each time period

Movement Time	Mean	Min	25%	Median	75%	Max	St. Dev.
April	61.2	34.7	54.0	60.7	67.5	98.9	9.06
August	88.5	42.1	79.1	86.5	96.5	193.2	12.58
September	98.9	67.0	89.5	97.7	107.1	178.0	12.39
Radius of Gyration	**Mean**	**Min**	**25%**	**Median**	**75%**	**Max**	**St. Dev.**
April	38.0	8.5	28.0	36.9	45.8	159.6	15.46
August	140.4	37.9	108.1	132.4	163.8	500.4	49.31
September	90.9	18.0	70.3	88.2	106.5	254.4	30.54

We tested the correlation between our two dependent variables (Figure 2-3) – Movement Time and Radius of Gyration – and found that the Pearson's correlation ranged from 0.37

to 0.53 among the time periods we are looking at. While these correlations are moderate, we find that they each capture a different aspect of mobility and are worth investigating separately.

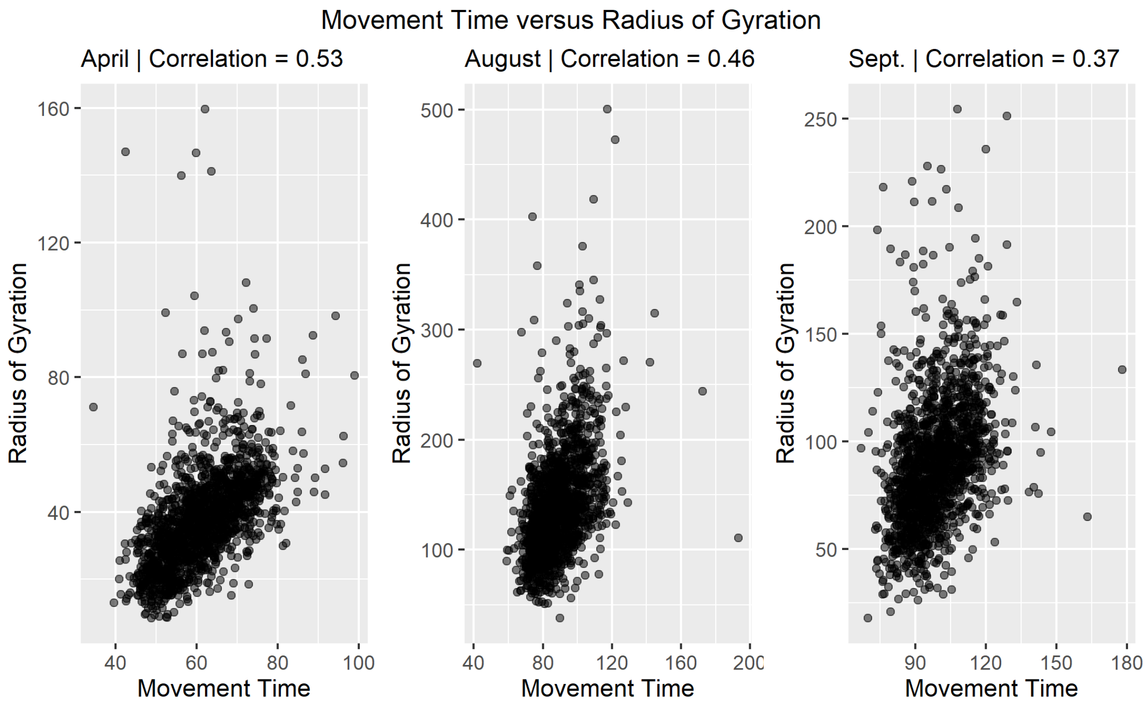


Figure 2-3: Scatterplots comparing the movement time and radius of gyration metrics across aggregate dissemination areas (ADAs; n = 1540) in Ontario, Canada during study periods in (a) April, (b) August, and (c) September. We also report the Pearson's r correlation value.

Similarly, we tested for multicollinearity among the independent variables. We found that none of the covariates have a correlation above an absolute value of 0.60, and in all cases the variance inflation factor was less than 3, suggesting that there were no collinearity issues.

Table 2-4: Correlation values between each of the covariates used in the spatial statistical analysis along with the Variance Inflation Factors

	AGE	INC	VIS	SEC	DET	VIF
Average Age (AGE)	1.00	-0.02	-0.45	-0.12	0.15	1.35

Median Income (INC)	-0.02	1.00	-0.39	0.60	0.31	2.88
Percentage Visible Minority (VIS)	-0.45	-0.39	1.00	0.15	-0.47	2.25
Percentage Postsecondary Educated (SEC)	-0.12	0.60	0.15	1.00	-0.12	2.33
Percentage Detached House (DET)	0.15	0.31	-0.47	-0.12	1.00	1.40

From the multivariate linear models, we found that almost all covariates have a significant relationship with movement time for all three time periods (Table 2-5). Specifically, we found that in all cases the Pct. Detached home variables was positively associated with relative mobility levels (for both movement time and larger radius of gyration), suggesting that areas with more detached homes did not change mobility as much as those with less detached homes. Similarly, post-secondary education levels were negatively associated with relative mobility levels in all cases except for the August model for Radius of gyration. We see varying relationships over time, and across two mobility measures, for the other covariates. We also found that in general the covariates explained a much greater level of the variance in the movement time measure (Adj. R2 0.50-0.62; Table 2-5) relative to the radius of gyration measure (Adj. R2 0.13-0.29; Table 2-5). However, the fact that all six of these linear models contain residuals with a significant and positive Moran's I (Table 2-5) indicates that there may be spatial effects that were not captured by the linear models. Therefore, we used Geographically Weighted Regression (GWR) to explore spatial non-stationarity that may be present in these relationships (Brunsdon et al., 1996).

Table 2-5: Results of the linear regression models run for each of the two mobility metrics and at each of the three time periods – April, August and September 2020

Covariate	**Movement Time**		**Radius of Gyration**	
April	**Estimate**	**P-Value**	**Estimate**	**P-Value**
(Intercept)	86.4	< 0.001	65.8	< 0.001
Average Age	0.205	< 0.001	0.185	0.063
Median Income	-0.0000494	< 0.001	-0.0000997	0.143
Pct. Visible Minority	-0.135	< 0.001	0.0271	0.139
Pct. Post Secondary Educated	-0.370	< 0.001	-0.499	< 0.001
Pct. Detached Home	0.0387	< 0.001	0.131	< 0.001
Adjusted R^2	0.62		0.29	

Moran's I of Residuals	0.25	< 0.001	0.07	< 0.001
August	**Estimate**	**P-Value**	**Estimate**	**P-Value**
(Intercept)	121.5	< 0.001	201.7	< 0.001
Average Age	0.00903	0.890	0.254	0.455
Median Income	-0.000341	< 0.001	-0.00139	< 0.001
Pct. Visible Minority	-0.242	< 0.001	-0.666	< 0.001
Pct. Post Secondary Educated	-0.312	< 0.001	-0.261	0.100
Pct. Detached Home	0.0926	< 0.001	0.206	< 0.001
Adjusted R^2	0.52		0.13	
Moran's I of Residuals	0.32	< 0.001	0.36	< 0.001
September	**Estimate**	**P-Value**	**Estimate**	**P-Value**
(Intercept)	121.4	< 0.001	105.8	< 0.001
Average Age	0.332	< 0.001	1.07	< 0.001
Median Income	-0.000345	< 0.001	-0.000139	0.339
Pct. Visible Minority	-0.222	< 0.001	-0.028	0.473
Pct. Post Secondary Educated	-0.315	< 0.001	-0.922	< 0.001
Pct. Detached Home	0.0401	< 0.001	0.108	< 0.001
Adjusted R^2	0.50		0.18	
Moran's I of Residuals	0.29	< 0.001	0.11	< 0.001

2.4.2 GWR Results

After building the GWR models using the optimization procedure, we found that the optimal nearest neighbour bandwidth sizes for the Movement Time model for April, August and September respectively are 116, 133 and 116 representing highly local patterns (given a study area of 1540 units). For the Radius of Gyration GWR models we found that the optimal bandwidths for April, August and September time periods are 358, 268 and 570 respectively, suggesting a less local relationship. In all cases, the GWR models resulted in improved global measures of goodness of fit over the global regression (Table 2-6), however there is a wide range of local R-squared values in the GWR models (Table 2-7), ranging anywhere from 0.18 to 0.97 for the most extreme case in the April movement time model. The global and local R-squared values suggest that the movement time models have a better fit than the ROG models.

Table 2-6: GWR global adjusted R-squared values, and bandwidths for each GWR model

	Movement Time		Radius of Gyration	
	Global Adj. R-squared	**Bandwidth**	**Global Adj. R-squared**	**Bandwidth**
April	0.73	116	0.32	358
August	0.71	133	0.39	268
September	0.66	116	0.23	570

Table 2-7: GWR local R-squared values, shown as percentiles

	Movement Time					Radius of Gyration				
	Min	**25%**	**50%**	**75%**	**Max**	**Min**	**25%**	**50%**	**75%**	**Max**
April	0.18	0.66	0.76	0.83	0.97	0.09	0.28	0.38	0.48	0.67
August	0.16	0.65	0.76	0.81	0.93	0.11	0.22	0.35	0.49	0.72
September	0.20	0.54	0.70	0.80	0.93	0.08	0.18	0.25	0.34	0.63

2.4.2.1 Number of Significant ADAs

In general, we see that most ADAs are non-significant in almost every case, except for post-secondary educated in April and September, average age with radius of gyration in September, and detached house with Radius of gyration in April (Table 2-8). This tells us that locally, the relationships between the covariates and the mobility metrics did not exist for most of Ontario. Interestingly, the number of negative post-secondary educated ADAs decreases by a lot in August before increasing again in September. However, maps of the significant parameter estimates (Appendix A) show the local areas where significant relationships were found, and that these varied by movement metric and covariate.

Table 2-8: Number of significantly positive ($p < 0.1$), significantly negative, and non-significant ADAs for each of the six GWR models that were run

	Movement Time			Radius of Gyration		
Average Age	Negative	Non-Sig	Positive	Negative	Non-Sig	Positive
April	16	1313	211	0	1480	60
August	83	1306	149	25	1322	191

September	56	1285	195	0	818	718
Median Income	Negative	Non-Sig	Positive	Negative	Non-Sig	Positive
April	264	1271	5	251	1267	22
August	376	1157	5	480	1048	10
September	308	1219	9	40	1496	0
Pct. Visible Minority	Negative	Non-Sig	Positive	Negative	Non-Sig	Positive
April	326	1113	101	83	1077	380
August	455	1029	54	552	963	23
September	569	967	0	4	1334	198
Pct. Post-Sec. Educ.	Negative	Non-Sig	Positive	Negative	Non-Sig	Positive
April	1065	475	0	1474	66	0
August	563	930	45	360	1050	128
September	685	850	1	1458	78	0
Pct. Detached House	Negative	Non-Sig	Positive	Negative	Non-Sig	Positive
April	98	1096	346	30	668	842
August	25	1067	446	70	1241	227
September	84	1131	321	434	572	530

Despite our global linear regression model suggesting that higher income was associated with greater decreases in movement time at all three time periods; our GWR doesn't appear to show median income as having a significant effect for most of Ontario. In April, we see some areas with a negative relationship with Radius of Gyration (which we would expect), but only in a small part of the York Region and some low-populated areas of Eastern Ontario. Similarly, looking at Movement time, we only see this negative relationship in specific parts of Toronto, and scattered around other specific parts of Ontario. The number of ADAs with a significant negative relationship increases in August, but they remain scattered around less dense population areas.

The percentage of visible minority population was mostly non-significant, but where it was significant it was more often negative than positive in its relation with Movement Time. This was also the case with Radius of Gyration in August, but the reverse in April and September. The ADAs with a positive relationship with both movement time and radius of gyration tend to show up in Toronto and its suburbs, particularly in April (Figure 2-4 and Figure 2-5), indicating that this positive relationship between visible minority and higher relative mobility tends to occur in urban and suburban areas, and does not exist in most other areas.

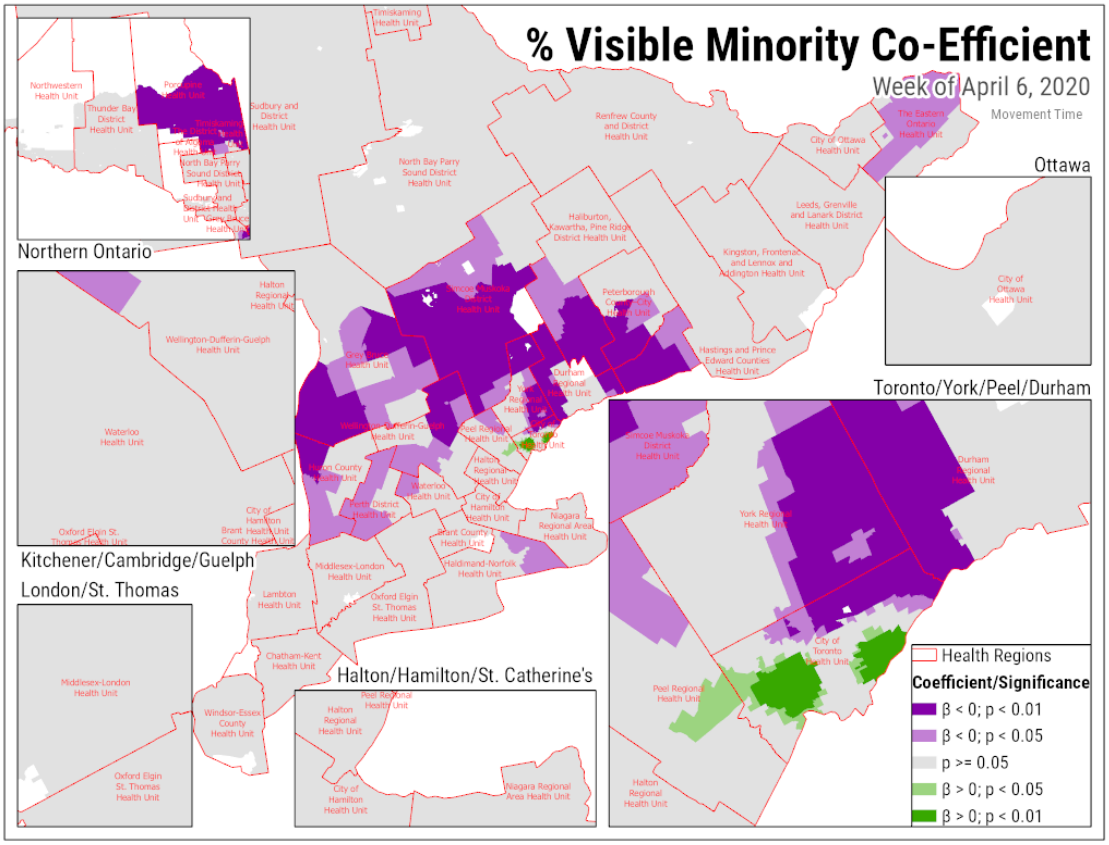


Figure 2-4: GWR Results for the Percentage Visible Minority covariate and Movement Time response variable in the April time period

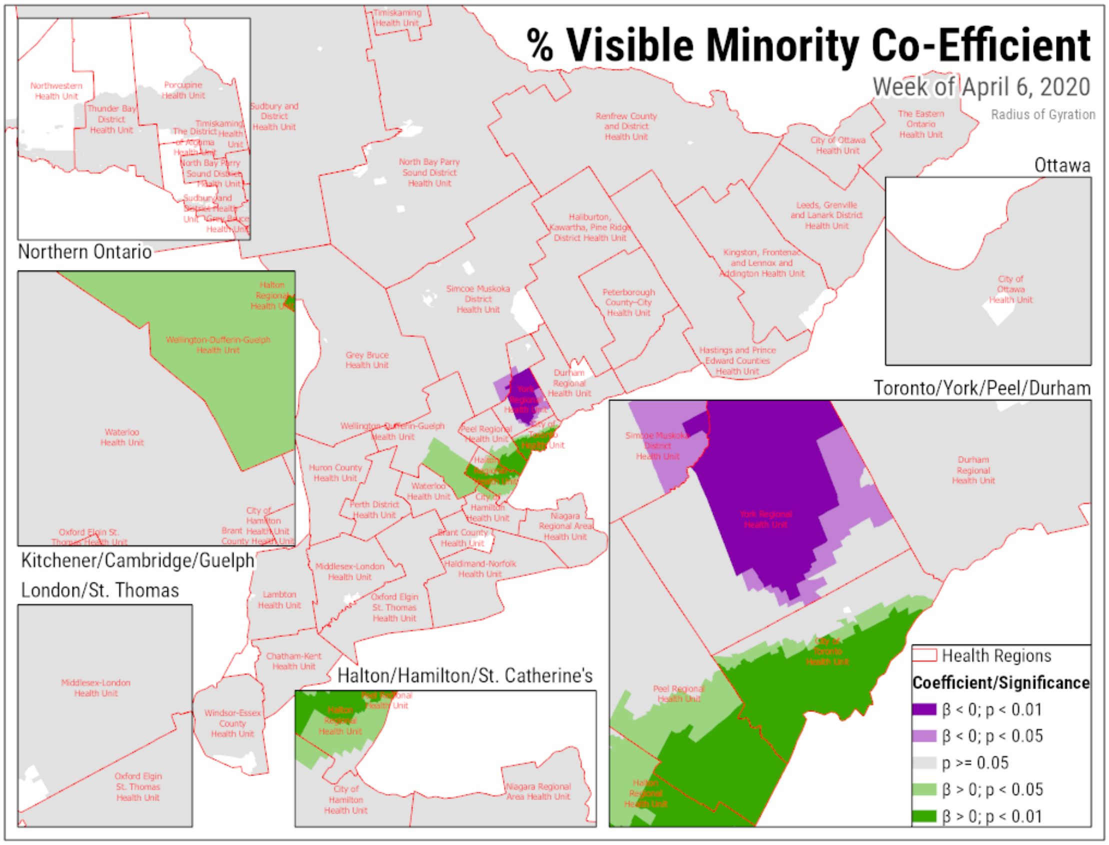


Figure 2-5: GWR Results for the Percentage Visible Minority covariate and Radius of Gyration response variable in the April time period

The relationship between post-secondary educated and both mobility metrics were negative across almost all of Southern Ontario in April (Figure 2-6), and was still mainly negative in August and September. This covariate has a significant relationship for the most ADAs in Ontario (Table 2-8). This supports the notion that areas with greater education levels were associated with lower relative mobility during all periods of the pandemic, with a few regional exceptions where no significant relationship was found (e.g., northern Ontario and the communities east of Toronto).

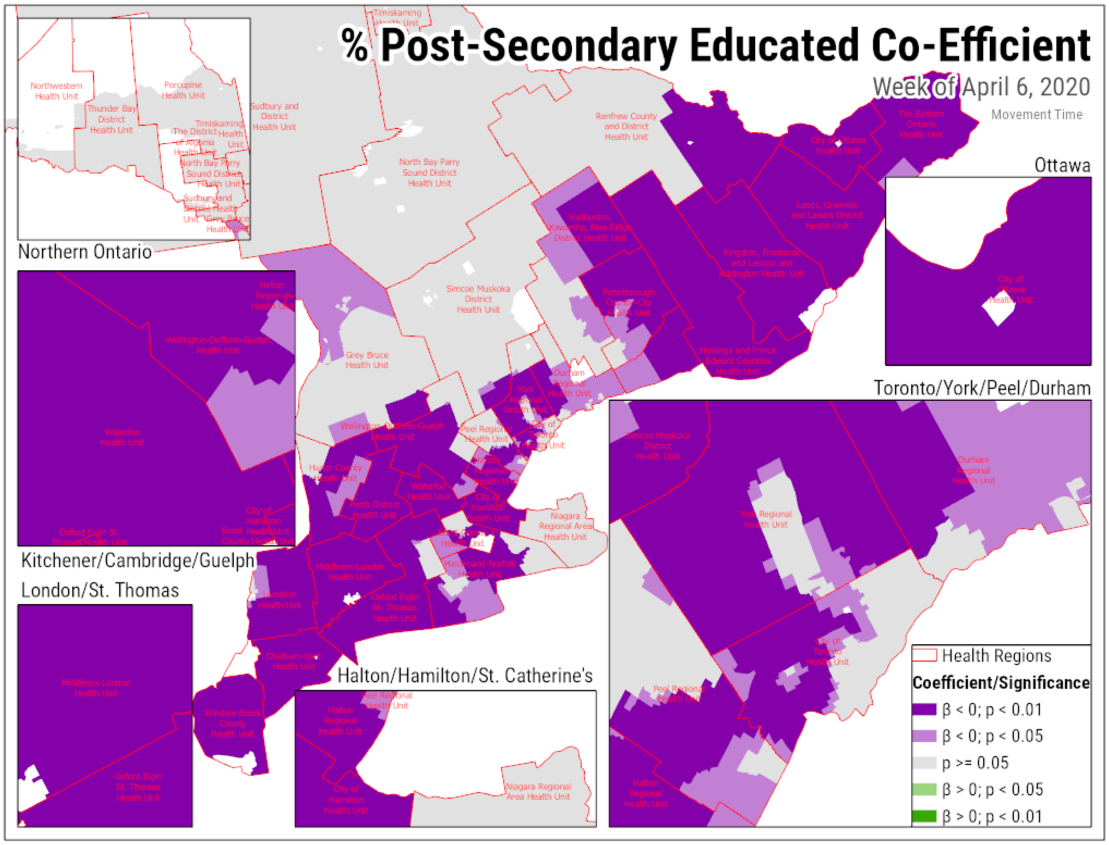


Figure 2-6: GWR Results for the Percentage Post-Secondary Educated covariate and Movement Time response variable in the April time period

We see a clear pattern between the Radius of Gyration and detached home, particularly in September (Figure 2-7). In Toronto and York Region, this relationship is almost all significantly negative in September, after being generally non-significant in April and August. We would expect this clear pattern, where there were greater mobility distances in neighbourhoods with less detached homes, or our representation of density. In contrast, many rural areas had a positive relationship.

