MOBILITY PATTERNS AT CROSSROADS?

A study focused on the influence of the COVID-19 pandemic on post-lockdown modal usage patterns in Toronto.

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1. INTRODUCTION

Since the COVID-19 pandemic began in early 2020 it has had a profound impact on mobility patterns across the globe. The enforced lockdowns (figures 1.1 & 1.2), social distancing policy and other mitigating measures have fundamentally influenced the way that people move around. While the full extent and duration of these these changes is not yet fully understood (Lee & Eom, 2022), significant changes in mobility patterns have been observed throughout the world (Bert, Schellong, Hagenmaier, Hornstein, Wegscheider & Palme, 2021; Kim, Seo & Choi, 2021). Therefore, due to the abrupt and significant changes observed in mobility patterns worldwide, there is an urgent need for a better understanding. Besides gaining insight into the specific ways that mobility patterns have changed since the start of the pandemic, it is essential to understand the extend and persistence of these changes and what it implies for policymakers and (future) transportation planning.

Located at the epicenter of the field of mobility are travel modes, which facilitate the act of travelling, allowing people to travel from origin to destination (Adey, 2017; Cresswell, 2006; 2010; Urry, 2002). Due to its interwovenness with mobility, scholars have found that most striking changes induced by the pandemic are observed in modal usage patterns (Paul, Chakraborty & Anwari, 2022; Rahman & Thill, 2022). Apart from reductions in total traffic volumes (Liu, Yue & Tchounwou, 2020), studies have observed significant changes in the modal split. Most notably was the decline in public transit, as was found that global public transportation ridership fell by 60 to 90 percent during the first months of the pandemic (Bert et al., 2020). Furthermore, studies indicated that cars were gaining modal share, like the active modes of walking and cycling (Abdullah, Dias, Muley & Shahin, 2020; Ehsani, Michael, Duren, Mui & Porter, 2021; Lee & Eom, 2022; Shaer & Haghsenas, 2021; Van der Drift, Wismans & Olde Kalter, 2021).

Figure 1.1 (left): Unusually empty streets in downtown Toronto during the start of the COVID-19 pandemic (SenicPhoto, 2020).
Figure 1.2 (right): Uncommon sighting of a fox in downtown Toronto during the lockdown (Osorio & Reuters, 2020).

Figure 1.3: A previous car-only street that is now shared with pedestrians and cyclists as part of the Quiet Streets program in Toronto (ActiveTO, 2021).

Since mobility plays such a crucial role in the everyday livelihoods of people and the environment (González, Hidalgo & Barabási, 2008), abrupt events like the COVID-19 pandemic and its ability to induce (short-term) significant changes in modal usage patterns requires continuous research. This served as a source of inspiration for this study to expand upon the (longer term) changes in modal usage patterns due to the COVID-19 pandemic. Therefore, this study analyzed traffic counts of cars, pedestrians and cyclists in Toronto during the pre-pandemic month of March 2019 and post-lockdown month of March 2022. By analyzing the daily modal volumes with daily COVID-19 pandemic related variables and other daily related variables, like weather, population characteristics and road classification, this study will consider how post-lockdown modal usage patterns have changed and what the influence of the COVID-19 pandemic was regarding those changes.

Now that the subject of this study has been briefly introduced, this chapter will further elaborate on the reasons for and relevance of this research (§1.1), which acted as an inspiration for this study's aim and main research question (§1.2). Lastly, the research design (§1.3) will provide insight in the structure of this study.

§1.1 Reason and relevance

Considering that it is likely that the pandemic and its associated global crisis will have a lasting impact on mobility (Chaudhary, Sodani & Das, 2020; Douglas, Katikireddi, Taulbut, McKee & McCartney, 2020), scholars have argued that the COVID-19 pandemic can be seen as a divider of eras, being the pre- and post-pandemic era. Despite the uncertainty about whether the pandemic is currently past its peak and if the changes in mobility it had induced will remain permanent or are short-lived, the need for continuous research remains (Lee & Eom, 2022). Thus, studies examining the potential long-term impact of the COVID-19 pandemic on mobility patterns is relevant to both science and society. This social and scientific relevance exists for four main reasons.

First and foremost, due to mobility playing a crucial role in society, understanding how the pandemic has affected both short and long-term modal usage patterns is paramount for both society and its policymakers. Mobility concernst the movement of people, goods and ideas, changes in volumes and ways that mobility is performed can have significant effects on society as mobility is intertwined with the essential social, economic and environmental spheres of society. Through analyzing and communicating existing changes in modal usage patterns, policymakers can become better informed and equipped to adapt its existing mobility offerings to comply with the changing needs and travel behavior of society (Adey, 2017; Barbosa et al., 2018; Cresswell, 2010; Merriman, 2009; Urry, 2002).

Secondly, most of the previous studies on the influence of COVID-19 on mobility were conducted during the pandemic heyday period (2020-2021), in which lockdowns, teleworking, online education and internet shopping which were commonplace. However, the COVID-19 pandemic will eventually fade away alike previous pandemics have done (Li, Blake & Cooper, 2010; Novelli, Gussing Burgess, Jones & Ritchie, 2018). Thus, studies are needed during times in which the COVID-19 pandemic has passed its peak (Ehsani et al, 2021).

Thirdly, the emergence of the Omicron coronavirus variant around the 2021-2022 turn of the year has led to a new phase in the COVID-19 pandemic. The rise of Omicron has thus allowed for a new phase of analysis on changing modal usage patterns as less restrictions on mobility meant that more people are going to be travelling than before in the pandemic (Daria & Islam, 2022, Taylor, 2022; Wang & Han, 2022). This provides the opportunity to study post-lockdown modal usage patterns and compare these with pre-pandemic periods.

Fourthly, the last reason stressing the need for analysis of modal usage patterns considers the methodological approach of as most of the preceding research on modal volumes and changes during the COVID-19 pandemic has utilized qualitative methods like web-surveys to (Abdullah et al., 2020; Borkowski, Jazdzewska-Gutta & Szmelter-Jarosz, Ehsani et al., 2021; Rahman & Thill, 2022). However, qualitative methodologies like questionnaires only contain a time- and context sensitive snapshot of the attitudes towards mobility and travel modes, not the actual travel behavior itself. Thus, *'…it is certainly possible that the actual behaviour of the respondents differs from their anticipated behaviours'* (Loa et al., 2021, p. 81). Therefore, a quantitative approach of actual counts of travel modes is more suited to study changes in modal usage patterns as it depicts the actual conducted travel behavior. While most of the current available studies have approached this subject in a qualitive way, there is a strong scientific relevance in this study as it utilizes quantitative traffic count data to observe changing modal usage patterns.

§1.2 Aim & main research question

Stemming from the reason and relevance of this study, this research wishes to contribute to a relatively small, but growing, amount of research and literature on modal usage patterns during times of less mitigating measures. Because of the recentness of the studied phenomenon at the time of research, being to study modal usage patterns when Omicron became the dominant coronavirus strain in early 2022, mobility data is scarce (Lee & Eom, 2022; Zhao et al., 2020) as many traffic agencies, governmental organizations and other mobility actors have not yet published adequate, recent and open-source data. Therefore, the number of current available studies examining post-lockdown modal usage patterns is limited – once more highlighting the scientific gap and relevance of this study. Nevertheless, despite the existing difficulties, this study is motivated to fulfill its aim being:

> *To provide insight in how the COVID-19 pandemic changed modal usage patterns in the post-lockdown era.*

To achieve this goal, the City of Toronto, Canada, was elected as study area. Toronto was chosen as it proved to be an exception for the existing data scarcity, as it was able to provide adequate traffic count data for March 2022. Hence, Toronto's modal usage patterns will be analyzed in this study. More specifically, the traffic counts of cars, pedestrians and cyclists in the pre-pandemic month of March 2019 will be compared with the post-lockdown month of March 2022.

Based upon literature (see §2.4.1 - §2.4.2), this study analyzes the impact of COVID-19 through government intervention in the form of policy strictness and through the public reaction towards the daily confirmed COVID-19 cases. Furthermore, once again based on literature (see §2.4.3 - §2.4.4), other related variables like weather, population characteristics, and road classification are included as well. In accordance with the aim of this study and the study area of Toronto, this has led to the formulation of the following main research question:

> *How did COVID-19 daily confirmed cases and policy strictness influence the modal volumes of cars, pedestrians and cyclists in Toronto during the post-lockdown period?*

By answering the main research question, this study intends to fill the gap in current literature as it is one of the first to examine modal usage patterns in the post-lockdown context. In doing so, this study will contribute to the understanding of the longer-term impacts of the COVID-19 pandemic on modal usage patterns.

§1.3 Research design

Now the reasons, relevancies, aim and main research question have been discussed, this section will provide insight on the structure of this study. After this chapter, the second chapter will elaborate on the theoretical foundation of this research in such a way that it provides a theoretically grounded backbone which will grant guidance for the subsequent phases of the research. Thereafter, the methodology (chapter 3) will disclose the specific approach of the research after which the fourth chapter will discuss the results of the conducted analysis. In the conclusion (chapter 5), the analysis results will be interpreted so that it is able to answer the main research question. Lastly, in the discussion (chapter 6) the results of this study will be put in perspective towards other literature and studies. Additionally, the discussion will consider study implications, reflections and limitations after which this study finalizes by providing recommendations for future research

2 - THEORATICAL FRAMEWORK

In this chapter the theoretical foundation upon which this research stands and will build further from will be discussed. This section will focus on relevant theories and literature that previously examined the influence of COVID-19 on mobility and, more specifically, on modal usage. In doing so, this chapter will provide a theoretical backbone to this study which will provide guidance for subsequent phases of this research.

§2.1 Relation between infectious diseases & travel mobility

During the first months of 2020, the entire world found itself at the dawning of a period of unprecedented challenges on an equal unprecedented scale. For the first time since the 1918-1920 influenza pandemic (Spanish flu), the emergence of the SARS-CoV-2 virus responsible for inducing the disease of COVID-19 positioned the global population with the biggest health crisis in a century. The COVID-19 pandemic proved once again, like previous infectiousness diseases, that its success depends strongly on travel mobility for several reasons. First, the virus itself should be mobile enough so that it can successfully infect other individuals while individual travel mobility is strongly related to the spread of infectious diseases (Creswell, 2021). Higher travel intensity increases the likelihood of successful transmission as the more trips are conducted, the more chance an infected traveler has for infecting others on its trip. Furthermore, the popularity and crowdedness of certain trip origins, destinations or travel modes increase spread as well: busy places and travel modes contain more possibilities for transmission (Alsaeedy & Chong, 2020). Besides the fact that the act of travelling provides opportunities for virus spread by itself, travelling is the action that both precedes and facilitates the physical-social interaction of people. These close-contact meetings provide the best opportunity for infectious diseases to spread as most transmissions occur when people are closely interacting. The more intimate and longer the nature of this interaction is, the more likely the possibility of contagion (Alessandretti, 2021; Giles et al., 2020).

Although health care systems have significantly improved over the last century, the continuous process of globalization have made the world a more connected place. This was particularly important for the COVID-19 pandemic, as the extensive 21st century aviation system provided opportunities for long-distance and cross border spread (Lau et al., 2020). Furthermore, the world during the COVID-19 pandemic contains more people and is more urbanized than during previous pandemics. This fosters virus spread through travel mobility due to more people being located more closely to one another (Rocklöv & Sjödin, 2020).

Considering all this, in a more densely populated world which is more closely and intensely connected as opposed to previous pandemics, SARS-CoV-2 could spread on an unprecedented pace, scope and scale (Da Silva Corrêa & Perl, 2022; Shrestha et al., 2020; Sigler et al., 2021; Zimmerman, Karabulut, Bilgin & Doker, 2020). Given the existence of a general scientific agreement over the fact that the COVID-19 pandemic will have a lasting and unprecedented impact on travel mobility (Kim, Seo & Choi, 2021), inspires this study to further assess these impacts and its components theoretically, in this chapter and empirically in the following chapters.

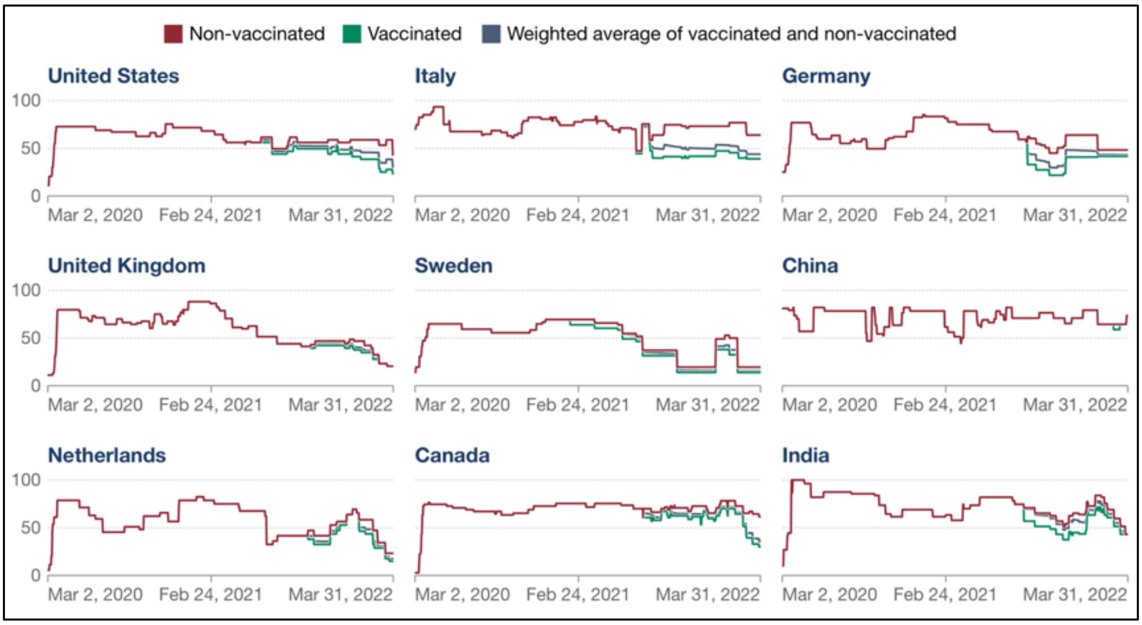
§2.2 Governmental intervention against the spread of COVID-19 through mobility restrictions

During the first months of 2020, governments throughout the world realized that COVID-19 was becoming a global pandemic and required intervention. Policymakers wanted to protect public health, safeguard the capacity, access and quality of health care systems while harmful social and economic policy side-effects were limited as much as possible. Thus, the incentive for limiting travel mobility arised as global lawmakers knew that by restricting travel movements the spread of COVID-19 could be offset partially (Awad-Núñez, Julio, Gomez, Moya-Gómez & González, 2021; Jenelius & Cebecauer, 2020; Shaer & Haghshenas, 2021).

The mitigating measures that were undertaken by policymakers differed between countries and varied over time. The Oxford Coronavirus Government Response Tracker (Hale et al., 2021) was created to assess national differences in stringency. This index calculates a value between 0 and 100 and is a composite measure of nine policy response metrics related to containment and closure, economic response, health systems and other responses. The most influential metrics for travel mobility are the closures of educational facilities, workplaces and public transport, the cancelation of public events, imposing restrictions on gathering size, internal movement and international travel and stay-at-home requirements. These metrics all relate to a more direct top-down decision-making by policymakers while a more indirect approach through financial support and public information campaigns was also utilized (Askitas, Tatsiramos & Verheyden, 2021).

In figure 2.1 below, the stringency index for several countries is visualized and it demonstrates the differences between national policies over time and, after the start of vaccination campaigns, over individual vaccination status. For example, countries like Sweden and the Netherlands generally imposed less strict policy than China and India and discriminated less on vaccination status than countries like Italy and Canada. In most countries the policy strictness follows the same dynamics as infection rates: a surge in COVID-19 cases most likely leads to stricter mitigating policy.

Figure 2.1: COVID-19 policy strictness index in different countries between March 2, 2020 and March 31, 2022 (Hale et al., 2021).



Due to variety in measures, time of implementation and enforcement strictness, the effect of individual measures has been a point of interest for scholars investigating the effect of single policy actions on the COVID-19 pandemic and the travel behavior of people. Despite the scientific interest and relevance regarding the individual effect of mitigating measures, the disentanglement of sole measures from the conglomerate of COVID-19 mitigating policy has proven to be difficult. The isolation a of individual measure is problematic, as mostly a single measure is implemented in combination with other measures or introduced in swift succession (International Monetary Fund, 2020; Parady, Taniguchi & Tagami, 2020). For instance, measures like closing schools and workplaces and restricting social events and group size have a negative effect on travel intensity regardless of the existence of policy specifically aiming to reduce the movement of people (Hörcher, Singh & Graham, 2021).

One of the few studies that attempted to isolate individual policy measure effectiveness was conducted by Askitas et al. (2021). In their study, daily COVID-19 incidences and mobility pattern data from 175 countries was used to disentangle individual measures while accounting for differences in timing and intensity of mitigating measures. The data was controlled for the influence of coexisting interventions which provided evidence that mitigating policy should be assessed in its entirety. It was argued that ignoring parallel measures can lead to biased predictions of effectiveness of individual measures. Their results suggests that the cancellation of large-scale public events, restrictions on group size and the closures of schools and workplaces are the most effective mitigating measures as these four interventions induced the greatest, statistically significant, drops in COVID-19 rates. Other policies such as stay-at-home requirements and international travel restrictions found to be either decelerating COVID-19 incidence growth or solely providing a brief beneficial effect in the beginning of the pandemic respectively. Regarding the mobility interventions of internal movement restrictions and shutdowns of public transportation, Askitas et al., (2021) argue that these measures did not lead to a significant decrease in COVID-19 incidences.

This contradicts other studies that state that limiting travel is an effective tool to limit the spread of infectious diseases, like COVID-19 (Awad-Núñez et al., 2021; Jenelius & Cebecauer, 2020; Shaer & Haghshenas, 2021). However, Askitas et al., 2021 (p. 11) argue that their results not necessarily show that mobility limitations are ineffective as it highlights more extensively that the time of implementation of certain policies matters more. The results rather suggest that when policies like closures of schools and workplaces, restrictions on social gatherings and cancellations of public events are imposed previously, mobility limitations are less effective as most of the raison d'être of the act of travelling has disappeared. Since the four most effective measures were mostly earlier implemented, there simply are not enough travelers left as these interventions generate most of internal mobility movements and public transport usage. The people that still want to travel are then of insufficient quantity and density to significantly increase the probability of infection among travelers. Thus, restricting travel movement and PT usage is less successful in mitigating the impact of COVID-19 as the four most influential interventions generate a spillover effect on travel mobility, through reducing the purpose and motivations of travel.

Other studies assessing individual effectiveness of mobility limitations on COVID-19 have found that stay-at-home policy was the most effective in decreasing COVID-19 incidences. However, remarks are made that the support and obedience for this measure declines over time. Consequently, other non-mobility-oriented measures like public information campaigns can, on the long run, overtake mobility limitations as the most effective mitigating measure (Courtemanche, Garuccio, Le, Pinkston & Yelowitz, 2020; Li et al., 2021). However, Shortall, Mouter and Van Wee (2022) argue that it is the specific composition of total policy that together influences both mobility and COVID-19 rather than (partly) assigning the effect to an individual measure. As a rule of thumb, the stricter the combination of mitigating measures, the more effective the total policy is in mitigating the harmful effects of the COVID-19 pandemic as more policy strictness leads to more public compliance (Hussain, 2020).

§2.3 Public reaction towards the COVID-19 pandemic through travel mobility

Even though governmental intervention did indeed prove to be influential in changing the (travel) behavior and attitudes of the public, solely assessing the top-down decision-making as catalysator for behavioral change would be to narrow. Aside from adapting, reacting and complying towards imposed mitigating policy from policymakers, the public is an actor on its own - capable of receiving, processing and adjusting their actions. Previous unfortunate events, like the 9/11 terrorist attacks and the 2002-2004 SARS-CoV-1 outbreak, have proven that the public adapts its travel behavior after these events had occurred (Hall, 2002). Thus, apart from behavioral changes being mandated through governmental intervention, the public takes self-initiated actions based upon information that they have gathered through media and social interaction. These public reactions can range from avoiding certain areas (Meloni et al., 2011), switching travel modes (Zafri, Khan, Jamal & Amal, 2022), changes in trip destinations (Van der Drift et al., 2021) and not travelling at all (De Vos, 2020).

