Chapter 3 COVID-19 in Toronto: Investigating the Spatial Impact of Retailers in the Food Retail and Food Service Sector



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3.1 Introduction

The novel coronavirus, SARS-CoV-2 (COVID-19), is a major disruptive event that has exposed the global economy to a series of threats and challenges (Hailu, 2020). Initially identified in Wuhan, China, COVID-19, caused by SARS-CoV-2 (severe acute respiratory syndrome), was declared as a global pandemic by the World Health Organization (WHO) on March 11, 2020. It has since spread rapidly around the world, and as of April 27, 2021, over 147.2 million cases have been confirmed. The COVID-19 pandemic has resulted in unprecedented economic crises, disproportionately affecting various sectors of the economy. Certain industries have been hit harder than others, leaving certain retailers more vulnerable to the consequences of the pandemic. Industries that rely on the movement of people have been the most impacted, while those that rely on the movement of information have been left relatively unscathed (Klein and Smith 2021).

The retailing sector makes up an increasingly large portion of the urban economy. The impacts of the COVID-19 outbreak on the food retailing sector in Canada have been significant and, to a great extent, unexpected. In order to slow down the transmission of the virus, governments worldwide have implemented restricted travel and social interactions known as "lockdown measures" as one of the key interventions to contain the spread of the virus. Other imposed regulations include self-isolation, social distancing, curfews, and stay-at-home orders. While these measures are vital to stop the spread of COVID-19, these measures have had a significant negative

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impact on the economy worldwide (Untaru and Han 2021). Restrictions on movement limited consumer's access to specific goods and services, challenging the stability and testing the resilience of many businesses. The sectors that rely predominately on high levels of human interaction, such as the retailing sector, have experienced the worst impact (Koren and Pető 2020). Due to the consequences of the pandemic and the severity of the health concerns of the COVID-19 virus, it resulted in the temporary closure of nonessential businesses. At the start of the pandemic, Canadian grocery stores experienced large-scale panic buying which led to many empty shelves. By the end of March 2020, most stores were closed to walk-in customers with the exception of grocery stores and pharmacies, which implemented strong social distancing rules in their premises. In addition to grocery stores, fast casual restaurants such as Starbucks and other national restaurant chains suspended in-store dining and seating, in favour of take-out, drive-through, and delivery services only.

Despite increasing scholarly interest on COVID-19 and its impact on the performance of food retailers and consumer shopping behavior, there is limited research exploring the spatial risk of COVID-19 on retailers in the food retail and food service sectors. Additionally, much of the current literature has studied the impact of COVID-19 on retail businesses by assessing retail sales data and consumer satisfaction rates during the pandemic; however, impact on location does not exist. As a result, an assessment of COVID-19's spatial impact on businesses based on their location is required to be able to understand which sectors or retailers will need to make strategic adjustments in order to adapt to a rapidly changing marketplace.

In an attempt to fill these gaps in the literature, this study aims to utilize spatial analysis techniques to understand the COVID-19 impact on retail locations. In this proposed research, the impact of COVID-19 on business locations in Toronto will be examined by investigating four retailers from the food retail and food service sectors which are Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws. The aim of this research is to explore the spatial distribution of COVID-19 cases over the past year in Toronto and the changing business dynamics due to the pandemic. The research study is based on a cross-comparative analysis on the distribution of COVID-19 and business density. Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws, which make up a large portion of the economy, will be explored to conduct a cross-economic comparison study on impact. This research seeks to address the following objectives:

- 1. To determine clusters of positive COVID-19 cases in Toronto and the locations of Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws
- 2. To determine retail locations that are within a COVID-19 hotspot
- 3. To explore the socio-economic characteristics that are associated with the identified locations

The hypothesis of this research paper is that based on the number of COVID-19 cases in an area, some retailers will suffer more than others depending on their location and distribution pattern. Understanding the spatial impact on business locations in the food retail and food service sectors in the study area provides important insights into future pandemic-related events, allowing retailers to be prepared for another occurrence because patterns are likely to be similar. This will highlight neighborhoods in Toronto that can be considered at-risk business locations due to

their high volumes of COVID-19 cases. Additionally, examining locations of risk against various socio-economic variables will allow retailers to implement strategies to attract customers to continue to shop at their store despite new COVID-19 regulations. Given the contributions of the food retail and food service sectors to the Canadian economy, analyzing the implications and effects of such disruptions on these retailers is critical as it helps understand where the sectors appear to be heading.

The structure of the paper is as follows. The literature review provides a comprehensive review of academics' theoretical and methodological contributions to the theories of the COVID-19 pandemic, changes in the business dynamics and consumer behavior, and its consequences to the food retail and food service sectors. The study area section describes where the study is taking place. The data section is an overview of the data sources used in the study and where it is collected. The methodology section provides a comprehensive description of the steps taken in the study. The results section presents the key results from the kernel density estimation (KDE), Global and Local Moran's I statistic, and geographically weighted regression. The discussion section discusses the findings of the analysis results, answers the hypothesis, explains the limitations, and presents next research steps. The paper concludes with a summary of the research findings.

3.2 Literature Review

3.2.1 Factors Influencing the COVID-19 Pandemic

The coronavirus pandemic has had a significant impact on a global scale. The recent outbreak of COVID-19 has caused many disruptions in the lives of people all over the globe. A number of research studies have assessed the global and regional impacts on epidemiological factors at a spatial scale combining several spatially explicit methods in health geography. Locational information of COVID-19 is critical to understand as it sets a framework for further epidemiological analysis of transmission characteristics (Vaz 2021). Populations of positive COVID-19 cases can be linked to many factors relating to the socio-economic and geodemographic characteristics of a neighborhood. Understanding this information can directly enable mitigation and spatial decision support (Vaz 2021; Shabani and Shahnazi 2020).

According to recent literature, the spatial distribution of COVID-19 is heterogeneous. Penerliev and Petkov (2020), Sannigrahi et al. (2020), Credit (2020), and Vaz (2021) investigate several socio-economic variables that are associated with high cases of COVID-19. Many key variables have been identified as important when understanding the spatial pattern of COVID-19. All of these studies demonstrate population density as a key variable in assessing COVID-19 transmission. According to the studies of Penerliev and Petkov (2020) and Sannigrahi et al. (2020), there is a direct correlation between the age structure of the population and the number of COVID-19 cases and deaths. Infections were more fatal among the population of above-working age. Credit (2020) found that Hispanic and Black neighborhoods had significantly higher case rates compared to neighborhoods that were dominated by non-Black and non-Hispanic racial groups. Furthermore, Vaz (2021) determined that neighborhoods with significant urban footprint and high crime rates were of particular concern for COVID-19 transmission. Transportation, education, income, and social vulnerability were key drivers in his study and were linked to the spread of COVID-19. Similarly, Sannigrahi et al. (2020) concluded that regions in European countries that were dominated by senior and old age population, poverty, and low income were at risk of COVID-19 infections. Through these findings, it is evident that high case rates of COVID-19 are related to factors of environmental injustice, social poverty, and marginalization.

