Income as a Determinant of the Speed of Transmission: Study of the Fifth Wave of SARS-CoV-2 in Toronto, Ontario

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Introduction

Since the first cases in 2019, the COVID-19 outbreak has taken the world by storm. As of writing this (April 2022), there are over five hundred million cases reported worldwide (World Health Organization 2022). With its ability to rapidly spread, the COVID-19 has had profound consequences in every facet of public and private life. Among these include medical, economic, and social spaces (Baena-Díez et al. 2020). Most importantly, these unsettling times have shone a light on pre-existing disparities within national health systems. For many researchers, this does not come as a surprise as socioeconomic factors influencing health outcomes have been noted ubiquitously throughout the world (Khalatbari-Soltani et al. 2020). According to Khalatbari-Soltani et al. (2020), there is even a link between those socio-economically disadvantaged and increased risk of infectious disease.

This research continues in a vein of spatial statistical studies which analyze COVID-19 incidence rates paired with a socio-economic factor. Building upon Khalatabari-Soltani, et al. (2020) and the socio-economic position (SEP) framework, this study seeks to examine the relationship between income levels, population density, and percentage of young adults against COVID-19 incidence rates. More specifically, the overarching objective of this study is to analyze the relationship between the noted socio-economic variables and incidence rates of COVID-19 during the fifth wave in Toronto, Ontario, Canada.

Background

Factors Related to COVID-19 Incidence

A person's income level affects how they go about their everyday lives. The associated behavioural pattern has been linked to change in health outcomes (Khalatbari-Soltani et al. 2020). Low income, for example, affects housing condition and leads to more tight housing arrangements. Such factors have been associated in the increased risk of infections for pathogens such as tuberculosis (Khalatbari-Soltani et al. 2020).

In Ontario, from January 21 to June 30, 2022, the most attributed workplace was manufacturing (Murti et al. 2021). Manufacturing accounted for 45% of outbreaks which totaled 65% of outbreak cases. Another notable sector was Transport and Warehousing (11% of outbreaks, 8% of outbreak cases). In Toronto, it has been observed the COVID-19 first infiltrate in high income communities before quickly spreading to lower income communities (Mishra et al. 2022). According to Mishra et al. (2022) lower income neighbourhoods were also defined by their higher dwelling densities and greater proportion of occupations that could not make the transition to remote work.

In addition, the susceptibility of adolescents (aged 10-19 years) and youth (aged 15-24 years) to COVID-19 has been a controversial research topic since the pandemic began (Rumain, Schneiderman, and Geliebter 2021). While several studies have concluded that young adults are significantly less susceptible to COVID-19 than older adults, others have found that the prevalence of COVID-19 for adolescents and youth to be significantly greater than that of older adults (Rumain, Schneiderman, and Geliebter 2021). In April 2021, COVID-19 cases were rising rapidly for young Canadians, with cases being highest among those aged 20 to 39 (Aziz 2021). Suggested factors that attribute to higher COVID-19 incidence among younger people include the reopening of high schools, colleges, and universities, larger and more frequent social gatherings and non-compliance with public health guidelines due to perceived low-risk of severe symptoms for the age group, and low income. (Aleta and Moreno 2020). Health-related behaviours of younger adults may also affect their susceptibility to COVID-19 infection (Abbasi 2020). In an online national survey of adolescents and young adults, vaping and the dual use of e-cigarettes and cigarettes heavily increased the chances of COVID-19 diagnosis (Gaiha, Cheng, and Halpern-Felsher 2020).

Lastly, Toronto has the densest urban core in the province and is one of the most densely populated regions in North America. This has made it susceptible to the ability of COVID-19 to rapidly spread. To date, there have been more than 300,000 reported cases with more than 4000 deaths (City of Toronto 2021). Within the city, there are several pockets that are denser than others, and this density is an important factor to look at. Population density is a measure of spatial distribution of people across space. In the case of Toronto, St James Town is the most densely populated neighbourhood in the city (Canadian Urban Institute 2016). Research around population density and its link to COVID-19 susceptibility is limited. Past literature has not shown a clear relationship between the two, with some noting a positive correlation (Hamidi and Hamidi 2021) while others deducing an insignificant relationship [Carozzi_Provenzano_Roth_2020]. This, as suggested by the entire catalogue of research, is connected to the regional variations connected to density. Some denser areas may have better services to limit their exposure to the virus, while others may be poorer and so may be more susceptible to the virus. It is important to explore this phenomenon in the context of Toronto, to understand the type of relationship found in the city.

COVID-19 Waves in Toronto

The first case of COVID-19 in Ontario (and Canada) was reported on January 25, 2020 (Nielsen 2020). As the virus began to spread, Ontario entered its first wave of COVID-19 on February 26, 2020. The first wave of COVID-19 lasted 188 days, ending on August 31, 2020 (Public Health Ontario 2021). As Ontario began loosening restrictions as part of its 3-stage reopening plan, people started getting together again, and observed cases began to rise. Ontario's second wave began September 2020 and ended in February 2021, with cases peaking in January 2021 (Public Health Ontario 2021). The third wave in Ontario was driven by the Alpha (B.1.1.7) variant, which was more transmissible (Detsky and Bogoch 2021). The third wave lasted from March to July 2021, and was the largest wave yet, with the peak number of new cases in a day in Ontario being 5067 (Public Health Ontario 2022). The emergence of the Delta variant (B.1.617.2) caused a smaller and shorter fourth wave in Ontario that lasted from August to October 2021. The largest number of new cases reported in a day in Ontario during the fourth wave was 878.