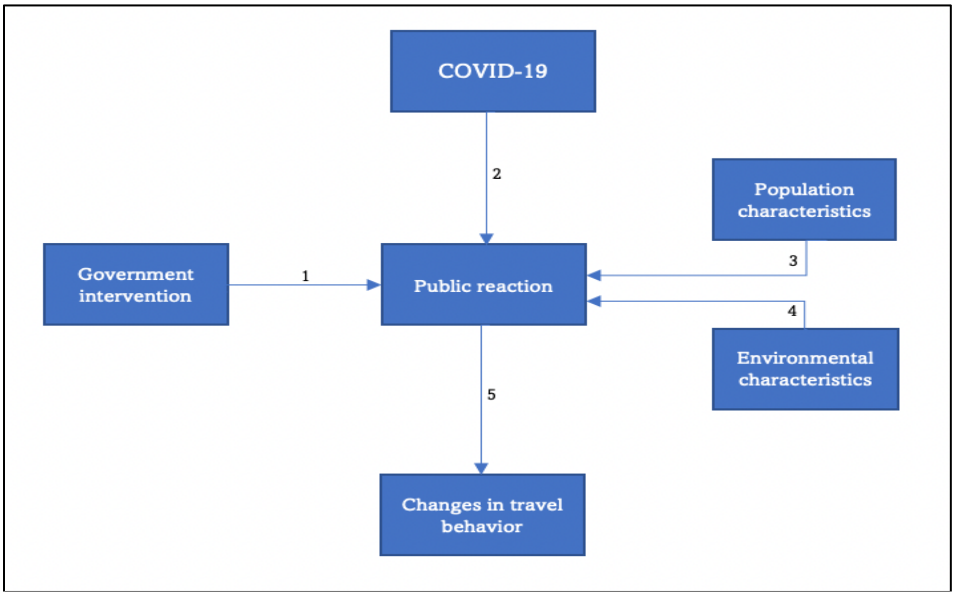
Being the core component that determines self-initiated changes in travel mobility behavior, Neuburger & Egger (2021, p. 1006) argue that *'… it is crucial to understand the relationship between risk perception and travel behavior'*. Risk perception refers to the individual interpretation of hazardous situations and is dependent on severity and characteristics of the perceived danger. As risk perception of individuals is formed on the individual level, risk assessments vary among people, this leads to differences in behavioral adaptations (Moreira, 2008; Sjöberg, Moen & Rundmo, 2004). Regarding the risk perception of infectious diseases like COVID-19, Floyd, Prentice-Dunn and Rogers (2000) argue the perceived danger is based upon the individual impression of the *susceptibleness* and *severity* of the virus. In this case, susceptibility concerns the perception of the likelihood of infection while severity refers to perceived impacts of the disease on health and well-being (Brewer, Chapman, Gibbons, Gerrard, McCaul & Weinstein, 2007). Yue, Lau, Chan and Ng (2021) and Harper, Satchell, Fido and Latzman (2020) name the rule that the more the public perceives COVID-19 as threatening, the more likely the public is to react and adapt its travel behavior towards it.

Additionally, scholars have found that media coverage on pandemics have increased the risk perception of public (Beirman, 2003; Wahlberg & Sjöberg, 2000), including perceived risk for the act of travelling (Hall, 2002; Meloni et al., 2011). Given the extensive media attention that the emerging and ongoing pandemic had received since it had commenced, one could expect that this had enhanced the risk perception on COVID-19 which, subsequently, triggers the public to change its travel behavior (Neuburger & Egger, 2021). Despite McKercher & Chon (2004) argue that the risk perception of travel during pandemics is not solely depended upon individual judgements since it is predominantly galvanized through the media and sentiment of the public, most scholars argue that policymakers have had the most influence on the public reaction towards the pandemic (Abulibdeh & Mansour, 2021; De Haas, Faber & Hamersma, 2020; Ferguson et al., 2020; Kraemer et al., 2020; Oka, Wei & Zhu, 2021). According to Yue et al. (2021), the reason for policymakers being the most influential in travel behavior of the public originates from the fact that the policymakers, through imposing mitigating measures, information campaigns and press conferences, have increased public compliance to these (mobility) mitigating measures as it both increases awareness and risk perception of COVID-19. Thus, the role of the policymakers and their mobility restricting measures are most decisive in changing the travel behavior of individuals.

§2.4 Theoretical changes in travel mobility patterns since the COVID-19 pandemic

Now both the policymakers and the public perspective on COVID-19 and travel behavior have been discussed in the previous two paragraphs, this paragraph will concern the theoretical changes in travel behavior itself due to COVID-19. To allow for better understanding of the underlying processes, figure 2.2 was created to provide conceptual insight in the direct and indirect interaction of relevant actors and factors with the COVID-19 pandemic and changes in travel behavior.

Figure 2.2: Conceptual framework of the process through which the COVID-19 pandemic induced changes in travel behavior.



§2.4.1 Government intervention

Starting with government intervention, which was directly influenced by COVID-19 as the ongoing and evolving pandemic situation required adequate adaptations in mitigating policy to offset potential negative consequences. When COVID-19 cases where either rising or already at a high level, policymakers were likely to impose mitigating policy to protect public health and health care capacity. On the other hand, when cases were declining or at a low-risk level, policymakers adjusted their mitigating policy by making it less strict. Apart from reacting towards the ongoing pandemic situation, scholars have suggested that the extensive media attention and the public sentiment also influenced the policy strictness: ranging from pressurizing policymakers to either lift or enhance the stringency of the mitigating measures (Apriliyanti, Utomo & Purwanto, 2021; Chakraborty, 2020; Malecki, Keating & Safdar, 2021; Nguyen & Nguyen, 2020; Robinson 1999; 2000; 2001; 2002; 2005; Yue et al., 2021). As was discussed in §2.2, mobility limitations were conceived as an effective tool by lawmakers who were intended to protect against the threats of the pandemic. Therefore, governments, dependent on the current pandemic situation, either restricted or lifted restrictions *(line 1)* which were influencing public travel behavior and its motivations (Askitas et al., 2021; Awad-Núñez et al., 2021; Jenelius & Cebecauer, 2020; Shaer & Haghshenas, 2021).

§2.4.2 Public reaction

Located at the center of the conceptual framework are the public and its reaction which was influenced in fourfold: by the COVID-19 pandemic, its associated mitigating policy and by population and environmental characteristics. First, COVID-19 was influential as people reacted and adjusted their behavior dependent on the ongoing pandemic situation *(line 2)*. The extensive media coverage on the pandemic, most notably are the news reports on the daily number of confirmed COVID-19 cases, was important in influencing the public reaction (Tsoy, Tirasawasdichai & Kurpayanidi, 2021). Second, the public reaction was influenced by government intervention *(line 1)* as the policy strictness determined both the access to travel modes and motivations for travelling. Furthermore, the stringency provided the public insight and guidance for understanding the severity of the pandemic situation which can lead to self-initiated changes in travel behavior (Harper et al., 2020; Yue et al., 2021). When the individual consideration of COVID-19 and government intervention are compared, scholars have argued that government intervention had a higher impact than the reaction of the public due to policies' capabilities to directly influence behavior, in this case the act of travelling (Askitas et al., 2021; Ferguson et al., 2020; Hussain, 2020; Rahman & Thill, 2022; Wang, Ge, Huang, 2022).

§2.4.3 Population characteristics

Apart from COVID-19 and its associated policy measures, characteristics of the public themselves are of importance for travel behavior as it influences the public and its reaction *(line 3)*. Population characteristics are decisive as travel behavior consist of choices made on the individual level (Scheiner, 2010; 2018). The first population characteristic is population density. Density could potentially influence modal usage patterns as previous studies have argued that high density areas typically contain less high-speed modes, higher volumes of active modes and more overall traffic intensity (Schafer & Victor, 2000; Buehler, 2011; Liu & Lam, 2014). The second influential population characteristic is sex, for scholars have argued that females are related to less work-related travel, less usage of active modes and less travel intensity overall (Ehlert & Wedemeier, 2022; Meurs & Haaijer, 2001; Muñoz, Monzon & Daziano, 2016). Thirdly, the population characteristic of age has shown in previous studies that it significantly affects travel behavior, particularly the modal usage. In general, scholars have argued that younger people use more active modes while older people use the car more often (Figueroa, Nielsen & Siren, 2014; Ha, Lee & Ko, 2020). Lastly, the fourth population characteristic is income as it affects overall travel ability through the selection and usage of travel modes. Typically, areas with a higher average income have higher rates of car-ownership resulting in higher modal shares for cars but lower shares for active modes (Schafer & Victor, 2000; Meurs & Haaijer, 2001; Papagiannakis, Baraklianos & Spyridonidou, 2018; Pucher & Renne, 2005).

§2.4.4 Environmental characteristics
The fourth and last factor influencing the public reaction concerns the characteristics of the environment in which the public lives and conducts travel *(line 4)*. First, climatological conditions are of importance as it determines travel mode choices (Thøgersen, 2006). Weather is most desicive for active modal usage, as previous studies suggested that lower temperature, more precipitation and higher windspeed is associated with less pedestrian and cyclist volumes (Böcker, Dijst & Faber, 2016; Ton, Duives, Cats, Hoogendoorn-Lanser & Hoogendoorn, 2019). Furthermore, the specific road classification is of importance. Scholars have argued that higher classed roadways contain more lanes, have higher speed limits and more traffic intensity as opposed to more local roads. As a result, more local roads contain a higher share of active travel modes (Schepers & Heinen, 2013; Winters, Terschke, Grant, Setton & Brauer, 2010).

§2.4.5 Changes in travel behavior
Now the influence of COVID-19, government intervention, population characteristics and environmental characteristics on the public and its reaction have been explained, the actual changes in travel behavior forms the concluding piece of the conceptual framework *(line 5)*. It is there where the focal point of this study lies: to understand if and how COVID-19 influenced travel behavior. In general, scholars have argued that overall travel intensity has decreased in comparison to pre-pandemic levels. The most striking changes when comparing pre-pandemic travel behavior with pandemic levels are witnessed in modal usage patterns, as Rahman & Thill (2022) have argued. The following paragraph (§2.5) will further elaborate on the actual changes scholars have witnessed in travel modes when pre-pandemic and pandemic modal usage patterns are compared.

§2.5 Actual changes in modal usage patterns since the COVID-19 pandemic
Now the process leading to travel change has been theoretically examined above, the actual changes in travel mobility needs to be discussed. First and foremost, if and by how much travel behavior will change differs from time to time and from place to place. As a result, generalizing these changes is troublesome as most studies focus on a single area for analysis. However, Rahman & Thill (2022) argue that the most striking changes are found in modal usage patterns regardless of the specific study area. Most notably change after COVID-19 pandemic had commenced was found for private modal usage which increased as opposed to non-private modes, like public transit or shared mobility options. This means that more people are driving a private car or are either walking or cycling – as was the case in a study by the Boston Consulting Group (Bert et al., 2021). During this study five thousand people in urban areas in the United States, Europe and China during April 2020 were examined. The results showed that, during lockdowns, modal intensity dropped across almost all modes. The most significant drop being in public transit as it dropped at least 60 percent when compared to pre-pandemic levels. Private vehicle usage, although it had dropped in intensity, depicted less significant decreases in modal usage in both the United States and China (between -21% to -59%) but remained significant in Europe with a drop of at least 60 percent. The most striking change was found in the modal usage of private bikes, e-scooters and walking as it increased by 21 to 59 percent in all three regions. Furthermore, the United States and China also depicted more usage of bike sharing options.

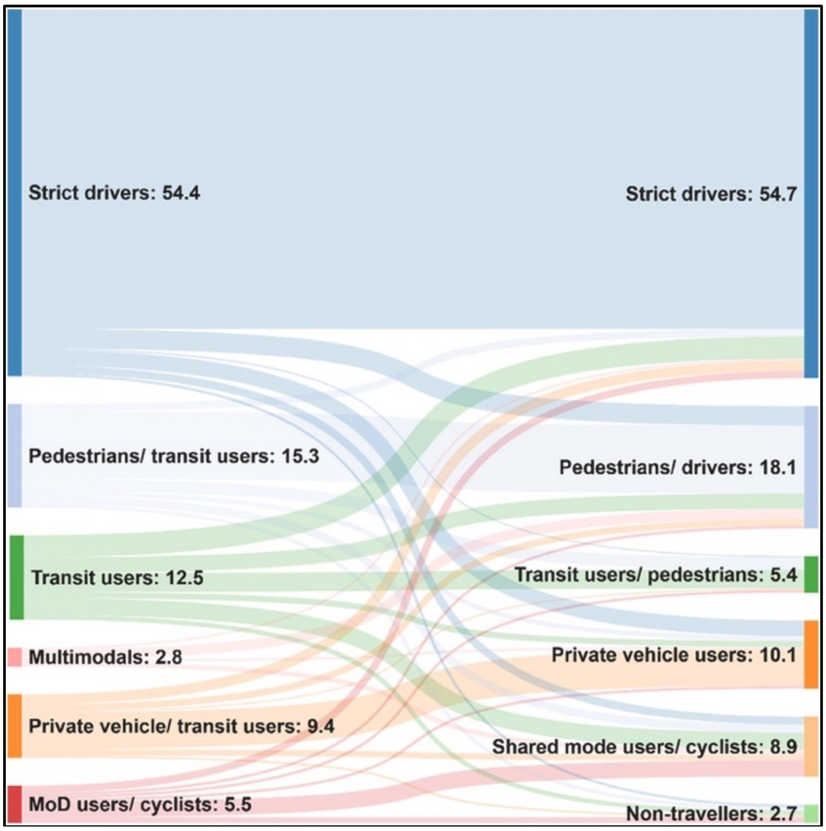
In a Toronto based study the impact of the pandemic on modal usage for non-mandatory trips was investigated (Loa et al, 2021). These non-mandatory trips can be divided in twofold: maintenance and discretionary activities (Castiglione, Bradley & Gliebe, 2014). The first activity being focused upon satisfying basic needs, like buying groceries and visiting medical facilities for healthcare, while the latter activity has fulfilling psychological needs at the focal point, including social interaction and recreation (Chen & Mokhtarian, 2006; Dharmowijoyo, Susilo & Karlström, 2018). As the pandemic influenced modal choice for voluntary purposes, Loa et al. (2021) studied how exactly the modal split has changed among inhabitants of the Greater Toronto Area by focusing on transitions between pre-pandemic and pandemic levels of modal usage. Figure 2.3 provides an overview of the results of the pre-pandemic and pandemic comparison of modality profiles – meaning the mode or combination of modes used by an individual for non-mandatory activities.

Figure 2.3: Pandemic modality profile probability based upon pre-pandemic modality profile in Greater Toronto Area in July 2020 (Loa et al., 2021, p. 83).

Pre-pandemic Modality Profile	**Pandemic Modality Profile**					
	Strict drivers	*Pedestrians/drivers*	*Private vehicle users*	*Shared mode users/cyclists*	*Transit users/pedestrians*	*Non-travellers*
Strict drivers	87.1%	5.4%	4.2%	2.2%	0.3%	0.8%
Pedestrians/transit users	7.2%	65.2%	4.8%	7.9%	11.6%	3.2%
Transit users	26.5%	18.7%	7.3%	19.9%	22.1%	5.5%
Private vehicle/transit users	15.8%	10.4%	58.7%	9.5%	2.2%	3.4%
Mobility-on-Demand users/cyclists	20.7%	6.4%	7.8%	43.3%	7.6%	14.2%
Multimodals	10.9%	51.4%	11.8%	24.4%	1.5%	0.0%

In table 2.3, it becomes clear that pre-pandemic modality profiles including the use of public transit have transitioned most notably to car-oriented pandemic modality profiles. For instance, of all individuals having a pre-pandemic modality profile of transit users, most (26.5%) have shifted to solely driving while the other two car-oriented pandemic modality profiles, pedestrians/drivers (18.7%) and private vehicle users (7.3%), also increased. This means that around 52.5 percent of previous transit users have, at least partially, shifted to cars. The same pattern is found within other transit included pre-pandemic modality profiles, as both pedestrians/transit users (77.2%) and private vehicle/transit users (84.9%) predominantly transitioned to pandemic modality profiles including car usage. This indicates that individuals using cars before the pandemic continue to do so during the pandemic while cars are also becoming a more popular mode for individuals with pre-pandemic modality profiles which involved less or no modal usage of cars – a transition visible in figure 2.4.

Figure 2.4: Relative transitions in modal share percentages from pre-pandemic (left) and pandemic (right) modality profiles in Greater Toronto Area in July 2020 (Loa et al., 2021, p. 80).



Car-oriented pandemic modality profiles where not alone in gaining modal share as active modes of travelling, as is visible in figure 2.4, also gained ground in the modal split. Regarding active modality profiles, the modal split for walking (+8.2%) and cycling (+3.4%) increased, as the July 2020 modal share increased from a pre-pandemic 15.3 to 23.5 percent and from 5.5 to 8.9 percent respectively. This increased popularity of active modes can, to some degree, be attributed to pre-pandemic transit users transitioning towards the pandemic modality profiles of pedestrian/drivers (18.7%), shared mode users/cyclists (19.9%) and transit users/pedestrians (22.1%). This means that over 60 percent of pre-pandemic transit users have transitioned to pandemic modality profiles which includes active modes. Loa et al. (2021) conclude and summarize their study results on changing modal usage patterns during the pandemic as follows:

> *Aside from the reduced prominence of public transit and increased prominence of private vehicles, the transition analysis suggests that active modes are playing a more prominent role in pandemic modality profiles than they did prior to the pandemic.*
>
> Loa et al. (2021, p. 81)

Paul et al. (2022) found similarity in modal usage change due to COVID-19. Their literature review of over 50 academic sources showed a similar shift to private modes and increased active modal usage. Additionally, the pre-existing mobility and modal usage patterns before the pandemic is of importance. In general, car-centric cities with a deeply rooted automobile rationality, displayed roughly stable and resilient modal splits: the modal usage of cars quickly returned to pre-pandemic levels and where only temporarily affected by the pandemic. Furthermore, in cities that contain more diverse multimodal mobility options, residents tend to avoid the use of non-private mobility options for shorter durations and less pronounced than in cities containing fewer modal options. In places where the mobility culture was evolving or was on the verge in doing so, the disruption of modal usage patterns made the COVID-19 pandemic a window of opportunity in which the pandemic was a catalysator for further or quicker change. This was specifically the case for cities who wanted to encourage active modes (Greene, Ellsworth-Krebs, Volden, Fox & Anantharaman, 2022).

However, much of the current available research provides solely insight on the short-term effects on modal usage, mostly during periods which were strongly influenced by the ongoing pandemic situation which, at that time, was perceived more seriously and threatening than during subsequent waves in latter stages of the pandemic. Despite the rarity of research studying the long-term effects on modal usage, the expectation exists that the increases in modal usage of private cars and active modes could continue after COVID-19 becomes less of a threat (Bert et al., 2021). This view is supported by studies that either predicted (De Vos, 2020) or provided results (Abdullah et al., 2020; Ehsani et al., 2021; Lee & Eom, 2022; Shaer & Haghsenas, 2021; Van der Drift et al., 2021) depicting the same dynamics of increased usage of private and active modes of travel at the cost of non-private modal options.

§2.6 Travel mobility after the COVID-19 pandemic

With most western countries lifting restrictions in early 2022 due to the Omicron variant, which had proved to be less threatening than its predecessors (Daria & Islam, 2022; Wang & Han, 2022), scholars increasingly started to think, make predictions and study travel mobility in times less affected by the ongoing pandemic situation. As travel mobility is less restricted overall, the modal usage patterns can be studied for analyzing whether modal usage will rebound to the pre-pandemic situation, continue to be the roughly the same as during the pandemic or if it had changed permanently (Lee & Eom, 2022).

Even though previous crises have shown that travel mobility can recover, and sometimes surpass, pre-crises levels (Hall, 2002; Li et al., 2010; Novelli et al., 2018), there currently is no scientific consensus on whether this will be the case for the COVID-19 pandemic. Nonetheless, there is general agreement over the fact that the COVID-19 pandemic had an unprecedented impact on travel mobility (Kim et al., 2021).

However, there are opposing views regarding the temporal extend and severity of this impact. In general, scholars have either not ruled or are supportive of the idea that the pandemic induced significant changes in mobility that will endure on the long run (Das, Boruah, Banerjee, Raoniar, Nama & Maurya, 2021; De Haas et al., 2020; Griffiths, Del Rio & Sovacool, 2021; Kellerman, 2022; Zhang, Hayashi & Frank, 2021).

Loa et al., (2021) describes and explains both perspectives on the persistence of the pandemic induced changes as follows:

> *On the one hand, a global pandemic is certainly significant enough to bring about long-term changes (…) Such a change would likely lead to an increased preference for individual modes and a reduced propensity for using public transit. On the other hand, given that the pandemic is effectively an external shock, the cessation of the pandemic could result in people returning to their pre-pandemic modality profile.*
>
> Loa et al. (2021, p 81)

Currently, as of late 2022, it is too soon to conclude whether the pandemic period can be understood as a divider of eras, where significant differences exist between pre-pandemic and post-pandemic periods. Hence, scholars are accentuating the need for continuous research on similarities and dissimilarities between pre- and post-pandemic eras (Lee & Eom, 2022). Most notably, studies should be conducted over longer time periods and during times that are less affected by both COVID-19 and its associated measures (De Haas et al., 2020). Until now, most studies focusing on this subject have been conducted during times in which both mobility and peoples' livelihoods are severely influenced by the pandemic, for example during the pandemic heyday years of 2020 and 2021. Borkowski et al. (2021) provide three research areas on which (future) COVID-19 and its influence on mobility should be assessed. First, studies should not focus solely on the short-term shock effects as it should focus more on implications on the long-term. Second, comparative studies should be conducted to compare changes over different geographical locations, although Zhao et al. (2020) and Lee & Eom (2022) have mentioned data availability, quality and limitations to be a factor of concern that needs to be addressed to allow for future adequate comparative studies. Thirdly, lastly and most importantly, Borkowski et al. (2021) emphasize the need for continuous analysis due to the evolving nature of the pandemic and the reaction of both policy makers and the public towards it.