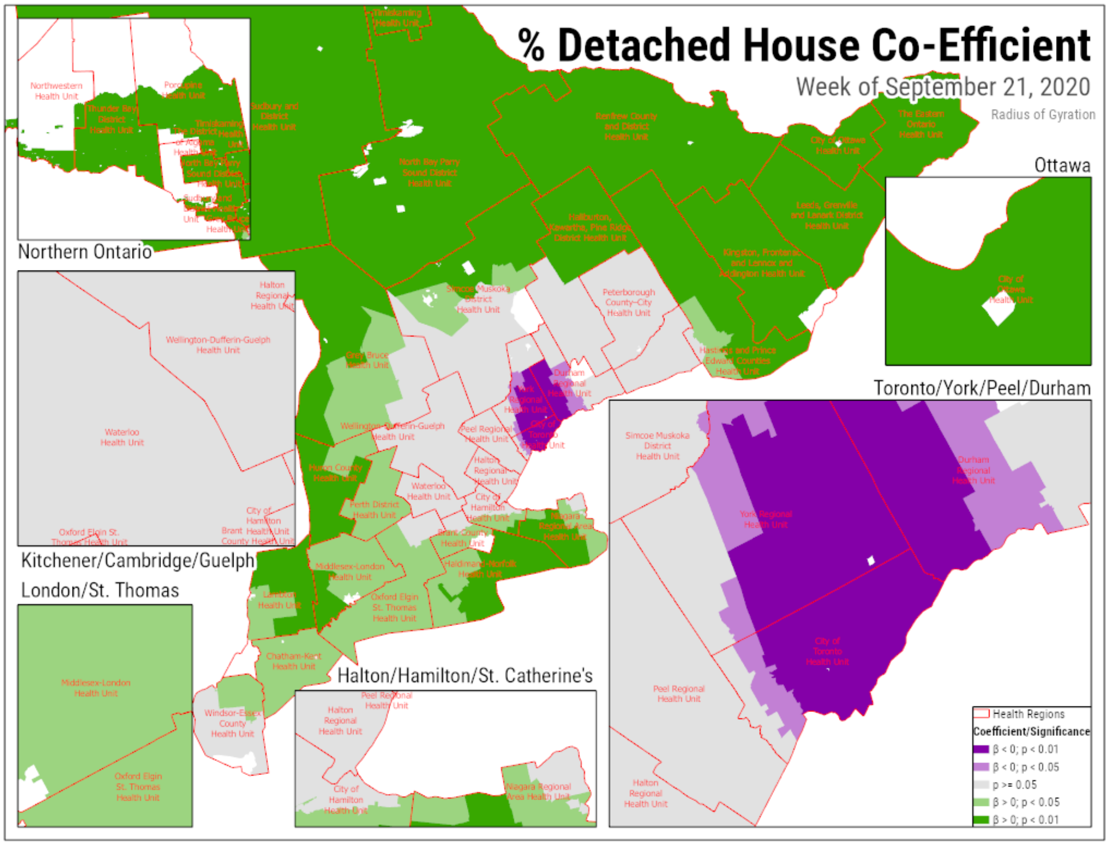


Figure 2-7: GWR Results for the Percentage Detached House covariate and Radius of Gyration response variable in the September time period

Median Income has a significantly negative relationship with both Movement Time and Radius of gyration in April, when looking at the global model for all of Ontario. However, our GWR accounting for spatial variation in this relationship shows that most parts of Ontario did not actually have a significant relationship with Movement Time, and there were no individual ADAs that had a significant relationship with Radius of Gyration in April.

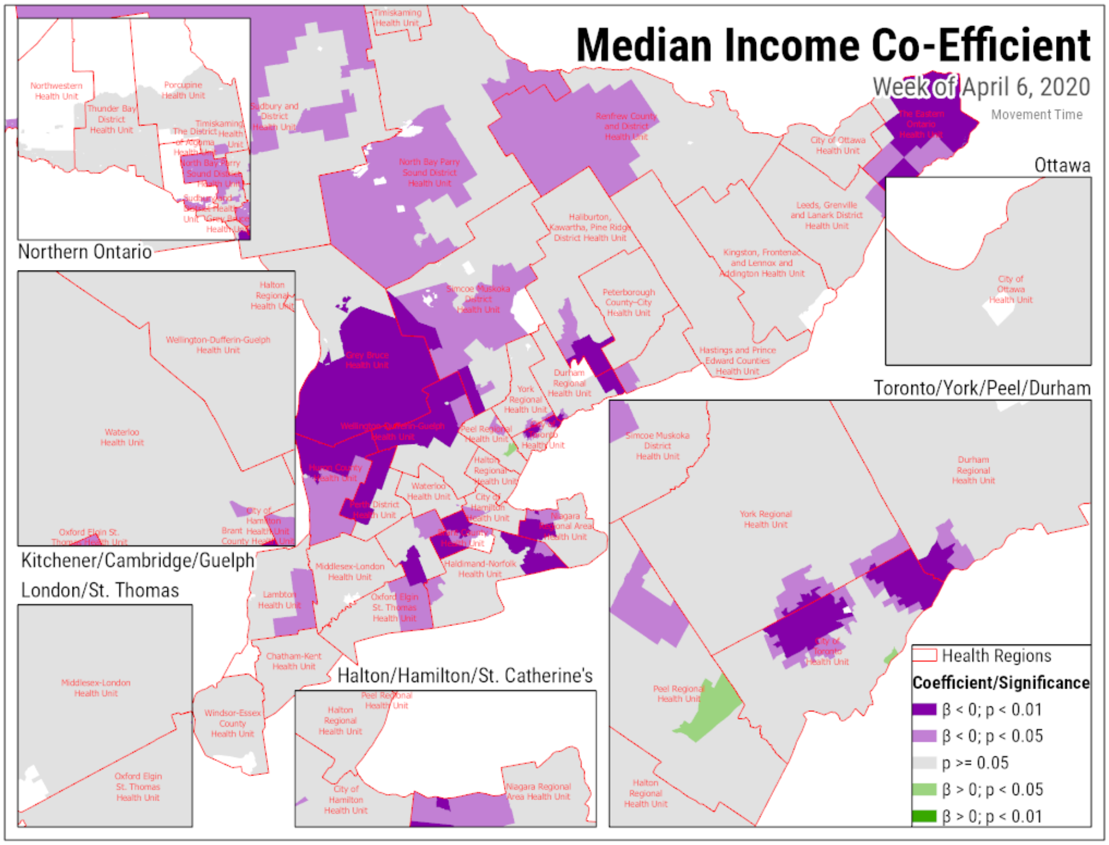


Figure 2-8: GWR Results for the Median Income covariate and Movement Time response variable in the April time period

Similarly, Average Age is generally mostly non-significant, and the significant ADAs do not have any clear pattern. The ROG model in September is an exception to this, with a large number of significantly positive ADAs in Northern and Western Ontario suggesting that in September areas with older populations in these regions had higher levels of relative mobility at this point in time.

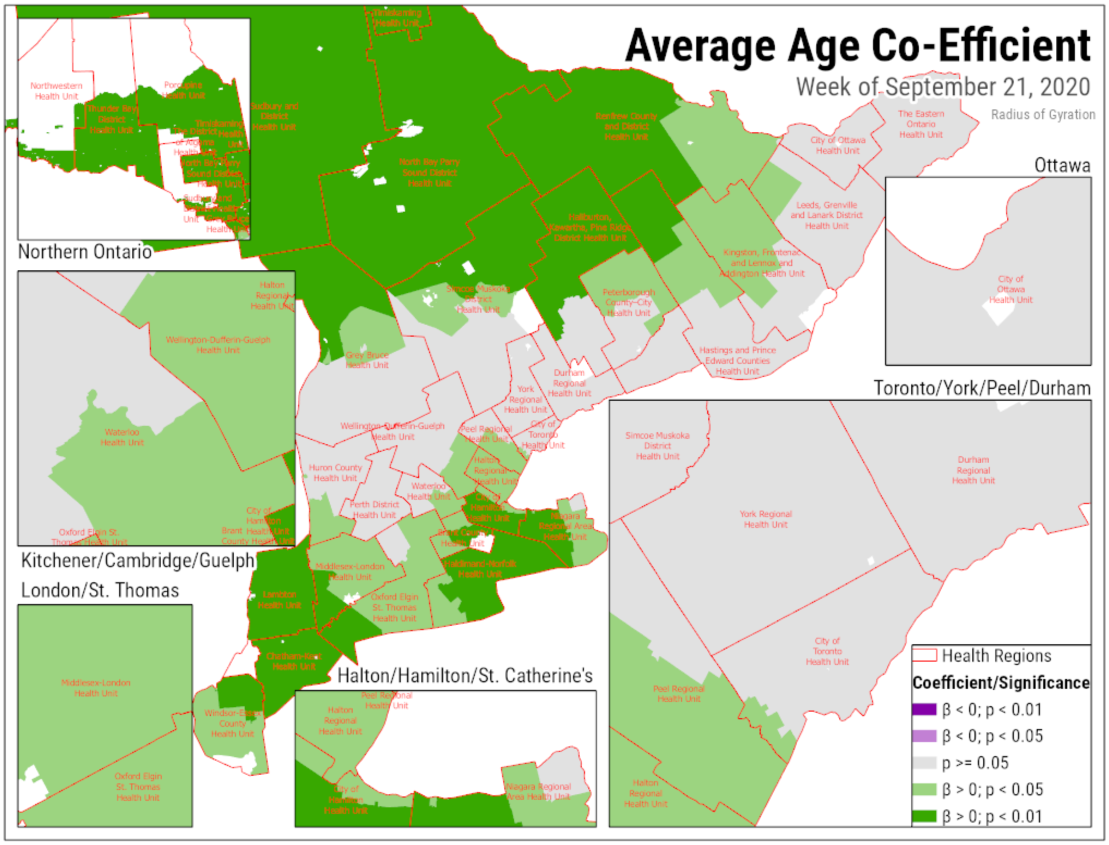


Figure 2-9: GWR Results for the Average Age covariate and Radius of Gyration response variable in the September time period

2.5 Discussion

The COVID-19 pandemic has brought about widespread shifts in mobility patterns as demonstrated by previous research, which requires us to rethink the way we understand mobility and it's the relationships with social factors (Bonaccorsi et al., 2020; Dasgupta et al., 2020; Huang et al., 2021; Jay et al., 2020; Lee et al., 2021; Long & Ren, 2021; Weill et al., 2020). Most notably, people living in suburban regions who we might have considered to be suburb to downtown office commuters, who previously had a relatively high level of mobility both in terms of time and distance (Axisa et al., 2012; Bai et al., 2020; Mercado & Páez, 2009; Newbold & Scott, 2013), had some of the largest decreases in mobility during the pandemic. This was particularly noticeable in the suburbs surrounding the City of Toronto, where we can see a sharp decrease in mobility after long daily commutes were no longer needed. This finding aligns with previous research (W. D. Lee et al., 2021) which shows that mobility reduction in England was greatest near London.

Our results are similar to those found in England, where a GWR was used to study spatial varying relationships between socio-demographic factors finding a similar level of variation in these relationships (Lee et al 2021). Our analysis improves upon that of Lee et al (2021) in that we use much finer spatial granularity (spatial unit size) which allows us to study finer-scale spatial relationships. Specifically, we use aggregated dissemination areas, which have a population of ~10k, whereas Lee et al. use Clinical Commissioning Groups (CCGs) of which there are 191 across all of England. This difference allows us to study these mobility-socio-demographic associations within a city (e.g., in the Greater Toronto Area) at the neighbourhood-level which would not be captured in larger spatial units. The use of a spatially varying model is important in the context of Ontario due to its urban-rural divide (Statistics Canada, 2004). The relatively small bandwidths of some of our models prove the importance of analysing these relationships at a local level, and suggest that a global model is not representative of all of Ontario.

Many of our results, compared to those of Long and Ren (2021), show different associations between similar mobility metrics and socio-demographic factors. Similarly, we do not see the same amount of significant associations using a local GWR model compared previous work using global models (Khattak et al., 2000; Manaugh et al., 2010; Mercado & Páez, 2009). This can be explained by the Modifiable Arial Unit Problem and Simpson’s Paradox (Fotheringham & Sachdeva, 2022), which explain how local associations may differ from associations found at a global level. Our work demonstrates the importance of performing analysis at a local level where associations are likely to vary greatly across space, as local spatial analysis can lead to different inferences compared to a global model.

Numerous studies have explored how mobility changes during COVID-19 have been associated with socio-demographic factors. For example, Huang et al. (2021) found that mobility decrease among bottom 20% income counties in the US was generally lower than among top 20% income counties, and that this was consistent among most states. Other studies showed that the amount of time spent at home was higher among lower income quintile groups compared to higher income quintile groups – the reverse of the pre-COVID trend (Jay et al., 2020; Weill et al., 2020), and that places in the US with less movement had a 17% higher annual household income (Dasgupta et al., 2020). Similarly, a study in Italy found that pandemic affected people differently based on their incomes, and based on the fiscal capacities of different municipalities (Bonaccorsi et al., 2020). However, it is clear from the results of our GWR model that there are very few instances of one covariate having a uniform association with mobility levels across the province Ontario, so it is misleading to make such general conclusions about the association between specific covariates and mobility, as these associations vary across space.

Post-secondary educated showed a significant effect for the most parts of Ontario, particularly in the April period. We would hypothesize that people in higher educated and more skill-based professions were more likely to be able to transition to working from home (Bartik et al., 2020; Jay et al., 2020). The GWR supports the fact that this is true across most of Ontario with almost all ADAs being significantly negatively associated with Radius of Gyration in April and September. We know that post-secondary students often have long commutes that can hinder their ability to participate in activities on campus (Allen & Farber, 2018). If the commutes of post-secondary students are also representative of the commutes of post-secondary educated individuals, then we would expect a large decrease in mobility in areas where these people tend to live – in urban and suburban areas around cities with major post-secondary institutions (Allen & Farber, 2018).

Previous research has shown that mobility for the elderly decreases in suburban areas (Roorda et al., 2010), so we may expect that the decrease in mobility among the elderly was smaller in suburban areas than in urban areas. However, our GWR model does not show any noticeable pattern that would align with this hypothesis. This is likely because we used the average age statistic, which can disguise the concentrations of older people due to the aggregation of ages by ADA. If we had used a percentage of people aged 65+ statistic, we might expect this to be negatively associated with mobility in urban areas and non-significant in suburban areas.

Visible Minority has a positive association with movement time and radius of gyration in urban areas in April, and negative in some suburban and rural municipalities. Positive associations can likely be explained by the fact that visible minorities in cities are less likely to have jobs that can be done from home, as visible minorities have historically been over-represented in jobs such as sales and service, clerical and other manual workers, processing, manufacturing and utilities (Samuel & Basavarajappa, 2006). Negative associations in suburban and rural areas can likely be explained by the fact that there are relatively few visible minorities living in these parts of Ontario according to census data, that the types of jobs found in these areas are different from the ones in more urban areas (Zarifa et al., 2019), and that the pandemic is less likely to have affected travel patterns for these people. The spatial concentration of certain ethnic groups in Canadian cities (Bauder & Sharpe, 2002) could also exaggerate the variability of the visible minority coefficient across space as the GWR bandwidth captures different concentrations of visible minorities across Ontario. Not captured in this analysis is the fact that different visible minority groups tend to have different levels of participation in different labour markets (Hou & Picot, 2003). For this analysis, we look at all visible minority groups as one group, however if further analysis was performed on separate visible minority groups, we would likely see differing levels of mobility among these different groups.

Detached homes has a positive association with movement time and radius of gyration in many parts of Ontario, most prominently in April and August. This could be explained by how people in less dense areas still have to travel similar distances for essential purposes during COVID-19, such as getting groceries (Widener et al., 2015). People in more dense areas are more likely to be able to access these necessary destinations while still greatly reducing their mobility.

While here we focus on spatially varying relationships across the province, previous studies, particularly Long and Ren (2021) in Ontario, demonstrate that the associations that we see are not always consistent over time. Temporal variability in these relationships can be observed in our work as we explored three different time points. While not implicit to our model, our results provide further evidence that the associations between mobility changes during the pandemic exhibit complex spatial temporal relationships with socio-demographic factors. This may be related to a variety of factors, including differences in infection rates across space and time (Bourdin et al., 2021), changes in pandemic restrictions that vary over time (Gatalo et al., 2021; Lee et al., 2021; Long & Ren, 2021), but also space (Bonaccorsi et al., 2020; W. D. Lee et al., 2021; Scala et al., 2020). In particular, previous research in Ontario, Canada, found that regionally targeted interventions did not result in substantial changes in inter-regional movement patterns (Long et al., 2021). But that does not mean that the mobility metrics we used here were not impacted by these restrictions.

In our analysis the month of February 2020 was used as the pre-pandemic baseline for the relative mobility metrics due to the data we were using only being available from January 2020 to December 2020. Ideally, mobility metrics would be compared to the same time in the previous year to account for seasonal variability in transportation patterns that occurs in Ontario (Clark et al., 2014; Stevens et al., 2022). For example, a relative mobility metric value of 100 during the summer months likely means that the actual mobility value was lower than the previous year in terms of distance and time, reflecting the seasonal nature of travel patterns in Ontario, Canada.

There are several potential sources of lack of representativeness in our data, as it relates to the measured trajectories and how the subset in our data reflects the real world (C. Chen et al., 2016). First, the trajectories captured by de-identified cell phone data is not a perfect trajectory of people's movement as spatial and temporal gaps can exist (Wang & Chen, 2018). This is particularly the case when comparing urban and rural areas, where the distribution of cell phone towers throughout space is inconsistent (C. Chen et al., 2014). Second, the fact that our data represents TELUS mobile phones could mean that our sample, although large, is not representative of the whole population of Ontario. There is likely a small bias towards younger to middle-aged mobile phone plan holders in our dataset since about 97% of people aged 18 to 34 subscribe to a mobile phone plan, and about 70% of people aged 65+ subscribe to a mobile phone plan (CRTC, 2019). Another study using the same dataset (Long & Ren, 2021) found that the number of cell phones in each ADA was proportional to the ADA populations, but that the sample proportion was slightly larger in areas with a lower ethno-cultural index value, and areas with higher population densities. In addition to the mobility data, the 2016 Census data that was used for socio-demographic data could lack representativeness due to the temporal mismatch between population characteristics from 2016, when the data is from, to 2020, the time period that way studied. Not only is this a long temporal gap, but the disturbance caused by the COVID-19 pandemic may have had an impact on people changing residences. However, this was the most up-to-date dataset for the time, and it is unlikely that the aggregated statistics that we used changed so significantly in a way that makes the 2016 Census data problematically unrepresentative.

2.6 Conclusions

We used two key measures of mobility capturing two aspects of human mobility patterns, Movement Time and Radius of Gyration, over the course of the COVID-19 pandemic in Ontario, measured from a large, representative sample of mobile devices. We then studied spatial variation in associations between patterns of mobility measured and socio-demographic using a geographically weighted regression model at three time periods in the year 2020. We found that these five socio-demographic factors exhibited spatially varying associations with mobility levels, in most cases differing from the associations in the global model. More specifically, for all the models we ran, most of the coefficients were significant in the global model, but were non-significant for most ADAs in their respective GWR models. In some cases, opposite associations were seen in different parts of Ontario.

Our results highlight the limitations of interpretations stemming from classical non-spatial regression models, which fail to capture the complete picture of how socio-demographic factors are associated with mobility changes during COVID-19 in Ontario, Canada. More specifically our results provide new inferences about how mobility levels changed during the pandemic.

2.7 Acknowledgements

This work was supported by the TELUS Data for Good Program. We are grateful for assistance from W. Li and J. Bettridge at TELUS who contributed to this project.

2.8 References

Abdullah, M., Dias, C., Muley, D., & Shahin, Md. (2020). Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transportation Research Interdisciplinary Perspectives*, *8*, 100255. https://doi.org/10.1016/j.trip.2020.100255

Abel, G. J., DeWaard, J., Ha, J. T., & Almquist, Z. W. (2021). The form and evolution of international migration networks, 1990–2015. *Population, Space and Place*, *27*(3), e2432. https://doi.org/10.1002/psp.2432

Akaike, H. (1998). Information Theory and an Extension of the Maximum Likelihood Principle. In E. Parzen, K. Tanabe, & G. Kitagawa (Eds.), *Selected Papers of Hirotugu Akaike* (pp. 199–213). Springer. https://doi.org/10.1007/978-1-4612-1694-0_15

Allen, J., & Farber, S. (2018). How time-use and transportation barriers limit on-campus participation of university students. *Travel Behaviour and Society*, *13*, 174–182. https://doi.org/10.1016/j.tbs.2018.08.003

Axisa, J. J., Scott, D. M., & Bruce Newbold, K. (2012). Factors influencing commute distance: A case study of Toronto's commuter shed. *Journal of Transport Geography*, *24*, 123–129. https://doi.org/10.1016/j.jtrangeo.2011.10.005

Bag, S., Kumar, S. K., & Tiwari, M. K. (2019). An efficient recommendation generation using relevant Jaccard similarity. *Information Sciences*, *483*, 53–64. https://doi.org/10.1016/j.ins.2019.01.023

Bai, X., Zhai, W., Steiner, R. L., & He, Z. (2020). Exploring extreme commuting and its relationship to land use and socioeconomics in the central Puget Sound. *Transportation Research Part D: Transport and Environment*, *88*, 102574. https://doi.org/10.1016/j.trd.2020.102574

Bartik, A. W., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. T. (2020). *What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys* (Working Paper No. 27422; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w27422

Bauder, H., & Sharpe, B. (2002). Residential segregation of visible minorities in Canada's gateway cities. *The Canadian Geographer / Le Géographe Canadien*, *46*(3), 204–222. https://doi.org/10.1111/j.1541-0064.2002.tb00741.x

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*(10), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., Schmidt, A. L., Valensise, C. M., Scala, A., Quattrociocchi, W., & Pammolli, F. (2020). Economic and social consequences of human mobility restrictions under COVID-19. *Proceedings of the National Academy of Sciences*, *117*(27), 15530–15535. https://doi.org/10.1073/pnas.2007658117

Bourdin, S., Jeanne, L., Nadou, F., & Noiret, G. (2021). Does lockdown work? A spatial analysis of the spread and concentration of Covid-19 in Italy. *Regional Studies*, *55*(7), 1182–1193. https://doi.org/10.1080/00343404.2021.1887471

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis*, *28*(4), 281–298. https://doi.org/10.1111/j.1538-4632.1996.tb00936.x

Buehler, R. (2011). Determinants of transport mode choice: A comparison of Germany and the USA. *Journal of Transport Geography*, *19*(4), 644–657. https://doi.org/10.1016/j.jtrangeo.2010.07.005

Chang, S., Pierson, E., Koh, P. W., Gerardin, J., Redbird, B., Grusky, D., & Leskovec, J. (2021). Mobility network models of COVID-19 explain inequities and inform reopening. *Nature*, *589*(7840), 82–87. https://doi.org/10.1038/s41586-020-2923-3

Chen, C., Bian, L., & Ma, J. (2014). From traces to trajectories: How well can we guess activity locations from mobile phone traces? *Transportation Research Part C: Emerging Technologies*, *46*, 326–337. https://doi.org/10.1016/j.trc.2014.07.001

Chen, C., Ma, J., Susilo, Y., Liu, Y., & Wang, M. (2016). The promises of big data and small data for travel behavior (aka human mobility) analysis. *Transportation Research Part C: Emerging Technologies*, *68*, 285–299. https://doi.org/10.1016/j.trc.2016.04.005

Chen, M., Kuzmin, K., & Szymanski, B. K. (2014). Community Detection via Maximization of Modularity and Its Variants. *IEEE Transactions on Computational Social Systems*, *1*(1), 46–65. https://doi.org/10.1109/TCSS.2014.2307458

Chen, M., Nguyen, T., & Szymanski, B. K. (2013). On Measuring the Quality of a Network Community Structure. *2013 International Conference on Social Computing*, 122–127. https://doi.org/10.1109/SocialCom.2013.25

Clark, A. F., Scott, D. M., & Yiannakoulias, N. (2014). Examining the relationship between active travel, weather, and the built environment: A multilevel approach using a GPS-enhanced dataset. *Transportation*, *41*(2), 325–338. https://doi.org/10.1007/s11116-013-9476-3

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, *Complex Systems*, 1695.