3.2.2 COVID-19 Impact on the Economy and Retail

The COVID-19 pandemic has been one of the biggest disruptive catastrophes in recent decades and has had a global effect on society and the economy. As economic concerns and restrictions continue to affect consumers worldwide, new buying and consumption patterns and behaviors have emerged (Untaru and Han 2021). This rapid shift in social behavior is directly impacting the economy (Kim et al. 2021). The impact on the retail sector is heterogeneous and depends on the combined effect of social distancing and lockdown measures. Retail enterprises are generally dependent on regular consumer traffic and face-to-face interaction, resulting in a severe reduction in market demand caused by the pandemic (Untaru and Han 2021). This is due to the nature of the retail environment. The dense, open, and public characteristics of retail stores were viewed as a major risk for the uncontrollable transmission of COVID-19. As a result, in an effort to minimize the risk of spreading the virus, business closures have become more common. For example, since the pandemic, Starbucks has reinvented its store estate across North America, making the decision in June 2020 to expand convenience-led formats, while closing up to 400 locations (Rushton, et al. 2021).

The impacts of the COVID-19 pandemic on the food retailing and food service sector in Canada continue to evolve with its long-term consequences still unknown. Prior to the pandemic, the food service industry has been rapidly expanding, accounting for more than 30% of the average Canadian's food expenditure (Goddard 2021). Household expenditures on food retail and food service changed significantly in response to public health concerns and government-implemented restrictions (Panzone et al. 2021). The actions taken under the states of emergency changed the reality of food purchasing. Many researchers believed that the shock would result in long-term structural changes, particularly toward online retailing (Rushton et al. 2021). Others predicted that the shock would be largely temporary, suggesting that shoppers would quickly revert to their old habits once restrictions are lifted (Goddard 2020).

3.2.3 Changes in Consumer Shopping Behavior and Consumption

The introduction of social distancing and lockdown measures to contain the spread of the virus imposed strict restrictions on the life of consumers and retailers (Panzone et al. 2021). Recent studies have revealed that the emergence of the COVID-19 pandemic and the extended periods of lockdown and quarantine have fundamentally changed consumer behavior, creating new consumption patterns in response to the perceived threat of the infection (Untaru and Han 2021; Koren and Pető 2020; Brandtner et al. 2021; Panzone et al. 2021).

3.2.3.1 Stockpiling and Hoarding

The shopping behavior resulted in shortages of products in grocery stores (e.g., toilet paper), which exacerbated people's concerns and have increased stockpiling behavior. Brandtner et al.'s (2021) research, which focused on the impact of COVID-19 on customer satisfaction by assessing physical grocery retailing, indicated that product unavailability is among the main factors of customer satisfaction. This uncertainty may lead customers to anticipate future demand by purchasing more than usual resulting in hoarding and stockpiling goods (Panzone et al. 2021). Multiple cases of panic buying and hoarding of nonperishable food items and cleaning and sanitary products have been observed worldwide. Ben Hassen et al. (2020) indicated that American consumers increased their expenditure during COVID-19 in an attempt to stockpile vital household products such as food. Given that food is the most important item, panic buying is a common human response to the crisis that is driven by a fear of running out of food. Furthermore, the act of stockpiling food and other necessities can also be a strategy to reduce the number of future shopping trips (Panzone et al. 2021). According to recent studies (Untaru and Han 2021; Goddard 2020), consumer health consciousness increased as a result of the pandemic as people realized the importance of the immune system and hygiene regarding fighting the virus. Therefore, consumers chose to adopt several health protective measures during shopping activities such as reducing shopping frequencies, minimizing the amount of time spent in stores, avoiding going to multiple stores, standing in crowded places, wearing gloves, and wearing masks in order to stay safe and reduce the risk of contracting the virus (Untaru and Han 2021).

3.2.3.2 Restaurant to Grocery Store Purchases

Furthermore, Goddard (2020) indicated that stay-at-home orders immediately changed the way individuals looked at food purchases. The shift in consumers' food purchasing from restaurants to grocery stores occurred quickly causing disruption in food supply chains. According to Statistics Canada, food expenditures shifted from food service to grocery store purchases on average across the year. Consumers

realized their vulnerability to the disease and the loss of employment, causing the change in food habits. With more time spent at home, consumers spent more time cooking, baking, and eating three meals a day at home (Ben Hassen et al. 2020), reducing out-of-home consumption, and experimenting in food purchasing and preparation (Panzone et al. 2021). The shutdown of sit-down dining restaurants had also switched food purchases to grocery stores, significantly changing the volume of types of foods purchased at grocery stores (Goddard 2020). The pandemic in Canada has changed the reality of food purchasing. This caused the food retailing sector to rapidly increase in sales through supermarkets and convenience stores, while the food service sector steadily declines.

3.2.3.3 Transition to Online Purchasing

The pandemic has also introduced Canadians to a multitude of purchasing options. This exposure has generated a demand for "omnichannel" shopping, the ability to shop through different methods such as online, in-store, or pickup, which is likely to be permanent (The Economist 2021). Many brick and mortar retailers adopted new customer servicing options which include curbside pickup and the expansion of home delivery services. Those unable to leverage e-commerce tools have seen their sales decline by up to 89% (Rushton, et al. 2021). Saba (2020), a business reporter from the Toronto Star, reported that Loblaws saw its e-commerce business grow 280% during the second quarter of the pandemic, making \$1.2 billion in e-commerce sales as of mid-July 2020 compared to \$1 billion in all of 2019. As of April 2018, only 28% of 1000 Canadian respondents had shopped for groceries online (Brown 2018). Due to COVID-19 and its impact on consumer behavior, retailers such as Starbucks indicated a desire to power convenience retail with its mobile ordering capability. Starbucks implemented a new strategy to expand pickup stores in dense markets, while the move to curbside, drive-thru, and walk-up windows are focused in suburban areas. Starbucks CEO, Kevin Johnson, said that the strategy "aligns closely with rapidly evolving customer preferences that have accelerated as a result of COVID-19, including higher levels of mobile ordering, more contactless pick-up experiences, and reduced in-store congestion" (Rushton et al. 2021). As a result of the pandemic, online shopping has become increasingly important and is encouraged to limit the spread. The closure of the food service industry has also made online purchasing critical. Therefore, the reality of consumer shopping behavior on food purchases have changed significantly and are heavily impacting retailers.

3.2.4 Applications and Methods Used

3.2.4.1 Qualitative Approaches

Several different methods have been conducted to assess the impact of COVID-19 on retail businesses. Brandtner et al. (2021) and Untaru and Han (2021) conducted an online self-administrated survey questionnaire to determine customer

satisfaction due to the pandemic. In addition to collecting data through online surveys, Brandtner et al. (2021) also used external sources like Google review platforms to gather information regarding customer satisfaction levels from selected retail chains in the form of star ratings and textual evaluation comments. This data was explored using appropriate text mining techniques which provided further insights by outlining factors that influence consumer satisfaction. While these studies used data collected through surveys to evaluate the impact of COVID-19 on grocery retailers from the viewpoint of the consumers, Panzone et al. (2021) and Kim et al. (2021) used retail sales data by applying a time series clustering model to determine the impact of changes in sales due to the COVID-19 outbreak. Results showed that some sectors gained, and others lost with significant changes in consumer shopping behavior. In the study of Ben Hassen et al. (2020), it was found that consumers in Oatar preferred online grocery shopping during COVID-19. Panzone et al. (2021) concluded that grocery store chains benefited from the disruption, while restaurants faced significant losses in revenues. Untaru and Han (2021) also revealed that protective measures utilized by retail establishments against COVID-19 exert an influence on customers' satisfaction during shopping.