All this taken into consideration, one can conclude that the COVID-19 pandemic has induced significant changes in modal usage patterns as non-active private modes of cars and active private modes of walking and cycling has gained modal share, most significantly from pre-pandemic transit users. Given the fact that these changes in modal usage patterns can pose both challenging problems and opportunities, continuous research on changing mobility patterns as a reaction to the evolving pandemic situation is necessary (Loa et al., 2021). In doing so, policymakers will be made aware of the COVID-19 induced permanent changes in mobility and its associated problems and opportunities it upholds.

Although it is perhaps too early to say that the post-pandemic era has begun (Lee & Eom, 2022), the rise of the less threatening COVID-19 variant Omicron in early 2022 has allowed policymakers and the public, for the first time in two years, to make mobility choices less impeded by the pandemic (Daria & Islam, 2022; Kim et al., 2021; Taylor, 2022; Wang & Han, 2022). This provides the first opportunity to analyze possible existing mobility pattern changes on the long-term in the post-lockdown era, in which the COVID-19 pandemic played a less significant and restricting role. Therefore, this study will aid policymakers in gaining insight in how modal usage patterns have evolved between pre-pandemic and post-pandemic periods - which will make policymakers better equipped to adjust mobility policy to the needs, challenges and opportunities of the future post-pandemic era.

3. METHODOLOGY

In the third chapter of this study, the methodology used for the analysis will be presented. First, the selection of Toronto as location for analysis will be justified followed by relevant contextual information of the study area. Thenceforth, the included dependent and independent variables will be explained after which the selected method of the negative binomial regression will be justified followed by assumption testing. Following this is the formulation of hypotheses after which the research quality assessment will expound upon the validity, suitability and reliability of this study. Lastly, the analysis protocol will clarify the operationalization for analysis. In doing so, this methodological chapter will present an overview over the approach for analysis.

§3.1 Study location selection: *Toronto*

Since it is the aim of this study to analyze the influence of COVID-19 on modal usage patterns, it is important to understand why this research was conducted in the city of Toronto. First and foremost, this selection is based upon data availability which had proved to be challenging when this study was extensively searching for appropriate and suitable data sources during Spring 2022. During the period of orienting on potential databases, this study has followed and studied open-data sources of 35 global cities (see appendix 3.1 for list of cities). Toronto was the only city which had publicly accessible, adequate and up-to-date databases on traffic volumes, including traffic intensity per travel mode. This is particularly important as the rise of the Omicron coronavirus variant around the 2021-2022 turn of the year allowed policymakers to adapt their mitigating policy by making it less strict (Daria & Islam, 2022; Taylor, 2022; Wang & Han, 2022). Since many studies have been conducted during the pandemic peak years of 2020 and 2021, the fact that Toronto's database is more up to date than others makes this the most suitable option for investigation as mobility was less restricted than in previous years. Therefore, March 2019 and March 2022 were selected for the study time frame because the latter month was the most recent month which contained sufficient data.

§3.2 Study context

For it is important to always interpret study results within its contextual environment, this paragraph will briefly provide an overview of relevant information regarding demographics, traffic & mobility, climate & the COVID-19 pandemic.

§3.2.1 Toronto demographics

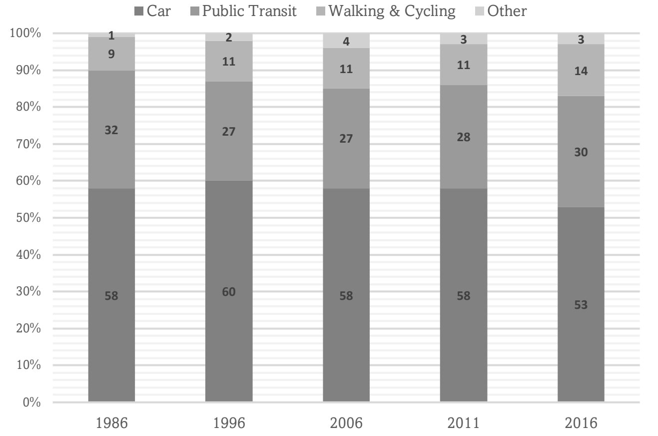
Located in the province of Ontario in southern Canada, the city of Toronto, with a total population of almost 2.8 million in 2021, is the most populous city in the country. Moreover, Toronto's city size (631.1km^2) and population density (4427,8 people per km^2) is also the highest in Canada (Statistics Canada, 2022a).

Toronto is known for its diverse racial and cultural composition population, with 47% of its inhabitants being (foreign-born) immigrants compared to 49% Canadian-born while the remaining share of population is classified as non-permanent residents. China (10%), the Philippines (9%) and India (6%) were represented most as country of birth among Toronto's immigrant population in 2016 (Toronto Public Health, 2019). Further statistical research state that Torontonians are on average 41.5 years old, earn a median after-tax income of 36,000 Canadian dollars per person and live in households that average 2.4 persons (Statistics Canada, 2022a). In terms of quality of life, Toronto is ranked 8th in the Global Liveability Index – making the city one of the most livable cities in the world (City of Toronto, 2022).

§3.2.2 Toronto traffic & mobility

Being the metropolis that Toronto is, the city has an extensive and busy transportation network. According to a 2016 travel survey conducted by Transportation Tomorrow Survey (2018), around 73% of households in the City of Toronto owned at least one vehicle. As figure 3.1 visualizes, during the 2016 morning rush hour (6:00-9:00 AM), most residents travel by car (53%), followed by public transit (30%) and walking and cycling (14%). The figure also highlights a trend in which automobiles are losing modal share while public transit and active modes are gaining share within the morning rush hour.

Figure 3.1: Modal split in percentages by travel mode during morning rush hour in City of Toronto (1986-2016)



Census data from 2016 provide roughly the same modal split, with cars (51%) also being the dominant mode for commuting of people aged 15 years and over, again followed by public transit (37%) and walking and cycling (11%). When Toronto's modal split is compared regionally, active modes usage is more than double than the rate of the rest of Ontario (5%). When compared with other Canadian cities, Ottawa and Montreal's rate for active transportation is similar, 10 and 12 percent respectively, while Vancouver (20%) reports the highest share of active transportation (Toronto Public Health, 2019).

§3.2.3 Toronto climate

Toronto's climate is categorized as a continental climate, which is influenced substantially by the proximity of the Great Lakes. Average temperatures vary from -4.2 °C in January to 22.2 °C in July. In terms of precipitation, Toronto receives about 834 mm every year (McGillivray, 2022).

Regarding the month of interest, in March average temperature is around -0.3 °C, varying from minimal -3.7 °C to 3.9°C. After February, March is the driest month in Toronto with an average of 59 mm precipitation. Torontonians can expect around 7 rainy days in March and an average wind speed of 17.4 kilometers an hour (Climate Data, n.d.; Weather Atlas, n.d.).

§3.2.4 Toronto and the COVID-19 pandemic

When on January 25th, 2020, the first positive case was identified, the COVID-19 timeline started in Toronto (Ontario Newsroom, 2020). With cases, hospitalizations and deaths rising in March, the Government of Ontario, together with the municipality of the Greater Toronto Area, declared a state of emergency and closed all educational and recreational facilities while encouraging its population to stay at home and only travel for essential purposes, like work and grocery shopping (Loa et al., 2021; Nielsen, 2021).

During the summer of 2020, most of these measures were either lifted or became less strict, until a second wave of infections ordered government intervention again. With vaccination campaigns starting off in 2021, mitigating policy became less strict starting from late May. Policy strictness remained stable during the autumn months of 2021 until the rise of the Omicron variant urged policymakers for stricter mitigating policy in December. After the new variant proved to be of less concern, almost all measures were phased out in the first months of 2022. On the 31st of March 2022, Ontario had experienced a total sum of 1,172,333 positive test results and 12,433 deaths related to COVID-19 since the beginning of the pandemic (Ontario COVID-19 Science Advisory Table, 2022).

§3.3 Dependent variable: traffic counts in Toronto in March 2019 & March 2022

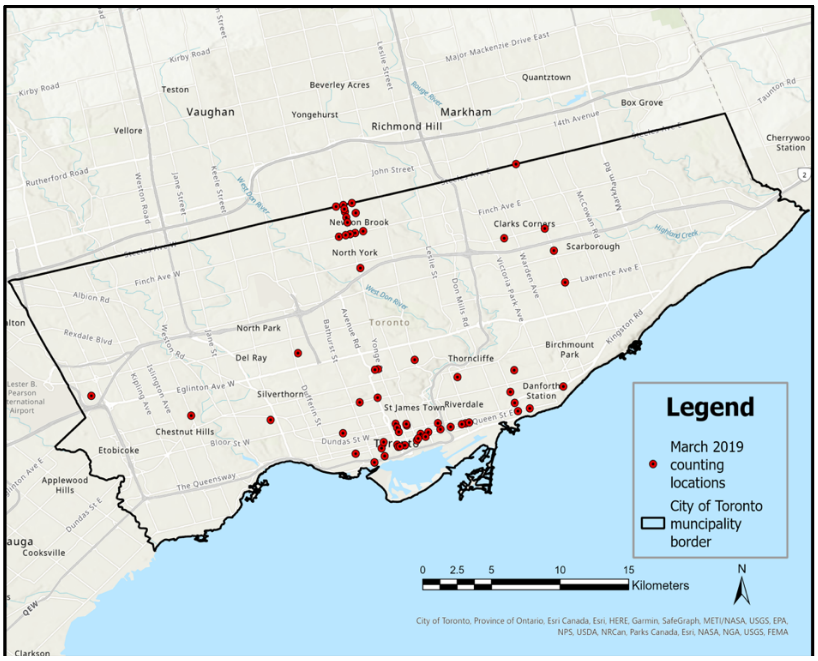
In general, the specific research question and objections determine the specific methods used after which the data is selected (Scheepers & Tobi, 2021). However, this research does it the other way round. This is due to the intention from this study to analyze mobility patterns both as recent as possible and in times in which mobility is less affected by restrictions. To analyze the impact of COVID-19 on travel modes, this research has chosen to use traffic counts at the core. After considering multiple data sources and portal from cities, including those listed in appendix 3.1, only the city of Toronto was able to provide adequate data for the most recent month being March 2022. Therefore, the traffic counts of March 2022 will be compared to a comparable pre-pandemic month, in this case March 2019. Thus, Toronto traffic count data in March 2019 and March 2022 will be compared to analyze the influence of COVID-19 on modal usage patterns.

The dataset used is named '*Traffic Volumes at Intersections for All Modes',* is provided by the Toronto Transportation Services (2022) and was retrieved from the open data catalogue of the City of Toronto. Since this dataset is updated frequently, it is important to note that this research used the version published on May 7th, 2022. In this dataset, counting takes place across different crossings within the Toronto municipality and is conducted by traffic cameras at crossing locations. For each 15-minute interval, total traffic volumes are counted and segmented by travel mode. In this study, stemming from the interest in individual modal choice, the travel modes that are accounted for are cars, pedestrians and cyclists.

Regarding timeframe, this research allocates the 15-minute interval data into three timeframes based upon the local rush hours (Toronto Police Services & City of Toronto, n.d.). The morning rush hour (AM) will start at 7:00 AM and end at 10:00 AM, followed by a timeframe in between the rush hours (IB) from 10:00 AM to 4:00 PM. Lastly, the afternoon rush hour (PM) begins at 4:00 PM and finishes at 6:00 PM. Within these timeframes, traffic volume will be summed by mode. Although this study realizes that the afternoon rush hour will probably last longer than 6:00 PM, this dataset does not provide adequate data past this time. By allocating the data into different groups, this research can take temporal aspects into consideration when investigating the influence of COVID-19 on travel modes.

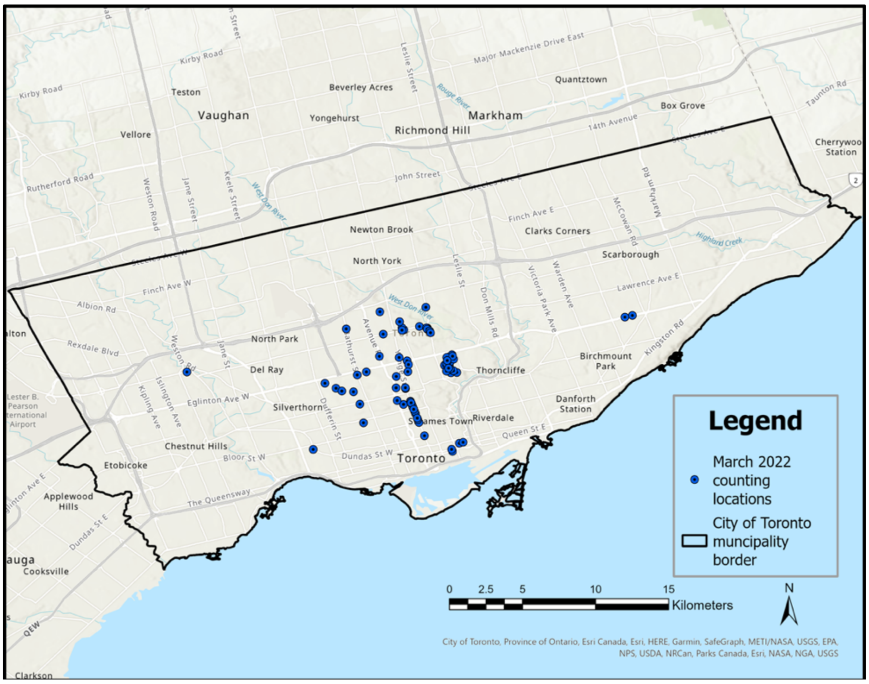
Furthermore, it is important to note that traffic volumes are not collected daily, meaning there are differences in both the number of daily counts, counting locations and type of day. In March 2019, traffic data was collected for 69 days across 62 different locations. Regarding type of day, 2019 counted 24 out of its 69 days in the weekend. In figure 3.2 a map is displayed depicting the traffic counting locations for March 2019.

Figure 3.2: March 2019 traffic count locations in Toronto.



In March 2022, data was collected for 77 days at 72 unique locations including 22 days in the weekend. See figure 3.3 below for an overview of counting locations in 2022.

Figure 3.2: March 2022 traffic count locations in Toronto.



As is visible in the two maps, all counts take place within the municipality of the City of Toronto (Toronto Information & Technology, 2019). Statistics regarding the traffic volumes in March 2019 and March 2022 can be found in table 3.4 below. It is important to note that the dependent variable of every counting category includes data of both the pre-pandemic month of March 2019 and the pandemic month of March 2022. The reason for not conducting separate analysis for March 2019 and March 2022 is due to high multicollinearity with included independent variables like the COVID-19 related variables when each month is analyzed individually. For more explanation see §3.5.1 and table 3.5.

Table 3.4 - Frequencies of all counting categories in Toronto (March 2019 + March 2022)

Counting category	Mean	Variance	Skewness	Std. Error Skewness	Kurtosis	Std. Error Kurtosis	Minimum	Maximum
Total all modes	*13415.61*	*94516673.27*	*1.036*	*0.201*	*0.723*	*0.399*	*276*	*44240*
AM total	3135.51	5960500.60	1.510	0.201	2.484	0.399	60	11968
IB total	6237.53	21636100.32	1.041	0.201	0.674	0.399	142	20658
PM total	4042.58	8665861.98	1.066	0.201	0.952	0.399	74	14124
Cars total	*10710.22*	*65073507.33*	*1.236*	*0.201*	*1.227*	*0.399*	*148*	*37920*
Cars AM	2606.08	4066457.14	1.304	0.201	1.461	0.399	25	9466
Cars IB	4995.14	15368271.14	1.395	0.201	1.897	0.399	87	18353
Cars PM	3109.00	5302467.63	1.177	0.201	1.033	0.399	36	10479
Pedestrians total	*2593.07*	*17040056.56*	*3.341*	*0.201*	*13.809*	*0.399*	*7*	*25798*
Pedestrians AM	504.62	1114468.79	6.128	0.201	43.543	0.399	0	8942
Pedestrians IB	1196.65	3099452.41	2.455	0.201	6.259	0.399	7	9284
Pedestrians PM	891.79	2349710.21	3.643	0.201	16.508	0.399	0	10206
Cyclists total	*112.32*	*33129.56*	*2.979*	*0.201*	*10.540*	*0.399*	*0*	*1098*
Cyclists AM	24.80	2738.45	4.769	0.201	25.908	0.399	0	365
Cyclists IB	45.74	4269.48	2.316	0.201	5.876	0.399	0	327
Cyclists PM	41.78	5172.77	2.820	0.201	9.010	0.399	0	416

§3.4 Independent variables
To test for the effects of the COVID-19 pandemic on the modal usage patterns, the analysis must incorporate other factors that could potentially influence effects. In doing so, this study hopes to isolate the impact of COVID-19 related factors on travel modes by assessing other, non-COVID-19 related, aspects. Based upon previous literature (§2.4) and the conceptual framework (figure 2.2) discussed in the theoretical framework, this study has selected independent variables referring to COVID-19, weather, population characteristics and road classification. In this paragraph, these included independent variables will be theoretically justified after which the statistics will be discussed. In the Appendix, frequencies and other statistics for the variables are visualized in a table for the dataset in total (Appendix 3.2), as well as by year (Appendix 3.3) and crossing type (Appendix 3.4).

§3.4.1 COVID-19: daily new cases (Canada) & Stringency Index (Ontario)
The first COVID-19 variable that is chosen are the confirmed daily positive test results for COVID-19 in Canada in thousands (*Daily new COVID-19 cases Canada*), retrieved from the COVID-19 pandemic database on the Our World in Data website (Ritchie et al., 2022). For every date on which traffic counts were conducted the date-related newly confirmed case numbers have been added. This study utilizes national cases rather than regional data since Ontario had changed its data methodology during March 2022, therefore regional data is not comparable for the entire month (Public Health Ontario, 2022). Naturally, case counts were zero in March 2019 while in 2022 this ranged from 3197 to 10976 cases with an average of 6990.53 newly cases per counting day.

Daily case numbers are preferred as it is located at the forefront of the pandemic situation: a rise in COVID-19 cases causes an increase in hospitalizations and fatalities in the following period. Although vaccination, herd immunity and the Omicron variant have tempered causality with health care occupancy and disease severity, rising COVID-19 cases continue to be related to increasing hospitalizations and deaths (Iyanda, Boakye, Lu & Oppong, 2022).

While daily case numbers predominately has an indirect effect on travel mobility through altering risk perception of individuals to choose a certain mode or not travel at all, COVID-19 mitigating policy has a more direct effect on mobility. Since mobility is an important factor in the spread of COVID-19, managing mobility is key for policymakers (Jenelius & Cebecauer, 2020; Awad-Núñez et al., 2021; Cresswell, 2021). Understanding that this policy could potentially influence the travel modes of interest, this study has chosen the index for policy strictness of COVID-19 mitigating measures in Ontario as the second COVID-19 variable (*Stringency Index Ontario)*. Known as the Oxford COVID-19 Government Response Tracker, this index provides insight in '*government policies related to closure and containment, health and economic policy* […] *for 19 policy areas, capturing variation in degree of response'* (Hale et al., 2021, p. 529).

The policy strictness data was retrieved from the website of the Blatvatnik School of Government & University of Oxford (2022) and allows for analyzing the influence of mitigating policy on travel mode usage. The reason for selecting the provincial level of Ontario lies in the fact that it was at this level policy was made that affected Toronto the most (Ontario Newsroom, 2020; Loa et al., 2021). Once again, March 2019 is scored zero on stringency as it had no mitigating policy. Policy stringency averaged 31.82 in 2022 as March contained two different stringency index scores, being 35.19 between 1 and 10 March and 22.22 between 22 and 31 March. This drop in index scores indicates that mitigating measures were partly lifted during March 2022.

§3.4.2 Weather: temperature, precipitation & windspeed
Since previous research has argued that climatological conditions can influence modal choice and usage (Böcker et al., 2016; Thøgersen, 2006; Ton et al., 2019), weather variables need to be included in the model. For every counting day in 2019 and 2022 the following weather variables are accounted for: average temperature in degrees Celsius (*temperature*), total precipitation in millimeters *(precipitation)* and average windspeed in kilometers an hour (*windspeed*). The historic weather data was retrieved from the website of Visual Crossing Corporation (n.d.) and provides average weather data as was recorded by local weather stations in Toronto.

Appendix 3.3 shows that the counting day average temperature varied between -10.2 °C and 6.2 °C in 2019 ($\bar{x} \approx 0.8$ °C) and between -6.3 °C and 9.4 °C in 2022 ($\bar{x} \approx -0.1$ °C). Counting days in 2019 averaged more precipitation with around 1.4 mm versus 0.1 mm in 2022, with the maximum precipitation being around 22.2 mm and 2.6 mm respectively. Average windspeed was higher in 2022 (29,8 km/h) than in 2019 (22,4 km/h) as was the minimum and maximum windspeed: 2019 varied between 16.7 and 40.4 km/h whilst 2022's windspeed ranged from 22.2 to 51.4 km/h.