Table 1: Waves of COVID-19 in Ontario

Wave	Associated Variant	Approx. Start	Approx. End	Peak Cases Per Day	Total Cases
1st	Original Strain	February 2020	August 2020	752	42,486
2nd	Original Strain	September 2020	February 2021	4,168	260,643
3rd	Alpha	March 2021	July 2021	5,067	24,7654
4th	Delta	August 2021	October 2021	878	49,704
5th	Omicron	December 2022	February 2022	19,373	469,955

The fifth wave of the pandemic lasted from the beginning of December 2021 until mid-February 2022. The catalyst for this was the emergence of a new, highly transmissible variant called Omicron. The variant, which was first reported globally in November 2021, has been thoroughly researched due to its scale and rate of infection. This research suggests that the variant is highly transmissible due to several factors. This includes the fact that Omicron is more likely to evade immunity from a previous infection, meaning that there is a high chance that you can get re-infected with COVID-19 (Pulliam et al. 2021). Other research suggests that the variant is up to 3.7% more infectious among vaccinated citizens than its predecessors (Mohsin and Mahmud 2022). During the fifth wave, it became the dominant strain and was responsible for 95% infections globally. In Ontario, the first Omicron cases were reported on November 28, 2021 (Government of Ontario 2021). During the Omicron wave, the highest number of new cases reported for a single day in the province was 19,373 (Public Health Ontario 2022).

This study will determine how average income, percentage of youths, and population density may affect the change in COVID-19 case rates between the first and last week of December 2021.

Study area

The analysis was conducted at the neighbourhood level for the City of Toronto (See Figure 1). 'Neighbourhood' is a geographic level specifically designed by the City of Toronto. They were created by city to help government and other planning organizations with obtaining socio-economic data (City of Toronto 2017). In total there are 140 unique areas, and their boundaries are based on the Canadian Census Track. Each neighbourhood may contain between two to five of these census tracts. The geography of neighbourhood was chosen for this study, as opposed to wards or dissemination blocks, not only to showcase acute changes within populations but due to the availability of both COVID-19 and the socio-economic data. The large number neighbourhoods also enable this study to capture diversity across the city.

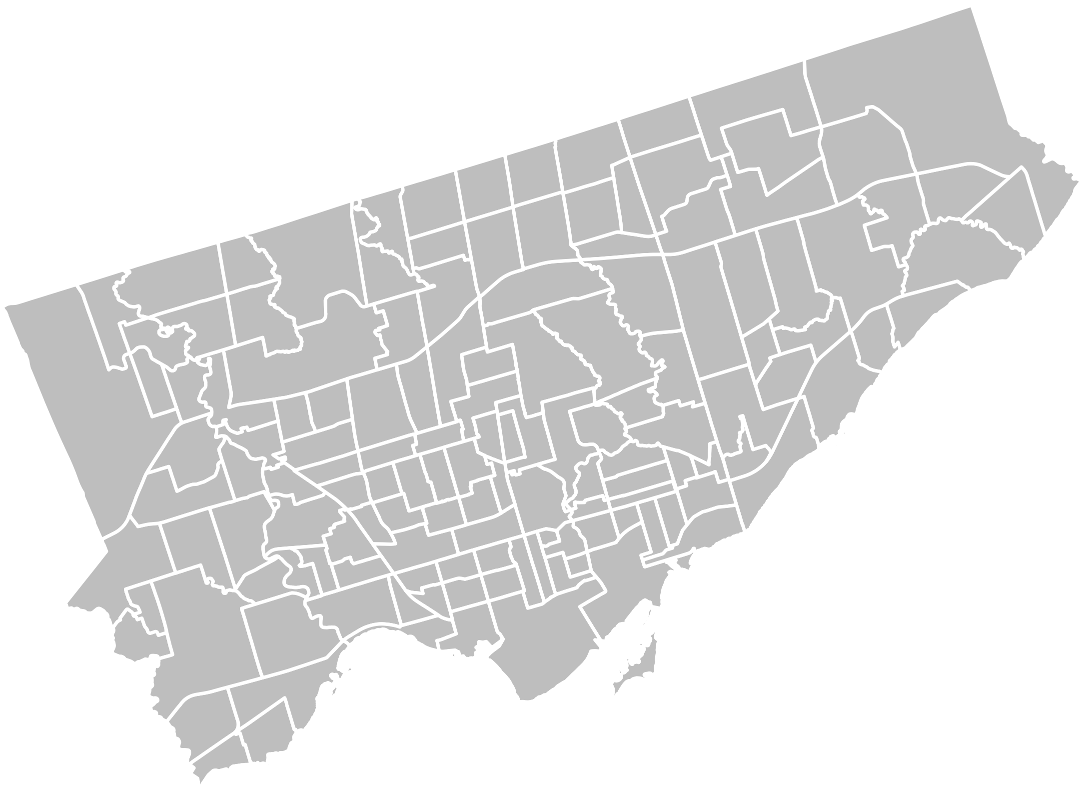

Figure 1: Neighbourhoods in Toronto, Ontario, Canada

Data

The shapefile used to delineate and map Toronto's neighbourhoods in this study was obtained from the "Neighbourhoods" file in the City of Toronto Open Data portal (City of Toronto 2022). Using the same portal, the COVID-19 data was retrieved from the dataset "COVID-19 Cases in Toronto" (Toronto Public Health 2022). The data was downloaded as a comma-separated values (CSV) file. This data is updated weekly by the city and reports each individual case as a record. The time period of interest was December 2021, corresponding to a peak in COVID-19 cases within the fifth wave of the pandemic in Ontario. The cases from the first week of December 2021 (Dec. 1 - Dec. 7) and the last week (Dec. 25 - Dec. 31) were filtered out and aggregated by neighbourhood. The average income, percentage of youth (18-24), and population density of each neighbourhood that was used in this study was derived from data in the "Neighbourhood Profile" dataset retrieved from Toronto Open Data (Toronto Social Development, Finance & Administration 2011).