3.2.4.2 Quantitative Approaches

Spatial techniques assessing the locational impact of the COVID-19 pandemic on business locations are limited; however, there are several different quantitative approaches that have been used to assess the spatial distribution of COVID-19. Rex et al. (2020) conducted an exploratory study, analyzing the spread of positive COVID-19 cases in the State of São Paulo, Brazil, using kernel density estimation (KDE). An extensive number of studies used simple visualization techniques to visualize the spatial distribution of COVID-19, either by choropleth maps or dot density maps. Many researchers utilized spatial autocorrelation techniques such as hotspot analysis, Global Moran's I, and Local Moran's I. Fan et al. (2020) employed hotspot analysis to quantify the spatial distribution of COVID-19 in China. Another research also conducted in China utilizes hotspot analysis to illustrate the spatial intensity of the COVID-19 infection in China (Tang et al. 2020). Similarly, Li et al. utilize Global and Local Moran's I to investigate clusters of COVID-19 incidences in China.

Many research studies have combined geographic visualization of the COVID-19 distribution to additional socio-economic and demographic characteristics. Several different approaches have also been used to explore the demographic and socio-economic variables associated with the spread of the virus. Regression models have been used extensively in many epidemiological studies. Credit (2020) and explored the spatial associations between sociodemographic, economic, and built environmental characteristics with COVID-19 activity using linear regression models. Furthermore, Sannigrahi et al. implemented global and local spatial regression models to assess the spatial association between the driving factors and COVID-19 cases and deaths. Likewise, Vaz (2021) conducted a stepwise backward regression model to establish key variables influencing the spread of the virus. Zhang and

Schwartz (2020) utilize multivariable regression models and conclude that there are strong positive correlations for socio-economic factors including population density, proportions of elderly residents, poverty, and percent population tested with COVID-19 morbidity or mortality. Similarly, Mollalo et al. (2020) applies a geographically weighted regression model to examine COVID-19 incidences in the United States, in relation to socio-economic, demographic, behavioral, topographical, and environmental factors. It was discovered that income inequality played a role in explaining COVID-19 incidence.

3.3 Study Area

The area of study in this paper is the City of Toronto, the most densely populated city in Canada, with a population density of 850 inhabitants per km², which is significantly higher than the average for Ontario municipalities. The City of Toronto is a unique study area as it is an urban area with the highest population density in Canada and a high level of socio-economic and cultural diversity. Given its high population density, Toronto is at risk of experiencing an excess of COVID-19 cases, which appears to be borne out of the numbers of infections and deaths in that city. As of April 27, 2021, Toronto has had 139,375 cases of COVID-19 infections and 3030 deaths (Fig. 3.1).

3.4 Data

The data used for this research is gathered from multiple sources and is summarized in Table 3.1. There are three main sets of data used for this analysis: case counts of positive COVID-19 infections, geographic locations of the four retailers (Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws), and the 2016 census data for Toronto consisting of the socio-economic variables of the study area. The data in this study is critical for the purpose of analyzing spatial clusters, distribution of retailers, and relationships among variables.

3.4.1 COVID-19 Data Gathering and Pre-processing

COVID-19 data for Toronto is collected at the neighborhood level from the City of Toronto Open Data Portal (2021). This variable represents the case counts of confirmed COVID-19 infections and deaths, containing information on the date the case was reported, the source of infection (whether it was by travel or close contact), the patient's gender, whether the patient was hospitalized, and whether the case was resolved or not. The cases were downloaded for four different timestamps

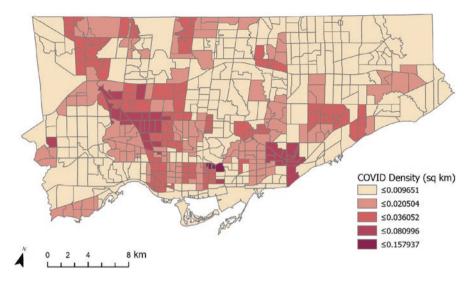


Fig. 3.1 COVID-19 density of cases from May 5, 2021

throughout the pandemic, May 1, 2020, September 5, 2020, January 12, 2021, and May 5, 2021. COVID-19 data is represented as case counts per Toronto neighborhood. To account for the population density, COVID-19 density is calculated using the population density and COVID-19 cases (Vaz 2021). This is represented by the following equation:

$$\operatorname{COV}_{d} = \frac{\frac{\operatorname{COV}_{n}}{p}}{A}$$

where $\text{COV}_d = \text{COVID-19}$ density, $\text{COV}_n = \text{number of COVID-19}$ cases, p = population, and $A = \text{area in km}^2$. Calculating COVID-19 density allows for a more thorough and integrative analysis of the spatial distribution of COVID-19.

Since this data is only made available at the neighborhood level, it is important to spatially downscale this data to census tracts (CTs), so that it can be used to analyze the spatial patterns of COVID-19 across the city at a more detailed spatial unit. This will eliminate the modifiable areal unit problem (MAUP) in the future when other analyses are being conducted at the CT level. It will also help effectively determine the relationships between COVID-19 clusters and retail locations through a spatial comparison. To spatially downscale COVID-19 data, Vaz (2021) conducts a zonal interpolation using population density to generate a higher accuracy of COVID-19 in Toronto. This approach can be implemented in this study to spatially downscale COVID-19 data to the CT level using the Humanitarian Data Exchange (HDX) data for population density in Canada.

Variable criteria	Data source	Year	Spatial unit	Justification	
COVID-19 case counts	City of Toronto	May 1, 2020	Neighborhood level	N/A	
		September 5, 2020			
		January 12, 2021			
		May 5, 2021			
Retail data Starbucks McDonald's Shoppers Drug Mart Loblaws	Yellow Pages Business Directory	2020	CSV	The choice in retailers provides a mix from fast casual restaurants to grocery stores. Being under the food retail and food service sector, they have shown a great importance to the economy	
Socio-economic variables • Low-income status • Low education • Visible minority • Recent immigrants • Subsidized housing • Unemployment	CHASS	2016	Census Tract	These variables were chosen because they were proven to hav a significant influence on COVID-19 from past research studies. Sannigrahi et al. (2020) and Vaz (2021) found that socio-economic factors such as income, education, and employment were crucial in determining the spatial relation of COVID-19 cases. Regions demonstrating a lower income, education, and employment had higher case rates. Immigration and visible minority population were also identified as important variables in this study	

Table 3.1 List of variables used

The HDX data is collected at a 1km spatial resolution and is extracted for Toronto using the boundary of the city. The population density for Toronto and the Toronto CTs are then used to conduct a zonal statistic, creating a density surface. This is then spatially joined with the case counts for COVID-19 using the field operation First. This results in a local zonal interpolation at the CT level making this substantially better than the standard neighborhood analysis.