§3.4.3 Population characteristics: population density, female population share, age & income

Since mobility choices are made on the level of the individual, this study must take characteristics of these individuals into account (Scheiner, 2010; 2018). The first step is to decide at which the geographical scale the population characteristics will be analyzed. As the geographical level of wards provided troubles with the clustering of counting locations, the level of aggregated dissemination areas (ADAs) in Toronto is chosen. ADA data was collected during 2021 Census of Population, the most recent available census data, and was collected from the website of Statistics Canada (2022b). ADAs have a population between 5,000 and 15,000 people. ADAs were selected by utilizing Geographical Information Systems (GIS) for creating a buffer of 300 meters around every counting location. This distance was chosen as it represents the average city block size in Toronto (Siksna, 1996; Hawkins, Ahmed, Roorda & Habib, 2022). Every ADA that intersected with the buffer will be selected to provide the population characteristics of that counting location through the operation of a spatial join. This study will refer to this area as the counting location area.

The first population characteristic is population density in thousand people per square kilometer, for density has proven to be related to modal choice patterns by other scholars (Schafer & Victor, 2000; Buehler, 2011; Liu & Lam, 2014). Regarding the population density of the areas withing the counting location buffer, ADA data on total population in thousands was divided by total land area so that it provided the population density per for that area. The variable *Population Density* averaged around 8.14 thousand people per km^2 in 2019 and 6.69 in 2022, varying between 0.52 – 26.25 and 11.23 – 27.04 thousand people per km^2 respectively.

The second population variable is sex, for scholars have argued that females are related to less work-related travel, less usage of active modes and less travel intensity overall (Ehlert & Wedemeier, 2022; Meurs & Haaijer, 2001; Muñoz et al., 2016). As regards to sex, this study calculated the percentage of women from the total population at the counting location area that identified as either male or female. The variable *Females%* averaged in 2019 51.13%, ranging between 44.74% and 54.12%, while 2022 averaged 52.51% and varied from 47.29% to 54.59%.

Thirdly, the average age of the counting location population will be accounted for. Scholars have stated that age significantly affects travel mode usage. Some findings include that younger people use more active modes while older people are more relying on cars as primary mode of transportation (Figueroa et al., 2014; Ha et al., 2020). To investigate the influence of age on modal usage, this study has calculated the weighted arithmetic mean of the variable *Age weighted average*. On average, the counting population was younger in 2019 ($\bar{x} = 41{,}04$ years) than in 2022 ($\bar{x} = 43{,}41$ years). The youngest counting area was in 2019 33,4 years old and in 2022 37,08 years of age. The most elderly areas in 2019 and 2022 were 47,33 and 48,49 years old respectively.

The last population characteristic in this study is income, more specifically the weighted arithmetic mean of total income in 2020 in thousand Canadian dollars of income-receiving respondents aged 15 years or older (*Income 2020 weighted average)*. Studies have shown that income affects both the selection and usage of travel modes as well as the ability to travel overall (Meurs & Haaijer, 2001; Papagiannakis et al., 2018; Schafer & Victor, 2000). To take income and its possible effect on travel modes into account, this study will control for average total income. In 2019 average total income was around \$58.62K, varying between \$30.77K and \$93.21K. Counting areas in 2022 were on average richer with a mean total income of \$90.43K, ranging from \$35.96K to \$195.60K.

§3.4.5 Crossing characterization: *road classifications*

As the counting takes places at crossings, it is important to gain insight in the type of roads at each crossing. Utilizing the Statistics Canada (2022c) road network files from the census year 2021, this study will be able to analyze the influence of certain roads. Within these road network files, roads are classified by different types of street features.

Regarding the counting locations, all crossing roads are either classified as arterial (rank 1), collector (rank 2) or local (rank 3). Arterial roads are characterized by having more lanes, higher speed limits and more traffic while local roads are characterized the other way around. Collector roads find themselves characterized between arterial and local roads. In 2019, the 69 counting days were conducted across 49 arterial, 27 collector and 53 local roads. Regarding the 77 counting days of 2022, the crossings contained 35 arterial, 20 collector and 75 local roads. On average, 2019 crossings contained higher ranked roads than 2022 (Appendix, 3.4).

Since the road classes will allow for multiple unique combinations, this study has chosen to simplify this as there are not enough counts for each unique road classification combination. Therefore, dummies are created to still be able to account for road classification in relation to travel mode volumes. Being centered between both arterial and local roads, collector roads have been selected as the reference variable for the dummy variables *Arterial dominant crossings* and *Local dominant crossings*. Since this study cannot account for every unique road class combination at each crossing, the dummies will focus on the highest ranked road at that crossing. For example, a crossing combination of the arterial, collector and local road classes will give a value of 1 to arterial and 0 to local while a crossing containing collector and local roads will give a 0 to both dummies. In doing so, this study will be able to provide insight in how travel volumes have evolved across different road classifications. Appendix 3.4, shows that 49 out of 69 counting locations in 2019 arterial was the highest ranked (49), followed by collector (12) and local (8) dominant crossings. In 2022, arterial roads were once again most dominant (35), above local (24) and collector dominant crossings (18).

§3.5 Method selection: negative binomial regression

For traffic volume data is the dependent variable of this analysis, the characteristics of count data are decisive. First and foremost, count data are non-negative integers since negative values for counts are not possible. Furthermore, count data is discrete, has no upper-limit and is randomly distributed (Chang, 2005). These count data characteristics call for caution when assuming a normal distribution and its related methods like the multiple linear regression (Gardner, Mulvey & Shaw, 1995; Abdel-Aty & Radwan, 2000).

Most of the time, count data is analyzed through a generalized linear framework model being either a Poisson model or negative binomial regression model (Ver Hoef & Boveng, 2007). The decisive factor in choosing between both models is based upon the relation between the mean and variance. The Poisson model entails the assumption of equidispersion, which means that the mean of the dependent variable is equal to the variance. When this is not the case, the data can either be underdispersed (mean < variance) or overdispersed (mean > variance). In the case of overdispersion, the negative binomial regression model is preferred (Daraghmi, Yi & Chang, 2012; 2014; Fairos, Wan Yaacob, Lazim & Yap, 2010; Hilbe, 2011; Miaou & Lum, 1993; Poch & Mannering, 1996).

Looking once more at table 3.4, the data indicates a non-normal distribution as Skewness is higher than 1. Likewise for Kurtosis apart from the categories *Total all modes, IB total & PM total*. Table 3.4 further shows that across all counting categories the variance is manifold the mean, which indicates beyond any doubt that overdispersion exists. Thus, the negative binomial regression will be the selected method for analysis.

§3.5.1 Assumptions of the negative binomial regression for dependent variables

The negative binomial regression demands for three elementary assumptions to be satisfied (Alobaidi, Shamany & Algamal, 2021). The first being the existence of overdispersion in the data, which indeed exists among the included data. Secondly, the mean parameter should be known. Since the dependent variable contains count data, the means are known (see table 3.4). Regarding the independent variables, mean parameters are once more given. Thus, the second assumption is also satisfied. Lastly, the third assumption desires that the distribution of observations is independent. This assumption is adhered to as the dependent variables are counted and categorized per travel mode thus limiting the possibility of individual modes being counted more than once across more than one mode. Furthermore, within each travel mode, the observations are again independent as counting takes place over longer periods of time (7:00 AM – 6:00 PM) rather than in smaller temporal intervals. Therefore, differences in modal use are less affected by temporal effects which again strengthens the satisfaction of the third assumption (Alobaidi et al., 2021, as cited in Algamal, 2012; Cameron & Trivedi, 2013; De Jong & Heller, 2008).

§3.5.2 Assumptions of the negative binomial regression for independent variables

The negative binomial regression includes the assumption of independence among independent variables, meaning that no multicollinearity exists among these variables. This study assesses multicollinearity in two different ways, the first being the examination of the Pearsons' correlation coefficient in the correlation matrix of independent variables and the second being Variance Inflation Factor (VIF). There is some consensus about a critical value of the Pearson's correlation coefficient as general rule of thumb (Kim, 2019; Senaviratna & Cooray, 2019). Although some scholars argue that Pearson's correlation coefficient should not be greater than 0.5, most studies favor a critical value of minimal 0.8 or 0.9 (Midi, Sarkar & Rana, 2010; Shrestha, 2020; Vatcheva & Lee, 2016). Hence, this study has chosen a Pearson's correlation coefficient of 0.8 and above as outermost edge for independent variables to be included in analysis. In table 3.5, the correlation matrix is visible.

Table 3.5: Correlation matrix

	Year	*Daily new COVID-19 cases Canada*	*Stringency Index Ontario*	*Temperature*	*Precipitation*	*Windspeed*	*Population density*	*Females%*	*Age weighted average*	*Income 2020 weighted average*	*Arterial dominant crossings*	*Local dominant crossings*
Year		**.903****	**.968****	-0.108	**-.266****	**.489****	-0.136	**.369****	**.342****	**.479****	**-.258****	**.236****
Daily new COVID-19 cases Canada	**.903****		**.779****	**-.198***	**-.226****	**.426****	-0.084	**.421****	**.456****	**.532****	-0.137	0.131
Stringency Index Ontario	**.968****	**.779****		-0.084	**-.266****	**.469****	-0.142	**.316****	**.247****	**.416****	**-.326****	**.310****
Temperature	-0.108	**-.198***	-0.084		-0.030	**-.232****	-0.115	-0.149	-0.045	-0.018	-0.062	-0.049
Precipitation	**-.266****	**-.226****	**-.266****	-0.030		0.044	0.111	-0.134	-0.154	-0.108	**.200***	-0.136
Windspeed	**.489****	**.426****	**.469****	0.000	0.044		-0.088	**.337****	**.261****	0.094	-0.083	0.043
Population density	-0.136	-0.084	-0.142	-0.115	0.111	-0.088		**-.412****	**-.572****	**-.230****	0.020	**-.188***
Females%	**.369****	**.421****	**.316****	-0.149	-0.134	**.337****	**-.412****		**.623****	**.234****	-0.034	**.190***
Age weighted average	**.342****	**.456****	**.247****	-0.045	-0.154	**.261****	0.000	**.623****		**.465****	0.102	0.062
Income 2020 weighted average	**.479****	**.532****	**.416****	-0.018	-0.108	0.094	**-.230****	**.234****	**.465****		0.072	0.068
Arterial dominant crossings	**-.258****	-0.137	**-.326****	-0.062	**.200***	-0.083	0.020	-0.034	0.102	0.072		**-.617****
Local dominant crossings	**.236****	0.131	**.310****	-0.049	-0.136	0.043	**-.188***	**.190***	0.062	0.068	**-.617****	

** $P \leq 0.05$ | ** $P \leq 0.01$*

When looking at the statistically significant correlations, this study concludes that the Pearson's correlation coefficient is below the cutoff value of 0.8 for every independent variable except year. Therefore, year will not be included in the analysis. All the other independent variables indicate that there are no implications regarding the existence of multicollinearity.

Apart from the COVID-19 related independent variables, no other variables are close to the cutoff value, thus allowing for the conclusion that this set of independent variables passes the Pearson's correlation coefficient test for multicollinearity. However, it is important to note that the variables *Daily new COVID-19 cases Canada* and *Stringency Index Ontario* are close to the maximum 0.8 cutoff value with a value of 0.779 as their Pearson's correlation coefficient. This comes as no surprise as both variables have a constant value in 2019 (0) as there were no cases or mitigating policy at that time, contrarily to 2022. Even though the value lies below the cut off value of 0.8, this study will analyze AIC and BIC values to determine whether both or one of the two COVID variables will be included. Lower AIC scores are better as it penalizes models including more parameters while BIC assesses the tradeoff between model complexity and fit (Alin, 2010; Burnham, Kenneth & Anderson, 2004; Daraghmi et al., 2012; Retallack & Ostendorf, 2020; Vrieze, 2012). Thus, for each counting category, three models are computed: the first including both COVID-19 variables, the second only including cases and the third solely including the stringency index.

The second way of testing for multicollinearity is through the examination of Variance Inflation Factor (VIF) through the operation of collinearity diagnostics. To satisfy multicollinearity assumptions, in accordance with most studies, the VIF valuations should lie below five while the VIF tolerance must be greater than 0.1 (Daoud, 2017; Midi et al., 2010; Niresh &. Velnampy, 2014; Shresta, 2020; Vatcheva & Lee, 2016).

In table 3.6 the VIF and VIF tolerance values are visible which shows that, for both VIF value as for VIF tolerance, every included independent variable show no indications for problems regarding multicollinearity. Once again and for the same reasons as previously discussed, the COVID-19 related variables come closest to the critical value, albeit with more margin than in the correlation matrix. The variable *Age weighted average* also shows higher VIF values than other included variables, even though the VIF stays clear of the cutoff value. This can partly be explained since age also showed significant correlations in the correlation matrix (table 3.5) for 7 out of 10 variables. All the other variables stay well clear of the VIFs cutoff value of 5. Regarding VIF tolerance values, all values are above the 0.1 cutoff value. All this suggests that no multicollinearity related issues are of existence.

Table 3.6: VIF and VIF tolerance values

Independent variable	**VIF**	**Tolerance**
Daily new COVID-19 cases Canada	4.175	0.240
Stringency Index Ontario	3.851	0.260
Temperature	1.171	0.854
Precipitation	1.174	0.852
Windspeed	1.595	0.627
Population density	1.829	0.547
Females%	1.905	0.525
Age weighted average	2.963	0.338
Income 2020 weigted average	1.735	0.576
Arterial dominant crossings	1.897	0.527
Local dominant crossings	1.865	0.536
Average values	**2.230**	**0.535**

Given all three multicollinearity test results, this study concludes that there are no indications that the selected set of variables are posing concerns regarding collinearity as all assumptions of the negative binomial regression are accounted for.

§3.6 Hypotheses

Now the dependent and independent variables have been introduced along with the method for analysis, this paragraph will formulate hypotheses based on the included independent variables. These hypotheses will be based upon earlier discussed literature and related research findings in the theoretical framework (§2.4 & §2.5). The hypotheses of this study can be found in table 3.7.

Table 3.7: Hypotheses

Variable group	Independent variable	Hypothesis	Supporting literature
COVID-19	*Daily new COVID-19 cases Canada*	H1: Higher daily new COVID-19 cases in Canada will negatively predict car volumes	Abdullah et al., 2020; Bert et al., 2020; De Vos, 2020; Ehsani et al., 2021; Greene et al., 2022; Lee & Eom, 2022; Loa et al., 2021; Paul et al., 2022; Shaer & Haghsenas, 2021; Van der Drift et al., 2021
		H2: Higher daily new COVID-19 cases in Canada will positively predict active modal volumes	
	Stringency Index Ontario	H3: Higher Stringency Index scores in Ontario will negatively predict car volumes	
		H4: Higher Stringency Index scores in Ontario will positively predict active modal volumes	
Weather	*Temperature*	H5: Higher temperature will positively predict active modal volumes	Böcker et al., 2016; Thøgerson, 2006; Ton et al., 2019
	Precipitation	H6: More precipitation will negatively predict active modal volumes	
	Windspeed	H7: Higher windspeed will negatively predict active modal volumes	
	Population density	H8: Higher population density will positively predict traffic volumes across all counting categories	Buehler, 2011; Liu & Lam, 2014; Schafer & Victor, 2000
Population characteristics	*Females%*	H9: Higher share of females in population will negatively predict active modal volumes	Ehlert & Wedemeier, 2022; Meurs & Haaijer, 2001; Muñoz et al., 2016
	Age weighted average	H10: Higher average age in population will negatively predict active modal volumes	Figueroa et al., 2014; Ha et al., 2020
	Income 2020 weighted average	H11: Higher average income in population will positively predict car volumes	Meurs & Haaijer, 2001; Papagiannakis et al., 2018; Pucher & Renne, 2005; Schafer & Victor, 2000
		H12: Higher average income in population will negatively predict active modal volumes	
Road classification	*Arterial dominant crossings*	H13: Arterial dominant crossings will positively predict traffic volumes across all counting categories	Schepers & Heinen, 2013; Winters et al., 2010
	Local dominant crossings	H14: Local dominant crossings will negatively predict traffic volumes across all counting categories	

§3.7 Research quality assessment

Before this study moves on towards the analysis section, this last paragraph will provide a brief overview on how this research copes with the important matters related to study validity, reliability and suitability.

3.7.1 Validity & suitability

Starting with validity which, according to Leung (2015, p. 325), concerns the 'appropriateness of the tools processes and data.' Important considerations for validity are conformity between the research question and the aim and methodology selection. Additionally, suitability is also important. To achieve suitability the study approach and process should fit the objective: methods should suit research design and allow for proper analysis and conclusions while contextual conditions are accounted for.

To incorporate both validity and suitability, this study has put its aim at the center stage: identifying the impact of COVID-19 on modal usage. Derived from this aim, this study's research question was formulated accordingly. Based on theoretical foundations and data availability, quality, and analysis possibilities, the negative binomial regression was chosen as best fitting method – a method which has proven to be a valid tool in assessing developments in traffic count data in many studies (Ver Hoef & Boveng, 2007). As this study has included independent variables grounded in theory, this study can isolate the impact of COVID-19 as it is able to control for contextual conditions of the data (weather, population characteristics, road classification). Thus, the study has a strong, theoretically and systematically proven, foundation and approach that will foster validity in the upcoming results and conclusions.

3.7.2 Reliability

Characterized as the 'replicability of the processes and the results', study reliability is crucial as it demands consistency in quantitative research (Leung, 2015, p. 326). To include consistency, this study has set clear boundaries in the study's object (traffic counts), time frame (March 2019 & March 2022) and contexts (COVID-19, weather, population characteristics, road classification). As this study includes control variables grounded in theory and it utilizes the May 2022 open data source from Toronto Transportation Services (2022), this study can be replicated which improves the reliability of this research. Additionally, the data collection was conducted by traffic cameras, thus objectivity is much more protected as opposed to data collection by individuals. Finally, the approach, count data, count data collection and control variables are the same for both March 2019 and March 2022 (Heale & Twycross, 2015). All this taken into consideration, this study will safeguard its reliability through conserving consistency continuously.

§3.8 Analysis protocol

To allow for better understanding of the analysis and results, this paragraph will provide insight in how the procedure of analysis will take place. First, the different counting categories. The order in which the counting categories will be analyzed will be from total traffic intensity to volumes per mode. Within each counting category, first the volumes between 7 AM and 6 PM *(Total)* will be analyzed after which traffic volumes is analyzed during the morning rush-hour between 7 AM and 10AM (*AM)* followed by period in-between the rush-hours stretching from 10 AM to 4 PM (*IB).* The last temporal division analyzed is the afternoon rush-hour between the hours of 4 PM and 6 PM (*PM).* Thus, first the *TOTAL* intensity will be assessed, followed by the temporal categories of *AM total, IB total* and *PM total.* Thereafter, total and temporal intensity will be analyzed per individual mode (cars, pedestrians & cyclists).

The analysis will be conducted in IBM SPSS Statistics, using the operation of Generalized Linear Models with the Negative Binomial with log link option. Since the COVID-19 related variables are close to the critical value of multicollinearity, three models are run: the first model including both COVID-19 cases and stringency index followed by models including either only cases or stringency index. For every counting category (Total all modes, cars, pedestrians & cyclists) and every temporal category (Total, AM, IB & PM), one of the three models is chosen based on the values for either Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC). Since every model contains different compositions of COVID-19 variables, the model with the lowest value for AIC and BIC will be chosen to analyze. Furthermore, the dispersion parameter of the negative binomial regression will be estimated by SPSS as this also provides the lowest values for both AIC and BIC (Burnham et al., 2004; Daraghmi et al., 2012; Retallack & Ostendorf, 2020; Vrieze, 2012).

After the general discussion of the results from the negative binomial regression model for every individual counting category, the analysis will further elaborate and interpret these results by comparing the results with the hypotheses formulated beforehand. In the last chapter, this study will answer the main research question, formulate conclusions and put these results in perspective.

Summarizing the approach and aim for the upcoming analysis chapter, this study will be able to examine the impact of COVID-19 on total traffic volume, traffic volume by mode and traffic volume by mode over different daytime periods while other (potentially) influential variables (weather, population characteristics & road classification) are accounted for.

4. ANALYSIS

After the previous methodology chapter had provided insight and guidelines in the approach for analysis, this chapter will contain the results. First, the results of each individual model will be described after which the results are compared with the hypotheses which were formulated in the previous chapter. In doing so, after conducting the analysis followed by discussing and interpreting the results, this study will be able to answer the main question and formulate conclusions in the next chapter.

§4.1 Total traffic volume

Starting off with the largest counting category of total all modes, consisting of the sum of cars, pedestrians and cyclists counted between 7:00 AM and 6:00 PM on counting days in both March 2019 and March 2022 in Toronto. The model including both COVID-19 independent variables was elected as it provided lower AIC and BIC values in comparison to models including only one COVID-19 variable (see appendix 4.1 for model comparisons of AIC & BIC values). Thus, a negative binomial regression was run through SPSS for this model and provided the table of 4.1 below. In this table, the Goodness of Fit test provides a Pearson Chi-Square Value/df of 1.101 – indicating that the whole model fits the data well. The Omnibus Test further shows that the whole model is significant which marks that the model, and its included set of predictors, are a better fit than the intercept only (null) model.