This dataset documents demographic and socioeconomic information for each of Toronto's neighbourhoods, including total population and the number of people of each age, using Canada's census data held every 5 years.

Methods

This study used RStudio to conduct the data pre-processing, that is cleaning of the original datasets. A unique method was ran to covered the date data in the COVID-19 case table into character data type. This was so the records could be parsed in respect to this studies period of interest.

The analysis was also done in RStudio using several R packages, including spatstat, tidyverse, ggplot2, dplyr, gridExtra, patchwork, and spdep to analyze the area data and find a potential relationship between the chosen independent variables (average income, percentage of 18-24 year old individuals, population density) and the dependent variable (fold change in COVID-19 case rates from the first to last week of December 2021) for the neighbourhoods of Toronto. For the initial visualization and analysis of the area data, choropleth maps and Moran's I were used to identify patterns in the data. Then, to gain more insight on the process behind these patterns, regression analysis was used to determine the relationship between the independent and dependent variables.

This document was also written and exported through R-Markdown with minimal adaptation from Steven V. Miller's template for academic manuscripts. See: http://svmiller.com/blog/2016/02/svm-r-markdown-manuscript/[https://github.com/svmiller/svm-r-markdown-templates/blob/master/svm-latex-ms.tex] and (https://github.com/svmiller/svm-r-markdown-templates/blob/master/svm-latex-ms.tex)

The data and code used in this project can be found on Github: https://github.com/lamj54/4GA3-Project. This document is also available as a RMarkdown file, which includes both the code and the text used to create this report.

Analysis

Data Exploration

First, to obtain a preliminary understanding of trends in the data, choropleth maps were used to visualize the fold change in COVID-19 cases between the first and last week of December 2021 (Figure 2), per capita income (Figure 3), population density (Figure 4), and the percentage of 18- to 24-year-old individuals in each neighbourhood in Toronto (Figure 5).

In Figure 2, it can be seen that the fold change for all neighbourhoods in Toronto is positive, indicating that they all experienced an increase in COVID-19 case rates in the last week of December 2021 compared to the first week of December 2021. In particular, the neighbourhoods coloured in a darker red and orange showed a significantly large fold change in COVID-19 rates in comparison to other neighbourhoods, which possibly signifies the location of COVID-19 hotspots during December 2021. Accordingly, the neighbourhoods located close to such spots seem to have relatively large fold changes as well, as shown through their light orange colour. Neighbourhoods with smaller fold changes, seen in yellow in the map, appear to be located further away from areas with more intense fold changes.

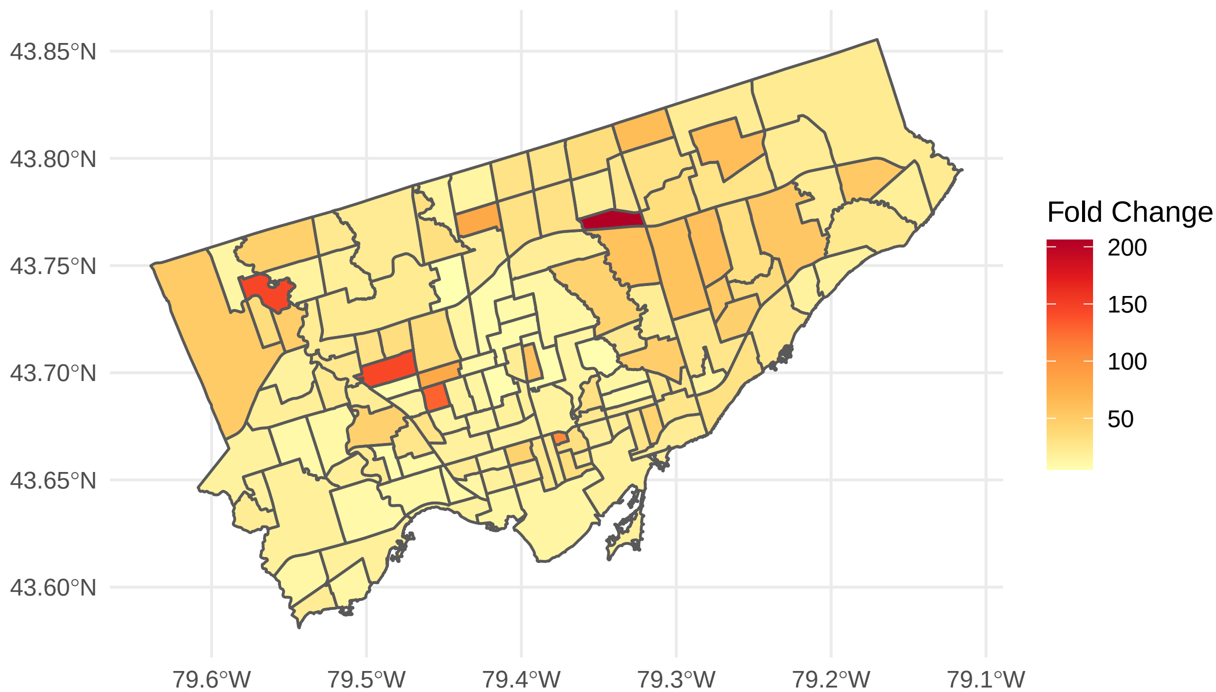

Figure 2: The change in COVID-19 rates (cases per 10,000) between the first and last week of December 2021 in Toronto by neighbourhood

Neighbourhoods with greater average income appear darker in colour on the map in Figure 3, showing that people with higher income tend to concentrate near the center of Toronto. Other neighbourhoods with high average income can be seen in the west of Toronto as well. From a visual comparison of Figures 2 and 3, it looks like the neighbourhoods with high average incomes have lower fold changes in COVID-19 case rates while the neighbourhoods with the highest fold changes are those with lower average incomes. In addition, the neighbourhoods with more moderate fold changes in light orange are also low income neighbourhoods. The neighbourhoods with the lowest fold changes in COVID-19 case rates in light yellow correspond to relatively high income areas as well. These comparisons suggest that average income is negatively correlated with the change in COVID-19 case rates.