3.4.2 Retail Data Gathering

Business locations of the four retailers in Toronto, Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws, are retrieved from Yellow Pages Business Directory and are collected as a CSV file. The reason why retailers from the food retail and food service sector were chosen for this analysis is due to its staple importance in retail. The choice in retailers provides a mix from fast casual restaurants to grocery stores. Being under the food retail and food service sector, they have shown a great importance to the economy. The retail location data retrieved from Yellow Pages include the address, city, province, postal code, and country of each of the Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws locations in Toronto. Data on each of the store locations were then used to geocode using the address locator in ArcGIS Pro into a shapefile of point features containing longitude and latitude coordinates for each retail location.

3.4.3 Socio-economic Data Gathering and Pre-processing

The 2016 census data for Toronto consisting of the socio-economic data of the study area are obtained from CHASS (2016) at the CT level. Census data provides a wide range of information pertaining to the population including social and economic factors.

Once the data is collected, the variables must be rated and standardized. All variables are rated into a percentage. Population variables are rated using the total population and household variables are rated using the total number of households. Rated variables are then standardized using the *z*-score method to ensure that all variables contribute evenly to a scale. Standardization refers to the process of subtracting the mean and dividing by the standard deviation. Standardized variables are variables that have been rescaled to have a mean of zero and a standard deviation of one. This process can be modeled as:

$$Z = \frac{x - \mu}{\sigma}$$

where *Z* = standard score, *x* = observed value, μ = mean of the sample, and σ = standard deviation of the sample. All independent variables are standardized using an automated tool in SPSS.

3.5 Methodology

The methodology for this research study (see Fig. 3.2) is separated into two sections. The first section is an exploratory spatial analysis of the study which includes a visual investigation of the distribution of COVID-19 incidences, comparing four different time periods during the pandemic, and the distribution of the selected retailer locations. With the use of GIS, this study utilizes techniques such as kernel density estimation and further progresses toward testing for spatial autocorrelation using spatial statistics. This exploratory visual investigation may be used to make conclusions about the clusters of confirmed cases of COVID-19 and the locations of Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws. This will help identify

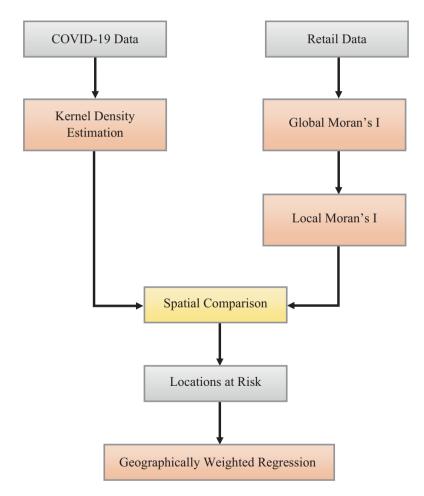


Fig. 3.2 Outline of methodology

retailers that have been impacted the most due to their location based on the distribution of COVID-19 cases across the city.

While the first section of the study provides a general overview of the distribution and overall spatial relationship of COVID-19 and business locations across the city, the second component of this study examines several socio-economic variables that have been proven to have an impact on COVID-19. This will help determine the neighborhood characteristics of the retailers that have and will continue to suffer the most due to the pandemic based on their location.

3.5.1 Kernel Density

To explore and compare the spatial distribution pattern of COVID-19 cases from the four different time periods in Toronto, kernel density estimation (KDE) is applied. The kernel density method is a probability density estimation technique used to identify cluster patterns based on point features. KDE calculates the density of point features around each output raster cell, producing a smoothed curved surface fitted over each point. The following formula models how the kernel density for points is calculated:

Density =
$$\frac{1}{(\text{radius})^2} \sum_{i=1}^{n} \left[\frac{3}{\pi} \cdot \text{pop}_i \left(1 - \left(\frac{\text{dist}_i}{\text{radius}} \right)^2 \right)^2 \right]$$

For dist_i < radius

where i = 1, ..., n are the input points, pop_i is the population field value of point *i*, and dist_i is the distance between point *i* and the (x, y) location.

This is done in ArcGIS using the Spatial Analyst tool, "Kernel Density," to produce a density estimation of COVID-19 density from May 1, 2020; September 5, 2020; January 12, 2021; and May 5, 2021. Prior to the kernel density estimation, COVID-19 data at the census tract level for each time period is converted into point data using the "Feature to Point" tool in ArcGIS Pro. These points are then used as the input parameter of the Kernel Density function. The population field that is used to weight the features is the COVID density calculations. This weights some features more heavily than others based on its value. The search radius, also known as the bandwidth, is computed for this estimation using the default bandwidth estimation method: Silverman's rule of thumb. This approach of calculating the default radius is resistant to spatial outliers and eliminates the ring around the points phenomena that often occurs with sparse datasets. This process of determining the kernel density estimation is applied for all four time periods and is masked within the Toronto boundary.

3.5.2 Assessing Spatial Autocorrelation: Using Global Moran's I

The Spatial Autocorrelation (Global Moran's I) tool is used to measure the spatial autocorrelation between each of the four selected retailers based on their feature locations and feature values. The Global Moran's I statistic looks at the spatial association of the entire study area where it determines the similarity of one object to another. Given a set of features and an associated attribute, it evaluates whether the pattern expressed is clustered, dispersed, or random. The values of the Global Moran's I statistic range from +1 (perfect cluster) to -1 (perfect dispersion) to 0 (random spatial pattern). The Moran's I statistics for spatial autocorrelation is represented as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2}$$

where z_i represents the standard deviation of an attribute for feature *i* from its mean $(x_i - \overline{X}), w_{i,j}$ represents the spatial weight between feature *i* and *j*, *n* represents the total number of features, and S_0 is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^n \sum_{j=1}^n W_{i,j}$$

Using ArcGIS, the Moran's I index was calculated for the four selected retailers, Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws. Prior to running the Global Moran's I, the number of stores for each selected retailer is aggregated by census tract by spatially joining the point locations of each retailer to the Toronto census tract boundary file. The input parameters for measuring spatial autocorrelation are the census tract shapefile and the count of each retailer. The Moran's I value is also associated with a *p*-value and *z*-score to indicate whether or not it is statistically significant in the model. The Global Moran's I index is run using the polygon contiguity edges and corners option for the Conceptualization of Spatial Relationships parameter. This option is used because polygon features are used in this analysis. For Contiguity edges corners, polygons that share an edge or corner will influence computations for the target features.

3.5.3 Local Moran's I Statistic

While the Global Moran's I statistic determines the spatial association of the entire study area, the Cluster and Outlier Analysis also known as the Anselin Local Moran's I (LISA) statistic is applied to visualize the distribution of features that are similar and dissimilar, visually presenting the spatial association with the Moran's I values. Given a set of weighted features and an analysis field, the tool identifies spatial clusters of features with high or low values as well as spatial outliers. It calculates a local Moran's I value, *z*-score, and pseudo *p*-value, representing the statistical significance of the computed index values, and a code representing the cluster type for each statistically significant feature. The local Moran's I statistic is represented as:

$$I_i = \frac{x_i - \underline{x}}{S_i^2} \sum_{j=1, j \neq 1}^n w_{i, j \left(x_j - \underline{x}\right)}$$

where x_i is an attribute for feature *i*, \underline{X} is the mean of the corresponding attribute, $w_{i,j}$ is the spatial weight between feature *i* and *j*, and:

$$S_{i}^{2} = \frac{\sum_{j=1, j\neq 1}^{n} \left(x_{j} - \underline{X}\right)^{2}}{n-1}$$

with *n* equating to the total number of features.