Dasgupta, N., Jonsson Funk, M., Lazard, A., White, B. E., & Marshall, S. W. (2020). *Quantifying the Social Distancing Privilege Gap: A Longitudinal Study of Smartphone Movement* (SSRN Scholarly Paper No. 3588585). Social Science Research Network. https://doi.org/10.2139/ssrn.3588585

De Montis, A., Caschili, S., & Chessa, A. (2013). Commuter networks and community detection: A method for planning sub regional areas. *The European Physical Journal Special Topics*, *215*(1), 75–91. https://doi.org/10.1140/epjst/e2013-01716-4

Dorn, A. van, Cooney, R. E., & Sabin, M. L. (2020). COVID-19 exacerbating inequalities in the US. *Lancet (London, England)*, *395*(10232), 1243–1244. https://doi.org/10.1016/S0140-6736(20)30893-X

Dueñas, M., Campi, M., & Olmos, L. E. (2021). Changes in mobility and socioeconomic conditions during the COVID-19 outbreak. *Humanities and Social Sciences Communications*, *8*(1), Article 1. https://doi.org/10.1057/s41599-021-00775-0

Fan, Y., Guthrie, A., & Levinson, D. (2012). Impact of light-rail implementation on labor market accessibility: A transportation equity perspective. *Journal of Transport and Land Use*, *5*(3), 28–39.

Farmer, C. J. Q., & Fotheringham, A. S. (2011). Network-Based Functional Regions. *Environment and Planning A: Economy and Space*, *43*(11), 2723–2741. https://doi.org/10.1068/a44136

Felstead, A., & Henseke, G. (2017). Assessing the growth of remote working and its consequences for effort, well-being and work-life balance. *New Technology, Work and Employment*, *32*(3), 195–212. https://doi.org/10.1111/ntwe.12097

Fillekes, M. P., Giannouli, E., Kim, E.-K., Zijlstra, W., & Weibel, R. (2019). Towards a comprehensive set of GPS-based indicators reflecting the multidimensional nature of daily mobility for applications in health and aging research. *International Journal of Health Geographics*, *18*(1), 17. https://doi.org/10.1186/s12942-019-0181-0

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, *486*(3), 75–174. https://doi.org/10.1016/j.physrep.2009.11.002

Fortunato, S., & Barthélemy, M. (2007). Resolution limit in community detection. *Proceedings of the National Academy of Sciences*, *104*(1), 36–41. https://doi.org/10.1073/pnas.0605965104

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2003). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. John Wiley & Sons.

Fotheringham, A. S., & Sachdeva, M. (2022). Scale and local modeling: New perspectives on the modifiable areal unit problem and Simpson's paradox. *Journal of Geographical Systems*. https://doi.org/10.1007/s10109-021-00371-5

Fotheringham, A. S., Yang, W., & Kang, W. (2017). Multiscale Geographically Weighted Regression (MGWR). *Annals of the American Association of Geographers*, *107*(6), 1247–1265. https://doi.org/10.1080/24694452.2017.1352480

Fransen, K., Farber, S., Deruyter, G., & De Maeyer, P. (2018). A spatio-temporal accessibility measure for modelling activity participation in discretionary activities. *Travel Behaviour and Society*, *10*, 10–20. https://doi.org/10.1016/j.tbs.2017.09.002

Gao, S., Rao, J., Kang, Y., Liang, Y., & Kruse, J. (2020). Mapping county-level mobility pattern changes in the United States in response to COVID-19. *SIGSPATIAL Special*, *12*(1), 16–26. https://doi.org/10.1145/3404820.3404824

Gatalo, O., Tseng, K., Hamilton, A., Lin, G., & Klein, E. (2021). Associations between phone mobility data and COVID-19 cases. *The Lancet Infectious Diseases*, *21*(5), e111. https://doi.org/10.1016/S1473-3099(20)30725-8

Gibbs, H., Liu, Y., Pearson, C. A. B., Jarvis, C. I., Grundy, C., Quilty, B. J., Diamond, C., & Eggo, R. M. (2020). Changing travel patterns in China during the early stages of the COVID-19 pandemic. *Nature Communications*, *11*(1), 5012. https://doi.org/10.1038/s41467-020-18783-0

Gollini, I., Lu, B., Charlton, M., Brunsdon, C., & Harris, P. (2014). GWmodel: An R Package for Exploring Spatial Heterogeneity using Geographically Weighted Models. *ArXiv:1306.0413 [Stat]*. http://arxiv.org/abs/1306.0413

González, M. C., Hidalgo, C. A., & Barabási, A.-L. (2008). Understanding individual human mobility patterns. *Nature*, *453*(7196), 779–782. https://doi.org/10.1038/nature06958

Grassi, R., Bartesaghi, P., Benati, S., & Clemente, G. P. (2021). Multi-Attribute Community Detection in International Trade Network. *Networks and Spatial Economics*, *21*(3), 707–733. https://doi.org/10.1007/s11067-021-09547-4

Green, M. B., & Meyer, S. P. (1997). An overview of commuting in Canada: With special emphasis on rural commuting and employment. *Journal of Rural Studies*, *13*(2), 163–175. https://doi.org/10.1016/S0743-0167(97)83095-1

Hamilton, R., & Rae, A. (2020). Regions from the ground up: A network partitioning approach to regional delineation. *Environment and Planning B: Urban Analytics and City Science*, *47*(5), 775–789. https://doi.org/10.1177/2399808318804226

Hanson, S., & Hanson, P. (1981). The Travel-Activity Patterns of Urban Residents: Dimensions and Relationships to Sociodemographic Characteristics. *Economic Geography*, *57*(4), 332–347. https://doi.org/10.2307/144213

Hasanzadeh, K. (2019). Exploring centricity of activity spaces: From measurement to the identification of personal and environmental factors. *Travel Behaviour and Society*, *14*, 57–65. https://doi.org/10.1016/j.tbs.2018.10.001

Hirsch, J. A., Winters, M., Clarke, P., & McKay, H. (2014). Generating GPS activity spaces that shed light upon the mobility habits of older adults: A descriptive analysis. *International Journal of Health Geographics*, *13*(1), 51. https://doi.org/10.1186/1476-072X-13-51

Hou, F., & Picot, G. (2003). Visible minority neighbourhood enclaves and labour market outcomes of immigrants. *Statistics Canada*. http://envision.ca/pdf/w2w/11f0019mie2003204.pdf

Huang, X., Li, Z., Jiang, Y., Ye, X., Deng, C., Zhang, J., & Li, X. (2021). The characteristics of multi-source mobility datasets and how they reveal the luxury nature of social distancing in the U.S. during the COVID-19 pandemic. *International Journal of Digital Earth*, *14*(4), 424–442. https://doi.org/10.1080/17538947.2021.1886358

Hubert, L., & Arabie, P. (1985). *Comparing partitions*. https://link.springer.com/article/10.1007/BF01908075

Jay, J., Bor, J., Nsoesie, E. O., Lipson, S. K., Jones, D. K., Galea, S., & Raifman, J. (2020). Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. *Nature Human Behaviour*, *4*(12), 1294–1302. https://doi.org/10.1038/s41562-020-00998-2

Kang, Y., Gao, S., Liang, Y., Li, M., Rao, J., & Kruse, J. (2020). Multiscale dynamic human mobility flow dataset in the U.S. during the COVID-19 epidemic. *Scientific Data*, *7*(1), Article 1. https://doi.org/10.1038/s41597-020-00734-5

Kar, A., Le, H. T. K., & Miller, H. J. (2022). What Is Essential Travel? Socioeconomic Differences in Travel Demand in Columbus, Ohio, during the COVID-19 Lockdown. *Annals of the American Association of Geographers*, *112*(4), 1023–1046. https://doi.org/10.1080/24694452.2021.1956876

Khattak, A. J., Amerlynck, V. J., & Quercia, R. G. (2000). Are Travel Times and Distances to Work Greater for Residents of Poor Urban Neighborhoods? *Transportation Research Record*, *1718*(1), 73–82. https://doi.org/10.3141/1718-10

Kim, S.-N. (2016). Two traditional questions on the relationships between telecommuting, job and residential location, and household travel: Revisited using a path analysis. *The Annals of Regional Science*, *56*(2), 537–563. https://doi.org/10.1007/s00168-016-0755-8

Kwan, M.-P. (1999). Gender, the Home-Work Link, and Space-Time Patterns of Nonemployment Activities. *Economic Geography*, *75*(4), 370–394. https://doi.org/10.1111/j.1944-8287.1999.tb00126.x

Lachapelle, U., Tanguay, G. A., & Neumark-Gaudet, L. (2018). Telecommuting and sustainable travel: Reduction of overall travel time, increases in non-motorised travel and congestion relief? *Urban Studies*, *55*(10), 2226–2244. https://doi.org/10.1177/0042098017708985

Lancichinetti, A., & Fortunato, S. (2011). Limits of modularity maximization in community detection. *Physical Review E*, *84*(6), 066122. https://doi.org/10.1103/PhysRevE.84.066122

Larsen, K., Gilliland, J., Hess, P., Tucker, P., Irwin, J., & He, M. (2009). The Influence of the Physical Environment and Sociodemographic Characteristics on Children's Mode of Travel to and From School. *American Journal of Public Health*, *99*(3), 520–526. https://doi.org/10.2105/AJPH.2008.135319

Lee, M., Zhao, J., Sun, Q., Pan, Y., Zhou, W., Xiong, C., & Zhang, L. (2020). Human mobility trends during the early stage of the COVID-19 pandemic in the United States. *PLOS ONE*, *15*(11), e0241468. https://doi.org/10.1371/journal.pone.0241468

Lee, W. D., Qian, M., & Schwanen, T. (2021). The association between socioeconomic status and mobility reductions in the early stage of England's COVID-19 epidemic. *Health & Place*, *69*, 102563. https://doi.org/10.1016/j.healthplace.2021.102563

Lenormand, M., Louail, T., Cantú-Ros, O. G., Picornell, M., Herranz, R., Arias, J. M., Barthelemy, M., Miguel, M. S., & Ramasco, J. J. (2015a). Influence of sociodemographic characteristics on human mobility. *Scientific Reports*, *5*(1), 10075. https://doi.org/10.1038/srep10075

Lenormand, M., Louail, T., Cantú-Ros, O. G., Picornell, M., Herranz, R., Arias, J. M., Barthelemy, M., Miguel, M. S., & Ramasco, J. J. (2015b). Influence of sociodemographic characteristics on human mobility. *Scientific Reports*, *5*(1), 10075. https://doi.org/10.1038/srep10075

Liang, Y., Yin, J., Pan, B., Lin, M., & Chi, G. (2021). Assessing the validity of SafeGraph data for visitor monitoring in Yellowstone National Park. *Travel and Tourism Research Association: Advancing Tourism Research Globally*. https://scholarworks.umass.edu/ttra/2021/research_papers/1

Long, J., Malekzadeh, M., Klar, B., & Martin, G. (2021). Do regionally targeted lockdowns alter movement to non-lockdown regions? Evidence from Ontario, Canada. *Health & Place*, 102668. https://doi.org/10.1016/j.healthplace.2021.102668

Long, J., & Ren, C. (2021). *Associations between mobility and socio-economic indicators vary across the timeline of the Covid-19 pandemic*. SocArXiv. https://doi.org/10.31235/osf.io/tca34

Long, J., & Reuschke, D. (2021). Daily mobility patterns of small business owners and homeworkers in post-industrial cities. *Computers, Environment and Urban Systems*, *85*, 101564. https://doi.org/10.1016/j.compenvurbsys.2020.101564

Lu, X., Wetter, E., Bharti, N., Tatem, A. J., & Bengtsson, L. (2013). Approaching the Limit of Predictability in Human Mobility. *Scientific Reports*, *3*(1), 2923. https://doi.org/10.1038/srep02923

Manaugh, K., Miranda-Moreno, L. F., & El-Geneidy, A. M. (2010). The effect of neighbourhood characteristics, accessibility, home–work location, and demographics on commuting distances. *Transportation*, *37*(4), 627–646. https://doi.org/10.1007/s11116-010-9275-z

Melamed, D. (2015). Communities of classes: A network approach to social mobility. *Research in Social Stratification and Mobility*, *41*, 56–65. https://doi.org/10.1016/j.rssm.2015.05.001

Mercado, R., & Páez, A. (2009). Determinants of distance traveled with a focus on the elderly: A multilevel analysis in the Hamilton CMA, Canada. *Journal of Transport Geography*, *17*(1), 65–76. https://doi.org/10.1016/j.jtrangeo.2008.04.012

Mokhtarian, P. L. (1991). Telecommuting and travel: State of the practice, state of the art. *Transportation*, *18*(4), 319–342. https://doi.org/10.1007/BF00186563

Morency, C., Paez, A., Roorda, M. J., Mercado, R., & Farber, S. (2011). Distance traveled in three Canadian cities: Spatial analysis from the perspective of vulnerable population segments. *Journal of Transport Geography*, *19*(1), 39–50. https://doi.org/10.1016/j.jtrangeo.2009.09.013

Newbold, K. B., & Scott, D. (2013). Migration, commuting distance, and urban sustainability in Ontario's Greater Golden Horseshoe: Implications of the Greenbelt and Places to Grow legislation. *Canadian Geographer*, *57*(4), 474–487. Scopus. https://doi.org/10.1111/j.1541-0064.2013.12044.x

Newman, M. E. J. (2006). Finding community structure in networks using the eigenvectors of matrices. *Physical Review E*, *74*(3), 036104. https://doi.org/10.1103/PhysRevE.74.036104

Newman, M. E. J., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, *69*(2), 026113. https://doi.org/10.1103/PhysRevE.69.026113

Oliver, N., Lepri, B., Sterly, H., Lambiotte, R., Deletaille, S., De Nadai, M., Letouzé, E., Salah, A. A., Benjamins, R., Cattuto, C., Colizza, V., de Cordes, N., Fraiberger, S. P., Koebe, T., Lehmann, S., Murillo, J., Pentland, A., Pham, P. N., Pivetta, F., … Vinck, P. (2020). Mobile phone data for informing public health actions across the COVID-19 pandemic life cycle. *Science Advances*, *6*(23), eabc0764. https://doi.org/10.1126/sciadv.abc0764

Páez, A., Mercado, R., Farber, S., Morency, C., & Roorda, M. (2009). *Mobility and Social Exclusion in Canadian Communities: An Empirical Investigation of Opportunity Access and Deprivation*.

Pappalardo, L., Pedreschi, D., Smoreda, Z., & Giannotti, F. (2015). Using big data to study the link between human mobility and socio-economic development. *2015 IEEE International Conference on Big Data (Big Data)*, 871–878. https://doi.org/10.1109/BigData.2015.7363835

Pareek, M., Bangash, M. N., Pareek, N., Pan, D., Sze, S., Minhas, J. S., Hanif, W., & Khunti, K. (2020). Ethnicity and COVID-19: An urgent public health research priority. *The Lancet*, *395*(10234), 1421–1422. https://doi.org/10.1016/S0140-6736(20)30922-3

Pawar, D. S., Yadav, A. K., Choudhary, P., & Velaga, N. R. (2021). Modelling work- and non-work-based trip patterns during transition to lockdown period of COVID-19 pandemic in India. *Travel Behaviour and Society*, *24*, 46–56. https://doi.org/10.1016/j.tbs.2021.02.002

Pepe, E., Bajardi, P., Gauvin, L., Privitera, F., Lake, B., Cattuto, C., & Tizzoni, M. (2020). COVID-19 outbreak response, a dataset to assess mobility changes in Italy following national lockdown. *Scientific Data*, *7*(1), 230. https://doi.org/10.1038/s41597-020-00575-2

Pons, P., & Latapy, M. (2005). Computing Communities in Large Networks Using Random Walks. In pInar Yolum, T. Güngör, F. Gürgen, & C. Özturan (Eds.), *Computer and Information Sciences—ISCIS 2005* (pp. 284–293). Springer. https://doi.org/10.1007/11569596_31

Primerano, F., Taylor, M. A. P., Pitaksringkarn, L., & Tisato, P. (2008). Defining and understanding trip chaining behaviour. *Transportation*, *35*(1), 55–72. https://doi.org/10.1007/s11116-007-9134-8

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020a). *Population mobility reductions during COVID-19 epidemic in France under lockdown*. 22.

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020b). Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: A population-based study. *The Lancet Digital Health*, *2*(12), e638–e649. https://doi.org/10.1016/S2589-7500(20)30243-0

Rae, A. (2017). The Geography of Travel to Work in England and Wales: Extracts from the 2011 Census. *Applied Spatial Analysis and Policy*, *10*(4), 457–473. https://doi.org/10.1007/s12061-016-9196-0

Reuschke, D., & Felstead, A. (2020). Changing workplace geographies in the COVID-19 crisis. *Dialogues in Human Geography*, *10*(2), 208–212. https://doi.org/10.1177/2043820620934249

Rietveld, P. (2011). Telework and the transition to lower energy use in transport: On the relevance of rebound effects. *Environmental Innovation and Societal Transitions*, *1*(1), 146–151. https://doi.org/10.1016/j.eist.2011.03.002

Roorda, M. J., Páez, A., Morency, C., Mercado, R., & Farber, S. (2010). Trip generation of vulnerable populations in three Canadian cities: A spatial ordered probit approach. *Transportation*, *37*(3), 525–548. https://doi.org/10.1007/s11116-010-9263-3

Rosvall, M., & Bergstrom, C. T. (2008). Maps of random walks on complex networks reveal community structure. *Proceedings of the National Academy of Sciences*, *105*(4), 1118–1123. https://doi.org/10.1073/pnas.0706851105

Samuel, J., & Basavarajappa, K. (2006). The Visible Minority Population in Canada: A Review of Numbers, Growth and Labour Force Issues. *Canadian Studies in Population [ARCHIVES]*, *33*(2), Article 2. https://doi.org/10.25336/P6KK7S

Santana, C., Botta, F., Barbosa, H., Privitera, F., Menezes, R., & Di Clemente, R. (2020). *Analysis of human mobility in the UK during the COVID-19 pandemic*. https://doi.org/10.13140/RG.2.2.33207.14240

Scala, A., Flori, A., Spelta, A., Brugnoli, E., Cinelli, M., Quattrociocchi, W., & Pammolli, F. (2020). Time, space and social interactions: Exit mechanisms for the Covid-19 epidemics. *Scientific Reports*, *10*(1), Article 1. https://doi.org/10.1038/s41598-020-70631-9

Sekulić, S., Long, J., & Demšar, U. (2019). *Geographical context in community detection: A comparison of a node- based and a link-based approach*. 6.