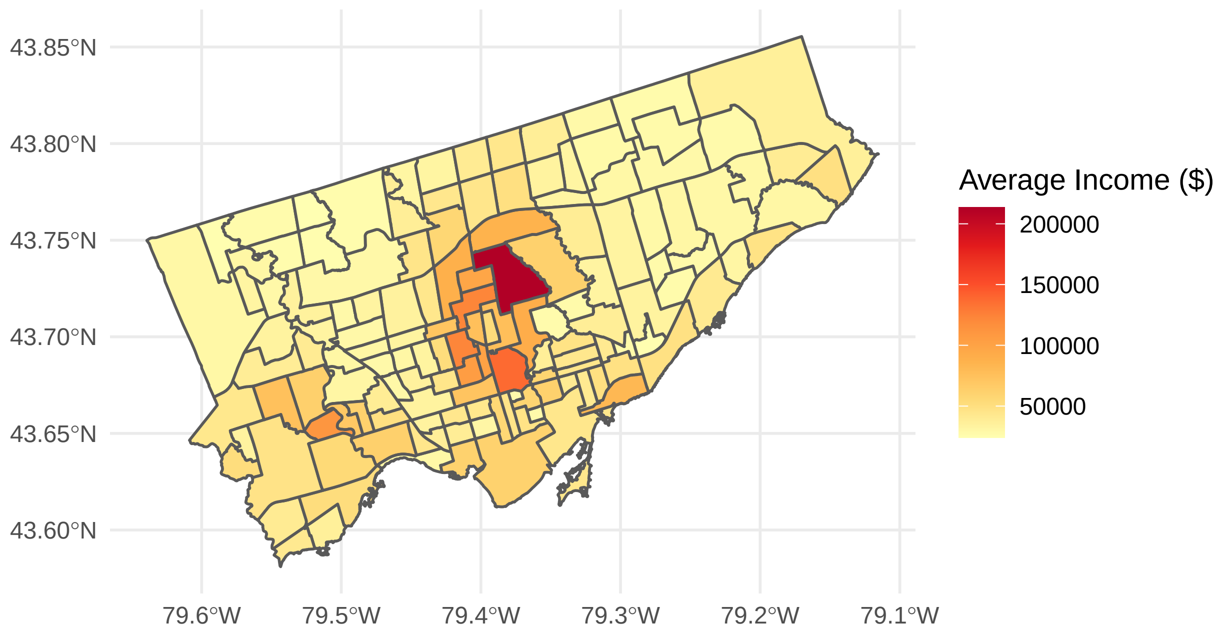

Figure 3: The average income of individuals in Toronto by neighbourhood

From Figure 4, it seems that there may be a greater population density in some of the neighbourhoods located towards the southern areas of Toronto. Population density appears to be lower in neighbourhoods located in the outskirts of the city. Comparing Figures 2 and 4, the neighbourhoods with very large fold changes do not have particularly high population densities, and the neighbourhoods with high population densities do not seem to have very high fold changes. Neighbourhoods with similar population densities appear to have different changes in COVID-19 case rates, which may indicate that its relationship with population density is very weak.