Using ArcGIS, the Cluster and Outlier Analysis tool is applied for each of the retailers (Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws), to identify areas of statistically significant clustering, dispersion, and spatial outliers using the Anselin Local Moran's I statistic. The tool is run using the contiguity edges and corner spatial relationship. A statistically significant positive cluster with a high positive *z*-score indicates that the surrounding features are similar regardless of whether they are clustered with high (high-high) or low (low-low) values. A statistically significant negative cluster with a low negative *z*-score indicates that the surrounding features are high to low (high-low) or low to high (low-high) values.

3.5.4 Geographically Weighted Regression

A geographically weighted regression (GWR) is applied to explore the socioeconomic characteristics of the identified COVID-19 hotspots. GWR is a local form of linear regression that is used to model spatially varying relationships. By fitting a regression equation to every feature in the dataset, GWR assesses a local model of the variable being predicted. Separate equations are constructed by incorporating the dependent and exploratory variables of the features falling with the neighborhood of each target feature. The Neighborhood Type and Neighborhood Selection Method parameters determine the shape and extent of each neighborhood analyzed. The dependent variable used for the GWR is COVID density from May 5, 2021, and the exploratory variables are low-income status, visible minority population, recent immigrants, subsidized housing, low education, and unemployment. All variables are rated and standardized. The parameters used for this analysis are Continuous for Model Type, Number of neighbors for Neighborhood Type, and Golden search for Neighborhood Selection Method. When using the Golden Search option, the tool determines the best values for the Number of neighbors parameter using the golden section search method by first determining the maximum and minimum distances and testing the AICc at various distances incrementally between them.

3.6 Analysis Results

This section presents the findings from the spatial and statistical methods applied in this study. It begins by describing the spatial distribution of COVID-19 and business locations in the City of Toronto. It then presents the results of spatial autocorrelation and explores the socio-economic characteristics associated with the COVID-19 hotspots using spatial regression techniques.

3.6.1 Spatial Distribution of COVID-19

Within the City of Toronto, confirmed cases of COVID-19 are unevenly distributed and found primarily in the Downtown core. The following figures resulting from the kernel density estimation of COVID-19 reveals areas where there is a high concentration of cases as well as areas where there is a medium and low concentration of cases. The distribution pattern resulting from the kernel density estimation can be used to analyze the movement of COVID-19 across Toronto throughout the past year starting from May 2020 to May 2021. Throughout the pandemic, it is evident that there are a high number of cases observed largely in Downtown Toronto, and the concentration of cases steadily decreases as you move outside the Downtown core. Looking at all four timestamps, as of May 1, 2020, the highest density of cases is found in Downtown Toronto with a medium-high density of cases found in York and East York, a medium density of cases in the east end of Toronto in Scarborough region and some areas in the west in Etobicoke. As of September 5, 2020, after the first wave of the pandemic, medium-high density of cases extends to west and north of Toronto near Etobicoke and North York. There is also a low-medium density of cases present in east end Toronto, extending to Scarborough, along Lake Ontario. After the second wave of the pandemic, January 12, 2021, the density of COVID-19 cases in most sections of Toronto has decreased with a significant concentration of cases remaining in the Downtown core. COVID density has decreased significantly in the west and east ends of Toronto, Etobicoke, and North York. Following the third wave of the pandemic, May 5, 2021, it is clear that the density of cases in the outer areas of Toronto has fallen substantially, with a high density of COVID-19 remaining in the Downtown core.

In all four time periods, there is a high concentration of cases found primarily in the Downtown core, indicating a potential COVID-19 hotspot due to its high population density. The movement of COVID density across Toronto throughout the pandemic poses a potential threat to retailers existing in one of these COVID-19 hotspots. In addition to the Kernel maps indicating areas with the highest occurrence density, it also demonstrates the probability of businesses being negatively impacted by the virus based on their location. Hot areas on the map represent areas where the pandemic will have the greatest impact on retailers, whereas cold areas on the map represents areas where the COVID-19 pandemic will have the least impact on retailers based on their location.

3.6.2 Spatial Distribution of Retailers

The spatial distribution pattern of Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws is explored through global and local indicators. Results from the Global Moran's I aim to describe and quantify the degree of spatial autocorrelation among the store locations of Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws. Table 3.2 summarizes the results from the Global Moran's I statistic. The Moran's I index ranges from -1 (negative spatial autocorrelation) to +1 (positive spatial autocorrelation), with values near 0 being closer to a random distribution. Its value is associated with a *z*-score and *p*-values and are important to determine the significance of the results.

Referring to Table 3.2, Starbucks exhibits a statistically significant association and a positive *z*-score value. Therefore, the null hypothesis can be rejected that there is no spatial independence in the distribution of Starbucks but rather a more spatially clustered spatial distribution. This indicates that Starbucks has a distribution that is <1% likelihood its clustered patterns that are the result of random chance. However, McDonald's, Shoppers Drug Mart, and Loblaws exhibit no statistical significance for its spatial patterning. Its Moran I Index is closer to 1, thus making their distribution of random chance.

	Moran's index	z-score	<i>p</i> -value	Pattern
Starbucks	0.327	14.996	< 0.001	Clustered
McDonald's	0.018	0.836	0.403	Random
Shoppers Drug Mart	0.036	1.591	0.112	Random
Loblaws	-0.019	-0.753	0.452	Random

Table 3.2 Spatial autocorrelation of retailers

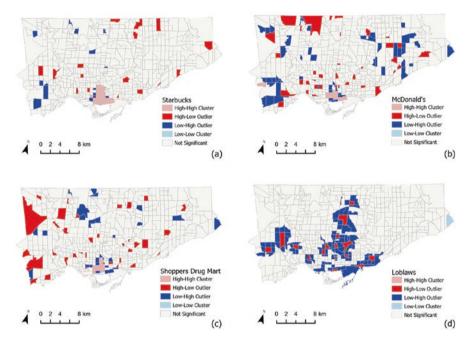


Fig. 3.3 (a) Hotspots and coldspots of Starbucks. (b) Hotspots and coldspots of McDonald's. (c) Hotspots and coldspots of Shoppers Drug Mart. (d) Hotspots and coldspots of Loblaws

Results from Local Moran's I further visualize the distribution of significant and insignificant spatial autocorrelation for each retailer. Figure 3.3a–d display the results from the Cluster and Outlier Analysis tool, displaying hotspots and coldspots of each retailer. Census tracts in shades of red represent positive spatial autocorrelation of high-high clusters or high-low outliers, while census tracts in shades of blue represent negative spatial autocorrelation of low-low clusters or low-high outliers. Starbucks, McDonald's, and Shoppers Drug Mart display a statistically significant cluster of high values (high-high cluster) in the Downtown core, indicating that the surrounding features have similar high values. Starbucks has the largest cluster present in Downtown Toronto which is explained by the Global Moran's I index that

indicated a clustered pattern. These retailers do not have any low-low clusters present in the dataset. While retailers are mainly clustered in the downtown region, spatial outliers of high-low and low-high values are present throughout the entire study area indicating that there is an outlier in which a high value is surrounded primarily by low values (high-low) and an outlier in which a low value is surrounded primarily by high values (low-high). Contrarily, Loblaws does not exhibit any highhigh clusters. As indicated from the Global Moran's I results, the distribution of Loblaws stores demonstrate a random pattern. Due to its random pattern, all Loblaws locations either are represented as a spatial outlier of high-low values or low-high values or are not significant on the map.