Shen, Y., Kwan, M.-P., & Chai, Y. (2013). Investigating commuting flexibility with GPS data and 3D geovisualization: A case study of Beijing, China. *Journal of Transport Geography*, *32*, 1–11. https://doi.org/10.1016/j.jtrangeo.2013.07.007

Shepherd, H. E. R., Atherden, F. S., Chan, H. M. T., Loveridge, A., & Tatem, A. J. (2021). Domestic and international mobility trends in the United Kingdom during the COVID-19 pandemic: An analysis of facebook data. *International Journal of Health Geographics*, *20*(1), 46. https://doi.org/10.1186/s12942-021-00299-5

Shin, E. J. (2019). Self-employment and travel behavior: A case study of workers in central Puget Sound. *Transport Policy*, *73*, 101–112. https://doi.org/10.1016/j.tranpol.2018.11.002

Spyratos, S., Vespe, M., Natale, F., Weber, I., Zagheni, E., & Rango, M. (2019). Quantifying international human mobility patterns using Facebook Network data. *PLOS ONE*, *14*(10), e0224134. https://doi.org/10.1371/journal.pone.0224134

Statistics Canada. (2004). *The Rural-Urban Income Gap Within Provinces: An Update to 2000 - ARCHIVED*. Statistics Canada. https://www150.statcan.gc.ca/n1/pub/21-006-x/21-006-x2004007-eng.pdf

Stevens, N. T., Sen, A., Kiwon, F., Morita, P. P., Steiner, S. H., & Zhang, Q. (2022). Estimating the Effects of Non-Pharmaceutical Interventions and Population Mobility on Daily COVID-19 Cases: Evidence from Ontario. *Canadian Public Policy*, *48*(1), 144–161. https://doi.org/10.3138/cpp.2021-022

Traag, V. A., Waltman, L., & van Eck, N. J. (2019). From Louvain to Leiden: Guaranteeing well-connected communities. *Scientific Reports*, *9*(1), 5233. https://doi.org/10.1038/s41598-019-41695-z

Vanhoof, M., Schoors, W., Van Rompaey, A., Ploetz, T., & Smoreda, Z. (2018). Comparing Regional Patterns of Individual Movement Using Corrected Mobility Entropy. *Journal of Urban Technology*, *25*(2), 27–61. https://doi.org/10.1080/10630732.2018.1450593

Wang, F., & Chen, C. (2018). On data processing required to derive mobility patterns from passively-generated mobile phone data. *Transportation Research Part C: Emerging Technologies*, *87*, 58–74. https://doi.org/10.1016/j.trc.2017.12.003

Warren, M. S., & Skillman, S. W. (2020). *Mobility Changes in Response to COVID-19* (arXiv:2003.14228). arXiv. https://doi.org/10.48550/arXiv.2003.14228

Weill, J. A., Stigler, M., Deschenes, O., & Springborn, M. R. (2020). Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proceedings of the National Academy of Sciences*, *117*(33), 19658–19660. https://doi.org/10.1073/pnas.2009412117

Widener, M. J., Farber, S., Neutens, T., & Horner, M. (2015). Spatiotemporal accessibility to supermarkets using public transit: An interaction potential approach in Cincinnati, Ohio. *Journal of Transport Geography*, *42*, 72–83. https://doi.org/10.1016/j.jtrangeo.2014.11.004

Wu, K., Tang, J., & Long, Y. (2019). Delineating the Regional Economic Geography of China by the Approach of Community Detection. *Sustainability*, *11*(21), Article 21. https://doi.org/10.3390/su11216053

Xiong, C., Hu, S., Yang, M., Luo, W., & Zhang, L. (2020). Mobile device data reveal the dynamics in a positive relationship between human mobility and COVID-19 infections. *Proceedings of the National Academy of Sciences*, *117*(44), 27087–27089. https://doi.org/10.1073/pnas.2010836117

Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). Human mobility and socioeconomic status: Analysis of Singapore and Boston. *Computers, Environment and Urban Systems*, *72*, 51–67. https://doi.org/10.1016/j.compenvurbsys.2018.04.001

Xu, Y., Shaw, S.-L., Zhao, Z., Yin, L., Fang, Z., & Li, Q. (2015). Understanding aggregate human mobility patterns using passive mobile phone location data: A home-based approach. *Transportation*, *42*(4), 625–646. https://doi.org/10.1007/s11116-015-9597-y

Xu, Y., Shaw, S.-L., Zhao, Z., Yin, L., Lu, F., Chen, J., Fang, Z., & Li, Q. (2016). Another Tale of Two Cities: Understanding Human Activity Space Using Actively Tracked Cellphone Location Data. *Annals of the American Association of Geographers*, *106*(2), 489–502. https://doi.org/10.1080/00045608.2015.1120147

Yang, X., Fang, Z., Yin, L., Li, J., Zhou, Y., & Lu, S. (2018). Understanding the Spatial Structure of Urban Commuting Using Mobile Phone Location Data: A Case Study of Shenzhen, China. *Sustainability*, *10*(5), Article 5. https://doi.org/10.3390/su10051435

You, G. (2022). The disturbance of urban mobility in the context of COVID-19 pandemic. *Cities*, *128*, 103821. https://doi.org/10.1016/j.cities.2022.103821

Yu, Q., Li, W., Yang, D., & Zhang, H. (2020). Mobile Phone Data in Urban Commuting: A Network Community Detection-Based Framework to Unveil the Spatial Structure of Commuting Demand. *Journal of Advanced Transportation*, *2020*, e8835981. https://doi.org/10.1155/2020/8835981

Zarifa, D., Seward, B., & Milian, R. P. (2019). Location, location, location: Examining the rural-urban skills gap in Canada. *Journal of Rural Studies*, *72*, 252–263. https://doi.org/10.1016/j.jrurstud.2019.10.032

Zhang, W., Chong, Z., Li, X., & Nie, G. (2020). Spatial patterns and determinant factors of population flow networks in China: Analysis on Tencent Location Big Data. *Cities*, *99*, 102640. https://doi.org/10.1016/j.cities.2020.102640

Zhang, W., Gong, Z., Niu, C., Zhao, P., Ma, Q., & Zhao, P. (2022). Structural changes in intercity mobility networks of China during the COVID-19 outbreak: A weighted stochastic block modeling analysis. *Computers, Environment and Urban Systems*, *96*, 101846. https://doi.org/10.1016/j.compenvurbsys.2022.101846

Zhao, X., Yan, X., Yu, A., & Van Hentenryck, P. (2020). Prediction and behavioral analysis of travel mode choice: A comparison of machine learning and logit models. *Travel Behaviour and Society*, *20*, 22–35. https://doi.org/10.1016/j.tbs.2020.02.003

Zhao, Z., Shaw, S.-L., Yin, L., Fang, Z., Yang, X., Zhang, F., & Wu, S. (2019). The effect of temporal sampling intervals on typical human mobility indicators obtained from mobile phone location data. *International Journal of Geographical Information Science*, *33*(7), 1471–1495. https://doi.org/10.1080/13658816.2019.1584805

Chapter 3

3 Change in functional travel regions of Ontario, Canada during the COVID-19 pandemic and their alignment with public health boundaries

3.1 Introduction

Starting on March 17, 2020, governmental restrictions on in-person gatherings and non-essential businesses were put in place in Ontario, Canada due to the spreading of COVID-19, causing many people's travel patterns to change. Throughout 2020, Ontario's specific restrictions at any given time varied in severity, and in some cases varied in their geographic scope (Long & Ren, 2021). This caused a major disruption in the urban and regional travel patterns that are typical to the province of Ontario and has given us reason to re-investigate patterns of travel flows within Ontario.

We know from previous transportation research that urban form tends to influence the distance factor of mobility, where people in denser, urban areas tend to travel shorter distances and have smaller activity spaces (Manaugh et al., 2010; Morency et al., 2011; Xu et al., 2018). We also know that major Ontario cities have large catchment areas in their surrounding regions where travel and economic activity tends to take place (Green & Meyer, 1997). There is well documented variation in terms of how far and long people tend to travel for various activities, which vary by a variety of socio-economic factors (Long & Reuschke, 2021b; Morency et al., 2011; Newbold & Scott, 2013; Roorda et al., 2010). Recently, we have connected changes in mobility patterns resulting from various restrictions caused by the COVID-19 pandemic across the world (Abdullah et al., 2020; Bartik et al., 2020; Chang et al., 2021; Fan et al., 2012; Gibbs et al., 2020; Huang et al., 2021; Jay et al., 2020; Pawar et al., 2021; Pullano et al., 2020a; Reuschke & Felstead, 2020; Scala et al., 2020; Stevens et al., 2022; Zhang et al., 2022).

The major shift in mobility patterns in Ontario gives us the opportunity to understand how regions were inter-connected by individual travel patterns during the COVID-19 pandemic and how this connectivity changed over the course of the pandemic. In doing so, one of the major focus of this research is to study whether regionally targeted restrictions effectively captured movement patterns. This is an important topic to address for two reasons: 1) government restrictions were regionally targeted causing specific economic harm in an effort to reduce transmission of COVID-19, and 2) at the time it was very unclear how best to implement such local or regionally targeted interventions. Previous research has shown that these regionally targeted interventions had little impact on inter-regional travel patterns of those targeted regions (Long et al., 2021). However, to date no work has proposed alternative and superior methods for implementing such regionalized interventions. Therefore, this chapter will explore how community detection methods for spatial flow networks can be used to generate regions that reflect mass mobility patterns.

We hypothesize that all computed community partitions based on the mobility data will better reflect patterns of movement of people than those based on Public Health Region (HR) boundaries which were used during the COVID-19 pandemic by the Ontario government. We also expect that the community partitions will change over time, indicating the change in travel patterns in Ontario throughout the pandemic. These results will give us a better understanding of how flow patterns changed in Ontario due to COVID-19 restrictions, and how regionally targeted restrictions could have been more optimally applied to reflect actual travel regions rather than somewhat arbitrary HR administrative boundaries.

3.2 Background

3.2.1 Functional Regions

A functional region can be defined as an area within which activities tend to take place, and between which travel is less likely to take place. Data-driven functional regions can be computed by observing actual travel patterns, represented by a flow matrix. A number of functional regionalization procedures have been established in geographical literature in three general classes: hierarchical clustering, multistage aggregation, and central place aggregation (Farmer & Fotheringham, 2011).

Community detection has several different applications in transportation research. Commuting regions, or Travel to Work Areas, can be determined using flow data that specifically describes people’s trips to work, giving an indication of where people travel to work from and how they use the transportation network to make their commutes (Hamilton & Rae, 2020; Rae, 2017). Import and export data can be used to create functional regions that represent countries with interconnected economies (Grassi et al., 2021). Migration data can be used to identify migration networks, which can help to study international migration patterns and how they change over time (Abel et al., 2021).

There are a number of methods for detecting communities from a graph, and several of them have been applied to mobility network data. The Louvain algorithm has been commonly applied to mobility flows data to detect functional regions and commuting zones (De Montis et al., 2013; Sekulić et al., 2019; Wu et al., 2019), though there are limitations of this method with the Leiden algorithm recently proposed as an alternative to Louvain (Traag et al., 2019) but has not yet had extensive use in transportation research. Other methods include the Fast Unfolding method (Blondel et al., 2008; Yu et al., 2020), Infomap (Rosvall & Bergstrom, 2008; Yang et al., 2018), Walktrap (Huang et al., 2021; Pons & Latapy, 2005; Zhang et al., 2022), and Leading Eigenvector (Melamed, 2015; Newman, 2006).

3.2.2 Community Structure during COVID-19

In general, three overall changes to mobility patterns due to COVID-19 restrictions have been observed in previous research: (1) lower overall mobility (Gibbs et al., 2020; Kang et al., 2020; M. Lee et al., 2020; Pepe et al., 2020; Santana et al., 2020; Shepherd et al., 2021; You, 2022) (2) shorter-distance trips being made and mobility becoming more localized (Abdullah et al., 2020; Dueñas et al., 2021; Kang et al., 2020; Pawar et al., 2021; Pullano et al., 2020a; Zhang et al., 2022), and (3) lower importance of regional hubs, such as business centres becoming less relevant in the mobility network (Bartik et al., 2020, 2020; Dueñas et al., 2021; Pawar et al., 2021; Pullano et al., 2020a; Reuschke & Felstead, 2020).

Generally, the only difference between mobility changes due to the pandemic in different regions across the world were the speed with which restrictions were imposed, and the lag at which people reacted to these restrictions, in some cases causing variation in the timing of the initial mobility drop by several weeks (You, 2022). The general pattern of mobility flow changes, was a decrease in flows from March to April, and an increase again in May, though not back to the pre-pandemic levels (Kang et al., 2020), with some slight local variations due to specific local restrictions in place (Gibbs et al., 2020; Long et al., 2021; Long & Ren, 2021). We have also seen that mobility changes due to pandemic restrictions varied based on socio-economic status (Dueñas et al., 2021; Kar et al., 2022; Long & Ren, 2021; Pullano et al., 2020b; Xu et al., 2018).

Different mobility studies use different definitions for inter-regional flows (aka outflows, or external mobility) (Long et al., 2021), but we have seen similar patterns of these longer distance flows decreasing during the pandemic throughout the world. Long-range spatial interactions decreased the most in the United States, with most movements becoming short-range movement to adjacent counties (Kang et al., 2020). Bogota, Columbia saw a decrease in the share of long-lasting trips (Dueñas et al., 2021), China saw the structure of mobility become more local (Zhang et al., 2022), and long-distance trips were disrupted in France more than short-distance ones (Pullano et al., 2020a). This is likely because people were more likely to make local trips for essential purposes such as grocery or healthcare (Abdullah et al., 2020; Pawar et al., 2021).

Mobility becoming more localized has a large effect on regional hubs, or places with important regional destinations such as businesses, retail, or services. Cities or regions with a core central business district saw a particularly large drop in inflows due to many of the people who would previously travel there regularly for work shifting to working from home (Bartik et al., 2020; Pawar et al., 2021; Reuschke & Felstead, 2020). There was a larger decrease in inter-regional trips in France than within-region trips (Pullano et al., 2020a). Some localities in Bogota lost 'relative relevance' during the pandemic, particularly central areas with services and workplaces (Dueñas et al., 2021). This also varies greatly across employment sector, and therefore by socio-economic status, as jobs in financial, professional and technical sectors are more likely to be able to be performed from home, while lower-skilled and higher-service work is less likely to be done from home (Felstead & Henseke, 2017), and the locations of these higher-service jobs tend to be less concentrated in major employment centres (Bartik et al., 2020). Areas that tend to gain 'relative relevance' are ones that are less centralized, but have high urbanization with heterogeneous socio-economic conditions (Dueñas et al., 2021).

3.2.3 Region-Level COVID-19 Restrictions in Ontario

Large-scale changes to mobility patterns first started in Ontario when a state-of-emergency was announced, with restrictions on businesses and social gatherings beginning March 17, 2020. In June and July, restrictions began being phased out due to lower COVID-19 case counts, with lower levels of restrictions throughout the summer. By October, there was an increase of cases again, and restrictions were re-applied to specific health regions starting in November, with the whole province returning to these restrictions on December 26, 2020.

There were several cases where restrictions were imposed at the Health Region level. In the first of these cases in July 2020, 10 of Ontario's 35 HRs were maintained under stricter restrictions, while the rest of the HRs had some restrictions removed. In the second of these cases in November 2020, two of the HRs, Toronto and Peel Region, had restrictions re-imposed ahead of the rest of the province.

3.3 Methods

3.3.1 Study Area

Our study area is made up of the 27 southernmost Public Health Units in Ontario, which we define in this study as Southern Ontario. This subset of Ontario was chosen as it is the part of Ontario where the largest amount of people live, and therefore where the largest amount of mobility takes place. The City of Toronto Health Unit is the largest health unit in the study area with over 2.7 million people (~22% of the study area), followed by Peel Regional Health Unit (~11%), York Regional Health Unit (~9%) and the City of Ottawa Health Unit (~7.5%). Many of the most populated health units tend to be relatively small in area, and likewise many of the least populated health units are very large in area.

Table 3-1: Southern Ontario public health units and their populations and areas

Public Health Unit	Population (2016)	Area (km)
Brant County Health Unit	134,943	1,204,750
Durham Regional Health Unit	645,862	2,760,862
Grey Bruce Health Unit	154,952	13,217,528

Haldimand-Norfolk Health Unit	109,652	4,562,550
Haliburton, Kawartha, Pine Ridge District Health Unit	179,083	10,493,210
Halton Regional Health Unit	548,435	1,039,066
City of Hamilton Health Unit	536,917	1,212,619
Hastings and Prince Edward Counties Health Unit	161,180	9,131,935
Huron County Health Unit	59,297	3,696,168
Chatham-Kent Health Unit	102,042	3,078,456
Kingston, Frontenac and Lennox and Addington Health Unit	193,363	8,174,790
Lambton Health Unit	126,638	4,172,674
Leeds, Grenville and Lanark District Health Unit	169,244	7,207,685
Middlesex-London Health Unit	455,526	3,523,025
Niagara Regional Area Health Unit	447,888	2,514,088
City of Ottawa Health Unit	934,243	2,985,534
Peel Regional Health Unit	1,381,739	1,346,784
Perth District Health Unit	76,796	2,337,001
Peterborough County-City Health Unit	138,236	4,380,546
The Eastern Ontario Health Unit	202,762	5,719,533
Simcoe Muskoka District Health Unit	547,274	12,863,692
Waterloo Health Unit	535,154	1,455,995
Wellington-Dufferin-Guelph Health Unit	284,461	4,393,925
Windsor-Essex County Health Unit	398,953	3,877,215
York Regional Health Unit	1,109,909	2,191,032
Oxford Elgin St. Thomas Health Unit	199,840	5,329,013
City of Toronto Health Unit	2,731,571	697,992
TOTAL	**12,565,960**	**123,567,667**

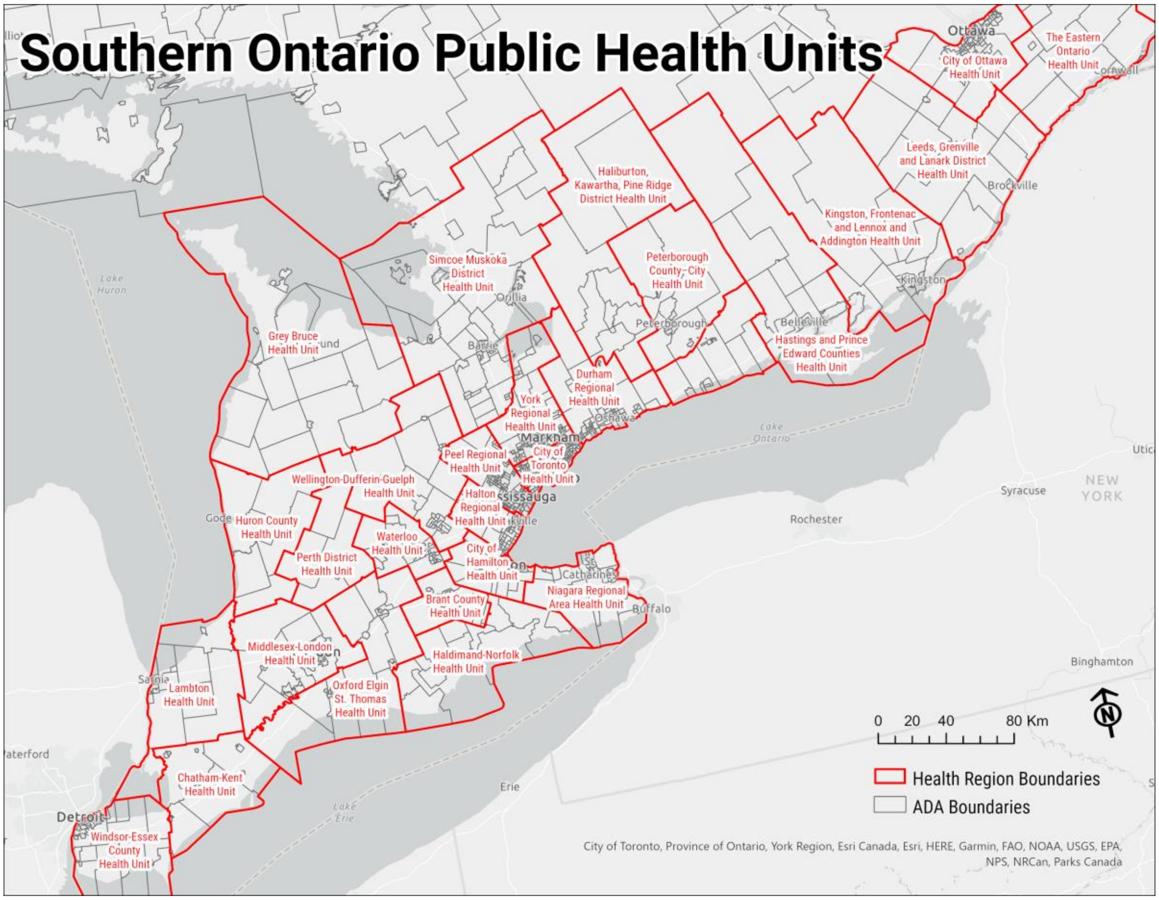


Figure 3-1: Study area with public health region boundaries

3.3.2 Data

3.3.2.1 Network Mobility Data

The data used for this research was obtained from TELUS Communications Inc. as part of their Data for Good program. These data are accessed via the TELUS Insights platform, which is a privacy-preserving system for analysing mass mobility patterns in Canada. The data comprise connections between mobile devices and cell tower receivers over time. As a device moves through space, it changes connections from receiver to receiver, generally connecting to the closest receiver. Cell tower receivers are distributed across space with a higher concentration in areas with higher population density and a lower concentration in areas with lower population density. For each connection, the data contain the start and end time of the connection, as well as geographic coordinates associated with the receiver. The data consists of approximately 3.5 million cellular devices in Ontario during the year 2020.

3.3.2.1.1 Estimating Home Neighbourhood Aggregate Dissemination Area

To estimate the home neighbourhood of each mobile device, clusters of receivers were identified based on a focal receiver and the surrounding receivers that the focal receiver directly connects to, termed handovers. The cluster of receivers with the greatest total dwell time of the device was labelled as the home cluster. A weighted average (by dwell time at each receiver) of the receivers that make up the home cluster was used to estimate the home neighbourhood of the device. We then identified the Aggregate Dissemination Area (ADA) census unit associated with the home neighbourhood estimate for each device using a spatial intersection. An ADA is an aggregated form of smaller census units, roughly representing 5000 to 15,000 people. The home neighbourhood estimate for each device is recomputed for each calendar month. There are a total of 1685 ADAs in Ontario, however only ADAs that included a minimum of 20 devices were used in subsequent analysis. In total, a subset of 1455 ADAs were included in the analysis here.

3.3.2.2 Flows

The dataset contains the number of flows between each pair of ADAs in Southern Ontario. To compute flows, we first identified what we term "stops" which were defined as a cell phone being detected at a single cell tower for a consecutive duration of 10 minutes or longer. A flow, was then defined every instance of a stop, with the cell phone's home ADA as the origin ADA and the location of the cell tower at which the cell phone was stopped as the destination ADA.