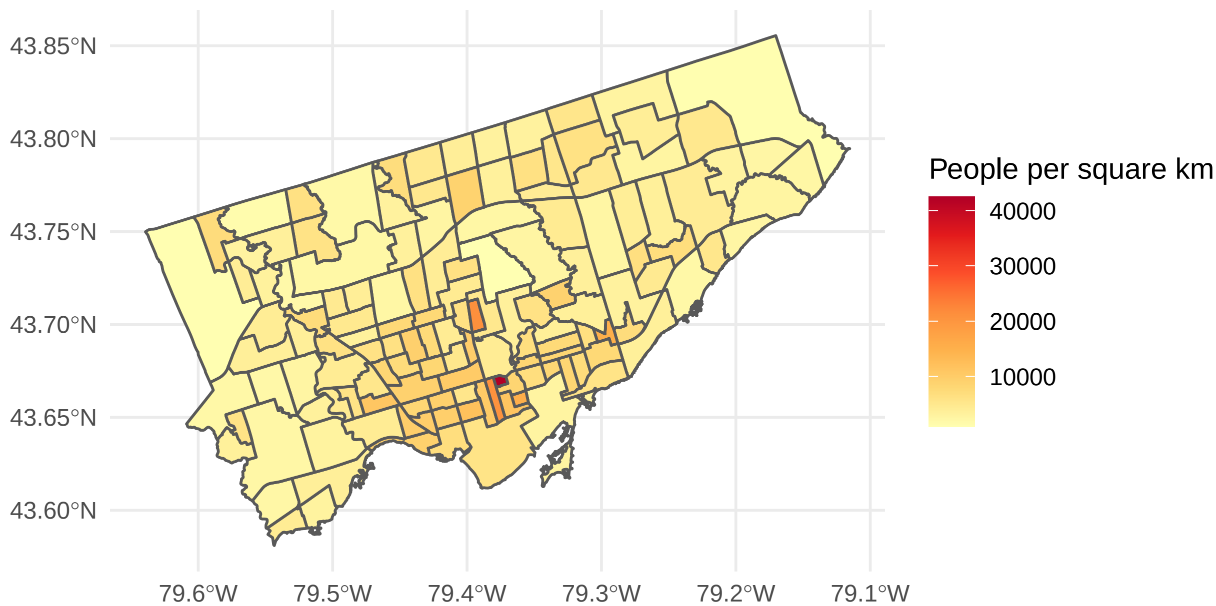

Figure 4: The population density of each neighbourhood in Toronto

Looking at Figure 5, there are a cluster of neighbourhoods in the south of Toronto, coloured in red, that have a particularly high percentage of 18- to 24-year-old individuals making up their population. In addition, a neighbourhood located near the north, in dark orange, has a relatively high percentage of 18- to 24-year-old individuals. Comparing this map to Figure 2, it seems that the neighbourhoods with higher percentages of youth have lower changes in COVID-19 case rates. Accordingly, the neighbourhoods with high fold changes have a relatively small percentage of youth in them. These observations may suggest that the percentage of youth in a neighbourhood is actually negatively correlated with change in COVID-19 rates.

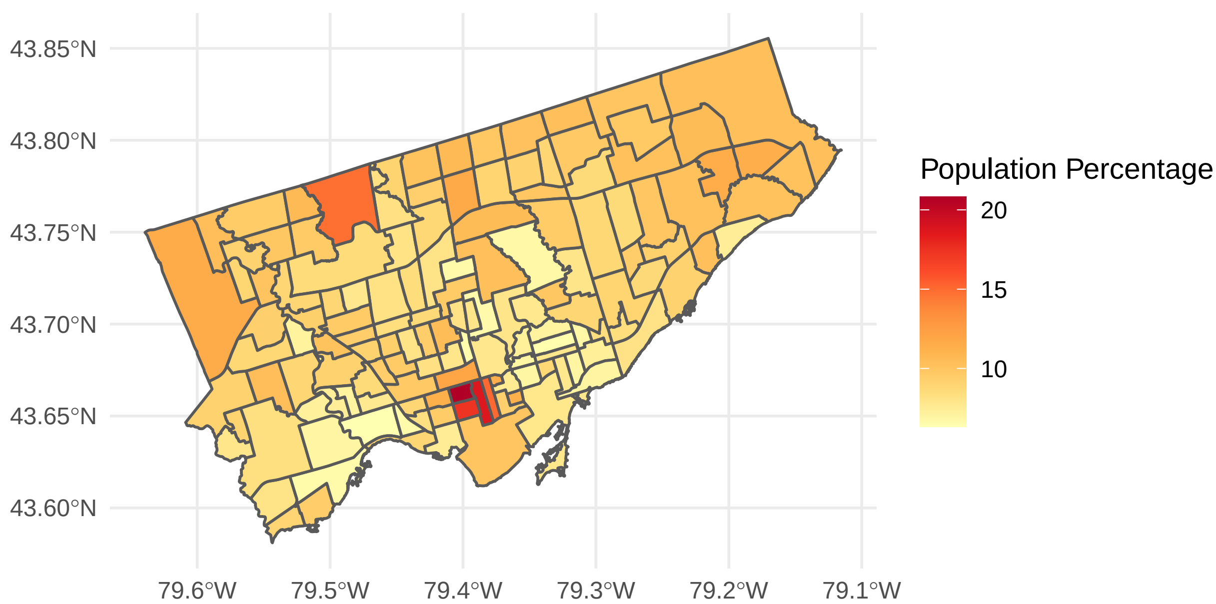

Figure 5: The percentage of 18 to 24 year old individuals in Toronto by neighbourhood

Spatial autocorrelation

Before doing a regression analysis to determine the relationship between the change in COVID-19 case rates and the predictor variables, an analysis of the pattern in the change in COVID-19 case rates must first be done. If its pattern is non-random, then regression analysis can be used to provide more information about the process that is creating this pattern.

To test whether a spatial pattern is random or non-random, Moran's I, a coefficient of spatial autocorrelation, can be calculated and used in a hypothesis test that assesses for spatial randomness. The null hypothesis of this test is that the pattern is spatially random.

The Moran's I statistic for this data is 0.089308782 and the p-value of the test is 0.01787. Since the p-value is less than 0.05, it is sufficiently small enough to reject the null hypothesis with a high degree of confidence. This means that the change in COVID-19 case rates is spatially autocorrelated, not spatially random. As well, since the Moran's I statistic is positive, it suggests that it is a non-random spatial pattern where high values tend to be with other high values, and low values tend to be with other low values. This agrees with the visual observation of the choropleth map of the change in COVID-19 case rates in Figure 2.