3.6.3 Cross-Comparative Analysis of COVID-19 and Retailer Distribution

Starbucks

Within the City of Toronto, locations of Starbucks coffee are highly populated in Downtown Toronto where there is also a high density of COVID-19 cases (see Fig. 3.4). These census tracts have the highest number of Starbucks of 11, 12, and 16 locations present in each CT. Locations of Starbucks are less clustered moving away from the Downtown core; however, these census tracts do have at least more than one Starbucks located in them. These areas also have a medium-high COVID

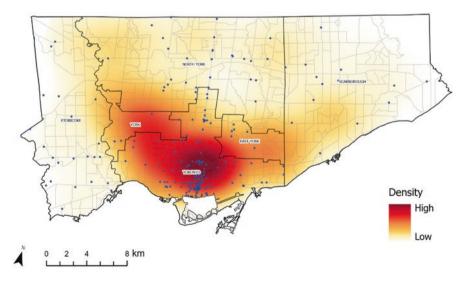


Fig. 3.4 Distribution of Starbucks in Toronto. (Note: COVID-19 cases as of May 5, 2021)

density. In the peripheral areas of Toronto, Starbucks locations are scattered around in the outer edges of Etobicoke, North York, and Scarborough where there is a low COVID density and are clustered along the TTC subway line where there is a low to medium density of COVID-19 cases.

The downtown core can be identified as high risk due to its high concentration of COVID-19 cases and Starbucks locations. There are over 50 Starbucks locations present in this hotspot and they are of high risk. Census tracts in York and east of Downtown Toronto are medium-risk locations for Starbucks as they have a medium-high density of COVID-19 cases and a medium concentration of Starbucks locations. Starbucks located in census tracts in North York are at low-medium risk due to their low-medium density of COVID-19. These areas also have some Starbucks located in them and could be of potential risk due to the lower density hotspots found in the outer areas of North York. In the outer edges of Toronto (Etobicoke and Scarborough), there is a lower impact for Starbucks as there is a low density of COVID-19 incidences.

McDonald's

Similar to the Starbucks locations, a portion of the McDonald's locations are concentrated in the downtown core of Toronto where there is a high density of COVID-19 cases (see Fig. 3.5). Although Downtown Toronto has a cluster of McDonald's locations, it is significantly fewer than Starbucks with an average of two McDonald's locations in each census tract in the downtown core. McDonald's locations in a COVID-19 hotspot in the Downtown core are at high risk due to their location. The McDonald's that are located east of Toronto, in York, and along the edge of Scarborough are at medium-high and low-medium risk because there is a high-medium concentration of cases in these areas. Although these McDonald's are

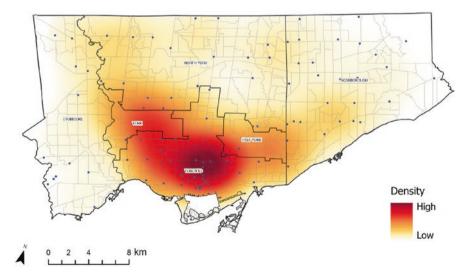


Fig. 3.5 Distribution of McDonald's in Toronto. (Note: COVID-19 cases as of May 5, 2021)

located in areas that have a medium concentration of COVID-19 cases, in the peripheral areas of Toronto, locations of McDonald's are scattered around the city. Due to their random pattern, in regions outside of the Downtown core, these locations are less likely to be impacted because they are not clustered in one area. There are fewer McDonald's locations that are present in a COVID-19 hotspot than Starbucks locations. Furthermore, results from the Global Moran's I statistic confirms that locations of McDonald's are distributed at random even though there is a small cluster of stores present in Downtown Toronto. Locations that exist on the outer edge of Etobicoke and Scarborough are at the lowest risk due to their low density of COVID-19.

Shoppers Drug Mart

Similar to McDonald's, locations of Shoppers Drug Mart are concentrated in the Downtown core and are scattered in the peripheral areas of the city (see Fig. 3.6). The areas in which Shoppers Drug Mart is the most concentrated are also areas with a high density of COVID-19. Census tracts belonging in the COVID-19 hotspot in Downtown Toronto contain over 25 Shoppers Drug Mart stores and are the most impacted by the COVID-19 pandemic. In the peripheral areas of the city, Shoppers Drug Mart locations are scattered across the city with no distinct pattern. This is also confirmed by the Global Moran's I statistic that the spatial distribution of Shoppers Drug Mart locations exhibits a random pattern even though it shows a small cluster of stores in the Downtown region. Similar to the other retailers, Shoppers Drug Mart located in the outer areas of Etobicoke and Scarborough are the least impacted by COVID-19 due to its low density of cases in these areas. Shoppers Drug Marts that are located in York and the shore of Scarborough are at

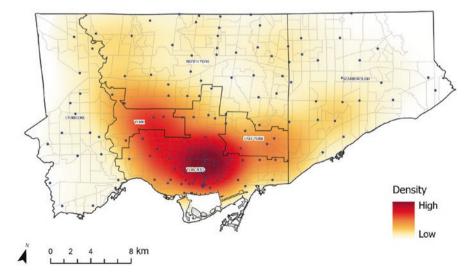


Fig. 3.6 Distribution of Shoppers Drug Mart in Toronto. (Note: COVID-19 cases as of May 5, 2021)

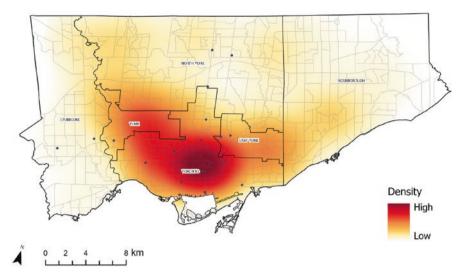


Fig. 3.7 Distribution of Loblaws in Toronto. (Note: COVID-19 cases as of May 5, 2021)

medium-high risk due to its medium concentration of cases. Shoppers Drug Mart locations in North York are at medium risk of being exposed to COVID-19 because census tracts in these areas have a medium density of COVID-19 cases.

Loblaws

Contrary to Starbucks, McDonald's, and Shoppers Drug Mart, locations of Loblaws are not clustered in Downtown Toronto (see Fig. 3.7). There is only one Loblaws store that is directly located in the downtown region which is also a hotspot for COVID-19. This means that this location of Loblaws is impacted the most by COVID-19. The Loblaws that are located around this hotspot are at medium-high risk since they are still located around the hotspot. The Loblaws that are located in Etobicoke and North York are impacted the least by COVID-19 because of its low concentration of cases in these areas.