We then aggregated individual flows to develop a provincial flow matrix, which contains the sum of all flows from each origin ADA to each destination ADA. To account for varying levels of mobile devices across different ADA regions, we normalize the flow matrix by dividing the outgoing flows by the number of mobile devices whose home location was the origin ADA, and multiplied by the 2016-based census population of the origin ADA. This normalized flow matrix is then representative of a data and populations scaled flow rate for each origin and destination ADA pair. Flows were calculated as the weekly sum of flows for each week in 2020. This weekly flow value was then divided by seven to give an average daily number of flows from each origin ADA to each destination ADA. The flows were then divided by the number of cell towers in the destination ADA to account for the fact that a flow is more likely to be detected in areas with a higher density of cell towers. The final normalized flow value (F) was input into a symmetric flow matrix by taking the average of the flows to and from each pair of ADAs j and j.

$$F_{i,j,w} = \left(\frac{1}{7}\right)\frac{\frac{x_{i,j,w}p_i}{h_i t_j} + \frac{x_{j,i,w}p_j}{h_j t_i}}{2} \tag{3-1}$$

$F_{i.j,w}$ is the normalized flows from ADA i to ADA j for week w

$x_{i.j,w}$ is the measured flows from ADA i to ADA j for week w, and flows in the opposite direction for $x_{j.i,w}$

p_i is the 2016 census-based population of ADA i

h_i is the number of mobile devices whose home locations is in in ADA i

t_i is the number of cell towers located within ADA i

3.3.3 Community Detection

3.3.3.1 Cluster Leading Eigen

To detect functional regions from flow data, we used the Cluster Leading Eigen (CLE) method (Newman, 2006). This method uses the modularity matrix of the network, $\boldsymbol{M}$, formed from the equation $\boldsymbol{M} = \boldsymbol{A} - \boldsymbol{P}$, where $\boldsymbol{A}$ is the adjacency matrix of the network (containing the strengths of the edges between each pair of nodes according to the flows matrix), and where $\boldsymbol{P}$ is a matrix containing the probability that there is an edge between two nodes in a random network with the same degrees of nodes as the actual network (or in the case of a weighted graph such as ours, the expected weight between two nodes in a random network). The eigenvector of $\boldsymbol{M}$ is calculated for its most positive eigenvalues, and the network is divided into two communities based on the signs of the elements of this vector, corresponding to nodes in the network. Each of these two communities can be further subdivided into two new communities using this process, and this process can continue until there is no case where further subdividing any communities will result in an increase to the overall modularity (Newman, 2006). This method is similar to many other methods in its attempt to minimize the modularity of the network, which is a measure of the number of edges observed within communities minus the number of edges expected within communities, as described further in Section 3.3.3.3. Having a number of within-group edges that is significantly larger than expected by random chance, or a number of between-group edges that is significantly higher than expected by random chance, indicates a significant community structure (M. Chen et al., 2014).

3.3.3.2 Community Detection Parameters

Four community detection scenarios were run for four different periods of time in 2020. Representing different levels of restrictions throughout the pandemic. Table 3-2 outlines these four time periods.

Table 3-2: Periods of time used for community detection and their importance

Partition	Dates	Importance
A	Feb 03 to Mar 02	Pre-Pandemic
B	Mar 16 to Apr 12	Start of Pandemic
C	Aug 10 to Sep 6	Higher summer mobility
D	Sep 21 to Oct 18	Higher mobility due to school returning

These date ranges were chosen to get an indication of flow patterns for times with different levels of mobility restrictions (Long et al., 2021). Time period A is a baseline indication of flows before restrictions started, B represents a time when almost all businesses were forced to close and mobility was at its lowest point, C represents a time when there were higher levels of mobility during the summer, and D represents a time when in-person school resumed but many jobs had not yet returned in person.

3.3.3.3 Modularity

In order to quantify the strength of community structure, Newman and Girvan (2004) defined the measure *modularity* as the sum of the number of flows between each pair of regions in the same community minus the expected number of flows between those two communities, normalized by the total number of flows in the entire matrix.

$$Q = \frac{1}{2f_{total}} \sum_{ij} \left(F_{ij} - \frac{f_i f_j}{2f_{total}} \right) \delta_{c_i c_j} \qquad (3\text{-}2)$$

F_{ij} is the element of the flows matrix between regions *i* and *j*

δ is the Kroneker delta function, which equals 1 when regions *i* and *j* are in the same community ($c_i = c_j$) and 0 otherwise

f_i is the total number of flows associated with region *i*

f_{total} is the total number of flows in the network

In equation (2), F_{ij} represents the actual number of flows between two regions, and $\frac{f_i f_j}{2f_{total}}$ represents the expected number of flows between those two regions. The difference between the actual and expected number of flows between two regions only contributes towards increasing the modularity if they are in the same community, indicated by the Kroneker delta function. To think about this intuitively, the modularity score will be higher when more region pairs have a higher number of flows between them than expected ($F_{ij} > \frac{f_i f_j}{2f_{total}}$) and they are in the same region (Kroneker delta function equals 1). Similarly, when region pairs have a lower number of flows between them than expected ($F_{ij} < \frac{f_i f_j}{2f_{total}}$), the total modularity will not be impacted so long as they are not in the same region (Kroneker delta function equals 0). Modularity can range from -1 to 1, with closer to 1 meaning that flows tend to occur largely within communities, closer to -1 meaning that flows tend to occur between communities, and closer to 0 meaning that flows tend to occur randomly relative to the communities.

To evaluate the four community detection partitions and the health regions, the modularity was calculated for each week, for each of these five scenarios. For the four community detection partitions, the results of the community detection algorithm were used to assign ADAs to communities, and for the Health Regions ADAs were assigned to their respective health region. Comparing modularity scores of the results of different community detection maps can help to understand patterns in the flow data. Farmer and Fotheringham (2011) use the modularity of functional regions, as well as the number of functional regions created by their algorithm, to compare commuting patterns of different demographic groups in Dublin, Ireland. It has been suggested that modularity should not be used to compare the quality of community structure for graphs of very different sizes as the modularity tends to increase with larger graphs and communities (Fortunato, 2010). If HRs have more communities and lower modularity, then we can be confident that the HRs communities are a lower quality than our algorithm-based communities.

Modularity can also be calculated for each community individually if only regions pairs contained in a single community are calculated. This can give an indication of which regions contribute more or less to the overall modularity of the study region, and gives an indication of the distribution of the communities' modularity scores. This was done for our five region partitions to compare their modularity distributions. Since the community-level modularity scores don't have a maximum of 1 and are affected by the total number of communities (with the total modularity being divided among more communities the more communities there are, resulting in smaller community-level modularity scores), community-level modularity scores were multiplied by the total number of communities. This makes the upper bound of the adjusted community-level modularity scores equal to the total number of communities instead of 1, but allows for comparison of distribution between partitions with different number of communities.

3.3.3.4 Similarity Score

To determine the similarity between the four partitions and the health regions, we define a similarity score to quantitatively measure the similarity of the communities. For a given ADA, i, in the set of all ADAs, A, the number of ADAs were counted in the following two sets: $\{C_{i,a} \cap C_{i,b}\}$ and $\{C_{i,a} \cup C_{i,b}\}$, where $C_{i,a}$ and $C_{i,b}$ are the sets of ADAs in the same community as i in the two partitions being compared, a and b. The cardinality (size) of the first set is divided by the cardinality of the second set to give the ADA-level similarity score S_i. The ADA-level similarity scores for all ADAs are averaged to get the similarity score between the two partitions, S. This equation summarizes this process:

$$S_{a,b} = \frac{\sum_i \frac{\left|\{C_{i,a} \cap C_{i,b}\}\right|}{\left|\{C_{i,a} \cup C_{i,b}\}\right|}}{|A|} \tag{3-3}$$

$S_{a,b}$ is the similarity score between partitions a and b

A is the set of all ADAs

i is an ADA in set A

C_i is the set of ADAs in the same community as i for a given partition

This similarity measure is similar to the Jaccard Similarity Co-efficient (Yu et al., 2020) which is used for an overlapping hierarchical clustering algorithm, as well as other applications comparing the similarity of partially overlapping sets (Bag et al., 2019). Other studies comparing the results of a community detection procedure have used different quantitative measures of similarity, such as the Rand Index (De Montis et al., 2013) and the Adjusted Rand Index (Hubert & Arabie, 1985). While these measures of similarity work for our purpose, we believe that our measure of similarity is simpler to compute and to understand.

3.3.4 Analysis

This analysis has two goals: (1) to determine regions that could be used to better restrict movement in Ontario during COVID-19, which will be demonstrated in our results by higher modularity scores for the four community partitions we tested than for Ontario's health regions throughout 2020; and (2) to measure the similarity between the four community partitions and the health regions, by calculating similarity scores. The analysis will start by calculating summary statistics of the flows data. It will then show the modularity scores of the four community detection partitions and the health regions for each week in 2020 to see whether or not flow patterns align with health regions, including maps of local ADA similarity scores between each community partition and the HRs to see if there are any geographic patterns where the communities line up with HRs. It will then explore how movement patterns changed over time, and how similar they aligned with the health regions by using a similarity score matrix. The igraph R package (Csardi & Nepusz, 2006) was used to perform the Cluster Leading Eigen community detection algorithm.

3.4 Results

3.4.1 Summary Statistics

The City of Toronto Health Unit is the largest health unit in the study area, accounting for over 2.26 billion of the destination flows of the 9.8 billion total flows in the study area in all of 2020 (23%). Peel Regional Health Unit followed with 979 million flows (10%), followed by York Regional Health Unit with 775 million flows (7%). Our data shows a large drop-off of total flows around mid-March, the time when restrictions were first imposed. Mobility began to recover after May and through the summer months. Our data does not show the same level of drop-off in mobility in mid-October when restrictions started to be put back in place in Ontario.

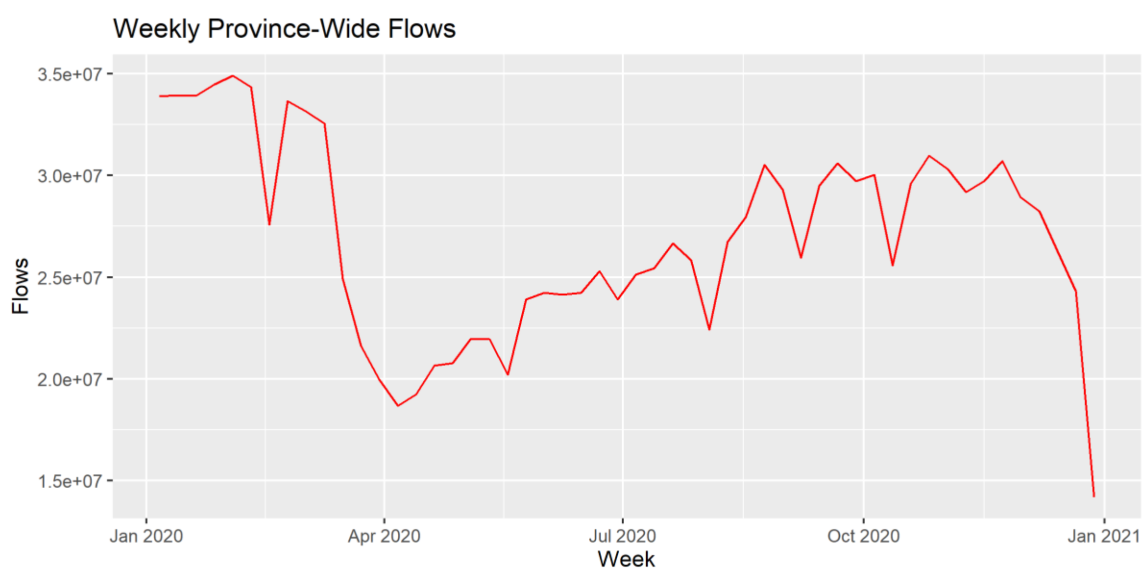


Figure 3-2: Weekly total province-wide flows

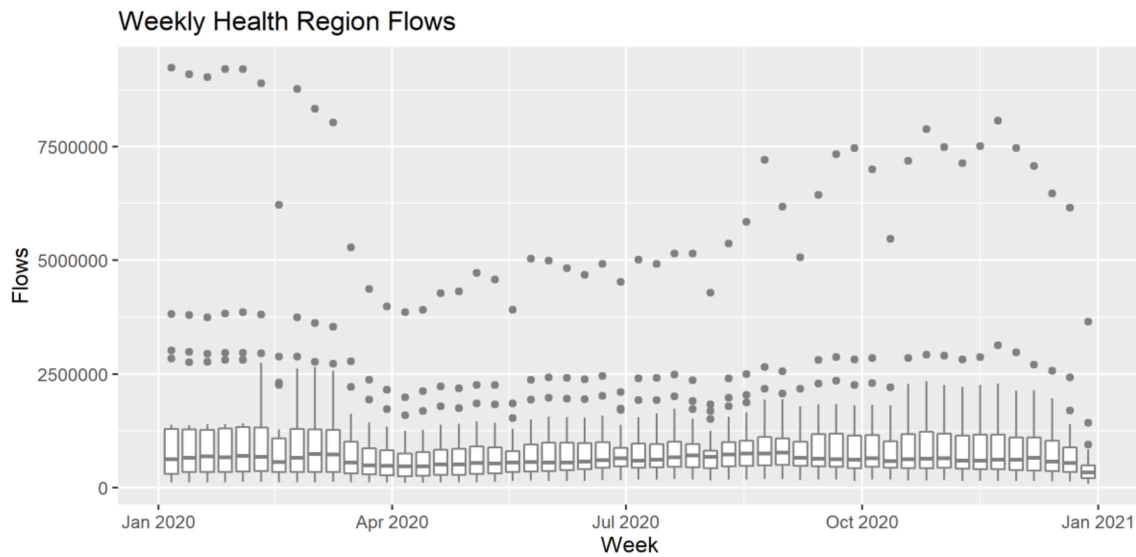


Figure 3-3: Weekly flows by health region

3.4.2 Results of Community Detection

The results of the community detection algorithm are shown geographically in Figure 3-4. Results for time period A, B, C and D were divided by the CLE algorithm into 14, 13, 11, and 10 communities, respectively.

The pre-pandemic communities (Partition A) show the City of Toronto to be almost all in the same community, connected with much of neighbouring regions Durham Region and York Region, but disconnected with neighbouring Peel Region. Outside of these areas, other major city-regions in Southern Ontario like Kitchener-Waterloo, London, Windsor, Barrie, Kitchener and Ottawa tend to be in their own communities, except for Hamilton and St. Catherine's being in the same community. After COVID restrictions started (Partition B), Toronto became split down the middle, divided into a Western Toronto and York Region community, and an Eastern Toronto, York Region and Durham Region community. These communities containing parts of Toronto do not extend as far into York and Durham regions as the communities in Partition A do. Peel remains distinct from the east, but combines with Halton in the west. The summer time period (Partition C) is similar to Partition A, but with some rural regions being consolidated, and with Toronto being split among three different communities. Partition D looks very similar to Partition C, but with some consolidation of communities in the northern part of the study area.

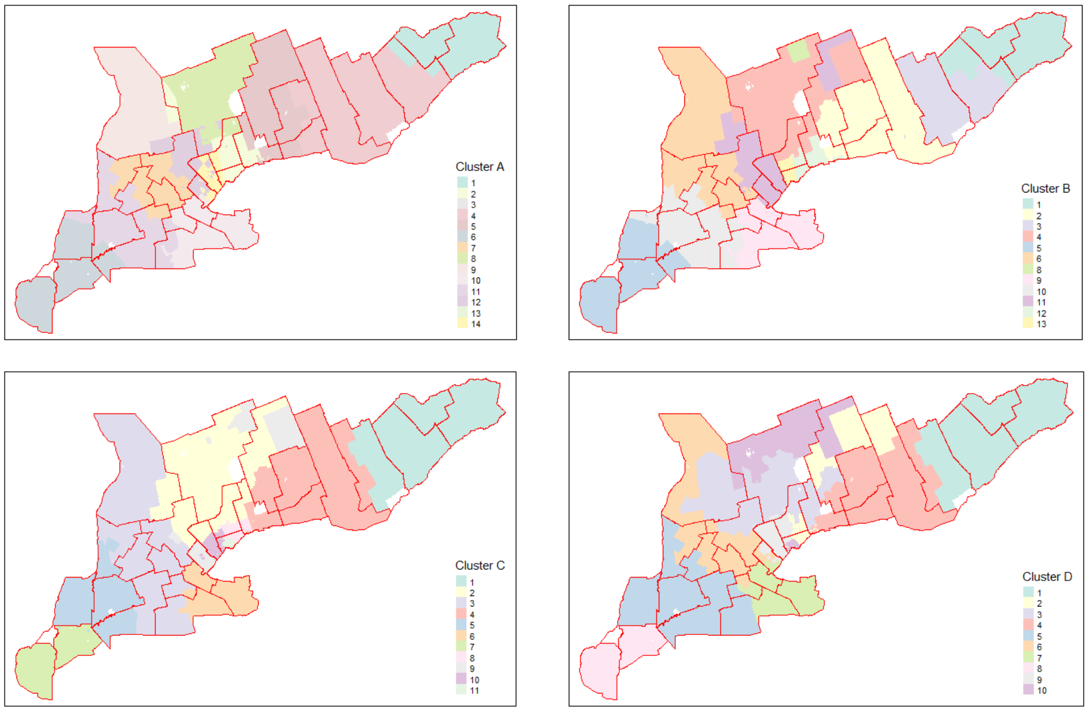


Figure 3-4: Community detections results for our four selected time periods

3.4.3 Total Modularity Scores

Modularity scores were computed for each of the community partitions and health regions, for each week of 2020. Figure 3-5 shows how the modularity changed over time. We can see that the modularity for the HRs remained below the modularity for each of the other flow-based partitions for all of 2020. This indicates that the communities created based on flows data are more representative of people’s travel patterns than the HRs. Partition A is the second lowest modularity throughout almost all of 2020, since this partition represents pre-pandemic travel when people were making a wide range of trips. Partition B has the highest modularity for all of 2020, since this partition represents the beginning of the pandemic when mobility was very low and people were generally staying very close to their homes for necessary travel. There was an increase in modularity from mid-March to around June, corresponding with the time when mobility decreased and people would have mostly been making trips within their functional region. The time period from July to

August represents a time when longer trips were being made due to reduced restrictions, which corresponds with a decrease in modularity as external flows were more likely to take place. In general, modularity has an inverse relationship with the amount of mobility taking place at any given time.

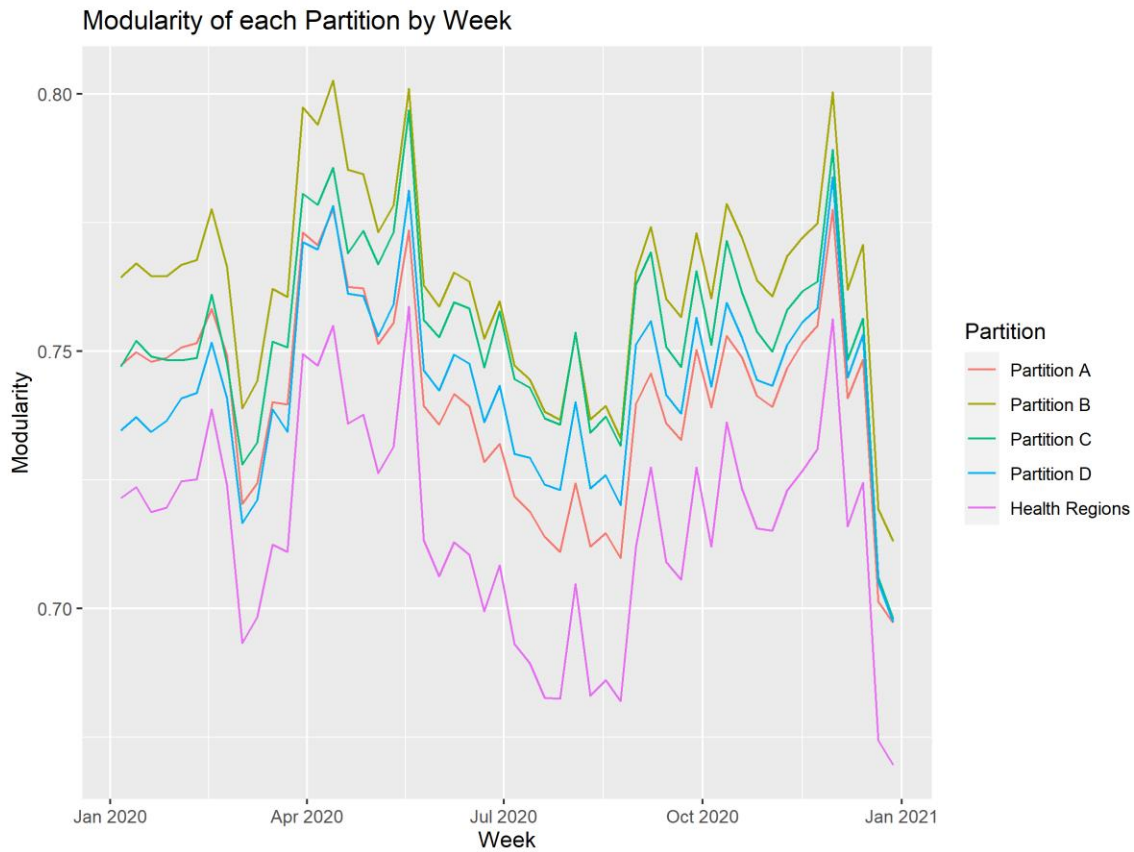


Figure 3-5: Modularity scores of four community partitions and HRs by week

3.4.4 Community-Level Modularity Scores

Measuring modularity at the community level highlights how some communities may contribute to the total network modularity more than others. In Figure 3-6, we can see that one or two outlier communities contribute a lot more to the total modularity for the HR partition than the rest of the communities. The highest outlier is the City of Toronto Health Unit, which has the most flows out of all the Southern Ontario health units. This indicates that even with the slightly lower median modularity for the HR partition compared to the four flow-based partitions, the HR modularity benefits greatly from one community with many internal flows.

Figure 3-6: Weekly adjusted local modularity by community

3.4.5 Partition Similarity

Partitions C and D are most similar with each other with a similarity score of 0.62. Partition C represents communities during the summer in August, and Partition D represents the communities during early fall in September and October, both of which were during times with relatively low COVID transmission and relatively high levels of mobility. The community partitions each have a similarity score with the HRs that is lower than any of the similarities among the community partitions. This suggests that none of the community partitions are similar to the HRs, and that HRs are not very representative of flow patterns. Partitions A and B, representing just before COVID in February and just after COVID restrictions started in March and April, have the second highest similarity score. This is despite the fact that many of the communities in the Toronto area change quite significantly. Partition B was most similar with the HRs, indicating that mobility patterns during the initial COVID restrictions were most aligned with the HRs.