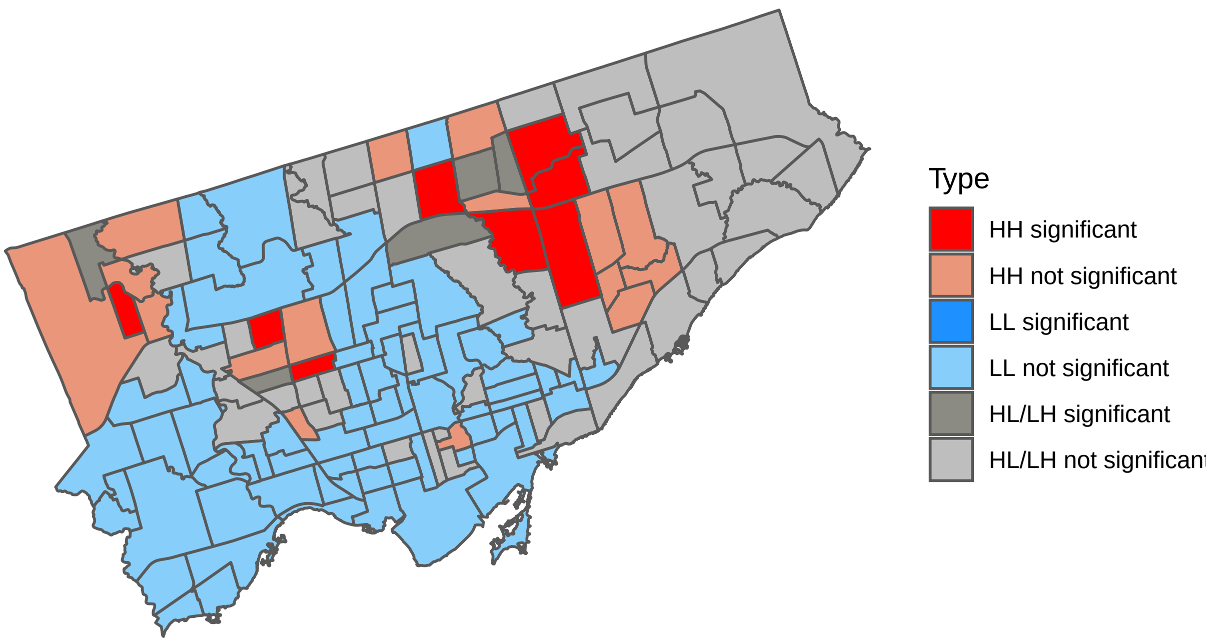

Figure 6: The categorization of neighbourhoods based on local Moran's I, a statistic that describes the autocorrelation of a specific location and its contribution to the global Moran's I statistic

Correspondingly, the map of local Moran's I, which breaks down Moran's I to examine the contribution of each area to the statistic, in Figure 6, shows that neighbourhoods with high fold changes are surrounded by other neighbourhoods that have high fold changes as well. Such regions are labelled "HH" for "High-High." On the other hand, the neighbourhoods with low fold changes in COVID-19 case rates are surrounded by those with similarly low fold changes, which are labelled "LL" for "Low-Low." Other possible combinations are "HL" and "LH" ("High-Low" and "Low-High"). Categorizing each neighbourhood in this way, in addition to showing whether a neighbourhood's local Moran's I is statistically significant and thus spatially autocorrelated, reveals the hot spots and cold spots that contribute significantly to the global Moran's I statistic. From Figure 6, it can be seen that there are several hot spots where COVID-19 case rates have increased significantly, displayed in bright red on the map.

Regression Analysis

Results of the Model

Now knowing that the change in COVID-19 case rates in Toronto's neighbourhoods is not spatially random, the question is what is the process behind the creation of this pattern? To gain more insight on this, a regression analysis can be used to determine the relationship between several independent variables and the changes in COVID-19 case rate.

Table 2: Linear regression model of fold change in COVID-19 case rates with respect to income, percentage of 18- to 24-year-old individuals, and population density

	Dependent variable:
	fold_increase
Intercept, Average Income, Percentage of 18-24 year olds, Population Density	-0.0003^{***}
	(0.0001)
perc_18_24	0.980
	(1.122)
pop_density	0.001
	(0.001)
Constant	29.225^{**}
	(12.026)
Observations	140
R^2	0.083
Adjusted R^2	0.063
Residual Std. Error	26.759 (df = 136)
F Statistic	4.112^{***} (df = 3; 136)
Note:	*p<0.1; **p<0.05; ***p<0.01

As seen in the results of the regression model in Table 2, the only independent variable that is statistically significant in the model is the average income of a neighbourhood. This is because the p-values for average income, percentage of individuals aged 18-24, and population in this model are 0.00462, 0.38397, and 0.28312 respectively. They indicate whether or not the null hypothesis, which states that a variable is not statistically significant in the regression model, should be rejected or not. Since the p-value for average income is less than 0.05, it is small enough to reject the null hypothesis with a high degree of confidence. This means that average income helps to explain the variance in the dependent variable, the change in COVID-19 case rates. On the other hand, the p-values for percentage of 18- to 24-year-old individuals and population density are large, leading to the null hypothesis being accepted. As a result, these two variables do not contribute significantly to the model. This result suggests that average income is a factor that influences the pattern of changes in COVID-19 case rates across Toronto's neighbourhoods, while the percentage of 18- to 24-years-old individuals and population density are not.

Moreover, Table 2 shows that the coefficient for average income is approximately -0.0003 (0.0002591 exactly), indicating that neighbourhoods with higher average incomes have smaller changes in COVID-19 case rates. Thus, higher income causes the growth in COVID-19 cases to slow, while lower income causes the growth in COVID-19 cases to accelerate. This agrees with our initial hypothesis. Individuals with lower income tend to have less means to protect themselves from COVID-19, due to factors such as lower income jobs being less accommodating of remote work.

Model Diagnostics

To determine whether the model has successfully retrieved all of the systematic pattern, its residuals need to be analyzed for randomness. If the residuals are non-random, this means that the model has failed to capture the entire pattern and must be adjusted to have random residuals.

The residuals can first be visualized with a map by plotting the sign of the residual for each neighbourhood (Figure 7). A positive residual indicates that the model overestimates the change in COVID-19 case rates, while a negative residual means that the model underestimates it.