3.6.4 Geographically Weighted Regression

Geographically weighted regression is used to explore the spatial variability of relationships between COVID-19 and the selected predictors. The variables being used to predict the dependent variable are low-income status, visible minority population, recent immigrants, subsidized housing, low education, and unemployment at the CT level. The regression model resulted in an AICc value of 4842.2. This is a measure of the model performance. The AICc value produced for this model is the smallest among all other models, indicating that this model provides a better fit to the observed data. The R-squared is a measure of goodness of fit. The GWR model results in a R-squared value of 0.76. This indicates that approximately 76% of the total variability of COVID-19 density in Toronto can be explained by the predictor variables, low-income status, visible minority population, recent immigrants, subsidized housing, low education, and unemployment.

Figure 3.8 illustrates the derived standardized residual values obtained from the GWR analysis. The residual map is an indicator of the model performance. It provides additional spatial and nonspatial information about the variation in the dependent variable that cannot be explained by the independent variables. There are seven classes in total with the green indicating the maximum residual values by standard deviation and purple indicating the minimum residual values by standard deviation. This map indicates the census tracts in which the regression model overpredicted or underpredicted COVID density. The areas in green indicate underpredictions where the actual values for COVID density are higher than the model estimated. The areas in purple indicate overpredictions where the actual values for COVID density are lower than the model estimated. The areas in white indicate the locations where the actual values and the values estimated from the model have little to no difference. There is a lot of spatial variability in the outer edges of Toronto in Etobicoke, Scarborough, and North York, while there is almost little to no variability or almost no difference at all in the central regions of Toronto. Areas in Toronto that contained a high concentration of COVID-19 were explained by the predicted variables. These are census tracts in Downtown Toronto, York, and East York where there is a strong correlation between COVID-19 and low-income status, visible minority population, recent immigrants, subsidized housing, low education, and unemployment. Although there are some areas in these regions where COVID-19 was either underpredicted or overpredicted, it is however not as significant as areas in Etobicoke,

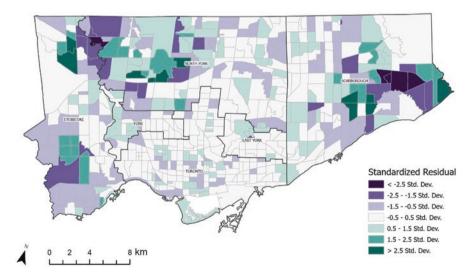


Fig. 3.8 Geographically weighted regression of COVID-19

North York, and Scarborough. These are also areas containing a medium or low concentration of COVID-19 cases.

3.7 Discussion

Understanding the relationship between the spatial pattern of the COVID-19 pandemic and the distribution of Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws in the City of Toronto is increasingly important as the dynamics of the COVID structure continue to change as the pandemic evolves. Although there are many existing literatures on COVID-19 and its impact on the food retail and food service sectors, very few investigate the impact on location and the characteristics of the locations at risk. Therefore, this paper aimed to address these gaps in the literature through spatial analysis techniques to understand the impact of COVID-19 on Starbuck's, McDonald's, Shoppers Drug Mart, and Loblaws locations. The spatial relationships between COVID-19 and business locations in the food retail and food service sectors provide important insights on patterns and connections present in the city as well as into future pandemic-related events. This allows retailers to be prepared for another occurrence because patterns are likely be similar. Additionally, assessing the spatial risk of coffee chains and grocery stores against various socioeconomic characteristics can highlight inequalities that are present within a region and strategies to attract consumers to continue to shop at their location despite the pandemic.

The purpose of this study is to use geospatial analysis techniques to assess the spatial distribution of COVID-19 and its impact on Starbuck's, McDonald's, Shoppers Drug Mart, and Loblaws locations. This study looked to investigate three main objectives. The first objective was to determine clusters of positive COVID-19 cases and analyze the distribution of the four retailers through kernel density and global and local indicators. The second objective was to conduct a cross-comparative analysis to determine retailer locations that were impacted the most by the COVID structure by comparing the movement of the COVID-19 pandemic and the hotspots of Starbuck's, McDonald's, Shoppers Drug Mart, and Loblaws. The third objective was to explore the socio-economic variables of the identified locations at risk.

3.7.1 Key Findings

This study has shown that positive COVID-19 cases are clustered in the Downtown core of the City of Toronto, and the concentration of cases steadily decreases as you move outside the Downtown core. A medium concentration of cases is located in the northern parts of Etobicoke and North York and extends from the downtown core to

Scarborough, along Lake Ontario. The Global and Local Moran's I statistics of the spatial distribution of Starbuck's, McDonald's, Shoppers Drug Mart, and Loblaws locations reveal that Starbucks experiences the most impact from the COVID-19 pandemic in the Downtown core. This is due to its clustered pattern resulting from the Global and Local indicators. Majority of the Starbucks locations across the City of Toronto are in a COVID-19 hotspot with over 50% of its locations located in Downtown Toronto. Although distribution of McDonald's and Shoppers Drug Mart stores demonstrated a random pattern as indicated by the Global Moran's I statistic, almost 30% of McDonald's and Shoppers Drug Mart locations are found in Downtown Toronto. These locations also experience the highest impact as they are also located in a positive cluster of COVID-19 incidences. Loblaws, having the lowest number of locations across Toronto, experiences the same amount of impact on its stores located in the Downtown core. However, the spatial structure of Loblaws is quite random and does not indicate any form of clustering, which this means that this retail chain is the least affected by the COVID-19 pandemic as it has only less than 10% of its stores located in a known hotspot for COVID-19.

The analysis was successful in revealing the locations with the highest concentration of COVID density and the retailers that are impacted the most. It is evident that the affected areas have accrued more impact on retailers instead of areas with less COVID cases. As a result, Starbucks experiences the most impact based on its location in the city, while Loblaws experiences the least impact. It is also important to note that fast casual restaurants (Starbucks and McDonald's) experience a significant decrease in sales as consumers start to buy less coffee during the pandemic. Past research suggested that the pandemic changed the reality of food purchasing. Restaurant purchases have been gradually decreasing. With more time spent at home, consumers spent more time cooking (Ben Hassen et al. 2020), thus reducing out-of-home consumption (Panzone et al. 2021). Additionally, results from the geographically weighted regression of COVID density across the City of Toronto suggest that locations at risk are associated with disadvantaged areas with low socio-economic status. Retailers located in disadvantaged areas are more likely to be impacted by COVID-19 as compared to those in more affluent areas. Particularly, areas with low socio-economic status and having a low education, low income, and low employment rate are at higher risk. However, it is evident that the Downtown core has a diverse socio-economic status as shown by the GWR results. Although there is diversity in economic status in the Downtown region, highly developed, high-density areas are also at-risk locations for businesses as transmission rates are more likely to be high when people are near each other. Therefore, continuing to implement other modes of shopping such as curbside pickup, drive-thru, mobile order, and home delivery services (such as Uber eats or skip the dishes) that require less contact and easy access to their food can allow consumers to continue to purchase from their store.

3.7.2 Contributions

By using spatial analysis techniques, this study produces new knowledge on the locational impact of COVID-19 on retailers in the food retail and food service sectors across the City of Toronto. The use of spatial analysis to assess the spatial risk of COVID-19 on business locations and the socio-economic status of these locations facilitate the monitoring of governmental risk measures to contain the disease and to evaluate their efficiency. This study demonstrates the need to prioritize retailers in COVID-19 hotspots to implement strategies to attract consumers to continue to purchase from their location despite new pandemic-related regulations.