Table 3-3: Similarity score matrix for four community partitions and HRs

	A	**B**	**C**	**D**	**HR**
A	1.00	0.58	0.49	0.50	0.40
B		1.00	0.49	0.49	0.41
C			1.00	0.62	0.38
D				1.00	0.35
HR					1.00

To determine whether the HRs are reflective of actual flow patterns, we look at the similarity scores between the HRs and the flow-based functional regions at the ADA level. This will show where in Southern Ontario our functional regions lined up with HRs and where they did not. Figure 3-7 shows that functional regions lined up well with several rural HRs, and even some urban-suburban HRs during some time periods, but the similarity between functional regions and HRs is generally low.

Figure 3-7: ADA similarity scores between HRs and community partitions A, B, C and D

3.5 Discussion

In our analysis, we used community detection as a way to aggregate raw flow data. Using community detection as an aggregation tool for flow data helps to observe overall mobility patterns, such as understanding commuting regions, and understanding which regions are more or less connected with each other. The need to simplify our flows dataset demonstrates the challenge of analysing big data, despite its usefulness in capturing large amounts of information (C. Chen et al., 2016a). Although simplifying a dataset will inevitably hide potentially interesting results in specific geographic areas, it makes it possible to understand big picture results. In our case, we may not be able to understand much about high trip-generating regions or how regions compare to each other, but we are able to understand generalized mobility patterns such as the geographic areas that people are more likely to travel within.

The results showing that flow-based partitions perform better in terms of community structure than Ontario's HR boundaries is in line with the results that we would expect. Since the flow-based partitions were created using actual flows data, it is expected that these communities would have a higher modularity score when being evaluated in terms of the flows matrix by which they were created. We would expect that these flow-based partitions would more accurately represent flow patterns than HRs that are defined based on municipal and regional boundaries.

The change in modularity over time confirms what we know about how mobility patterns changed over time due to pandemic restrictions (Gibbs et al., 2020; Kang et al., 2020; Long et al., 2021; Long & Ren, 2021; Xu et al., 2016). A higher modularity from March to May and from September onward implies more within-community flows, meaning less long distance trips being made. The dip in modularity during the summer months suggests more between-community flows, or more long distance trips. The four partitions' relative modularities and number of communities also tell us about overall mobility patterns. The fact that Partition A had the lowest modularity scores of the four partitions from April onwards indicates that functional regions during the pre-pandemic time period were not reflective of travel patterns after pandemic restrictions were implemented and for the rest of 2020. The fact that Partition A has the largest number of communities likely indicates that flows during this time period were most difficult to represent by a fewer number of functional regions, indicating less structured mobility patterns. However, the reasoning for Partition B also having a larger number of communities is likely due to the reverse reason, where people were making many short distance trips within smaller areas, making it easier to partition regions into smaller groups. Our prior knowledge of overall mobility patterns during this time period helps us in interpreting these results.

Ontario's HRs were used as administrative boundaries to implement regionally-targeted pandemic restrictions, with more restrictions in areas with greater levels of COVID infections. However, our analysis shows that these HR boundaries did not line up well with observed flow patterns at different stages of the pandemic. This means that Ontario's regionally-targeted restrictions may not have had their intended effect, as people's natural flow patterns often had the tendency to cross these boundaries, reducing the usefulness of these restrictions. In some rural HRs, flow patterns did tend to line up with HRs, and these areas have lower population and therefore lower overall mobility to begin with, but several urban and suburban HRs show a large amount of inter-HR mobility, and these are areas with large populations and therefore greater overall mobility. Implementing restrictions with boundaries that reflect observed mobility patterns may have been more effective in reducing COVID spread. The fact that functional regions did not always line up well with HRs aligns with the results of Long et al. (2021), who found that even during the regionally-targeted phases of the lockdown in Ontario, flows did not decrease between HRs compared to non-regionally targeted lockdown phases, suggesting that flows generally did not align with HRs.

When observing the change in functional regions across the four partitions, we can make observations about how flow patterns changed over time. We can see that the City of Toronto becomes less linked with parts of York and Durham Regions when restrictions are imposed. This likely reflects the reduction in suburban commuting into the downtown core of Toronto. Interestingly, we see that Peel Region remains in a separate community from Toronto for all four time periods, suggesting that municipalities in Peel Region like Mississauga and Brampton may be less linked to Toronto than other surrounding regions, which could be a result of demographic attributes (Morency et al., 2011; Newbold & Scott, 2013). Other major cities across southern Ontario tend to be in their own functional regions, with large areas surrounding them. This could reflect the regional nature of the small to medium sized cities in Ontario, with large catchment areas for commuting and other economic activities connecting cities and their surrounding regions (Green & Meyer, 1997). Each community outside of the Greater Toronto Area in Partition A (Figure 3-4) can be associated with a major city near the centre of the community: Kitchener-Waterloo (community 7), London (community 11), Windsor (community 6), Kingston (community

4), Ottawa (community 1), Barrie (community 8), plus Hamilton and St. Catherine's in the same community (community 10). The communities across Southern Ontario tend to be divided across major highways 400, 401 and 403, with these highways connecting almost all communities across Southern Ontario in all four partitions. This shows that Ontario's transportation patterns make it unlikely for a region to exist that is not connected to one of these highways.

In our analysis, a flow is defined as a stop being made by a mobile device outside of its home location, with the home location as the origin and the stop location as the destination. In many other studies, a flow is defined to be more representative of a trip, with the starting point of a trip being the origin and the ending point being the destination (Kang et al., 2020; Pepe et al., 2020; Yang et al., 2018). The implication of this is that a trip is only counted in one direction in our analysis rather than one trip in each direction, and does not necessarily give an indication of the path being taken if multiple stops are made outside the home location. This can be beneficial for understanding typical commuting to work or school patterns, as we are more easily able to distinguish between where people live and where people are participating in activities. But as a consequence, we are not able to capture any effects of trip chaining (Primerano et al., 2008) as all stops have the home location as the origin point.

Creating functional regions by maximizing modularity has two known issues. In some cases, it tends to split large communities into smaller communities, and in other cases, it tend to merge communities together that are smaller than a certain threshold, dependant on the total number of edges in the network and the degree of interconnectivity between communities (M. Chen et al., 2013; Lancichinetti & Fortunato, 2011). This second problem is known as the *resolution limit problem* (Fortunato & Barthélemy, 2007). While these issues relate more to the process of the community detection algorithm, it could also potentially point to limitations of using modularity to compare between different partitions. The maximum modularity of a graph tends to grow as the size of the graph and the number of communities increases (Fortunato, 2010). Here, we are comparing graphs of the same size, but we are comparing partitions of different numbers of communities, which could be a limitation of our modularity comparison method.

There is a potential lack of representativeness in our dataset due to potential biases in how flows are captured. First, the fact that our data represents TELUS mobile phones could mean that our sample, although large, is not representative of the whole population of our study area. There may be a bias towards younger to middle-aged mobile phone plan holders in our dataset since about 97% of people aged 18 to 34 subscribe to a mobile phone plan, and about 70% of people aged 65+ subscribe to a mobile phone plan (CRTC, 2019). Second, the distribution of cell phone towers in urban areas is more dense than in rural areas, and therefore may be more likely to detect a flow in an urban area from traveling a short distance compared to a rural area (C. Chen et al., 2016a). We accounted for this by normalizing flows by the number of cell towers in the destination ADA, but it is difficult to determine whether this adjustment accurately corrects for the bias.

3.6 Conclusions

We used community detection to study patterns of travel flows for Southern Ontario during the COVID-19 pandemic measured from a large sample of mobile devices. We used community detection to determine how flow patterns changed throughout the year 2020, and to determine whether Ontario's Public Health Unit boundaries were representative of flow patterns, by computing metrics describing and comparing community detection partitions such as modularity and a similarity score. In general, we found HR boundaries were not reflective of mobility patterns overall, and that the similarity between regions derived based on mobility flows and HR boundaries was lowest at the peak of the pandemic. We found that mobility decreased and became more localized during the first and second wave of COVID infections and their resulting government-imposed restrictions, due to the higher modularity scores of the partition representing the beginning of the pandemic, and due to the higher modularity scores of all partitions during the peak lockdown weeks. We also found that Ontario's Public Health Unit boundaries were not reflective of flow patterns in urban and suburban areas, but were more reflective of flow patterns in rural areas. This suggests the potential that regionally targeted COVID restrictions may have been better applied to regions representative of actual travel flow patterns, such as our functional regions, rather than Ontario's HR boundaries. From a methods perspective, our approach demonstrates another example of how community detection can be used to aggregate flow data to understand mobility patterns in large network mobility datasets. This research offers more new insight into how mobility was affected by the COVID-19 pandemic.

3.7 Acknowledgements

This work was supported by the TELUS Data for Good Program. We are grateful for assistance from W. Li and J. Bettridge at TELUS who contributed to this project.

3.8 References

Abdullah, M., Dias, C., Muley, D., & Shahin, Md. (2020). Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transportation Research Interdisciplinary Perspectives*, *8*, 100255. https://doi.org/10.1016/j.trip.2020.100255

Abel, G. J., DeWaard, J., Ha, J. T., & Almquist, Z. W. (2021). The form and evolution of international migration networks, 1990–2015. *Population, Space and Place*, *27*(3), e2432. https://doi.org/10.1002/psp.2432

Bag, S., Kumar, S. K., & Tiwari, M. K. (2019). An efficient recommendation generation using relevant Jaccard similarity. *Information Sciences*, *483*, 53–64. https://doi.org/10.1016/j.ins.2019.01.023

Bartik, A. W., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. T. (2020). *What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys* (Working Paper No. 27422; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w27422

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*(10), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Bourdin, S., Jeanne, L., Nadou, F., & Noiret, G. (2021). Does lockdown work? A spatial analysis of the spread and concentration of Covid-19 in Italy. *Regional Studies*, *55*(7), 1182–1193. https://doi.org/10.1080/00343404.2021.1887471

Chang, S., Pierson, E., Koh, P. W., Gerardin, J., Redbird, B., Grusky, D., & Leskovec, J. (2021). Mobility network models of COVID-19 explain inequities and inform reopening. *Nature*, *589*(7840), 82–87. https://doi.org/10.1038/s41586-020-2923-3

Chen, C., Ma, J., Susilo, Y., Liu, Y., & Wang, M. (2016). The promises of big data and small data for travel behavior (aka human mobility) analysis. *Transportation*

Research Part C: Emerging Technologies, *68*, 285–299. https://doi.org/10.1016/j.trc.2016.04.005

Chen, M., Kuzmin, K., & Szymanski, B. K. (2014). Community Detection via Maximization of Modularity and Its Variants. *IEEE Transactions on Computational Social Systems*, *1*(1), 46–65. https://doi.org/10.1109/TCSS.2014.2307458

Chen, M., Nguyen, T., & Szymanski, B. K. (2013). On Measuring the Quality of a Network Community Structure. *2013 International Conference on Social Computing*, 122–127. https://doi.org/10.1109/SocialCom.2013.25

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, *Complex Systems*, 1695.

De Montis, A., Caschili, S., & Chessa, A. (2013). Commuter networks and community detection: A method for planning sub regional areas. *The European Physical Journal Special Topics*, *215*(1), 75–91. https://doi.org/10.1140/epjst/e2013-01716-4

Dueñas, M., Campi, M., & Olmos, L. E. (2021). Changes in mobility and socioeconomic conditions during the COVID-19 outbreak. *Humanities and Social Sciences Communications*, *8*(1), 1–10. https://doi.org/10.1057/s41599-021-00775-0

Fan, Y., Guthrie, A., & Levinson, D. (2012). Impact of light-rail implementation on labor market accessibility: A transportation equity perspective. *Journal of Transport and Land Use*, *5*(3), 28–39.

Farmer, C. J. Q., & Fotheringham, A. S. (2011). Network-Based Functional Regions. *Environment and Planning A: Economy and Space*, *43*(11), 2723–2741. https://doi.org/10.1068/a44136

Felstead, A., & Henseke, G. (2017). Assessing the growth of remote working and its consequences for effort, well-being and work-life balance. *New Technology, Work and Employment*, *32*(3), 195–212. https://doi.org/10.1111/ntwe.12097

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, *486*(3), 75–174. https://doi.org/10.1016/j.physrep.2009.11.002

Fortunato, S., & Barthélemy, M. (2007). Resolution limit in community detection. *Proceedings of the National Academy of Sciences*, *104*(1), 36–41. https://doi.org/10.1073/pnas.0605965104

Gibbs, H., Liu, Y., Pearson, C. A. B., Jarvis, C. I., Grundy, C., Quilty, B. J., Diamond, C., & Eggo, R. M. (2020). Changing travel patterns in China during the early stages of the COVID-19 pandemic. *Nature Communications*, *11*(1), 5012. https://doi.org/10.1038/s41467-020-18783-0

Grassi, R., Bartesaghi, P., Benati, S., & Clemente, G. P. (2021). Multi-Attribute Community Detection in International Trade Network. *Networks and Spatial Economics*, *21*(3), 707–733. https://doi.org/10.1007/s11067-021-09547-4

Green, M. B., & Meyer, S. P. (1997). An overview of commuting in Canada: With special emphasis on rural commuting and employment. *Journal of Rural Studies*, *13*(2), 163–175. https://doi.org/10.1016/S0743-0167(97)83095-1

Hamilton, R., & Rae, A. (2020). Regions from the ground up: A network partitioning approach to regional delineation. *Environment and Planning B: Urban Analytics and City Science*, *47*(5), 775–789. https://doi.org/10.1177/2399808318804226

Huang, X., Li, Z., Jiang, Y., Ye, X., Deng, C., Zhang, J., & Li, X. (2021). The characteristics of multi-source mobility datasets and how they reveal the luxury nature of social distancing in the U.S. during the COVID-19 pandemic. *International Journal of Digital Earth*, *14*(4), 424–442. https://doi.org/10.1080/17538947.2021.1886358

Hubert, L., & Arabie, P. (1985). *Comparing partitions*. https://link.springer.com/article/10.1007/BF01908075

Jay, J., Bor, J., Nsoesie, E. O., Lipson, S. K., Jones, D. K., Galea, S., & Raifman, J. (2020). Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. *Nature Human Behaviour*, *4*(12), 1294–1302. https://doi.org/10.1038/s41562-020-00998-2

Kang, Y., Gao, S., Liang, Y., Li, M., Rao, J., & Kruse, J. (2020). Multiscale dynamic human mobility flow dataset in the U.S. during the COVID-19 epidemic. *Scientific Data*, *7*(1), 390. https://doi.org/10.1038/s41597-020-00734-5

Kar, A., Le, H. T. K., & Miller, H. J. (2022). What Is Essential Travel? Socioeconomic Differences in Travel Demand in Columbus, Ohio, during the COVID-19 Lockdown. *Annals of the American Association of Geographers*, *112*(4), 1023–1046. https://doi.org/10.1080/24694452.2021.1956876

Lancichinetti, A., & Fortunato, S. (2011). Limits of modularity maximization in community detection. *Physical Review E*, *84*(6), 066122. https://doi.org/10.1103/PhysRevE.84.066122

Lee, M., Zhao, J., Sun, Q., Pan, Y., Zhou, W., Xiong, C., & Zhang, L. (2020). Human mobility trends during the early stage of the COVID-19 pandemic in the United States. *PLOS ONE*, *15*(11), e0241468. https://doi.org/10.1371/journal.pone.0241468

Long, J. A., Malekzadeh, M., Klar, B., & Martin, G. (2021). Do regionally targeted lockdowns alter movement to non-lockdown regions? Evidence from Ontario, Canada. *Health & Place*, 102668. https://doi.org/10.1016/j.healthplace.2021.102668

Long, J., & Ren, C. (2021). *Associations between mobility and socio-economic indicators vary across the timeline of the Covid-19 pandemic*. SocArXiv. https://doi.org/10.31235/osf.io/tca34

Long, J., & Reuschke, D. (2021). Daily mobility patterns of small business owners and homeworkers in post-industrial cities. *Computers, Environment and Urban Systems*, *85*, 101564. https://doi.org/10.1016/j.compenvurbsys.2020.101564

Manaugh, K., Miranda-Moreno, L. F., & El-Geneidy, A. M. (2010). The effect of neighbourhood characteristics, accessibility, home–work location, and demographics on commuting distances. *Transportation*, *37*(4), 627–646. https://doi.org/10.1007/s11116-010-9275-z

Melamed, D. (2015). Communities of classes: A network approach to social mobility. *Research in Social Stratification and Mobility*, *41*, 56–65. https://doi.org/10.1016/j.rssm.2015.05.001

Morency, C., Paez, A., Roorda, M. J., Mercado, R., & Farber, S. (2011). Distance traveled in three Canadian cities: Spatial analysis from the perspective of vulnerable population segments. *Journal of Transport Geography*, *19*(1), 39–50. https://doi.org/10.1016/j.jtrangeo.2009.09.013

Newbold, K. B., & Scott, D. (2013). Migration, commuting distance, and urban sustainability in Ontario's Greater Golden Horseshoe: Implications of the Greenbelt and Places to Grow legislation. *Canadian Geographer*, *57*(4), 474–487. Scopus. https://doi.org/10.1111/j.1541-0064.2013.12044.x

Newman, M. E. J. (2006). Finding community structure in networks using the eigenvectors of matrices. *Physical Review E*, *74*(3), 036104. https://doi.org/10.1103/PhysRevE.74.036104

Newman, M. E. J., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, *69*(2), 026113. https://doi.org/10.1103/PhysRevE.69.026113

Pawar, D. S., Yadav, A. K., Choudhary, P., & Velaga, N. R. (2021). Modelling work- and non-work-based trip patterns during transition to lockdown period of COVID-19 pandemic in India. *Travel Behaviour and Society*, *24*, 46–56. https://doi.org/10.1016/j.tbs.2021.02.002

Pepe, E., Bajardi, P., Gauvin, L., Privitera, F., Lake, B., Cattuto, C., & Tizzoni, M. (2020). COVID-19 outbreak response, a dataset to assess mobility changes in Italy following national lockdown. *Scientific Data*, *7*(1), 230. https://doi.org/10.1038/s41597-020-00575-2

Pons, P., & Latapy, M. (2005). Computing Communities in Large Networks Using Random Walks. In pInar Yolum, T. Güngör, F. Gürgen, & C. Özturan (Eds.), *Computer and Information Sciences—ISCIS 2005* (pp. 284–293). Springer. https://doi.org/10.1007/11569596_31

Primerano, F., Taylor, M. A. P., Pitaksringkarn, L., & Tisato, P. (2008). Defining and understanding trip chaining behaviour. *Transportation*, *35*(1), 55–72. https://doi.org/10.1007/s11116-007-9134-8

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020a). *Population mobility reductions during COVID-19 epidemic in France under lockdown*. 22.

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020b). Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: A population-based study. *The Lancet Digital Health*, *2*(12), e638–e649. https://doi.org/10.1016/S2589-7500(20)30243-0

Rae, A. (2017). The Geography of Travel to Work in England and Wales: Extracts from the 2011 Census. *Applied Spatial Analysis and Policy*, *10*(4), 457–473. https://doi.org/10.1007/s12061-016-9196-0

Reuschke, D., & Felstead, A. (2020). Changing workplace geographies in the COVID-19 crisis. *Dialogues in Human Geography*, *10*(2), 208–212. https://doi.org/10.1177/2043820620934249

Roorda, M. J., Páez, A., Morency, C., Mercado, R., & Farber, S. (2010). Trip generation of vulnerable populations in three Canadian cities: A spatial ordered probit approach. *Transportation*, *37*(3), 525–548. https://doi.org/10.1007/s11116-010-9263-3

Rosvall, M., & Bergstrom, C. T. (2008). Maps of random walks on complex networks reveal community structure. *Proceedings of the National Academy of Sciences*, *105*(4), 1118–1123. https://doi.org/10.1073/pnas.0706851105

Santana, C., Botta, F., Barbosa, H., Privitera, F., Menezes, R., & Di Clemente, R. (2020). *Analysis of human mobility in the UK during the COVID-19 pandemic*. https://doi.org/10.13140/RG.2.2.33207.14240

Scala, A., Flori, A., Spelta, A., Brugnoli, E., Cinelli, M., Quattrociocchi, W., & Pammolli, F. (2020). Time, space and social interactions: Exit mechanisms for the Covid-19 epidemics. *Scientific Reports*, *10*(1), 13764. https://doi.org/10.1038/s41598-020-70631-9

Sekulić, S., Long, J., & Demšar, U. (2019). *Geographical context in community detection: A comparison of a node- based and a link-based approach*. 6.

Shepherd, H. E. R., Atherden, F. S., Chan, H. M. T., Loveridge, A., & Tatem, A. J. (2021). Domestic and international mobility trends in the United Kingdom during the COVID-19 pandemic: An analysis of facebook data. *International Journal of Health Geographics*, *20*(1), 46. https://doi.org/10.1186/s12942-021-00299-5

Stevens, N. T., Sen, A., Kiwon, F., Morita, P. P., Steiner, S. H., & Zhang, Q. (2022). Estimating the Effects of Non-Pharmaceutical Interventions and Population Mobility on Daily COVID-19 Cases: Evidence from Ontario. *Canadian Public Policy*, *48*(1), 144–161. https://doi.org/10.3138/cpp.2021-022

Traag, V. A., Waltman, L., & van Eck, N. J. (2019). From Louvain to Leiden: Guaranteeing well-connected communities. *Scientific Reports*, *9*(1), 5233. https://doi.org/10.1038/s41598-019-41695-z

Wu, K., Tang, J., & Long, Y. (2019). Delineating the Regional Economic Geography of China by the Approach of Community Detection. *Sustainability*, *11*(21), 6053. https://doi.org/10.3390/su11216053

Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). Human mobility and socioeconomic status: Analysis of Singapore and Boston. *Computers, Environment and Urban Systems*, *72*, 51–67. https://doi.org/10.1016/j.compenvurbsys.2018.04.001

Xu, Y., Shaw, S.-L., Zhao, Z., Yin, L., Lu, F., Chen, J., Fang, Z., & Li, Q. (2016). Another Tale of Two Cities: Understanding Human Activity Space Using Actively Tracked Cellphone Location Data. *Annals of the American Association of Geographers*, *106*(2), 489–502. https://doi.org/10.1080/00045608.2015.1120147

Yang, X., Fang, Z., Yin, L., Li, J., Zhou, Y., & Lu, S. (2018). Understanding the Spatial Structure of Urban Commuting Using Mobile Phone Location Data: A Case Study of Shenzhen, China. *Sustainability*, *10*(5), 1435. https://doi.org/10.3390/su10051435

You, G. (2022). The disturbance of urban mobility in the context of COVID-19 pandemic. *Cities*, *128*, 103821. https://doi.org/10.1016/j.cities.2022.103821

Yu, Q., Li, W., Yang, D., & Zhang, H. (2020). Mobile Phone Data in Urban Commuting: A Network Community Detection-Based Framework to Unveil the Spatial Structure of Commuting Demand. *Journal of Advanced Transportation*, *2020*, e8835981. https://doi.org/10.1155/2020/8835981

Zhang, W., Gong, Z., Niu, C., Zhao, P., Ma, Q., & Zhao, P. (2022). Structural changes in intercity mobility networks of China during the COVID-19 outbreak: A weighted stochastic block modeling analysis. *Computers, Environment and Urban Systems*, *96*, 101846. https://doi.org/10.1016/j.compenvurbsys.2022.101846

Chapter 4

4 Conclusion

This thesis explored several details of changes in mobility patterns during the COVID-19 pandemic in Ontario, Canada. This issue was worth investigating due to the long history of knowledge we have about human mobility patterns, and how everything we had known about human mobility was uprooted as soon as COVID-19 restrictions were imposed. As was the case previously, human mobility is strongly tied to a range of other subjects, including social geography, infrastructure, and statistical analysis (Allen & Farber, 2018b; C. Chen et al., 2016b; Fillekes et al., 2019; González et al., 2008; Hasanzadeh, 2019; Hirsch et al., 2014; Lachapelle et al., 2018; Lenormand et al., 2015a; Long & Reuschke, 2021b; Lu et al., 2013; Morency et al., 2011; Páez et al., 2009; Roorda et al., 2010; Spyratos et al., 2019; Vanhoof et al., 2018; Xu et al., 2018; X. Zhao et al., 2020). The COVID-19 pandemic changed the perspective we needed to take to understand the interplay between human mobility and these other topics.