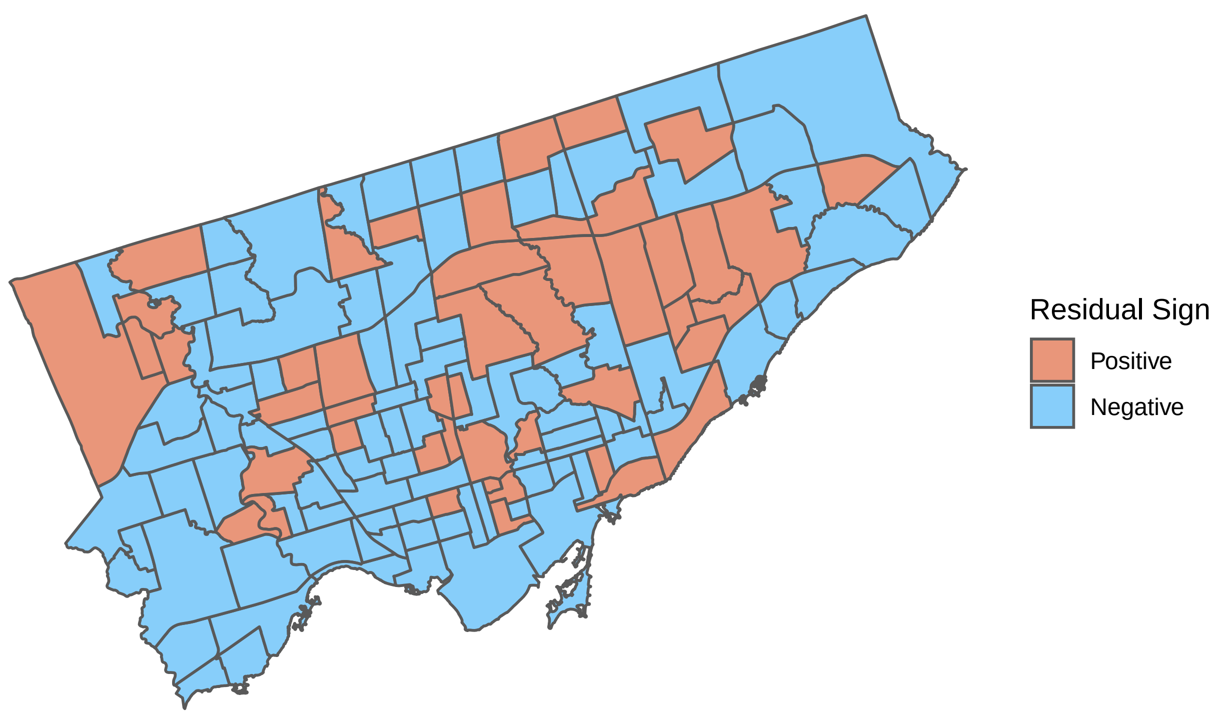

Figure 7: Map of the sign of the residuals from the regression model for each neighbourhood

From a visual observation of Figure 7, there does not appear to be any obvious clusters of positive or negative residuals. To obtain a more concrete conclusion, the Moran's I coefficient can be used in a hypothesis test again to test for spatial randomness.

The result of the Moran's I hypothesis test supports the visual observation of Figure 7. The null hypothesis of the test is that the pattern analyzed is spatially random. The p-value is 0.1871, which is greater than 0.05

and thus large enough to accept the null hypothesis. Consequently, the residuals of this regression model is random, indicating that the model successfully capture all of the pattern within the changes in COVID-19 case rates across Toronto's neighbourhoods. This means that the model does not need to be adjusted since its assumption that the residuals are independent has not been violated, so the results obtained from the model (summarized in Table 2) are valid.

Conclusion

Overall, the changes in COVID-19 case rates across neighbourhoods in Toronto show spatial autocorrelation, as found using Moran's I. A regression analysis of the change in COVID-19 case rates with respect to average income, percentage of 18- to 24-year-old individuals, and population density was also done. It revealed that there is a connection between average income and changes in the rates of COVID-19 cases, with neighbourhoods with lower income having greater changes in COVID-19 case rates. This means that a lower average income can quicken the growth in COVID-19 cases. In addition, the results of the regression show that other socio-economic factors, the percentage of 18- to 24-year olds and the population density in a neighbourhood, did not have a clear connection with the COVID-19 case changes. It is recommended that, for the future, more research should be done on the relationship with socio-economic variables and changes in COVID-19 cases. Socio-economic factors are complex factors that need to be further explored to verify the relationships found in this study.

Identifying groups of individuals from a socio-economic perspective is the first step to establishing that a person's socioeconomic position may be as much of an indicator in predicting health outcomes as a pre-existing medical condition. In establishing such similarities, governing healthcare bodies may extend precautionary recommendations to people with specific socio-economic conditions, thus providing a more in-depth and informed disease prevention plan. In a pursuit of identifying groups of the populations who are more susceptible to poorer outcomes when combating health problems, more research in this area needs to be undertaken.

References

10 Abbasi, Jennifer. 2020. "Younger Adults Caught in COVID-19 Crosshairs as Demographics Shift." *JAMA* 324 (21): 2141–43. https://doi.org/10.1001/jama.2020.21913.

Aleta, Alberto, and Yamir Moreno. 2020. "Age Differential Analysis of COVID-19 Second Wave in Europe Reveals Highest Incidence Among Young Adults," November, 2020.11.11.20230177. https://doi.org/10.1101/2020.11.11.20230177.

Aziz, Saba. 2021. "'Hit the Hardest': Why COVID-19 Cases Are Rising Among Young Canadians - National | Globalnews.ca." *Global News*. https://globalnews.ca/news/7731485/covid-variant-cases-young-canadians/.