Table 4.1 Analysis of total traffic intensity				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	7.155	***	1.8700	1280.615
Daily new COVID-19 cases Canada	-0.064	*	0.0254	0.938
Stringency Index Ontario	-0.014	*	0.0059	0.986
Temperature	0.001		0.0135	1.001
Precipitation	-0.028		0.0225	0.972
Windspeed	0.008		0.0084	1.008
Population density	0.016		0.0136	1.016
Females %	0.034		0.0380	1.035
Age weighted average	0.006		0.0229	1.006
Income 2020 weighted average	0.003		0.0019	1.003
Arterial dominant crossings	0.364	**	0.1390	1.439
Local dominant crossings	-0.638	***	0.1635	0.528
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	146.436		133	1.101
Log Likelihood	-1477.111			
AIC	2980.223			
BIC	3019.010			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	95.884		11	<.001
* $P \leq 0.05$ | ** $P \leq 0.01$ | *** $P \leq 0.001$				

Table 4.1 further provides insight in the model parameters for total traffic volume (for entire SPSS output see appendix 4.2). Regarding COVID-19, both *Daily new COVID-19 cases Canada* (B = -0.064, SE = 0.0254) and *Stringency Index Ontario* (B = -0.014, SE = 0.0059) proved to be significant and negative predictors of the log count of total traffic intensity in Toronto. The incidence rate ratio (IRR) indicates that for every one unit increase in COVID-19 cases in thousands, the counting incidence rate of total traffic volume decreases by 6.2 percent. For every one unit increase in stringency, total traffic volume is expected to drop by around 1.4 percent. Thus, COVID-19 is significantly and negatively related to total traffic volume.

Regarding controlling variables, the weather- and population characteristics related variables did not show significant regression coefficients. In this model, only road classification variables proved to be significant predictors outside of COVID-19 related variables. The expected loc count of total traffic volume on the reference category of collector dominant crossings is lower than on *Arterial dominant crossings* (B = 0.364, SE = 0.1390) but higher on *Local dominant crossings* (B = -0.638, SE = 0.1635). Looking at the IRR and comparing both included crossing categories to the reference category of collector dominant crossings individually, arterial crossings indicate around 43.9 percent more traffic counts while traffic volume on local crossings is around 47.2 percent less.

§4.1.1 Total traffic volumes during AM rush-hour

The second model that is run contains the traffic volume over all modes during the AM rush-hour in Toronto between 7:00 AM and 10:00 AM. The model including both COVID-19 independent variables provided lower AIC and BIC values in comparison to models including only one COVID-19 variable (see appendix 4.1 for model comparisons of AIC & BIC values). With both COVID-19 independent variables included, a negative binomial regression was run with SPSS (see appendix 4.3 for entire output). The Goodness of Fit and Omnibus Test in table 4.2 indicated that the current model suits the data well and is significantly better than the intercept only model respectively. Thus, the model parameters in table 4.2 can be analyzed.

Table 4.2 Analysis of total traffic intensity during morning rush-hours				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	6.024	***	1.8672	413.331
Daily new COVID-19 cases Canada	-0.062	*	0.0258	0.940
Stringency Index Ontario	-0.017	**	0.0060	0.983
Temperature	0.015		0.0139	1.015
Precipitation	-0.075	***	0.0205	0.928
Windspeed	0.020	*	0.0089	1.020
Population density	-0.005		0.0138	0.995
Females %	0.038		0.0374	1.039
Age weighted average	-0.010		0.0227	0.990
Income 2020 weighted average	0.004	*	0.0020	1.004
Arterial dominant crossings	0.304	*	0.1409	1.355
Local dominant crossings	-0.535	***	0.1657	0.586
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	146.134		133	1.099
Log Likelihood	-1268.099			
AIC	2562.198			
BIC	2600.985			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	86.991		11	<.001
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

Starting with *Daily new COVID-19 cases Canada* (B = -0.062, SE = 0.0258), which is a significant negative predictor of morning traffic - for every one thousand cases added the incidence rate of AM traffic volume decreases by a factor of 0.940 (-6%). The *Stringency Index Ontario* (B = -0.017, SE = 0.0060) also is a significant negative predictor, as the incidence rate of AM traffic counts decrease by a factor of 0.983 (-1.7%) for every one unit increase on the stringency index. Therefore, COVID-19 is both significantly and negatively related to morning rush hour traffic volumes.

Regarding weather variables, both *Precipitation* (B = -0.075, SE = 0.0205) and *Windspeed* (B = 0.020, SE = 0.0089) are significant predictors. For every added millimeter of precipitation that falls, morning traffic is decreased by 7.2 percent. Contrary to the negative predictor of precipitation, windspeed is a positive predictor: for every one kilometer an hour acceleration in windspeed, AM traffic volume increases with a factor of 1.02 roughly.

The *Income 2020 weighted average* (B = 0.004, SE = 0.0020) is the only significant predictor from the population characteristics. For every one unit increase in income, AM rush-hour traffic volume is expected to increase by a factor of 1.004. This means that a higher average 2020 income in aggreggate dissemination areas within a 300 meter perimeter of a counting location is related to higher traffic volumes during the morning rush-hour.

Both road classification variables proved to be significant predictors for AM traffic when referenced to collector dominant crossings. *Arterial dominant crossings* (B = 0.304, SE = 0.1409) was a positive predictor, indicating a log AM traffic count increase of 0.304 points as opposed to collector dominant crossings while *Local dominant crossings* (B = -0.535, SE = 0.1657) negatively predict AM traffic, with a log count decrease of 0.535 in comparison to collector dominant crossings. This translates to 35.5 percent more and 41.4 percent less AM rush-hour traffic when arterial and local dominant crossings are compared to collector dominant crossings respectively.

§4.1.2 Total traffic volumes druing off-peak hours

To analyze the total traffic intensity between rush-hours, the third model focusses upon total traffic volume between 10:00 AM and 4:00 PM (*IB total)*. Models including either only COVID-19 cases or the stringency index contained higher values for AIC and BIC than the model inculding both COVID-19 related independent variables (see appendix 4.1). Therefore, the negative binomial regression was run on the latter model and provided satisfactory results regarding the Goodness of Fit and Omnibus Test in table 4.3, indicating that the current model both suits the data well and is a significant improvement over the intercept-only model. For the entire SPSS output see the appendix 4.4. Due to these satisfying test results the model parameters in table 4.3 can be investigated.

Table 4.3 Analysis of total traffic intensity during off-peak hours				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	6.151	***	1.9286	469.179
Daily new COVID-19 cases Canada	-0.066	*	0.0260	0.936
Stringency Index Ontario	-0.012		0.0061	0.989
Temperature	-0.006		0.0139	0.994
Precipitation	-0.006		0.0245	0.994
Windspeed	0.002		0.0084	1.002
Population density	0.024		0.0139	1.024
Females %	0.029		0.0394	1.029
Age weighted average	0.020		0.0236	1.021
Income 2020 weighted average	0.002		0.0020	1.002
Arterial dominant crossings	0.405	**	0.1430	1.500
Local dominant crossings	-0.680	***	0.1678	0.506
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	147.633		133	1.110
Log Likelihood	-1365.746			
AIC	2757.491			
BIC	2796.278			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	99.514		11	<.001
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

When analyzing the impact of the COVID-19 variables, daily cases was a significant predictor while mitigating policy (p = 0.058) was not. The variable of *Daily new COVID-19 cases Canada* (B = -0.066, SE = 0.0260) negatively predicted traffic intensity between AM and PM rush-hours: for every thousand COVID-19 cases added the off-peak traffic counts decrease by a factor of 0.936 which translates into a 6.4 percent drop. Thus, counting days containing more newly confirmed positive test results for COVID-19 are related to having less traffic volume during off-peak hours, between 10:00 AM and 4:00 PM.

Regarding controlling variables, both variable groups of weather and population characteristics did not contain any significant predictors. Road classification variables were significant predictors, as *Arterial dominant crossings* (B = 0.405, SE = 0.1430) contained around 50 percent more off-peak traffic volume than the reference category of collector dominant crossings. The *Local dominant crossings* (B= -0.680, SE = 0.1678) contained around 48.4 percent less traffic than the reference category.

§4.1.3 Total traffic volumes during the PM rush-hour

The following model focusses on the traffic intensity between the hours of 4:00 PM and 6:00 PM. Alike previous models analyzing total traffic volumes, the model including both COVID-19 cases and stringency index provided the lowest AIC and BIC values when compared to models including only one of two COVID-19 related variables (see appendix 4.1). Thus, the model incorporating both daily cases and stringency was elected to conduct a negative binomial regression on (for entire SPSS output see appendix 4.5). Resulting from this computation the table 4.4 was created, displaying the Goodness of Fit and Omnibus Test results, indicate that the data suits the model well and is significantly better than the intercept-only (null) model respectively.

Table 4.4 Analysis of total traffic intensity during afternoon rush-hours				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	5.994	***	1.8711	401.188
Daily new COVID-19 cases Canada	-0.058	*	0.0253	0.943
Stringency Index Ontario	-0.015	*	0.0060	0.985
Temperature	0.004		0.0135	1.004
Precipitation	-0.032		0.0224	0.969
Windspeed	0.009		0.0084	1.009
Population density	0.020		0.0136	1.020
Females %	0.039		0.0382	1.040
Age weighted average	-0.001		0.0231	0.999
Income 2020 weighted average	0.003		0.0019	1.003
Arterial dominant crossings	0.348	*	0.1385	1.416
Local dominant crossings	-0.669	***	0.1634	0.512
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	144.659		133	1.088
Log Likelihood	-1301.168			
AIC	2628.335			
BIC	2667.122			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	98.650		11	<.001
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

Given the satisfactory test results in table 4.4, the model parameters can be analyzed. Starting with the COVID-19 related variables, the model states that both *Daily new COVID-19 cases Canada* (B = -0.058, SE = 0.0253) and *Stringency Index Ontario* (B = -0.015, SE = 0.0060) are significant and negative predictors of total traffic during the PM rush-hour. For every thousand units increase in COVID-19 cases, the PM rush hour traffic volume is expected to drop by around 5.7 percent. Regarding the strictness of mitigating policy, every one unit increase in the Ontario stringency index drops PM rush-hour traffic by 1.5 percent. Therefore, COVID-19 can be understood to have a negative effect on afternoon rush-hour traffic volumes as both COVID-19 related variables are significantly and negatively related.

Apart from COVID-19 related variables, the only controlling variables that provided significant predictors of PM rush-hour traffic were the road classification variables. On *Arterial dominant crossings* (B = 0.348, SE = 0.1385), one could expect 41.6 percent more PM rush-hour traffic than on collector dominant crossings while *Local dominant crossings* (B = -0.669, SE = 0.1634) contained roughly 48.8 percent less traffic volume respectively.

§4.2 Car-oriented models

Table 4.5 shows that, all car-oriented models did not provide the lowest AIC and BIC scores for the model incorporating both COVID-19 cases and the Stringency Index. As opposed to the models analyzing total traffic, pedestrians and cycling intensities, the four car-oriented models displayed the lowest AIC and BIC values for the model only including daily new COVID-19 cases. Therefore, this study only includes daily new COVID-19 cases as related COVID-19 independent variable in the analysis focusing on the modal intensity of cars.

Table 4.5 AIC and BIC value comparison of car-oriented models with different COVID-19 variables included	**AIC**	**BIC**
Cars total (COVID-19 cases & Stringency Index)	2918.416	2957.202
Cars total (only COVID-19 cases)	2917.055	2952.859
Cars total (only Stringency Index)	2929.830	2965.633
Cars AM (COVID-19 cases & Stringency Index)	2509.469	2548.255
Cars AM (only COVID-19 cases)	2509.425	2545.228
Cars AM (only Stringency Index)	2518.472	2554.276
Cars IB (COVID-19 cases & Stringency Index)	2697.311	2736.097
Cars IB (only COVID-19 cases)	2695.654	2731.457
Cars IB (only Stringency Index)	2708.492	2744.295
Cars PM (COVID-19 cases & Stringency Index)	2556.446	2595.233
Cars PM (only COVID-19 cases)	2554.859	2590.662
Cars PM (only Stringency Index)	2568.736	2604.540

§4.2.1 Cars: total intensity

The fifth model of this study will analyze the modal intensity of cars in Toronto between the hours of 7 AM and 6 PM in March 2019 and 2022. For this model only the COVID-19 related variable of cases was included. A negative binomial regression was run where the Goodness of Fit and Omnibus Test indicated that the data suits the model well and is significantly superior to the null model respectively (see table 4.6). For the entire SPSS output, see appendix 4.6. Given the satisfactory results in model fit, the parameters in table can be analyzed.

Table 4.6 Analysis of total car intensity				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	5.681	**	1.8685	293.369
Daily new COVID-19 cases Canada	-0.111	***	0.0195	0.895
Temperature	-0.006		0.0137	0.995
Precipitation	-0.017		0.0223	0.983
Windspeed	0.005		0.0079	1.005
Population density	0.001		0.0134	1.001
Females %	0.038		0.0383	1.039
Age weighted average	0.037		0.0223	1.037
Income 2020 weighted average	0.001		0.0019	1.001
Arterial dominant crossings	0.413	**	0.1412	1.511
Local dominant crossings	-0.632	***	0.1622	0.532
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	138.104		134	1.031
Log Likelihood	-1446.528			
AIC	2917.055			
BIC	2952.859			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	92.392		10	<.001
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

The model argues that *Daily new COVID-19 cases Canada* (B = -0.111, SE = 0.0195) is a significant and negative predictor. Since COVID-19 cases is a negative predictor for total car traffic volume, the IRR of 0.895 indicates that for every thousand units increase in COVID-19 cases the modal usage of cars is decreased by 10.5 percent. Thus, the more COVID-19 cases on a given day, the less car intensity is expected.

Regarding the controlling variables, both the weather- and population-related variables did not prove to be significant predictors for total car volumes . However, road classification was significant though, as total car intensity on *Arterial dominant crossings* (B = 0.413, SE = 0.1412) is expected to be 51.1 percent higher than on collector dominant crossings. For *Local dominant crossings* (B = -0.632, SE = 0.1622) the direction of effect was reversed, as on this specific type of crossing 46.8 percent less cars were counted than on the reference category of collector dominant crossings.

§4.2.2 Cars: AM rush-hour intensity

To analyze the modal usage of cars during the AM rush-hour (7:00 AM – 10:00 AM), the sixth model of this study was run. This model only included the COVID-19 variable of cases due to having lower AIC and BIC scores (see table 4.5). For the total SPSS output see Appendix 4.7. The Goodness of Fit in table 4.7 shows that the data has a good fit to the model. The Omnibus Test in table 4.7 further argues that this model is a significant improvement over the intercept-only model. Due to satisfying results in these tests, the model parameters can be studied.

Table 4.7 Analysis of car intensity during morning rush-hours				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	4.018	*	1.8888	55.581
Daily new COVID-19 cases Canada	-0.113	***	0.0196	0.893
Temperature	0.005		0.0139	1.005
Precipitation	-0.060	**	0.0207	0.941
Windspeed	0.014		0.0083	1.014
Population density	-0.010		0.0139	0.990
Females %	0.049		0.0380	1.050
Age weighted average	0.024		0.0222	1.025
Income 2020 weighted average	0.002		0.0020	1.002
Arterial dominant crossings	0.400	**	0.1436	1.491
Local dominant crossings	-0.576	***	0.1654	0.562
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	136.326		134	1.017
Log Likelihood	-1242.713			
AIC	2509.425			
BIC	2545.228			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	86.358		10	<.001
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

Starting with the COVID-19 variable of *Daily new COVID-19 cases Canada* (B = -0.113, SE = 0.0196) which is a significant and negative predictor for car intensity during the morning rush-hour. For every thousand more COVID-19 cases on a day, the modal usage of cars is expected to decrease by around 10.7 percent. This indicates that COVID-19, in this case the daily positive test results on the national level, has a negative impact on car volumes as the more cases on a given day is related to less overall modal usage of cars.

Looking at the controlling variables focused upon weather and population characteristics, only the weather-related variable of *Precipitation* (B = -0.060, SE = 0.0207) proved to be significant in predicting AM rush-hour car intensity. As precipitation is a negative predictor, the more rain, snow or hail on a given day, the less car intensity is expected between 7 AM and 10 AM. The IRR of 0.941 of precipitation indicates that for every one unit (= millimeters) increase in precipitation AM rush-hour car intensity drops by 5.9 percent.

Furthermore, both road classification variables are significant. When both *Arterial dominant crossings* (B = 0.400, SE = 0.1436) and *Local dominant crossings* (B = -0.576, SE = 0.1654) are compared to the reference category of collector dominant crossings, arterial crossings contain 49.1 percent more car traffic while local dominant crossings have 43.8 percent less car intensity during the AM rush-hour.

§4.2.3 Cars: intensity between AM and PM rush-hour

The seventh model of this study focusses upon the modal usage of cars between the hours of 10:00 AM and 4:00 PM. As table 4.5 made clear, the model only including COVID-19 cases proved to be the best choice to perform the negative binomial regression on. The entire SPSS output of this model can be found in appendix 4.8. Looking at the Goodness of Fit test results in table 4.8, the results indicate that the data suits the current model well. The Omnibus test, also found in table 4.8, further argues that the current model is significantly better than the intercept-only (null) model. Thus, the parameter estimates can be analyzed.

Table 4.8 Analysis of car intensity during off-peak hours				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	4.970	**	1.9213	144.075
Daily new COVID-19 cases Canada	-0.109	***	0.0202	0.896
Temperature	-0.010		0.0140	0.990
Precipitation	0.002		0.0240	1.002
Windspeed	0.001		0.0080	1.001
Population density	0.006		0.0137	1.006
Females %	0.034		0.0396	1.035
Age weighted average	0.041		0.0229	1.042
Income 2020 weighted average	0.001		0.0020	1.001
Arterial dominant crossings	0.430	**	0.1447	1.537
Local dominant crossings	-0.673	***	0.1661	0.510
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	143.190		134	1.069
Log Likelihood	-1335.827			
AIC	2695.654			
BIC	2731.457			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	94.956		10	<.001
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

COVID-19 cases proved to be a significant and negative predictor as the IRR of 0.896 of the variable *Daily new COVID-19 cases Canada* (B = -0.109, SE = 0.0202) indicates that for every thousand cases added the off-peak modal usage of cars is expected to drop by 10.4 percent. This means that the more COVID-19 cases on a given day, the less cars are counted between 10 AM and 4 PM.

Regarding controlling variables, weather and population characteristics did not provide significant predictors. Road classification was significant, as *Arterial dominant crossings* (B = 0.430, SE = 0.1447) counted 53.7 percent more cars than on collector dominant crossings while *Local dominant crossings* (B = -0.637, SE = 0.1661) counted 49.0 percent less cars respectively.

§4.2.4 Cars: PM rush-hour traffic intensity

The last car-oriented model concerns the modal usage of cars between the afternoon rush-hours of 4:00 PM and 6:00 PM. As was visible in table 4.5, the model including only the COVID-19 cases was the best choice due to having lower AIC and BIC values. Thus, on this model was conducted a negative binomial regression, for which the entire SPSS output is in the appendix at 4.9. The Goodness of Fit in table 4.9 indicates that the data suits well to the current model while the Omnibus Test argues that the current model is a significant improvement over the intercept-only model. Therefore, the parameter estimates in table 4.9 can be studied to provide insight in what are significant predictors for afternoon rush-hour modal usage of cars.

Table 4.9 Analysis of car intensity during afternoon rush-hours				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	4.517	*	1.8522	91.603
Daily new COVID-19 cases Canada	-0.111	***	0.0192	0.895
Temperature	-0.005		0.0136	0.995
Precipitation	-0.017		0.0221	0.983
Windspeed	0.006		0.0079	1.007
Population density	0.003		0.0133	1.003
Females %	0.035		0.0381	1.035
Age weighted average	0.039		0.0224	1.040
Income 2020 weighted average	0.001		0.0019	1.001
Arterial dominant crossings	0.396	**	0.1401	1.485
Local dominant crossings	-0.628	***	0.1610	0.534
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	131.964		134	0.985
Log Likelihood	-1265.429			
AIC	2554.859			
BIC	2590.662			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	93.105		10	<.001
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

Starting with *Daily new COVID-19 cases Canada* (B = -0.111, SE = 0.0192) which was a significant and negative predictor for PM rush-hour car intensity. For every thousand COVID-19 cases increase on a day, the PM car intensity drops by 10.5 percent. Thus, the more COVID-19 cases the less afternoon rush-hour modal usage of cars is expected.

Looking at the controlling variables, both weather and population characteristics variable groups did not provide a single significant predictor. However, road classification was significant, as *Arterial dominant crossings* (B = 0.396, SE = 0.1401) counted 48.5 percent more cars while *Local dominant crossings* (B = -0.628, SE = 0.1610) counted 46.6 percent less cars when both crossing types are compared to the reference category of collector dominant crossings.