At the start of the pandemic, there was a rush for many geographers to understand the details of how mobility patterns had changed since the start of the pandemic, and there was plenty of information and observations made just within the first few months (M. Lee et al., 2020; Warren & Skillman, 2020; Xiong et al., 2020). While this rapid approach to understand shifting mobility patterns using big data has been beneficial, our research has been able to review this early work and build on its shortcomings.

4.1 General Summary

This thesis explored the changes in human mobility patterns in Ontario throughout the year 2020, during which the COVID-19 pandemic occurred and created a large disturbance to typical mobility patterns. There were two analytical chapters, each focusing on a specific aspect of mobility. Chapter 2 focused on how mobility indicators were associated with socio-demographic variables using a Geographically Weighted Regression model, and Chapter 3 focused on shifting travel regions determined by a community detection algorithm based on flows data.

4.2 Chapter 2 Results

In Chapter 2, we saw how movement time and radius of gyration were associated with five socio-demographic indicators at three different time periods during the pandemic, and we observed how these associations vary spatially by using a geographically weighted model. There was a challenge coming to a clear consensus on how each socio-demographic indicator impacts mobility, as the maps of the model coefficients were very complex with values varying across most of Ontario. It was expected that we would see a clear pattern for each association, possibly with either a positive or negative association covering most of Ontario. Instead, we saw a large amount of variability in associations across the province, with relatively small geographic pockets of common results. Due to the difficulty of determining specific associations from the model, we focused heavily on the fact that results do in fact vary greatly by geography, and the effect of the Simpson's Paradox on these results.

4.2.1 Do associations between socio-demographic variables and mobility metrics vary across Ontario?

To see if associations between socio-demographic variables and mobility metrics vary across space in Ontario, we used a Geographically Weighted Regression (GWR) model, which computes a separate model for each geographic unit in the dataset using only the data from itself and nearby geographic units. By only taking into account data in local areas, you are able to see how associations differ in different parts of Ontario, without these local variations being drowned out by the many potentially conflicting local associations that go into a global model.

The results of our GWR are clear that associations vary quite dramatically across the province. Most maps showing positive, negative, or non-significant associations between each mobility metric and each socio-demographic variable have no clear pattern across the whole province. We are only able to come to conclusions about associations for specific geographic regions, such as the City of Toronto or Northeastern Ontario. These complex results make it difficult to form any generalized conclusions, but it is useful for understanding patterns in specific geographic contexts due to the spatially granular results.

4.2.2 Did people with lower socio-economic status have higher relative mobility during COVID-19?

It is difficult to come to generalized conclusions about how mobility was affected by specific socio-demographic indicators due to the spatially varying nature of these associations mentioned above. However, certain results show us associations that we might expect in specific parts of Toronto. For example, lower median income, an indicator of lower socio-economic status, is associated with higher relative movement time during the April time period in a number of specific parts of Ontario, including some of the inner suburbs of Toronto. We see this negative association more often than a positive association, but most of Ontario has a non-significant association, so we cannot make this conclusion for all of Ontario. Similarly, we see a positive association between visible minority and movement time in specific portions of Toronto, but we also see the reverse association in suburban areas surrounding Toronto as well as some rural areas. It is safe to conclude that lower socio-economic status was generally associated with higher relative mobility during the early stages of the pandemic, keeping in mind that these associations vary across the province.

4.3 Chapter 3 Results

In chapter 3, we saw how travel regions generated from flows data changed over the course of the pandemic, as well as how well the travel regions lined up with Ontario's health regions (HRs). There were a number of challenges in arriving at these results, mostly related to the choice of community detection algorithm and results not necessarily showing what we would expect. First, the choice of community detection algorithm took some time, with a number of different options being tested. Initially, it was a priority to use a hierarchical algorithm to allow flexibility in the number of communities created. We ended up finding that cutting communities at different points along the dendogram often led to questionable region splits. Second, we found that the data we were using led to suboptimal partitions, likely due to the unusual distribution of flows by ADA, with some ADAs having an unusually high number of flows. Normalizing raw flows by the number of cell towers in the destination ADA seemed to give more sensible partitions and modularity results. The modularity calculation also led to some complications as this was done manually to ensure consistency between the algorithm-generated partitions and the HRs.

4.3.1 Do functional regions in Southern Ontario change over the course of the COVID-19 pandemic?

Although we do not have data to compare with how much functional regions typically change before of the pandemic, our results do show that functional travel regions changed over the course of 2020, particularly in urban and suburban areas. Communities in the Greater Toronto Area were quite dynamic, with some communities growing, shrinking, and covering different parts of the region. On the other hand, rural communities tend to be relatively stable, coving large but consistent areas of the province, with two communities occasionally consolidating into one.

4.3.2 Do functional regions in Southern Ontario align with Ontario's Public Health Unit boundaries, to which regionally targeted pandemic restrictions were applied?

As there were times during the pandemic where regionally targeted restrictions were imposed by the provincial government based on HR boundaries, we thought it would be useful to determine whether the HR boundaries accurately reflected travel patterns. If the regionally targeted restrictions were intended to prevent COVID transmission in higher case regions while allowing certain activities in lower risk areas, then it is important to ensure that the regions to which restrictions are applied reflect the regions within which people generally travel. We found that in urban and suburban areas, the functional regions generally did not line up with HR boundaries, whereas certain rural functional regions generally did line up with HR boundaries. We observed this qualitatively by overlaying the functional regions on the HR boundaries on a map and seeing that there are often several functional regions within individual urban and suburban HRs, and that there is often only one functional region covering several rural HRs. We also observed this quantitatively by calculating a similarity score similar to the Jaccard Similarity Co-efficient, where many ADAs have a low similarity score across the study area, and the only high similarity scores are found in rural areas.

4.4 Limitations

As is always going to be the case for passively collected mobile phone data, we run into the challenge in this thesis with the fact that mobile phone location data is not perfect, and a number of assumptions need to be made. The 10-minute stop time cut-off is a major assumption that was made for in our data, as it affects how both our mobility metrics from Chapter 2 and the flows data from Chapter 3 are calculated. There are a number of considerations that must go into the choice of the length of time a mobile device is stationary for it to be considered a stop (Wang & Chen, 2018). First, you must make sure the timeframe is long enough so that short stops as part of someone's trip is not counted as a stopover. On certain modes such as public transit, where longer stopovers at transit terminals are made waiting for a connection, some degree of inaccuracy may be inevitable. However, making the cut-off too short, such as below 5 minutes, there would be too many stops that occur as part of one's journey counted as a stopover. The density of cell towers must also be taken into account, as a mobile device must traverse between cell tower ranges in order to be detected as moving. In areas where cell towers are farther apart it takes a longer distance travelled, and therefore more time, to be detected as in motion. On the other hand, you must also make sure the timeframe for being identified as a stopover is short enough. If it is too long, it is possible that quick stops, at a grocery store for example, may not be detected. This could particularly affect urban areas where destinations are close in proximity and people may be more likely to make shorter stops, and where there is a higher density of cell towers. We have seen previous studies use 5 minutes, but we believe with the cell tower density issue, and the fact that it is probably safer to err on the side of missing short stopovers than adding stopovers that never happened, we chose a longer timeframe of 10 minutes.

Using any non-random sample always has the possibility of sampling bias affecting the results. In our case, it is possible that certain people are over-represented in our sample, especially if certain people are more likely to have or carry a cell phone than others, and if mobility patterns vary among these people. Since our sample is so large, it is easier to say that it is representative of the population, however it is still possible that certain groups of people are missed due to our non-random sample. Additionally, due to the fact that the quality of our data is dependent on cell tower density which differ substantially between urban and rural settings, there are potential geographic biases in our data. This was accounted for in the calculation of mobility measures in Chapter 2 by ensuring that a sufficiently long time threshold was used to consider a mobile device to be in motion versus being stopped. A longer threshold was required to ensure that a mobile device travelling through an area with a lower density of cell towers has sufficient time to traverse cell tower radii within the time threshold. In Chapter 3, this geographic bias was accounted for by dividing flow counts by the cell tower density in the destination ADA, since a flow may be more likely to be detected in areas with higher density of cell towers, as a mobile device does not need to travel as far to traverse a cell tower radius.

The choice of covariates to use in a model is always an important decision and can have a large effect on the results. In our analysis in Chapter 2, we made our best effort to choose covariates that cover a wide range of socio-demographic factors that have been shown to impact mobility in the past, and we ensured that none of the covariates exhibit multicolliniearity, however it is always possible that there are factors at play that have been missed.

We believe our choice of community detection algorithm in Chapter 3 provides results that are reflective of travel regions in Ontario, however our preliminary work for this chapter seemed to show that results can vary by algorithm and by parameters used. For example, the Leiden algorithm is another method of community detection (Traag et al., 2019), and it includes a resolution parameter that affects the size of the resulting communities. We also could have used a hierarchical clustering method, in which case we would have to decide where we cut the dendogram. Our analysis and choice of algorithm is certainly a statistically sound choice, but we recognize that other choices could have resulted in different results.

4.5 Future Directions

The COVID-19 pandemic caused a great disturbance in many people's lives; however, disturbances of this magnitude are rare. It was important to study the impact of the pandemic on people's mobility patterns, despite the fact that we may never see anything that affects mobility in this manner again. So why did we even bother to study mobility during the COVID-19 pandemic? Do we have anywhere to take this research in the future? While we may never see mobility impacted in this specific way again, the useful takeaway from this research is magnifying the importance of mobility in people's daily lives, what happens when non-essential trips no longer take place, and how different people experience mobility differently.

We know that the ability to move between important locations is essential to people's lives. Although different travel purposes have different levels of importance for different people, we know that people need to travel to work, school, shop for groceries or other essential items, attend healthcare appointments, as well as other non-essential but still important trips such as entertainment or recreation related activities. The study of mobility pre-COVID has always taken for granted that these destinations will always be available and that trip patterns to specific destinations are unlikely to change dramatically. Studying mobility during the pandemic has shown us what travel patterns look like when people are only making the most necessary trips. It is interesting to note how much of our transportation network, particularly the public transit network, has been designed around historic travel patterns, primarily facilitating commuting trips from the suburbs into the downtown core. We have seen how this is the type of trip that decreased the most when working in person is no longer necessary. This indicates that less emphasis will need to be placed on these trips in future transportation research, especially if working from home continues. We also saw that trips became more localized, showing that in an emergency, people are able to access essentials within or near their own neighbourhood. This indicates that we should be putting more emphasis on urban development that encourages local travel so that longer distance trips are less necessary in the future.

We do not know for sure if we will face another situation in the future where we are only able to perform essential trips, so what is the benefit of studying a time when only essential trips were allowed? A future direction that this work could lead to is providing a baseline if what the minimum level of mobility in our society is. This could be useful for any future work looking at how mobility could be reduced in the future to reduce energy consumption, congestion, and greenhouse gas emissions. We know that some amount of mobility will always be required, and the early stages of the pandemic show what the minimum amount of mobility would be under certain conditions. This may not be a realistic target to aim for, but it does tell us how much of a change can be made by some very doable interventions, such as working from home.

Social geographers are always interested in how different people experiences parts of their lives differently, and mobility during the COVID-19 pandemic is a perfect example of this. Previous mobility research has shown that people with lower socio-economic status often spend more time and travel longer distances making their daily trips. During COVID-19, we were able to see this play out differently, where people of lower socio-economic status were often forced to continue making their trips for essential purposes, whereas people of higher socio-economic status were able to remain at home when necessary. This understanding can be carried forward to future research by understanding that people of lower socio-economic status are more limited in their travel flexibility, and that policies aiming to reduce or change people's travel are likely to have less of an effect on certain people compared to others with more flexibility.

4.6 Summary

In summary, this thesis looks at how mobility patterns changed due to restrictions imposed to reduce the spread of COVID-19 over the course of 2020. Transportation geographers have produced extensive research looking at general human mobility patterns as it relates to commuting to work, participation in activities, and transportation infrastructure. Due to the large disturbance to typical mobility patterns that the COVID-19 pandemic caused, we thought it was important to investigate how these previous mobility patterns changed, especially since we know that different people have different experiences with mobility. This work was also particularly interesting because we were able to use a big dataset containing mobile phone location data, giving us a very large and temporally dense sample that we expect to be very representative of the population. Chapter 2 showed how people's mobility changes during the pandemic were often related to socio-demographic factors, but that these associations varied greatly across space. Chapter 3 showed us how functional travel regions shifted over time timeline of the pandemic, and that these observed travel regions differed from Ontario's HR boundaries that were used at certain times to impose regionally targeted COVID restrictions. While we may not see another major disturbance to human mobility in the future the way we did with the COVID-19 pandemic, this research still offers transportation geography researchers useful information related to the importance of mobility in people's lives how people experience mobility differently, and how we can adapt to shifting mobility needs in the future.

4.7 References

Allen, J., & Farber, S. (2018). How time-use and transportation barriers limit on-campus participation of university students. *Travel Behaviour and Society*, *13*, 174–182. https://doi.org/10.1016/j.tbs.2018.08.003

Chen, C., Ma, J., Susilo, Y., Liu, Y., & Wang, M. (2016). The promises of big data and small data for travel behavior (aka human mobility) analysis. *Transportation Research Part C: Emerging Technologies*, *68*, 285–299. https://doi.org/10.1016/j.trc.2016.04.005

Fillekes, M. P., Giannouli, E., Kim, E.-K., Zijlstra, W., & Weibel, R. (2019). Towards a comprehensive set of GPS-based indicators reflecting the multidimensional nature of daily mobility for applications in health and aging research. *International Journal of Health Geographics*, *18*(1), 17. https://doi.org/10.1186/s12942-019-0181-0

González, M. C., Hidalgo, C. A., & Barabási, A.-L. (2008). Understanding individual human mobility patterns. *Nature*, *453*(7196), 779–782. https://doi.org/10.1038/nature06958

Hasanzadeh, K. (2019). Exploring centricity of activity spaces: From measurement to the identification of personal and environmental factors. *Travel Behaviour and Society*, *14*, 57–65. https://doi.org/10.1016/j.tbs.2018.10.001

Hirsch, J. A., Winters, M., Clarke, P., & McKay, H. (2014). Generating GPS activity spaces that shed light upon the mobility habits of older adults: A descriptive analysis. *International Journal of Health Geographics*, *13*(1), 51. https://doi.org/10.1186/1476-072X-13-51

Lachapelle, U., Tanguay, G. A., & Neumark-Gaudet, L. (2018). Telecommuting and sustainable travel: Reduction of overall travel time, increases in non-motorised travel and congestion relief? *Urban Studies*, *55*(10), 2226–2244. https://doi.org/10.1177/0042098017708985

Lee, M., Zhao, J., Sun, Q., Pan, Y., Zhou, W., Xiong, C., & Zhang, L. (2020). Human mobility trends during the early stage of the COVID-19 pandemic in the United States. *PLOS ONE*, *15*(11), e0241468. https://doi.org/10.1371/journal.pone.0241468

Lenormand, M., Louail, T., Cantú-Ros, O. G., Picornell, M., Herranz, R., Arias, J. M., Barthelemy, M., Miguel, M. S., & Ramasco, J. J. (2015). Influence of sociodemographic characteristics on human mobility. *Scientific Reports*, *5*(1), 10075. https://doi.org/10.1038/srep10075

Long, J., & Reuschke, D. (2021). Daily mobility patterns of small business owners and homeworkers in post-industrial cities. *Computers, Environment and Urban Systems*, *85*, 101564. https://doi.org/10.1016/j.compenvurbsys.2020.101564

Lu, X., Wetter, E., Bharti, N., Tatem, A. J., & Bengtsson, L. (2013). Approaching the Limit of Predictability in Human Mobility. *Scientific Reports*, *3*(1), 2923. https://doi.org/10.1038/srep02923

Morency, C., Paez, A., Roorda, M. J., Mercado, R., & Farber, S. (2011). Distance traveled in three Canadian cities: Spatial analysis from the perspective of vulnerable population segments. *Journal of Transport Geography*, *19*(1), 39–50. https://doi.org/10.1016/j.jtrangeo.2009.09.013

Páez, A., Mercado, R., Farber, S., Morency, C., & Roorda, M. (2009). *Mobility and Social Exclusion in Canadian Communities: An Empirical Investigation of Opportunity Access and Deprivation*.

Roorda, M. J., Páez, A., Morency, C., Mercado, R., & Farber, S. (2010). Trip generation of vulnerable populations in three Canadian cities: A spatial ordered probit approach. *Transportation*, *37*(3), 525–548. https://doi.org/10.1007/s11116-010-9263-3

Spyratos, S., Vespe, M., Natale, F., Weber, I., Zagheni, E., & Rango, M. (2019). Quantifying international human mobility patterns using Facebook Network data. *PLOS ONE*, *14*(10), e0224134. https://doi.org/10.1371/journal.pone.0224134

Traag, V. A., Waltman, L., & van Eck, N. J. (2019). From Louvain to Leiden: Guaranteeing well-connected communities. *Scientific Reports*, *9*(1), 5233. https://doi.org/10.1038/s41598-019-41695-z

Vanhoof, M., Schoors, W., Van Rompaey, A., Ploetz, T., & Smoreda, Z. (2018). Comparing Regional Patterns of Individual Movement Using Corrected Mobility Entropy. *Journal of Urban Technology*, *25*(2), 27–61. https://doi.org/10.1080/10630732.2018.1450593

Wang, F., & Chen, C. (2018). On data processing required to derive mobility patterns from passively-generated mobile phone data. *Transportation Research Part C: Emerging Technologies*, *87*, 58–74. https://doi.org/10.1016/j.trc.2017.12.003

Warren, M. S., & Skillman, S. W. (2020). *Mobility Changes in Response to COVID-19* (arXiv:2003.14228). arXiv. https://doi.org/10.48550/arXiv.2003.14228

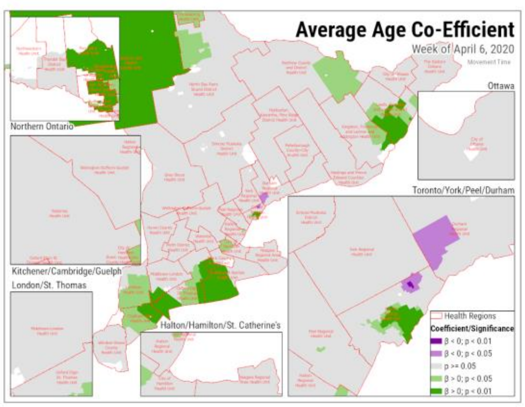
Xiong, C., Hu, S., Yang, M., Luo, W., & Zhang, L. (2020). Mobile device data reveal the dynamics in a positive relationship between human mobility and COVID-19 infections. *Proceedings of the National Academy of Sciences*, *117*(44), 27087–27089. https://doi.org/10.1073/pnas.2010836117

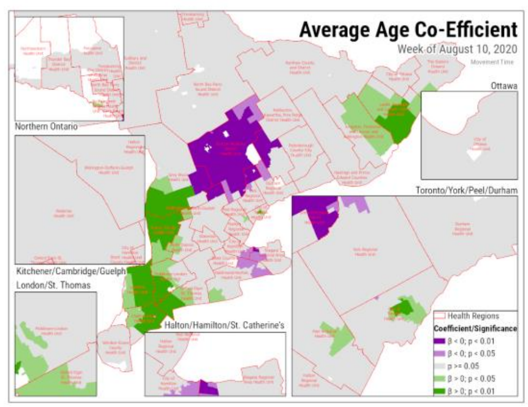
Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). Human mobility and socioeconomic status: Analysis of Singapore and Boston. *Computers, Environment and Urban Systems*, *72*, 51–67. https://doi.org/10.1016/j.compenvurbsys.2018.04.001

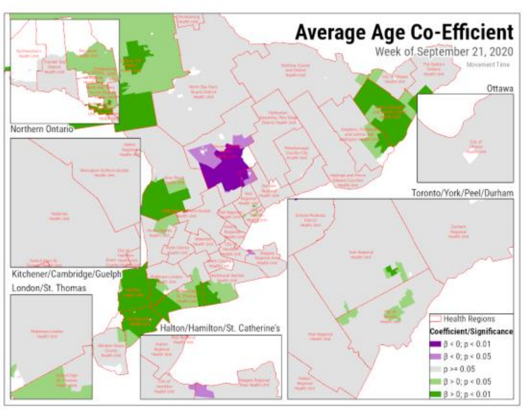
Zhao, X., Yan, X., Yu, A., & Van Hentenryck, P. (2020). Prediction and behavioral analysis of travel mode choice: A comparison of machine learning and logit models. *Travel Behaviour and Society*, *20*, 22–35. https://doi.org/10.1016/j.tbs.2020.02.003

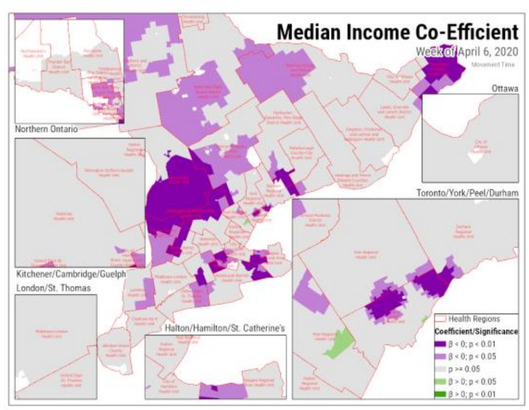
Appendices

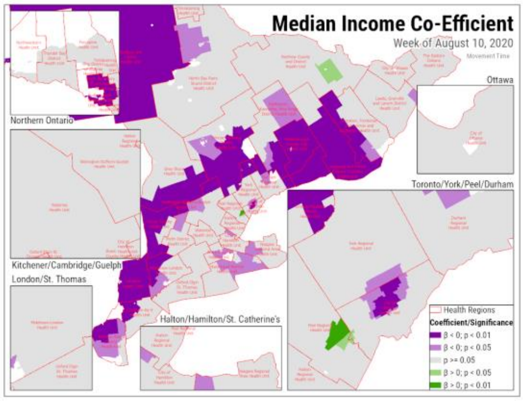
Appendix A: Chapter 2 GWR model results for each combination of mobility measure (2), covariate (5), and time period (3) for a total of 30 maps.