Baena-Díez, Jose Miguel, María Barroso, Sara Isabel Cordeiro-Coelho, Jorge L. Díaz, and María Grau. 2020. "Impact of COVID-19 Outbreak by Income: Hitting Hardest the Most Deprived." *Journal of Public Health (Oxford, England)* 42 (4): 698–703. https://doi.org/10.1093/pubmed/fdaa136.

Canadian Urban Institute. 2016. "TOcore Neighbourhood Population Profiles," July, 46.

City of Toronto. 2017. "Neighbourhood Profiles." *City of Toronto*. City of Toronto. https://www.toronto.ca/city-government/data-research-maps/neighbourhoods-communities/neighbourhood-profiles/.

———. 2021. "COVID-19: Case Counts." *City of Toronto*. City of Toronto. https://www.toronto.ca/home/covid-19/covid-19-pandemic-data/covid-19-weekday-status-of-cases-data/.

———. 2022. "Neighborhood Shapefile." Social Development, Finance & Administration.

Detsky, Allan S., and Isaac I. Bogoch. 2021. "COVID-19 in Canada: Experience and Response to Waves 2 and 3." *JAMA* 326 (12): 1145–46. https://doi.org/10.1001/jama.2021.14797.

Gaiha, Shivani Mathur, Jing Cheng, and Bonnie Halpern-Felsher. 2020. "Association Between Youth Smoking, Electronic Cigarette Use, and COVID-19." *Journal of Adolescent Health* 67 (4): 519–23. https://doi.org/10.1016/j.jadohealth.2020.07.002.

Government of Ontario. 2021. "Ontario Confirms First Two Cases of Omicron Variant." Government. *News.ontario.ca*. https://news.ontario.ca/en/statement/1001241/ontario-confirms-first-two-cases-of-omicron-variant.

Hamidi, Shima, and Iman Hamidi. 2021. "Subway Ridership, Crowding, or Population Density: Determinants of COVID-19 Infection Rates in New York City." *American Journal of Preventive Medicine* 60 (5): 614–20. https://doi.org/10.1016/j.amepre.2020.11.016.

Khalatbari-Soltani, Saman, Robert C. Cumming, Cyrille Delpierre, and Michelle Kelly-Irving. 2020. "Importance of Collecting Data on Socioeconomic Determinants from the Early Stage of the COVID-19 Outbreak Onwards." *J Epidemiol Community Health* 74 (8): 620–23. https://doi.org/10.1136/jech-2020-214297.

Mishra, Sharmistha, Huiting Ma, Gary Moloney, Kristy C. Y. Yiu, Dariya Darvin, David Landsman, Jeffrey C. Kwong, et al. 2022. "Increasing Concentration of COVID-19 by Socioeconomic Determinants and Geography in Toronto, Canada: An Observational Study." *Annals of Epidemiology* 65 (January): 84–92. https://doi.org/10.1016/j.annepidem.2021.07.007.

Mohsin, Md, and Sultan Mahmud. 2022. *Omicron SARS-CoV-2 Variant of Concern: A Review on Its Transmissibility, Immune Evasion, Reinfection, and Severity.* Preprint. In Review. https://doi.org/10.21203/rs.3.rs-1316171/v1.

Murti, Michelle, Camille Achonu, Brendan T. Smith, Kevin A. Brown, Jin Hee Kim, James Johnson, Saranyah Ravindran, and Sarah A. Buchan. 2021. "COVID-19 Workplace Outbreaks by Industry Sector and Their Associated Household Transmission, Ontario, Canada, January – June, 2020." *Journal of Occupational & Environmental Medicine* Publish Ahead of Print (April). https://doi.org/10.1097/JOM.0000000000002201.

Nielsen, Kevin. 2020. "A Timeline of COVID-19 in Ontario | Globalnews.ca." *Global News*. https://globalnews.ca/news/6859636/ontario-coronavirus-timeline/.

Public Health Ontario. 2021. "Hospitalizations and Deaths Among COVID-19 Cases in Ontario: Waves 1, 2, 3 and 4." Public Health Ontario. https://www.publichealthontario.ca/-/media/documents/ncov/epi/covid-19-hospitalizations-deaths-ontario-quick-epi-summary.pdf?sc_lang=en.

———. 2022. "Ontario COVID-19 Data Tool." Data Tool. *Public Health Ontario*. https://www.publichealthontario.ca/en/Data-and-Analysis/Infectious-Disease/COVID-19-Data-Surveillance/COVID-19-Data-Tool.

Pulliam, Juliet R. C., Cari van Schalkwyk, Nevashan Govender, Anne von Gottberg, Cheryl Cohen, Michelle J. Groome, Jonathan Dushoff, Koleka Mlisana, and Harry Moultrie. 2021. "Increased Risk of SARS-CoV-2 Reinfection Associated with Emergence of the Omicron Variant in South Africa," December, 2021.11.11.21266068. https://doi.org/10.1101/2021.11.11.21266068.

Rumain, Barbara, Moshe Schneiderman, and Allan Geliebter. 2021. "Prevalence of COVID-19 in Adolescents and Youth Compared with Older Adults in States Experiencing Surges." *PloS One* 16 (3): e0242587. https://doi.org/10.1371/journal.pone.0242587.

Toronto Public Health. 2022. "COVID-19 Cases in Toronto." City of Toronto Open Data. https://open.toronto.ca/dataset/covid-19-cases-in-toronto/.

Toronto Social Development, Finance & Administration. 2011. "Neighbourhood Profiles." Open Data Toronto. https://open.toronto.ca/dataset/neighbourhood-profiles/.

World Health Organization. 2022. "WHO Coronavirus (COVID-19) Dashboard." https://covid19.who.int.