§4.3 Pedestrian-oriented models

Walking will be the first active mode that will be analyzed in this paragraph. Starting with analyzing total pedestrian volumes first, the mode of walking will be further analyzed during AM rush-hours, between both AM and PM rush-hours and, lastly, during the PM rush-hour.

§4.3.1 Pedestrians: total traffic intensity

The ninth model of this analysis will assess the total volumes of pedestrians between 7:00 AM and 6:00 PM in Toronto in March 2019 and 2022. As is visible in appendix 4.1, the model including both COVID-19 cases and policy strictness provides the lowest values for AIC and BIC and, thus, is the model of choice. A negative binomial regression was performed (see appendix 4.10 for entire SPSS output) which provided arguments indicating that the data suits well to the model (see Goodness of Fit in table 4.10) and is significantly better than the intercept-only model (see Omnibus Test in table 4.10). Thus, the parameter estimates can be analyzed.

Table 4.10 Analysis of total pedestrian intensity				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	10.568	***	3.0235	38869.646
Daily new COVID-19 cases Canada	0.164	***	0.0449	1.179
Stringency Index Ontario	-0.066	***	0.0110	0.936
Temperature	0.025		0.0213	1.025
Precipitation	-0.057		0.0432	0.945
Windspeed	0.018		0.0136	1.018
Population density	0.066	**	0.0216	1.068
Females %	0.025		0.0629	1.025
Age weighted average	-0.121	***	0.0377	0.886
Income 2020 weighted average	0.002		0.0036	1.002
Arterial dominant crossings	0.276		0.2350	1.317
Local dominant crossings	-0.460		0.2707	0.631
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	135.219		133	1.017
Log Likelihood	-1222.654			
AIC	2471.309			
BIC	2510.096			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	115.275		11	0.000
$*P \leq 0.05$ | $**P \leq 0.01$ | $***P \leq 0.001$				

Starting with the COVID-19 related variables, both *Daily new COVID-19 cases Canada* (B = 0.164, SE = 0.0449) and *Stringency Index Ontario* (B = -0.066, SE = 0.0110) are significant predictors. However, the direction of prediction is different as COVID-19 cases are positive indicators while mitigating policy is a negative indicator for total pedestrian intensity. This means that for every thousand added COVID-19 cases, the incidence rate of pedestrian counts increases by 17.9 percent. The Stringency Index shows a reverse effect, where for every one unit increase in policy strictness the incidence rate drops approximately 6.4 percent. Thus, regarding total pedestrian volumes, the effect of the COVID-19 variables is opposite of one another.

Weather related variables did not provide any significant predictors for morning rush hour pedestrian volumes. Regarding population characteristics, *Population density* (B = 0.066, SE = 0.0216) was a significant and positive predictor of morning pedestrian counts: for every increase in population density around the counting location by thousand people per square kilometer, the incidence rate of pedestrian count increases by 6.8 percent. The population characteristic of *Age weighted average* (B = -0.121, SE = 0.0377) was also a significant predictor, albeit negative as a one unit increase in the weighted average age around the counting location decreases the incidence rate of pedestrian counts by 11.4 percent.

Lastly, both independent variables of road classifications were insignificant. Thus, the road classification structure of the crossings could not significantly affect the volumes of pedestrians throughout the day of counting.

§4.3.2 Pedestrians: AM rush-hour traffic intensity

The first period of day to be investigated for pedestrian traffic volumes is the AM rush-hour, spanning from 7:00 AM until 10:00 AM. For this specific model, the AIC and BIC values are the lowest when both COVID-19 related variables are included, as is visible in appendix 4.1. A negative binomial regression was performed (for entire SPSS output see appendix 4.11) and provided the table 4.11. In the Goodness of Fit test, it becomes clear that the data suits well to the model while the Omnibus Test argues that this model is significantly better than the null model. Therefore, the parameter estimates in table 4.11 can be analyzed.

Table 4.11 Analysis of pedestrian intensity during morning rush-hours

Model parameters	**β**		**SE**	**IRR**
(Intercept)	10.013	***	3.0170	22312.883
Daily new COVID-19 cases Canada	0.150	***	0.0449	1.162
Stringency Index Ontario	-0.068	***	0.0108	0.935
Temperature	0.048	*	0.0217	1.050
Precipitation	-0.113	***	0.0355	0.893
Windspeed	0.030	*	0.0139	1.030
Population density	0.036		0.0220	1.037
Females %	0.017		0.0616	1.017
Age weighted average	-0.138	***	0.0370	0.871
Income 2020 weighted average	0.005		0.0036	1.005
Arterial dominant crossings	0.080		0.2378	1.084
Local dominant crossings	-0.138		0.2694	0.871
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	152.727		133	1.148
Log Likelihood	-996.171			
AIC	2018.342			
BIC	2057.129			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	99.009		11	<.001

** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*

Once again, *Daily new COVID-19 cases Canada* (B =0.150, SE = 0.0049) was a significant positive predictor while *Stringency Index Ontario* (B = -0.068, SE = 0.0108) was a significant negative predictor, this time for the log count of pedestrians during the morning rush-hour. Every thousand units increase in COVID-19 cases leads to an increase in pedestrian count by around 16.2 percent, while a one unit increase in mitigating policy leads to a 6.5 percent drop. Hence, although both COVID-19 are significant predictors of AM pedestrian counts, the direction of effect differs from one another.

During the morning rush hour, all weather variables proved to be significant predictors for pedestrians. Positive predictors were *Temperature* (B = 0.048, SE = 0.0217) and *Windspeed* (B = 0.030, SE = 0.0139, p = 0.032). For every one unit increase in temperature and windspeed the incidence rate of AM pedestrian count increases by 5 percent and 3 percent respectively. *Precipitation* (B = -0.113, SE = 0.0355) was a negative and significant predictor, as for every added millimeter of precipitation the incidence rate of morning rush-hour pedestrian counts decreases by 10.7 percent.

Regarding the characteristics of the population surrounding the counting location, only *Age weighted average* (B = -0.138, SE = 0.0370) was a significant (negative) predictor of morning rush hour pedestrian volumes. When the average age is increased by one year, the incident rate of AM pedestrian counts decreases by 12.9 percent. Lastly, a certain road classification structure being dominant at a crossing did not provide any significant predictors for the volumes of pedestrians between 7:00 AM and 10:00 AM.

§4.3.3 Pedestrians: traffic intensity between AM and PM rush-hours

To analyze the volumes of pedestrians outside of rush-hours, this section will study the modal usage of walking between the hours of 10:00 AM and 4:00 PM. For this model, the lowest AIC and BIC values were found in the model including both COVID-19 related variables (see appendix 4.1). Thus, the eleventh negative binomial regression model of this study was run with both cases and stringency included and can be found entirely in the Appendix at 4.12. Once again, the Goodness of Fit proved that the data is a good fit for the model while the Omnibus Test indicates that this model is superior to the intercept-only model. As this model passed the tests for data suitability and significancy, the model parameters in table of 4.12 can be used for analysis.

Table 4.12 Analysis of pedestrian intensity during off-peak hours				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	9.438	**	3.0906	12552.610
Daily new COVID-19 cases Canada	0.166	***	0.0458	1.181
Stringency Index Ontario	-0.064	***	0.0113	0.938
Temperature	0.011		0.0219	1.011
Precipitation	-0.024		0.0513	0.976
Windspeed	0.014		0.0137	1.014
Population density	0.075	***	0.0219	1.078
Females %	0.014		0.0646	1.014
Age weighted average	-0.098	*	0.0393	0.907
Income 2020 weighted average	0.000		0.0038	1.000
Arterial dominant crossings	0.365		0.2404	1.441
Local dominant crossings	-0.578	*	0.2744	0.561
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	137.212		133	1.032
Log Likelihood	-1106.248			
AIC	2238.495			
BIC	2277.282			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	117.005		11	0.000
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

Starting with the COVID-19 related variables, the predictors were significant and either positive, in the case of *Daily new COVID-19 cases Canada* (B = 0.166, SE = 0.0458), or of negative nature, in the case of *Stringency Index Ontario* (B = -0.064, SE = 0.0113). When the COVID-19 cases are increased by one thousand, the incidence rate of pedestrian counts between rush-hours is expected to increase by around 18.1 percent. For mitigating policy, every one unit increase in strictness will cause off-peak pedestrian counts to drop by 6.2 percent. Thus, although both COVID-19 variables are significant predictors, it is important to note that the direction of their effect are opposite.

Moving on to the controlling variables, weather-related variables were not significant but both *Population density* (B = 0.075, SE = 0.0219) and *Age weighted average* (B = -0.098, SE = 0.0393) were significant population characteristics predictors. Density is a positive predictor where for every thousand unit increase in density, the incidence rate of pedestrian counts increases by 7.8 percent. Age was a negative predictor meaning that for every one year increase the incidence rates for the modal usage of walking decreases by 9.3 percent.

Regarding crossing characteristics, only the variable of *Local dominant crossings* (B = -0.578, SE = 0.2744) was a significant predictor. Being a predictor of negative nature, local dominant crossings counted around 43.9 percent less pedestrians outside of rush-hours than the reference category of collector dominant crossings.

§4.3.4 Pedestrians: PM rush-hour traffic intensity

The twelfth model of this analysis will be the last pedestrian-oriented model. In this model the volumes of pedestrians will be analyzed during the PM rush-hour, between the hours of 4:00 PM and 6:00 PM. As was the case for all previous pedestrian-oriented model, the lowest AIC and BIC values were given for the model including both COVID-19 related variables (see appendix 4.1). A negative binomial regression was run and the results in the Goodness of Fit and Omnibus Test in table 4.13 stated that the data fits the model well and is significantly better than the intercept-only model respectively - the entire SPSS output can be found in the appendix at 4.13. Thus, due to these satisfying results, the parameter estimates in table 4.13 can be further analyzed.

Table 4.13 Analysis of pedestrian intensity during afternoon rush-hours

Model parameters	**β**		**SE**	**IRR**
(Intercept)	8.720	**	3.1031	6123.189
Daily new COVID-19 cases Canada	0.171	***	0.0464	1.186
Stringency Index Ontario	-0.069	***	0.0115	0.933
Temperature	0.029		0.0219	1.030
Precipitation	-0.064		0.0426	0.938
Windspeed	0.019		0.0143	1.019
Population density	0.074	***	0.0222	1.077
Females %	0.042		0.0648	1.043
Age weighted average	-0.128	***	0.0384	0.880
Income 2020 weighted average	0.003		0.0037	1.003
Arterial dominant crossings	0.270		0.2404	1.311
Local dominant crossings	-0.577	*	0.2808	0.562
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	132.179		133	0.994
Log Likelihood	-1058.181			
AIC	2142.363			
BIC	2181.149			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	120.432		11	0.000
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

As was the same for every previous pedestrian-oriented result regarding COVID-19 related variables, *Daily new COVID-19 cases Canada* (B = 0.171, SE = 0.0464) was a significant and positive predicto. For every thousand added COVID-19 cases the incident rate of pedestrian count during PM rush-hour increases by 18.6 percent. Likewise for *Stringency Index Ontario* (B = -0.069, SE = 0.0115), which was again a significant and negative predictor where for every one unit increase in policy strictness the incident rate of afternoon rush-hour pedestrian counts decreased by 6.7 percent.

Weather related variables did not contain a single significant predictor, to the contrary of population characteristics where both *Population density* (B = 0.074, SE = 0.0222) and *Age weighted average* (B = -0.128, SE = 0.0384) are conceived as significant predictors of the incidence rate of PM pedestrian volumes. For every thousand unit increase in population density the incidence rate of pedestrian counts between 4:00 PM and 6:00 PM increases by 7.7 percent. The effect of age is reverse as the PM pedestrian incidence rate decreases by 12 percent when average age is risen by one year.

Lastly, *Local dominant crossings* (B = -0.577, SE = 0.2808) was the only significant (negative) predictor for road classification when it was referred to collector dominant crossings. On local dominant crossings, the incidence rate of pedestrian volume during the PM rush-hour decreases by 43.8 percent when compared to the reference category of collector dominant crossings.

§4.4 Cyclists-oriented models

The second and last active mode that will be analyzed is the modal usage of bikes in Toronto in March 2019 and March 2022. First, the total modal volumes will be analyzed regardless of period of day after which cyclists' intensity will be analyzed in three different daytime periods: AM rush-hour, between AM and PM rush-hour and PM rush-hour.

§4.4.1 Cyclists: total traffic intensity

The thirteenth model of this analysis will be the first cyclists-oriented model. In this model, cycling intensity will be analyzed between the hours of 7:00 AM and 6:00 PM. The modal structure of choice is the model including both COVID-19 related variables due to having lower AIC and BIC scores (see appendix 4.1). With this model, a negative binomial regression was run (see appendix 4.14 for entire SPSS output). The results indicate that the data fits the model well (Goodness of Fit in table 4.14) while the model also is significantly better than the null model which solely incorporates the intercept (Omnibus Test in table 4.14). Therefore, the parameters in table 4.14 can be used for analysis.

Table 4.14 Analysis of total cycling intensity				
Model parameters	**β**		**SE**	**IRR**
(Intercept)	15.890	***	3.3763	7956964.921
Daily new COVID-19 cases Canada	0.327	***	0.0479	1.387
Stringency Index Ontario	-0.060	***	0.0112	0.942
Temperature	0.102	***	0.0233	1.108
Precipitation	-0.126	***	0.0347	0.882
Windspeed	0.010		0.0149	1.010
Population density	0.071	**	0.0232	1.074
Females %	-0.231	***	0.0711	0.793
Age weighted average	-0.021		0.0415	0.979
Income 2020 weighted average	0.001		0.0042	1.001
Arterial dominant crossings	0.318		0.2316	1.375
Local dominant crossings	-0.105		0.2702	0.900
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	191.731		133	1.442
Log Likelihood	-756.059			
AIC	1538.119			
BIC	1576.906			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	119.458		11	0.000
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

Firstly, while focusing upon the COVID-19 related variables, the model states that *Daily new COVID-29 cases Canada* (B = 0.327, SE = 0.0479) is a significant and positive predictor: for every increase of COVID-19 cases by thousand, the incidence rate of total cyclists increases by 38.7 percent. Additionally, the *Stringency Index Ontario* (B = -0.060, SE = 0.0112) is also a significant predictor although the effect is reversed as a one unit increase in policy strictness will lead to 5.8 percent drop in the incidence rate of cyclists between 7:00 AM and 6:00 PM. Thus, it is important to note that, even though both COVID-19 related variables are significant predictors for total cycling intensity, the direction of effect are opposite: positive with daily case counts but negative for stringency.

Moving on to the controlling variables. Starting with the weather-related variables, where both *Temperature* (B = 0.102, SE = 0.0233) and *Precipitation* (B = -0.126, SE = 0.0347) are significant predictors. For every increase in temperature by 1 degree Celsius, the incidence rate of total cyclists increases by 10.78 percent. When precipitation increases by 1 millimeter, the same incidence rate drops by 11.81 percent. The population characteristics of *Population density* (B = 0.071, SE = 0.0232) and *Females%* (B = -0.241, SE = 0.0711) were significant predictors, the first being positive of nature and the latter negative. When population density is increased by a thousand units, the incidence rate of total cyclists increases by 7.4 percent. The effect is reverse for the relative share of females, as for every 1 percent increase in female share the incidence rate drops by 20.7 percent.

Lastly, the road classification variables did not provide a single significant predictor. Thus, the specific road classification structure of a crossing at the counting location was not significantly related to volumes of cyclists between 7:00 AM and 6:00 PM.

§4.4.2 Cyclists: AM rush-hour traffic intensity

To analyze the bike counts during the AM rush-hours, between 7:00 AM and 10:00 AM, the fourteenth negative binomial regression model was run. Both COVID-19 related variables were included as this composition provided the lowest values for AIC and BIC (see appendix 4.1). The entire SPSS output of this model can be found in the appendix at 4.15. In table 4.15 the Goodness of Fit indicates that this model contains data that fits well while the Omnibus Test states that the model also is significantly better than the intercept-only (null) model. Consequently, the model parameters in table 4.15 can be analyzed to assess the modal usage of bikes during the morning rush-hour.

Table 4.15 Analysis of cycling intensity during morning rush-hours

Model parameters	**β**		**SE**	**IRR**
(Intercept)	16.880	***	3.6538	21425770.559
Daily new COVID-19 cases Canada	0.318	***	0.0525	1.375
Stringency Index Ontario	-0.071	***	0.0121	0.931
Temperature	0.110	***	0.0259	1.116
Precipitation	-0.144	***	0.0408	0.866
Windspeed	0.008		0.0161	1.008
Population density	0.027		0.0262	1.028
Females %	-0.269	***	0.0727	0.764
Age weighted average	-0.018		0.0467	0.983
Income 2020 weighted average	0.001		0.0042	1.001
Arterial dominant crossings	0.120		0.2597	1.127
Local dominant crossings	-0.103		0.3011	0.903
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	216.916		133	1.631
Log Likelihood	-543.014			
AIC	1112.028			
BIC	1150.814			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	98.650		11	0.000

** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*

Once again, the COVID-19 related variables provided significant predictors, being the positive predictor of *Daily new COVID-19 cases Canada* (B = 0.318, SE = 0.0525) and the negative predictor of *Stringency Index Ontario* (B = -0.071, SE = 0.0121). For every 1000 increase in COVID-19 cases, the incidence rate for AM cyclists count increase by around 37.5 percent. The negative predictive nature of mitigating policy implies that for every 1 unit increase in strictness, the incidence rate for morning rush-hour cyclists declines by 6.9 percent.

Temperature (B = 0.010, SE = 0.0259) is the first significant predictor for weather variables. Being positive of nature, a one-degree Celsius increase relates to an increase in the incidence rate for AM cyclists by 11.6 percent. On the other hand, *Precipitation* (B = -0.144, SE = 0.0408) is a significant weather predictor as well. Since precipitation is negative of nature, more rainfall is associated with less cycling: for every 1-millimeter increase in precipitation causes a 13.4 percent decline in the counts of cyclists between 7:00 AM and 10:00 AM.

Regarding population characteristics in the proximity of counting locations, only *Females%* (B = -0.269, SE = 0.0727) is a significant predictor. Being a negative predictor, every 1 percent increase in female share of the total neighborhood population leads the incidence rate of cyclists' volume during the morning rush-hour to drop by 23.6 percent.

Lastly, the road classification structure of crossings did not provide any significant predictors in comparison to the reference category of collector dominant crossings.

§4.4.3 Cyclists: traffic intensity during off-peak hours

This section will analyze bike counts between the hours of 10:00 AM - 4:00 PM and will provide this research with the ability to analyze the modal usage of cycling between rush-hours. The entire SPSS output of the fifteenth negative binomial regression model can be found in Appendix 4.16. For this model, the AIC and BIC values were lowest for the model including both COVID-19 cases and policy stringency (see appendix 4.1). This model, as the Goodness of Fit in table 4.16 makes visible, contains data that fits well to the model. Furthermore, as Omnibus Test in table 4.16 shows, the current model is superior to the intercept-only (null) model. Due to satisfying results in these two tables, the model parameters in table 4.16 can be analyzed to assess off-peak cycling volumes.

Table 4.16 Analysis of cycling intensity during off-peak hours

Model parameters	**β**		**SE**	**IRR**
(Intercept)	12.430	***	3.2860	250195.225
Daily new COVID-19 cases Canada	0.287	***	0.0468	1.333
Stringency Index Ontario	-0.050	***	0.0110	0.951
Temperature	0.080	***	0.0233	1.083
Precipitation	-0.112	**	0.0380	0.894
Windspeed	0.009		0.0146	1.009
Population density	0.083	***	0.0224	1.087
Females %	-0.185	**	0.0695	0.831
Age weighted average	-0.023		0.0399	0.977
Income 2020 weighted average	0.003		0.0041	1.003
Arterial dominant crossings	0.425		0.2246	1.530
Local dominant crossings	-0.086		0.2725	0.918
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	163.059		133	1.226
Log Likelihood	-635.370			
AIC	1296.739			
BIC	1335.526			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	110.141		11	0.000

** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*

Focusing on COVID-19, both variables are significant. *Daily new COVID-19 cases Canada* (B = 0.287, SE = 0.0468) is a positive predictor where an increase of COVID-19 cases by a thousand will cause a 33.3 percent increase in the incidence rate of cyclists between 10:00 AM and 4:00 PM. The other COVID-19 related variable of *Stringency Index Ontario* (B = -0.050, SE = 0.0110), although it was also significant, was a negative predictor of nature as every one unit increase in strictness causes the incidence rate of cyclists in between the rush-hours to drop by 4.9 percent approximately.

Regarding climatological conditions, *Temperature* (B = 0.080, SE = 0.0233) was a significant positive predictor: for every one-degree Celsius increase in temperature, the incidence rate of in between rush-hours cyclists rises by 8.3 percent. *Precipitation* (B = -0.112, SE = 0.0380) was a significant negative predictor as for every 1-millimeter increase in precipitation the incidence rate of cyclists between 10:00 AM and 4:00 PM decreases by 10.6 percent.

Two out of four population characteristics variables were significant predictors of off-peak cycling: *Population density* (B = 0.080, SE = 0.0224) and *Females%* (B = -0.185, SE = 0.0695). The positive predictor of density reports an estimate effect size where every increase in population density by a thousand will lead to an increase in the incidence rate of in between rush-hour cyclists by 8.7 percent. The share of females is a negative predictor on the same incidence rate: for every 1 percent increase in the female share among the population leads to a 16.9 percent decrease.