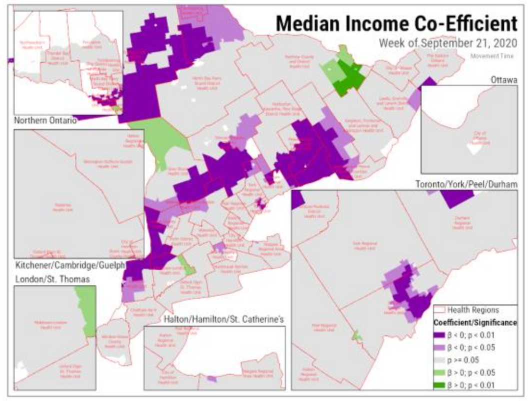


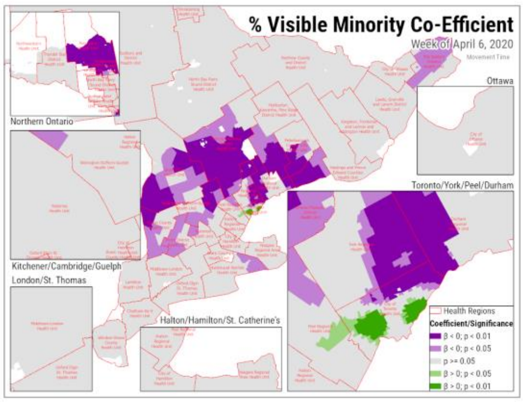


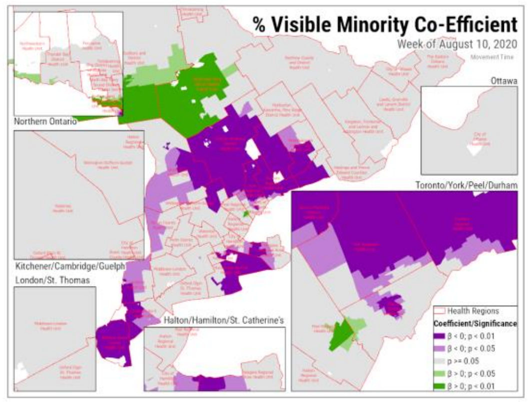


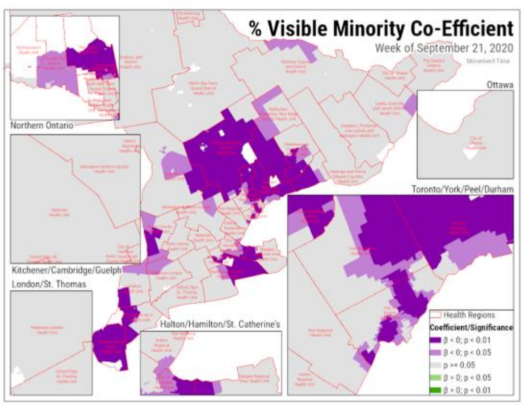


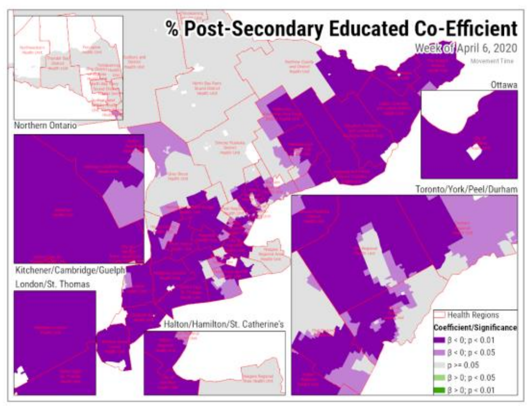

Median Income Co-Efficient
Week of August 10, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

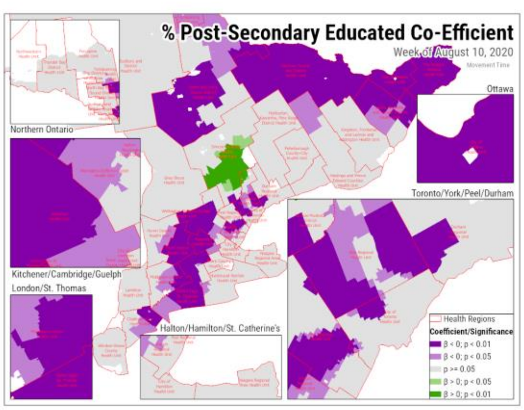

Median Income Co-Efficient
Week of September 21, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

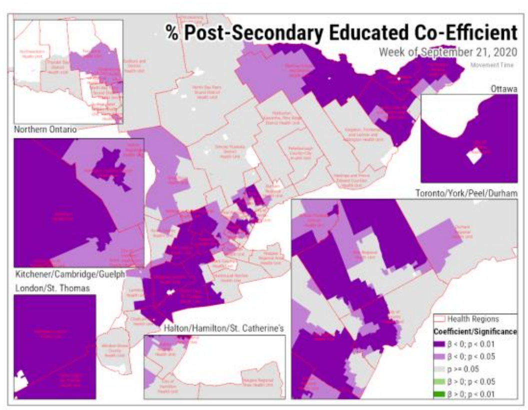

% Visible Minority Co-Efficient
Week of April 6, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

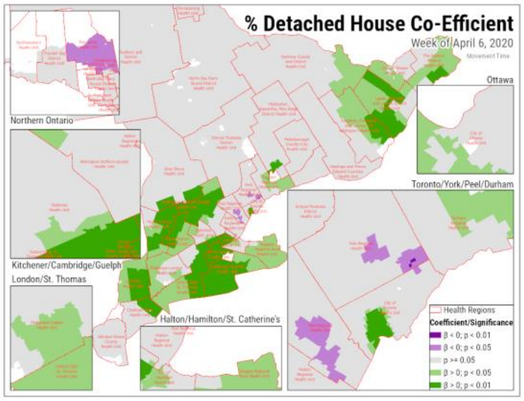

% Visible Minority Co-Efficient
Week of August 10, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

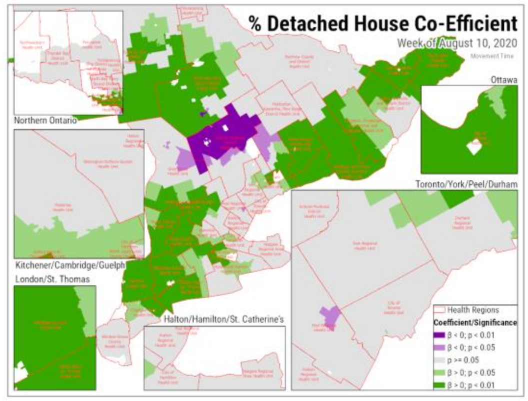

% Visible Minority Co-Efficient
Week of September 21, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

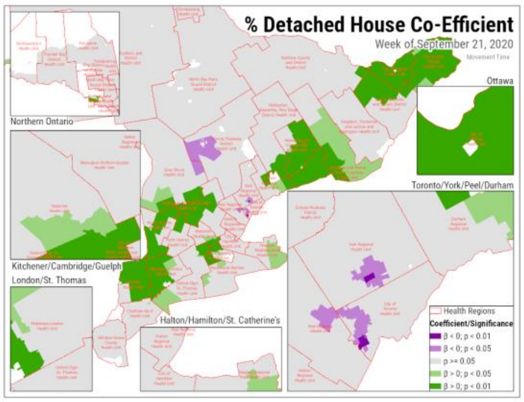

% Post-Secondary Educated Co-Efficient
Week of April 6, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

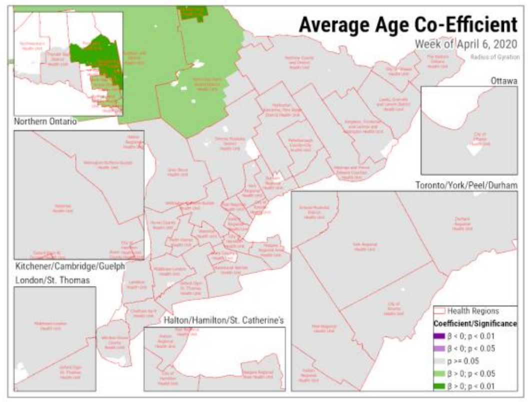

% Post-Secondary Educated Co-Efficient
Week of August 10, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

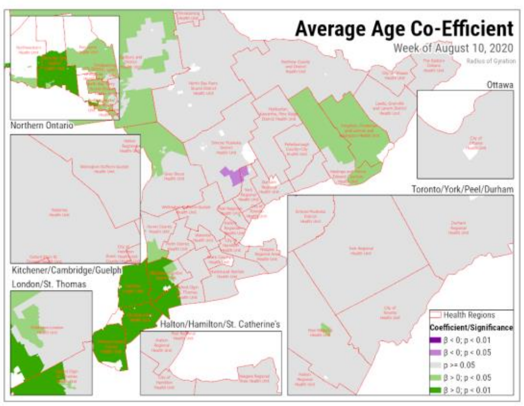

% Post-Secondary Educated Co-Efficient
Week of September 21, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

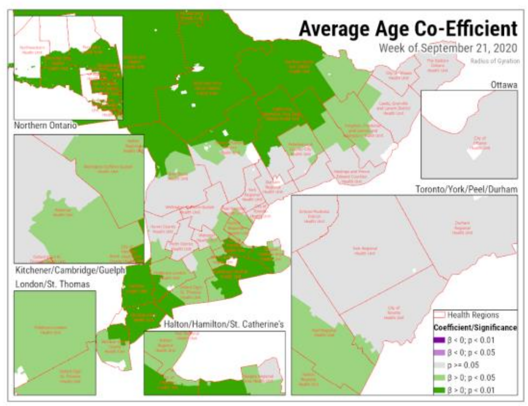

% Detached House Co-Efficient
Week of April 6, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

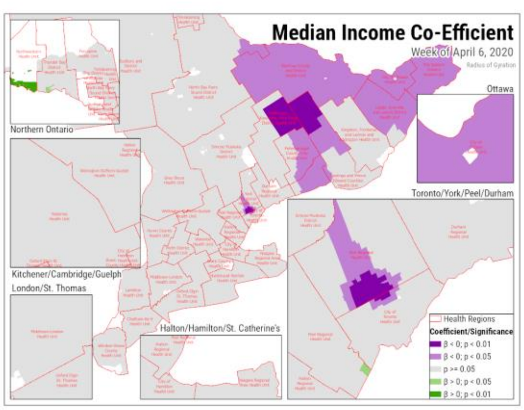

% Detached House Co-Efficient
Week of August 10, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

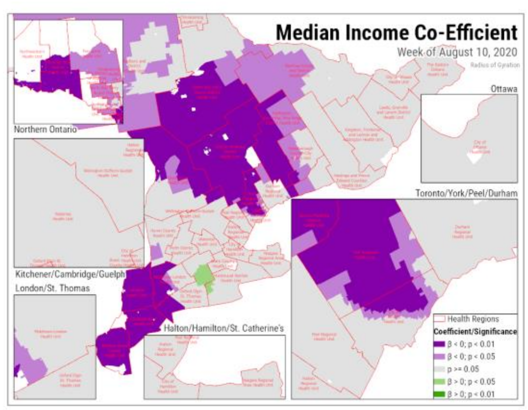

% Detached House Co-Efficient
Week of September 21, 2020
Movement Time
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

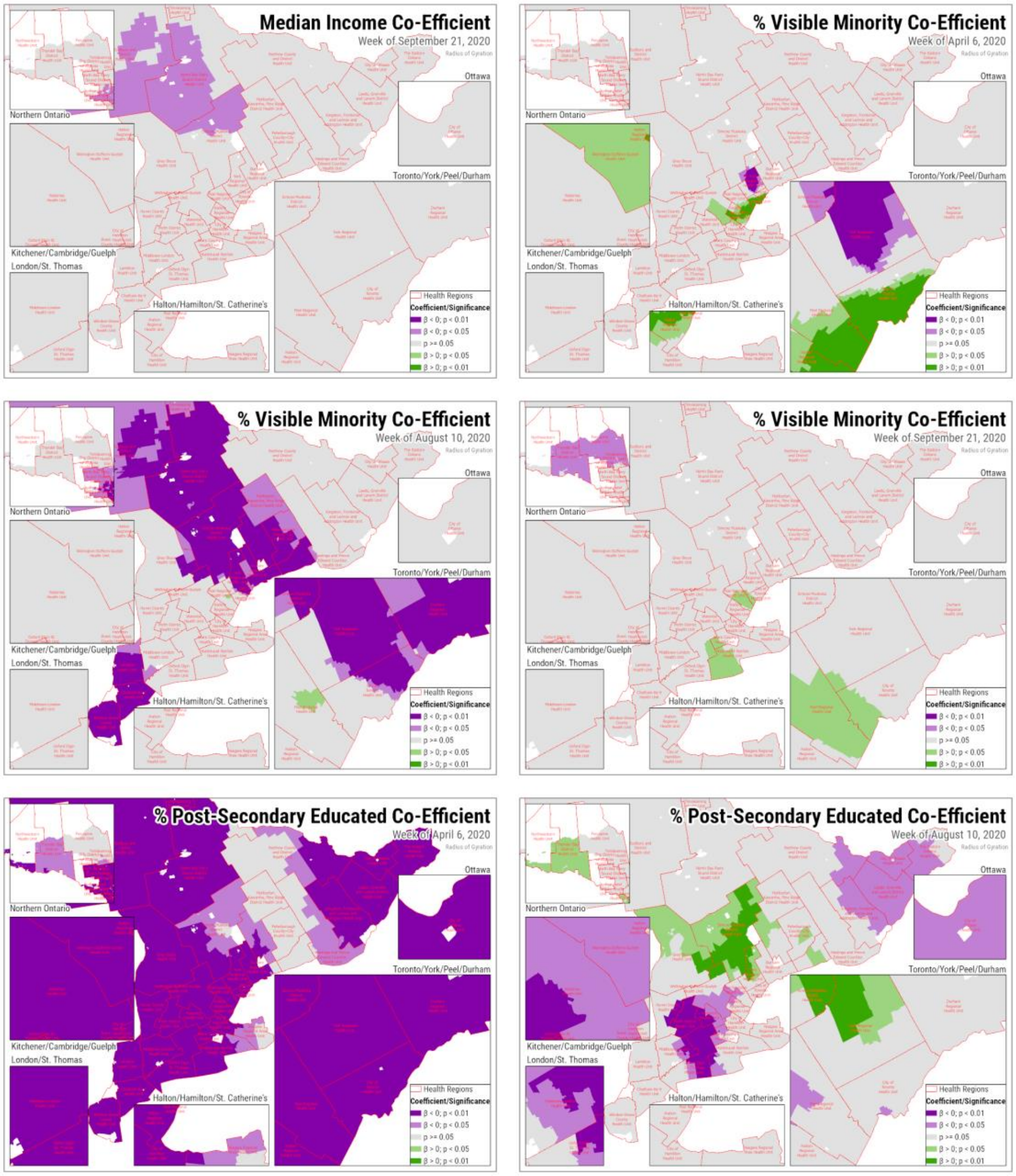

Average Age Co-Efficient
Week of April 6, 2020
Radius of Gyration
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

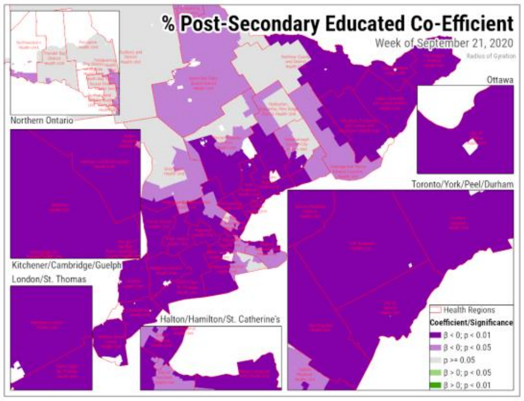

Average Age Co-Efficient
Week of August 10, 2020
Radius of Gyration
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

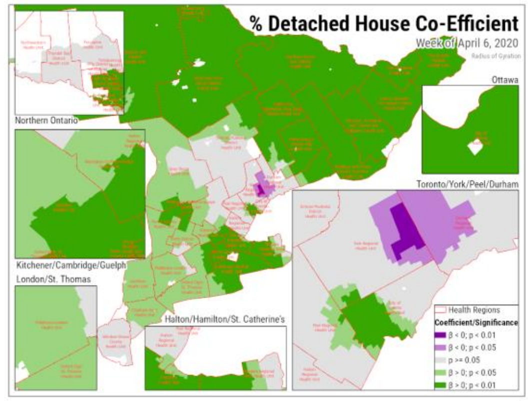

Average Age Co-Efficient
Week of September 21, 2020
Radius of Gyration
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

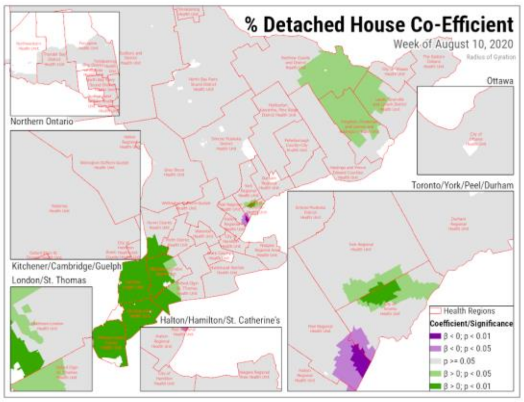

Median Income Co-Efficient
Week of April 6, 2020
Radius of Gyration
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

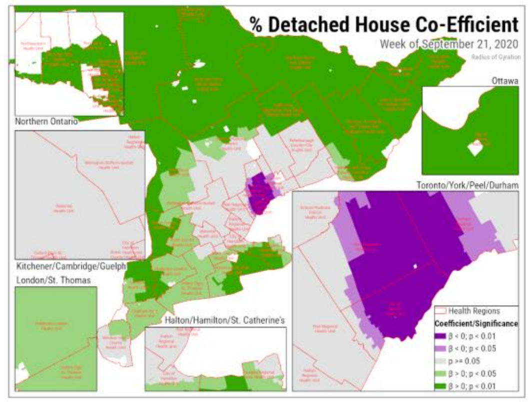

Median Income Co-Efficient
Week of August 10, 2020
Radius of Gyration
Northern Ontario
Ottawa
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01


Median Income Co-Efficient
Week of September 21, 2020
% Visible Minority Co-Efficient
Week of April 6, 2020
% Visible Minority Co-Efficient
Week of August 10, 2020
% Visible Minority Co-Efficient
Week of September 21, 2020
% Post-Secondary Educated Co-Efficient
Week of April 6, 2020
% Post-Secondary Educated Co-Efficient
Week of August 10, 2020
Ottawa
Northern Ontario
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01


% Post-Secondary Educated Co-Efficient
Week of September 21, 2020
Radius of Gyration
Ottawa
Northern Ontario
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01


% Detached House Co-Efficient
Week of April 6, 2020
Radius of Gyration
Ottawa
Northern Ontario
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01


% Detached House Co-Efficient
Week of August 10, 2020
Radius of Gyration
Ottawa
Northern Ontario
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01


% Detached House Co-Efficient
Week of September 21, 2020
Radius of Gyration
Ottawa
Northern Ontario
Toronto/York/Peel/Durham
Kitchener/Cambridge/Guelph
London/St. Thomas
Halton/Hamilton/St. Catherine's
Health Regions
Coefficient/Significance
β < 0; p < 0.01
β < 0; p < 0.05
p >= 0.05
β > 0; p < 0.05
β > 0; p < 0.01

Curriculum Vitae

Name:	Ben Klar
Post-secondary Education and Degrees:	University of Toronto Toronto, Ontario, Canada 2015-2020 B.A.
Honours and Awards:	Social Sciences and Humanities Research Council (SSHRC) Canada Graduate Scholarships-Master's Award (CGSM) 2021-2022
	Western ECCE Student Associate Achievement Award 2021-2022
	Canadian Association of Geographers Undergraduate Award 2019-2020
Related Work Experience:	Teaching Assistant The University of Western Ontario 2020-2022
Other Related Experience:	Esri Canada Centres of Excellence Student Associate 2020-2022

Publications:

Long, J. A., Malekzadeh, M., Klar, B., & Martin, G. (2021). Do regionally targeted lockdowns alter movement to non-lockdown regions? Evidence from Ontario, Canada. *Health & Place*, 102668.

Conference Presentations:

Klar, B. & Long J. (2021 July 7-11). Socio-demographic factors affecting human mobility during COVID-19. *2021 Annual Meeting of the Canadian Association of Geographers.* Price George, British Columbia, Canada [virtual]