In response to the declaration of public emergency status and the changes in consumer behavior, many actions have been taken by the food service, food retail, and the government to ensure the safety of their consumers. As grocery store demand started rising, grocery store chains and supermarkets hired more employees and also provided additional support to employees by raising wages (Goddard 2020). Grocery store chains have also installed protective plastic shields to protect cashiers and adopted customer management strategies to maintain safe distances between customers. This includes limiting the number of customers in a store, encouraging customers to make payments by cards, and marking distances at which consumers waiting in line should adhere to (Untaru and Han 2021). Food service restaurants have also adopted contactless delivery or pickup options. These extra protective measures taken by grocers and food service have also led to decline in their revenue. Despite COVID-19 lockdowns, reported that Canada's largest grocers saw its revenue rise during the second quarter; however, profits declined due to high pandemic-related costs including employee pay raises. Loblaw Companies Ltd.'s revenue increased in the second quarter of the pandemic to 7.4% compared to last year which is almost \$12 billion. However, the company that owns the Loblaws supermarket chain and Shoppers Drug Mart saw its net earnings drop 29% over the same quarter last year to \$266 million. As reported in the Toronto Star, this was due to pandemic-related costs, which included a one-time incentive of \$25 million for retail and distribution center workers, as well as \$180 million spent on a temporary pay raise for staff. The corporation spent a total of \$282 million on safety measures, including the temporary wage increase (Saba 2020).

3.7.3 Limitations

One of the limitations of this study was data availability. Exact case counts of COVID-19 are not available for Toronto at the CT level. If this information were available, a more in-depth examination of COVID-19 density could be used to strengthen the study's findings. This will also eliminate the limitations of the modifiable areal unit problem (MAUP) because all other data used in this study was collected at the CT level. Therefore, to minimize the amount of distortion in this study,

zonal interpolation was utilized to generate a higher accuracy of data by combining Humanitarian Data Exchange (HDX) data for population density and COVID-19 data at the neighborhood level.

Another limitation was the presence of ecological fallacy. The assumption is made that all retailers existing in a COVID-19 hotspot will experience the same impact. This applies to the inferences that were made based on the spatial comparison of the kernel density estimation of COVID-19 cases and the retail locations. It is not ideal to conclude that all store locations of a retailer in a COVID hotspot are subject to experience the same impact. This is because there are so many other factors that need to be considered, like the retailers' target market. For example, it is not certain that all Starbucks locations present in a COVID hotspot will be affected the same. Some locations will decline, while some will continue to thrive. This will depend on their exact location in the hotspot. If a Starbucks is located near public transit or in a corporate building, they are likely to be visited more than others because of the commuters and corporate workers in the city.

3.7.4 Future Research and Next Steps

While exploratory, this study examines the social and economic determinants of health in locations of risk due to the current pandemic. To further expand on this research, environmental determinants such as air pollution, crime, and violence could be explored as these have been proven to be indicators of at-risk communities due to marginalization from past research. Further investigation with these variables can help draw clear conclusions on the assumed spatial risk of Starbuck's, McDonald's, Shoppers Drug Mart, and Loblaws.

3.8 Conclusion

This preliminary investigation of COVID-19 using kernel density estimation suggests that the spatial distribution of COVID-19 incidences in the City of Toronto is uneven, with a high density of cases present in the Downtown core. Through Global and Local indicators, this study also revealed that the spatial pattern of Starbucks, McDonald's, and Shoppers Drug Mart is spatially clustered in areas with a high concentration of positive COVID-19 cases. Results determine the spatial risk of COVID-19 on business locations, revealing that Starbucks experienced and will continue to experience the most impact from the pandemic due to its spatially clustered infrastructure in the Downtown core. McDonalds and Shoppers Drug Mart experience the second most impact, while Loblaws experiences the least impact due to its random distribution. Results from the geographically weighted regression model indicate a high correlation with COVID-19 and low socio-economic status further allowing for a better understanding of the characteristics associated with the retail locations at risk from COVID-19. Areas of low socio-economic status with low income, low educations, and low employment rates experience the highest number of cases and have the most impact on retailers.

The findings of the present research indicated the critical importance of the spatial risk of COVID-19 and its locational impact on retailers in the food retail and food service sectors across the City of Toronto. While this research study has given an insight into Toronto's food industry, the findings in this research could also be applied within markets beyond Toronto. Through the assessment of Starbucks, McDonald's, Shoppers Drug Mart, and Loblaws, it is vital to note that COVID-19 does not only have an impact on retailers across Toronto but rather a global impact on retailers worldwide. Beyond the current crisis's public health challenges, governments, international agencies, and businesses have all struggled in different ways to respond to this global risk.

As one of the primary interventions to halt the spread of the virus, governments around the world have put restrictions on travel and social activities known as "lock-down measures." Self-isolation, social distancing, curfews, and stay-at-home orders are among the other imposed regulations. While these precautions are necessary to prevent the spread of COVID-19, they have had a substantial negative impact on the global economy and businesses worldwide. As economic concerns and restrictions continue to affect consumers worldwide, new buying and consumption patterns and behaviors have emerged (Untaru and Han 2021). Recent literature revealed that social distancing and lockdown measures have fundamentally changed consumer shopping behavior and consumption. It has been estimated that worldwide e-commerce increased by 20% in 2020 (Avşar 2021). Anticipating the changing consumer preferences and demands has been a major challenge for marketers.

Epidemics have a disproportionate effect on cities. The current pandemic has been met by unequal responses in different countries (Skegg et al. 2021), leading to unequal impacts worldwide. From this present research, it is clear that retailers clustered in COVID-19 hotspots are hit the hardest. As a result, it is possible that in a post-pandemic spatial equilibrium, the agglomeration premium diminishes, and retailers find it less attractive to locate in cities (Koren and Pető 2020). This pandemic has allowed businesses to evolve and learn from the pandemic, providing important insights into future pandemic-related events, allowing retailers to be prepared for another occurrence. Although COVID-19 vaccines are being distributed in a number of countries, this does not mean the pandemic has been resolved. Cases of COVID-19 continue to rise and lockdown measures in some countries are still in place. Such conclusions drawn from this research can provide retailers from different markets around the world to prepare for the longer-term implications and remediate the shorter-term shocks. It is known that COVID-19 has caused the retail industry to change immensely. However, the long-term social, economic, and health impacts of the virus are still unknown. Retailers that are unsuccessful in adapting to the changes caused by the pandemic will suffer. Through this research, it is easy to understand which sectors or retailers need to make strategic adjustments in order to adapt to a rapidly changing marketplace. Retailers will need to implement strategies to attract consumers to continue to shop at their store despite the risk of COVID-19 and its new regulations. It is critical for businesses to keep an eye on potentially high-impact events in the short term as well as the longer-term landscape in order to establish and maintain resilience. This is important for businesses and the global community to navigate the risks and opportunities ahead in a sustainable manner, strengthen their resilience to future shocks, and progress toward long-term prosperity.

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