Road classification did not provide any significant predictors, even though the p-value of arterial dominant crossings came close (p = 0.059) it still was not below the 0.05 significancy level. Thus, road classification has no significant on the incidence rates of in between rush-hours cyclists when both arterial and local dominant crossings are compared to the reference category of collector dominant crossings.

§4.4.4 Cycling: PM rush-hour traffic intensity

Being the last cyclist and active mode-oriented model, as well as the final model of the entire analysis, this studies' sixteenth negative binomial regression model will analyze cycling volumes during the PM rush-hour (4:00 PM – 6:00 PM). Alike the modal structure of all the previous analysis on active modal intensity, this model includes both COVID-19 variables of cases and stringency as it provided the lowest AIC and BIC values (see appendix 4.1). The entire SPSS output is visible in appendix 4.17. This model, according to the Goodness of Fit and Omnibus Test in table 4.17, suits the data well and is significantly superior to the intercept-only (null) model respectively. Therefore, the model parameters can be analyzed to assess cycling volumes during the afternoon rush-hour.

Table 4.17 Analysis of cycling intensity during afternoon rush-hours

Model parameters	**β**		**SE**	**IRR**
(Intercept)	16.474	***	3.8263	14280478.468
Daily new COVID-19 cases Canada	0.395	***	0.0550	1.485
Stringency Index Ontario	-0.068	***	0.0127	0.935
Temperature	0.122	***	0.0255	1.129
Precipitation	-0.133	***	0.0408	0.876
Windspeed	0.008		0.0167	1.008
Population density	0.073	**	0.0259	1.076
Females %	-0.247	**	0.0805	0.781
Age weighted average	-0.040		0.0474	0.961
Income 2020 weighted average	-0.001		0.0048	0.999
Arterial dominant crossings	0.279		0.2584	1.322
Local dominant crossings	-0.259		0.3016	0.772
Goodness of Fit	**Value**		**df**	**Value/df**
Pearson Chi-Square	189.150		133	1.422
Log Likelihood	-596.572			
AIC	1219.144			
BIC	1257.931			
Omnibus Test	**Value**		**df**	**Sig.**
Likelihood Ratio Chi-Square	119.891		11	0.000
** P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001*				

Once again, both COVID-19 related variables are significant predictors and with the same directional estimates of effect size as *Daily new COVID-19 cases Canada* (B = 0.395, SE = 0.0550) is a positive predictor while the *Stringency Index Ontario* (B = -0.068, SE = 0.0127) is a predictor of negative nature. The estimate of effect size of COVID-19 cases can be interpreted that for every 1000 cases increase in daily COVID-19 cases, the incidence rate of PM rush-hour cyclists counts increases by 48.5 percent. Regarding mitigating policy, every one unit increase in strictness leads to a 6.5 percent decrease in the PM rush-hour incidence rate of cyclists.

Temperature (B = 0.122, SE = 0.0127) and *Precipitation* (B = -0.133, SE = 0.0408, p = 0.001) showed that these variables are significant predictors of afternoon rush-hour cycling volumes, being of positive and negative nature respectively. When the values of the significant predictors increase by one unit, the incidence rates of PM rush-hour cycling increase by 12.9 percent in the case of rising temperature, while these rates drop by 12.4 percent due to more precipitation.

The first predictor of population characteristics that is significant is *Population density* (B = 7.323E-05). Being positive of nature, every increase in density by one thousand people per square kilometer will lead to an increase in the incidence rate of PM cyclists counts by 7.6 percent. *Females%* (B = -0.247, SE = 0.0805) is the second negative predictor. For this variable is a positive predictor, every 1 percent increase in female share relates to a 21.9 percent decline in the incidence rate of afternoon rush-hour counts of cyclists.

Lastly, road classification did not provide any significant predictors. Thus, it can be concluded that the incidence rates of PM rush-hour cyclists cannot be significantly predicted by the road class structure of crossings when compared to the reference category of collector dominant crossings.

§4.5 Comparison of analysis results with hypotheses

Now all the 16 negative binomial regression models have been discussed in the previous paragraphs, this paragraph will compare the analysis results with the hypotheses which were formulated beforehand in the methodology chapter at §3.6 (see table 3.7). Table 4.18 presents an overview of the analysis results is upon which the hypotheses will be either accepted or rejected per counting category.

Table 4.18: Overview table of analysis results on significancy (Sig.), incidence rate ratio (IRR) and one unit increase effect (OUIE)

Counting category	Parameters	Daily new COVID-19 cases Canada	Stringency Index Ontario	Temperature	Precipitation	Windspeed	Population density	Females%	Age weighted average	Income 2020 weighted average	Arterial dominant crossings	Local dominant crossings
Total all modes	Sig.	*	*								**	***
	IRR	0.938	0.986	1.001	0.972	1.008	1.016	1.035	1.006	1.003	1.439	0.528
	OUIE	-6.2%	-1.4%	+0.1%	-2.8%	+0.8%	+1.6%	+3.5%	+0.6%	+0.3%	+43.9%	-47.2%
AM total	Sig.	*	**		***	*				*	*	***
	IRR	0.940	0.983	1.015	0.928	1.020	0.995	1.039	0.990	1.004	1.355	0.586
	OUIE	-6.0%	-1.7%	+1.5%	-7.2%	+2.0%	-0.5%	+3.9%	-1.0%	+0.4%	+35.5%	-41.4%
IB total	Sig.	*									**	***
	IRR	0.936	0.989	0.994	0.994	1.002	1.024	1.029	1.021	1.002	1.500	0.506
	OUIE	-6.4%	-1.1%	-0.6%	-0.6%	+0.2%	+2.4%	+2.9%	+2.1%	+0.2%	+50.0%	-49.4%
PM total	Sig.	*	*								*	***
	IRR	0.943	0.985	1.004	0.969	1.009	1.020	1.040	0.999	1.003	1.416	0.512
	OUIE	-5.7%	-1.5%	+0.4%	-3.1%	+0.9%	+2.0%	+4.0%	-0.1%	+0.3%	+41.6%	-48.8%
Cars total	Sig.	***									**	***
	IRR	0.895		0.995	0.983	1.005	1.001	1.039	1.037	1.001	1.511	0.532
	OUIE	-10.5%		-0.5%	-1.7%	+0.5%	+0.1%	+3.9%	+3.7%	+0.1%	+51.1%	-46.8%
Cars AM	Sig.	***			**						**	***
	IRR	0.893		1.005	0.941	1.014	0.990	1.050	1.025	1.002	1.491	0.562
	OUIE	-10.7%		+0.5%	-5.9%	+1.4%	-1.0%	+5.0%	+2.5%	+0.2%	+49.1%	-43.8%
Cars IB	Sig.	***									**	***
	IRR	0.896		0.990	1.002	1.001	1.006	1.035	1.042	1.001	1.537	0.510
	OUIE	-10.4%		-1.0%	+0.2%	+0.1%	+0.6%	+3.5%	+4.2%	+0.1%	+53.7%	-49.0%
Cars PM	Sig.	***									**	***
	IRR	0.895		0.995	0.983	1.007	1.003	1.035	1.040	1.001	1.485	0.534
	OUIE	-10.5%		-0.5%	-1.7%	+0.7%	+0.3%	+3.5%	+4.0%	+0.1%	+48.5%	-46.6%
Peds total	Sig.	***	***				**		***			
	IRR	1.179	0.936	1.025	0.945	1.018	1.068	1.025	0.886	1.002	1.317	0.631
	OUIE	+17.9%	-6.4%	+2.5%	-5.5%	+1.8%	+6.8%	+2.5%	-11.4%	+0.2%	+31.7%	-36.9%
Peds AM	Sig.	***	***	*	***	*			***			
	IRR	1.162	0.935	1.050	0.893	1.030	1.037	1.017	0.871	1.005	1.084	0.871
	OUIE	+16.2%	-6.5%	+5.0%	-10.7%	+3.0%	+3.7%	+1.7%	-12.9%	+0.5%	+8.4%	-12.9%
Peds IB	Sig.	***	***				***		*			*
	IRR	1.181	0.938	1.011	0.976	1.014	1.078	1.014	0.907	1.000	1.441	0.561
	OUIE	+18.1%	-6.2%	+1.1%	-2.4%	+1.4%	+7.8%	+1.4%	-9.3%	–	+44.1%	-43.9%
Peds PM	Sig.	***	***				***		***			*
	IRR	1.186	0.933	1.030	0.938	1.019	1.077	1.043	0.880	1.003	1.311	0.562
	OUIE	+18.6%	-6.7%	+3.0%	-6.2%	+1.9%	+7.7%	+4.3%	-12.0%	+0.3%	+31.1%	-43.8%
Bike total	Sig.	***	***	***	***		**	***				
	IRR	1.387	0.942	1.108	0.882	1.010	1.074	0.793	0.979	1.001	1.375	0.900
	OUIE	+38.7%	-5.8%	+10.8%	-11.8%	+1.0%	+7.4%	-20.7%	-2.1%	+0.1%	+37.5%	-10.0%
Bike AM	Sig.	***	***	***	***			***				
	IRR	1.375	0.931	1.116	0.866	1.008	1.028	0.764	0.983	1.001	1.127	0.903
	OUIE	+37.5%	-6.9%	+11.6%	-13.4%	+0.8%	+2.8%	-23.6%	-1.7%	+0.1%	+12.7%	-9.7%
Bike IB	Sig.	***	***	***	**		***	**				
	IRR	1.333	0.951	1.083	0.894	1.009	1.087	0.831	0.977	1.003	1.530	0.918
	OUIE	+33.3%	-4.9%	+8.3%	-10.6%	+0.9%	+8.7%	-16.9%	-2.3%	+0.3%	+53.0%	-8.2%
Bike PM	Sig.	***	***	***	***		**	**				
	IRR	1.485	0.935	1.129	0.876	1.008	1.076	0.781	0.961	0.999	1.322	0.772
	OUIE	+48.5%	-6.5%	+12.9%	-12.4%	+0.8%	+7.6%	-21.9%	-3.9%	-0.1%	+32.2%	-22.8%

* P ≤ 0.05 | ** P ≤ 0.01 | *** P ≤ 0.001

§4.5.1 H1: Higher daily new COVID-19 cases in Canada will negatively predict car volumes

As the results of the four car-oriented models show, daily new COVID-19 cases in thousands was a significant predictor. With IRR ranging between 0.896 (Cars PM) and 0.893 (Cars AM), COVID-19 cases was a negative predictor amongst all car-oriented models. This in in line with previous studies found similar effects where COVID-19 cases had a negative impact on car volumes (see supporting literature of H1 in table 3.7). Thus, hypothesis 1 is accepted.

§4.5.2 H2: Higher daily new COVID-19 cases in Canada will positively predict active modal volumes

Although COVID-19 cases negatively predicted cars, previous studies have shown that during the COVID-19 pandemic active modes of travel have grown in terms of volumes and modal share (see supporting literature H2 in table 3.7). This study provides similar results, as there were significantly more pedestrians and cyclists counted on days containing more daily confirmed COVID-19 cases. For walking, the IRR varied between 1.162 (Peds AM) and 1.186 (Peds PM) while it ranged between 1.333 (Bike IB) and 1.485 (Bike PM) for cycling. Therefore, hypotheses 2 is accepted as COVID-19 cases was a significant and positive predictor of active modal volumes.

§4.5.3 H3: Higher Stringency Index scores in Ontario will negatively predict car volumes

Since the inclusion of the independent variable Stringency Index Ontario did not provide lower AIC and BIC scores (see table 3.5), the third hypotheses of this study cannot be tested.

§4.5.4 H4: Higher Stringency Index scores in Ontario will positively predict active modal volumes

Previous research has argued that during the COVID-19 pandemic people have been using active travel options more (see supporting literature H4 in table 3.7). However, our results indicate the opposite effect: higher stringency index scores significantly and negatively predict traffic volumes of both pedestrians and cyclists. With pedestrians' IRRs ranging from 0.938 (Peds IB) and 0.933 (Peds PM) and cyclists' IRRs lying between 0.951 (Bike IB) and 0.931 (Bike AM), the Stringency Index Ontario significantly and negatively predicted all volumes of models focused on active modal usage.

Although both COVID-19 cases and Stringency Index proved to be significant predictors, the direction of effect is opposite. This requires explanation, which is provided by figure 4.19. In this figure, it becomes visible that during March 2022 the Stringency Index value decreased - indicating that mitigating measures were lifted somewhere between 10 and 22 March 2022. On the other hand, daily confirmed COVID-19 cases did not decrease during the month of March 2022. In fact, there is a trend with higher daily case counts towards the end of March 2022.

As is seen in figures 4.20 and 4.21, there are higher counting day averages of both walking and cycling towards the end of March 2022 as well. This explains why COVID-19 cases is a positive predictor: near the end of the month there are higher daily confirmed cases and higher counting day averages for the active modes of walking and cycling. The reason for the Stringency Index Ontario being a predictor of negative nature lies in the fact that the policy becomes less strict during March 2022 while average counting day volumes of pedestrians and cyclists increase towards the end of March 2022.

However, despite this explanation of why the direction of effects differ from each individual COVID-19 related independent variable, the fourth hypothesis of this study will be rejected.

Figure 4.19: COVID-19 related variable values on March 2022 counting days in Toronto

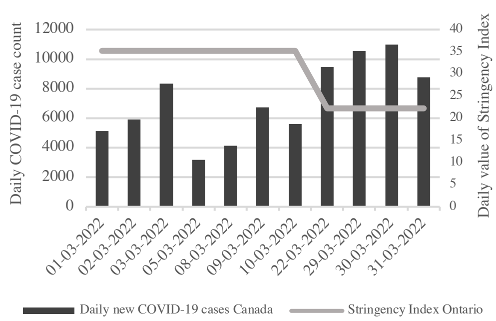


Figure 4.20: March 2022 counting day average of total pedestrian intensity in Toronto

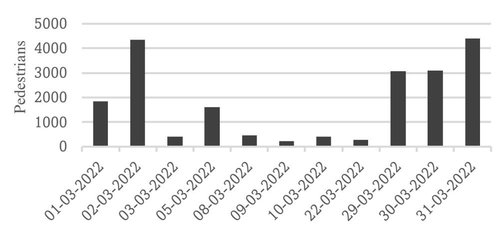
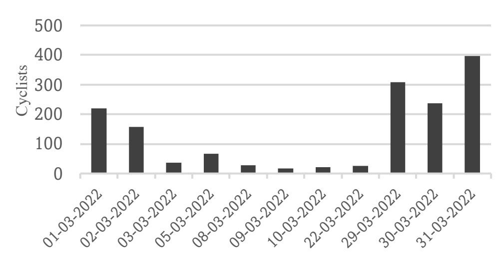


Figure 4.21: March 2022 counting day average of total cycling intensity in Toronto



§4.5.5 H5: Higher temperature will positively predict active modal volumes

Previous studies analyzing the impact of temperature on active modal usage patterns have argued that higher temperatures are related to higher volumes of active travel modes (see supporting literature H5 in table 3.7). When looking at the results of this study, the same pattern is seen with pedestrian volumes during the morning rush-hours: the higher the average counting day temperature, the more pedestrians are counted between the hours of 7 AM and 10 AM. The same pattern is seen with cyclists regardless the time of day as temperature was a significant and positive predictor of cycling during all four bike-oriented models. Thus, hypotheses 5 can be accepted for all bike-oriented models but not for every pedestrian-oriented model as only morning rush-hours pedestrian volumes is significantly predicted by a higher temperature.

§4.5.6 H6: More precipitation will negatively predict active modal volumes

With active modal users being less protected from precipitation, previous studies have shown that on days with precipitation there are less people walking and cycling than on clear days (see supporting literature H6 in table 3.7). Regarding the pedestrian-oriented models, more precipitation was only a significant and negative predictor for morning rush-hour pedestrian volumes. For cycling, precipitation proved to be a significant predictor of negative nature in all the four cycling-oriented models. Therefore, hypothesis 6 can only be accepted for morning rush-hour pedestrian volumes and for all models focusing on cycling volumes.

§4.5.7 H7: Higher windspeed will negatively predict active modal volumes

Alike precipitation, previous research have shown that higher windspeeds is associated with less volumes of pedestrians and cyclists (see supporting literature H7 in table 3.7). However, our study results show a opposite pattern: for every active mode counting category where windspeed was significant, windspeed was a positive predictor. Hence, the seventh hypothesis of this study is rejected for all counting categories.

§4.5.8 H8: Higher population density will positively predict traffic volumes all counting categories

Previous studies have shown that densely populated areas contain more traffic than less dense areas (See supporting literature H8 in table 3.7). Looking at the results of this study, this the case for all active mode-oriented models except the models looking at pedestrian and cycling volumes during the morning rush-hour. Thus, hypothesis 8 is accepted for active modal intensities between the peak hours, during the afternoon rush-hour and between 7 AM and 6 PM. The same hypothesis is rejected for all car-oriented models and AM rush-hour active modal volumes.

§4.5.9 H9: Higher share of females in population will negatively predict active modal volumes

Areas containing a higher share of females among its population was a significant and negative predictor for all cycling-oriented models. This is in line with previous studies who found higher cycling volumes in areas with a higher share of male inhabitants (see supporting literature H9 in table 3.7). Hence, regarding cycling, hypothesis 9 is accepted while it is rejected for the active mode of walking as it did not prove to be a significant predictor for that mode.

§4.5.10 H10: Higher average age in population will negatively predict active modal volumes

Scholars have previously argued that areas housing younger people depict higher volumes of pedestrians and cyclists (see table 3.7 for supporting literature H10). In the analysis of this study, the same was the case for pedestrians as all pedestrian-oriented models show that a higher weighted average age in the counting location area is associated with less volumes of pedestrians. Regarding cycling, age did not prove to be a significant predictor. Thus, hypothesis 10 is accepted for pedestrians but rejected for cyclists.

§4.5.11 H11: Higher average income in population will positively predict car volumes

The results of this study show that income was only a significant predictor for the counting category of *AM total*, depicting the total traffic intensity during the morning rush-hour between 7 AM and 10 AM. Being a significant predictor of positive nature, counting areas earning a higher total income per person in 2020 contain higher total traffic volumes during the morning rush-hour period. This is in line with previous studies indicating that richer areas contain more traffic (see table 3.7 for supporting literature H11). Hence, the eleventh hypothesis of this study is only accepted for total traffic volumes during the morning rush-hour. Thus, the hypothesis is rejected for total traffic volumes during the entire counting day (7 AM – 6 PM), during the off-peak hours and PM rush-hours as well as for all car-oriented counting categories.

§4.5.12 H12: Higher average income in population will negatively predict active modal volumes

Despite previous research arguing that income is related to active modal volumes (for supporting literature of H12, see table 3.7), this study has not found similar effects when analyzing the modal volumes of walking and cycling. Consequently, hypothesis 12 is rejected for all active mode-oriented models.

§4.5.13 H13: Arterial dominant crossings will positively predict traffic volumes across all counting categories

Previously, studies have provided results that roads which are higher in hierarchy contain more traffic intensity regardless of travel mode (see supporting literature H13 in table 3.7). In this study, the same effect is found in the models looking at total traffic intensity and all car-oriented models. Therefore, hypothesis 13 is accepted for these beforementioned models but is rejected for the models focusing on pedestrians and cyclists as arterial dominant crossings was not a significant predictor.

§4.5.14 H14: Local dominant crossings will negatively predict traffic volumes across all counting categories

Scholars have argued that roads of less hierarchy contain lower overall traffic volumes (see table 3.7 for supporting literature of H14). In this study, the same effect is found in the models looking at total traffic intensity, all car-oriented models and pedestrian volumes during the off-peak period and afternoon rush-hour. For these models, local dominant crossings contained predicted significantly less traffic than on the reference category of collector dominant crossings. Hence, hypothesis 14 is accepted for these models but is rejected in the case of total pedestrian intensity, morning rush-hour pedestrian volumes and for all cycling-oriented models.

5. CONCLUSION

Since the beginning of the COVID-19 pandemic in early 2020, many studies have observed significant changes in mobility patterns (Bert et al., 2021; Kim et al., 2021; Paul et al., 2022). Most notably were the changes in modal usage patterns as people were using more cars and active modal options (walking & cycling) during the pandemic as opposed to the pre-pandemic period (Abdullah et al., 2020; Ehsani et al., 2021; Lee & Eom, 2022; Shaer & Haghsenas, 2021; Van der Drift et al., 2021). However, most of these studies were conducted in times characterized by imposed mitigating measures like lockdowns, social distancing and stay-at-home policies. Although these studies provided the much-needed insight on how modal usage patterns was influenced during the 2020-2021 peak years of the pandemic, there is more understanding required on the persistence of these changes, specifically during times less affected by the pandemic and its side-effects.

Since the Omicron coronavirus variant became dominant at the 2021-2022 turn of the year, policymakers have started to lift their mitigating measures – making the travel choices, options and behavior of people the freest since the start of the pandemic. This development and change in the pandemic situation provides a window of opportunity for this study in which the pre-pandemic and post-lockdown differences in modal usage patterns can be investigated. To evaluate the post-lockdown influence of COVID-19 on modal usage patterns, this study has analyzed traffic count data in Toronto during the pre-pandemic month of March 2019 and the post-lockdown month of March 2022. The traffic count data, which were obtained through the open data portal of the City of Toronto (Toronto Transportation Services, 2022), was analyzed through four modal categories: total traffic intensity, cars, pedestrians and cyclists. These four categories where once more divided into categories based upon the time of day, being the entire counting day (7 AM – 6 PM), morning rush-hour (7 AM – 10 AM), off-peak period (10 AM – 4 PM) and afternoon rush-hour (4 PM – 6 PM). This allowed this study to analyze traffic volumes per mode and per daytime period.

To capture the influence of COVID-19, both daily confirmed COVID-19 cases in Canada (Ritchie et al., 2022) and the daily value of the Stringency Index in Ontario (Blatvatnik School of Government & University of Oxford (2022) were included in models analyzing total traffic, pedestrian and cyclist volumes. Regarding car volumes, only daily COVID-19 cases was included as it provided lower AIC and BIC scores. Apart from COVID-19 related variables, this study included other independent variables based upon previous literature and research findings. These variables included counting day related weather statistics in Toronto (temperature, precipitation & windspeed), population characteristics in proximity of the counting location (density, female share, age & income) and the road classification of the counting location (arterial, collector or local dominant crossings).

In total, this study analyzed daily traffic count data of 146 counting locations in Toronto, which included 69 counting days in March 2019 and 77 counting days in March 2022. By running a negative binomial regression model for each of the 16 counting categories (four modal categories divided in four temporal categories), while accounting for other potentially relevant variables to travel mode intensity, this study intended to fulfill its aim to examine the impact of the COVID-19 pandemic on modal usage volumes. With the values of the COVID-19-related variables at a constant zero during March 2019, the different daily values of the same variables during post-lockdown month of March 2022 allowed this study to see whether COVID-19 had a significant impact on modal usage volumes and if this impact was positive or negative in nature as opposed to the pre-pandemic month of March 2019. Now the analysis has been conducted and discussed in the previous chapter, this study is now able to formulate an answer to the main research question:

> *How did COVID-19 daily confirmed cases and policy strictness influence the modal volumes of cars, pedestrians and cyclists in Toronto?*

Starting with cars, where the daily amount of newly confirmed COVID-19 cases in Canada proved to be a significant and negative predictor in all car-oriented models. This indicates that on days containing more daily confirmed COVID-19 cases there are significantly less cars counted during the entire counting day, including morning and afternoon rush-hours and the off-peak period. Thus, the pandemic negatively influenced the traffic volumes of cars.

Moving onto active modal volumes, this study provides results that indicate that the COVID-19 pandemic had a significant influence on the modal volumes of walking and cycling regardless the time of day. However, the direction of the influence of the included COVID-19-related variables were opposite: daily COVID-19 cases positively predicted active modal volumes while the Stringency Index was a negative predictor. The reason for these differing outcomes can be found when the March 2022 trends for active modal volumes, daily COVID-19 cases and Stringency Index is analyzed (see §4.5.4 and figures 4.19 – 4.21). Due to the higher infectious nature of the then dominant coronavirus strain Omicron, COVID-19 cases were rising as March 2022 progressed. At the same time, Omicron posed a lower risk to public health allowing for mitigating measures to be less strict resulting in less barriers for mobilitiy (Daria & Islam, 2022; Taylor, 2022; Wang & Han, 2022). By combining the viral characteristics of Omicron and its associated policy adaptations with the trend of higher active modal volumes towards the end of March 2022 explains the dichotomy in direction of effects of COVID-19 cases and policy strictness.

Al this taken into consideration, this study summarizes and concludes regarding the main research question that the COVID-19 pandemic had a significant influence on volumes of cars, pedestrians and cyclists. However, the direction of effect differs per travel mode and per COVID-19 related variable while it was not affected by time of day. While daily confirmed cases of COVID-19 significantly predicted less volumes of cars, significantly higher volumes of active modes were counted on days containing (more) confirmed cases. Regarding the strictness of the policy aiming to mitigate harmful effects of COVID-19, the study results argue that stricter policy is significantly associated with less volumes of active modes. Thus, this study concludes that COVID-19 cases had a positive effect on active modal volumes while policy strictness negatively influenced the traffic intensity of cars, pedestrians and cyclists.

6. DISCUSSION

Now this study has answered its main research question and formulated its final conclusions, this chapter will form the closing piece of this study. First, findings of this study will be put in perspective towards results from other related studies and theory whereafter relevant implications of the results of this study will be discussed. Thereafter, there will be reflected upon this study, including its limitations. Lastly, this study closes off by providing suggestions for future research.

§6.1 Study findings in perspective to previous research

Notwithstanding that, as of late 2022, it still is too soon to formulate final conclusions on the degree, direction and magnitude of the lasting impact of COVID-19, an increasing amount of literature and scholars have argued that the pandemic is likely to have enduring (long-term) consequences and influence on travel mobility, most notably on modal usage patterns with increasing volumes of active modes (Paul et al., 2022). Most mobility experts feel the same way, as a study by Zhang et al. (2021) displayed that the lion’s share of participating experts (64.8%), specialized in mobilities or other related disciplines, supported the view that the COVID-19 pandemic will induce significant changes in mobility policy within five years. Apart from policymakers, the perspective of the public is important as people have gotten acquainted and accustomed to different mobility behaviors during the pandemic.

Kellerman (2022), after doing research on possible post-COVID mobility patterns, concluded that:

> *Post-COVID mobilities will presumably reflect people's basic needs or triggers for mobilities, their pre-COVID, and COVID mobility experiences, as well as some societal-economic forces pushing for mobility changes.*
>
> Kellerman (2022, p.12)

This study provides similar evidence as its results indicate that COVID-19 had a significant impact on modal usage patterns. However, if these changes continue to exist in the post-pandemic era is uncertain: previous crises have shown that travel mobility can recover and sometimes even surpass pre-crises levels (Li et al., 2010; Novelli et al., 2018). Hence, there currently is no scientific consensus on whether this will be the case for the COVID-19 pandemic even though there is a general agreement over the fact that the COVID-19 pandemic had an unprecedented impact on travel mobility (Kim et al., 2021). However, the temporal extend and severity of this impact is unknown as scholars have either not ruled or are supportive of the idea that the pandemic induced significant changes in mobility that will endure on the long run (Das et al., 2021; De Haas et al., 2020; Griffiths et al., 2021; Kellerman, 2022; Zhang et al., 2021).Loa et al., (2021) describes and explains both perspectives on the persistence of the pandemic induced changes as follows:

> *On the one hand, a global pandemic is certainly significant enough to bring about long-term changes (…) Such a change would likely lead to an increased preference for individual modes and a reduced propensity for using public transit. On the other hand, given that the pandemic is effectively an external shock, the cessation of the pandemic could result in people returning to their pre-pandemic modality profile.*
>
> Loa et al. (2021, p 81)

Considering all this, whether this study has provided evidence of a significant long-term change in mobility patterns remains to be seen and proven in the future. Nevertheless, the results of this study are alike previous scientific research indicating more people traveling on foot or by bike than before the COVID-19 pandemic (Abdullah et al., 2020; Ehsani et al., 2021; Lee & Eom, 2022; Shaer & Haghsenas, 2021; Van der Drift et al., 2021). Furthermore, the results indicate that the pandemic modal usage patterns continue during the early stages of the post-lockdown period in which mitigating measures are lifted. When people continue to prefer using more active travel modes than before has consequences. These will be discussed in the following paragraph.

§6.2 Implications of this study

The results of this study imply several indications for society and its policymakers. First, the data shows that policymakers have an effective tool in hand with regard to decreasing total traffic intensity, most notably on pedestrians and cyclists volumes - a result which has also been found in previous research (Askitas et al., 2021; Awad-Núñez et al., 2021; Jenelius & Cebecauer, 2020; Shaer & Haghshenas, 2021). By adapting the strictness of their policy based upon the changing dynamic a current ongoing crisis, in this case the COVID-19 pandemic, policymakers can significantly affect the mobility of its people when deemed necessary.

Second, the data shows that the March active modal usage patterns had increased during the COVID-19 pandemic as daily cases were a significant and positive predictor of pedestrians and cyclists counts. This fact is thought-provoking. Despite the decreasing influence of teleworking, online education and stay-at-home policy in March 2022, meaning there were less motivations to travel than in March 2019, there were more active travel mode users counted on days with more COVID-19 cases on that day. If the trend of rising volumes of pedestrians and cyclists continues to exist in the future adaptation is required from both society and the policymakers. More active modal users means more vulnerable travelers are sharing the road with other (quicker) modes like cars. Thus, raising societal awareness and enhancing the road safety of these active modes should become the focal point of future mobility policy. This is particularly the case in car-dominant cities, like Toronto and other Northern-American cities, as in these cities motorists are not yet accustomed to sharing the roads with more vulnerable active mode users (Greene et al., 2022; Paul et al., 2022). Policymakers should act upon this as soon as possible as times with less mobility restricting measures could be accompanied by a rise in overall traffic meaning that even more active modal users are sharing the road with rising numbers of commuter traffic. This also includes motorists who were previously teleworking and have not yet been accustomed to more pedestrians and cyclists in traffic. Thus, there is a strong incentive for policymakers to focus upon what changing modal usage patterns implies for their jurisdictions.

Lastly, as our results indicate a rising trend of active modal usage during the COVID-19 pandemic, this trend can act as a window of opportunity for policymakers to promote active modes even further. Stimulating active modes will help policymakers and society as it can reduce congestion, environmental pollution and the consumption of space that are associated with motorized travel modes which are dependent on finite sources of fossil fuels (Jasiński, 2022; Moreno, Allam, Chabaud, Gall & Pratlong, 2021). For people to continue their more active modal pandemic mobility patterns or even further increase the modal share of active modes, scholars have argued that policymakers should invest more in improving the infrastructure to accommodate rising numbers of pedestrians and cyclists. Apart from creating more bike lanes and walking paths (Ehsani et al., 2021; Pan, Geertman, Deal, Jiao & Wang, 2022; Zubair, Karoonsoontawong & Kanitpong, 2022) active travel should become more attractive in financial terms. This can be achieved through subsidies while non-active private modal usage are discouraged at the same time (Das et al., 2021; Griffiths et al., 2021). Thus, policymakers can capitalize on the window of opportunity provided by the COVID-19 pandemic induced trend of more active modal traffic. There lies a unique chance to make travelling more sustainable, environmentally friendly, less space-consuming and healthy.

§6.3 Study reflection, limitations & future research recommendations

Reflecting on the process and results of this research, this study argues that analyzing modal usage patterns is both as difficult as it is necessary. The difficulty in analyzing quantitative traffic volumes originates from limited availability of quality and up-to-date traffic databases. Hence, only Toronto was elected as the city of analysis as it was the only city containing adequate traffic data which was recent enough to study traffic in times less restricted by the COVID-19 pandemic and its related policy measures. Preferably, the same analysis was conducted in multiple, different study areas as this enables for comparisons between results (Lee & Eom, 2022; Zhao et al., 2020). As of now, this study only considers Toronto which makes it difficult to generalize these results. Thus, this study stresses the need for future studies analyzing traffic volumes in several places so that potential patterns or differences between places can be assessed.

Furthermore, due to data constraints, this study was only able to compare one month (March) during the pre-pandemic and pandemic. This makes it difficult to make assumptions for other months or time period, including the post-pandemic era. Moreover, despite the decreases in policy stringency in March 2022, it still was a month which was influenced by the COVID-19 pandemic and the remaining mitigating measures. Hence, this study wishes for future studies to conduct research on longer timeframes. Studies conducted ruing times which are even less affected by COVID-19 will t be able to tell whether pre-pandemic, pandemic and post-lockdown mobility patterns differ significantly from post-pandemic mobility patterns (Borkowski et al., 2021; De Haas et al., 2020). For example, this study encourages research to be conducted during March 2023 in Toronto.

As time passes on, more and more cities will be able to provide the needed traffic data necessary for the same analysis which was conducted for Toronto. Nevertheless, this study will be able to provide policymakers insight in how modal usage patterns have changed from the pre-pandemic era to times which were less impeded by the COVID-19 pandemic. However, as of late 2022 and early 2023, it is too soon to conclude whether the pandemic period can be understood as a divider of eras in which significant differences exist between pre-pandemic and post-pandemic periods. Hence, this study, in accordance with other scholars, accentuates the need for continuous research on similarities and dissimilarities between pre- and post-pandemic eras (Lee & Eom, 2022). In doing so, policymakers can become better equipped to make future mobility safer, smarter, healthier, and environmentally friendly.

References

Abdel-Aty, M. A., & Radwan, A. (2000). Modeling traffic accident occurrence and involvement. *Accident Analysis &Amp; Prevention*, *32*(5), 633–642. https://doi.org/10.1016/s0001-4575(99)00094-9

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

Abulibdeh, A., & Mansour, S. (2021). Assessment of the Effects of Human Mobility Restrictions on COVID-19 Prevalence in the Global South. *The Professional Geographer*, *74*(1), 16–30. https://doi.org/10.1080/00330124.2021.1970592

ActiveTO. (2021). *ActiveTO – Quiet Streets* [Photo]. https://www.toronto.ca/explore-enjoy/recreation/activeto/activeto-quiet-streets/

Adey, P. (2017). *Mobility* (2nd ed.). Routledge.

Alessandretti, L. (2021). What human mobility data tell us about COVID-19 spread. *Nature Reviews Physics*, *4*(1), 12–13. https://doi.org/10.1038/s42254-021-00407-1

Algamal, Z. Y. (2012). Diagnostic in Poisson Regression Models. *Electronic Journal of Applied Statistical Analysis*, *5*(2), 178–186. https://doi.org/10.1285/i20705948v5n2p178

Alin, A. (2010). Multicollinearity. *Wiley Interdisciplinary Reviews: Computational Statistics*, *2*(3), 370–374. https://doi.org/10.1002/wics.84

Alobaidi, N. N., Shamany, R. E., & Algamal, Z. Y. (2021). A New Ridge Estimator for the Negative Binomial Regression Model. *Thailand Statistician*, *19*(1), 116–125. https://www.researchgate.net/publication/348326537_A_New_Ridge_Estimator_for_the_Negative_Binomial_Regression_Model

Alsaeedy, A. A. R., & Chong, E. K. P. (2020). Detecting Regions At Risk for Spreading COVID-19 Using Existing Cellular Wireless Network Functionalities. *IEEE Open Journal of Engineering in Medicine and Biology*, *1*, 187–189. https://doi.org/10.1109/ojemb.2020.3002447

Apriliyanti, I. D., Utomo, W. P., & Purwanto, E. A. (2021). Examining the policy narratives and the role of the media in policy responses to the COVID-19 crisis in Indonesia. *Journal of Asian Public Policy*, *15*(3), 541–557. https://doi.org/10.1080/17516234.2021.1954770

Askitas, N., Tatsiramos, K., & Verheyden, B. (2021). Estimating worldwide effects of non-pharmaceutical interventions on COVID-19 incidence and population mobility patterns using a multiple-event study. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-81442-x

Awad-Núñez, S., Julio, R., Gomez, J., Moya-Gómez, B., & González, J. S. (2021). Post-COVID-19 travel behaviour patterns: impact on the willingness to pay of users of public transport and shared mobility services in Spain. *European Transport Research Review*, *13*(1). https://doi.org/10.1186/s12544-021-00476-4

Barbosa, H., Barthelemy, M., Ghoshal, G., James, C. R., Lenormand, M., Louail, T., Menezes, R., Ramasco, J. J., Simini, F., & Tomasini, M. (2018). Human mobility: Models and applications. *Physics Reports*, *734*, 1–74. https://doi.org/10.1016/j.physrep.2018.01.001

Beirman, D. (2003). *Restoring Tourism Destinations in Crisis: A strategic marketing approach* (1st ed.). Routledge.

Bert, J., Schellong, D., Hagenmaier, M., Hornstein, D., Wegscheider, A. K., & Palme, T. (2021, January 26). *How COVID-19 Will Shape Urban Mobility*. BCG Global. https://www.bcg.com/publications/2020/how-covid-19-will-shape-urban-mobility

Blatvatnik School of Government & University of Oxford. (2022). *Oxford Covid-19 Government Response Tracker*. Blatvatnik School of Government, University of Oxford. https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker

Böcker, L., Dijst, M., & Faber, J. (2016). Weather, transport mode choices and emotional travel experiences. *Transportation Research Part A: Policy and Practice*, *94*, 360–373. https://doi.org/10.1016/j.tra.2016.09.021

Borkowski, P., Jażdżewska-Gutta, M., & Szmelter-Jarosz, A. (2021). Lockdowned: Everyday mobility changes in response to COVID-19. *Journal of Transport Geography*, *90*, 102906. https://doi.org/10.1016/j.jtrangeo.2020.102906

Brewer, N. T., Chapman, G. B., Gibbons, F. X., Gerrard, M., McCaul, K. D., & Weinstein, N. D. (2007). Meta-analysis of the relationship between risk perception and health behavior: The example of vaccination. *Health Psychology*, *26*(2), 136–145. https://doi.org/10.1037/0278-6133.26.2.136

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

Burnham, K. P., & Anderson, D. R. (2004). Multimodel Inference. *Sociological Methods &Amp; Research*, *33*(2), 261–304. https://doi.org/10.1177/0049124104268644

Cameron, A. C., & Trivedi, P. K. (2013). Regression Analysis of Count Data. *Technometrics*, *41*(4), 371. https://doi.org/10.2307/1271358

Castiglione, J., Bradley, M., & Gliebe, J. (2014). Activity-Based Travel Demand Models: A Primer. *He National Academies Press*. https://doi.org/10.17226/22357

Chakraborty, S. (2020). How Risk Perceptions, Not Evidence, Have Driven Harmful Policies on COVID-19. *European Journal of Risk Regulation*, *11*(2), 236–239. https://doi.org/10.1017/err.2020.37

Chaudhary, M., Sodani, P. R., & Das, S. (2020). Effect of COVID-19 on Economy in India: Some Reflections for Policy and Programme. *Journal of Health Management*, *22*(2), 169–180. https://doi.org/10.1177/0972063420935541

Chen, C., & Mokhtarian, P. L. (2006). Tradeoffs between Time Allocations to Maintenance Activities/Travel and Discretionary Activities/Travel. *Transportation*, *33*(3), 223–240. https://doi.org/10.1007/s11116-005-2307-4

City of Toronto. (2022). *2022 Global Liveability Index*. toronto.ca. https://www.toronto.ca/city-government/data-research-maps/toronto-progress-portal/world-rankings-for-toronto/2022-global-liveability-index/

Climate Data. (n.d.). *CLIMATE TORONTO (CANADA)*. https://en.climate-data.org/north-america/canada/ontario/toronto-53/

Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., & Yelowitz, A. (2020). Strong Social Distancing Measures In The United States Reduced The COVID-19 Growth Rate. *Health Affairs*, *39*(7), 1237–1246. https://doi.org/10.1377/hlthaff.2020.00608

Cresswell, T. (2006). *On the Move: Mobility in the Modern Western World* (1st ed.). Routledge.

Cresswell, T. (2010). Towards a Politics of Mobility. *Environment and Planning D: Society and Space*, *28*(1), 17–31. https://doi.org/10.1068/d11407

Cresswell, T. (2021). Valuing mobility in a post COVID-19 world. *Mobilities*, *16*(1), 51–65. https://doi.org/10.1080/17450101.2020.1863550

Da Silva Corrêa, L., & Perl, A. (2022). Global cities, hypermobility, and Covid-19. *Cities*, *122*, 103537. https://doi.org/10.1016/j.cities.2021.103537

Daoud, J. I. (2017). Multicollinearity and Regression Analysis. *Journal of Physics: Conference Series*, *949*, 012009. https://doi.org/10.1088/1742-6596/949/1/012009

Daraghmi, Y. A., Yi, C., & Chiang, T. (2012). Space-time multivariate Negative Binomial regression for urban short-term traffic volume prediction. *2012 12th International Conference on ITS Telecommunications*. https://doi.org/10.1109/itst.2012.6425198

Daraghmi, Y. A., Yi, C., & Chiang, T. (2014). Negative Binomial Additive Models for Short-Term Traffic Flow Forecasting in Urban Areas. *IEEE Transactions on Intelligent Transportation Systems*, *15*(2), 784–793. https://doi.org/10.1109/tits.2013.2287512

Daria, S., & Islam, M. R. (2022). The SARS-CoV-2 omicron wave is indicating the end of the pandemic phase but the COVID-19 will continue. *Journal of Medical Virology*. https://doi.org/10.1002/jmv.27635

Das, S., Boruah, A., Banerjee, A., Raoniar, R., Nama, S., & Maurya, A. K. (2021). Impact of COVID-19: A radical modal shift from public to private transport mode. *Transport Policy*, *109*, 1–11. https://doi.org/10.1016/j.tranpol.2021.05.005

De Haas, M., Faber, R., & Hamersma, M. (2020). How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. *Transportation Research Interdisciplinary Perspectives*, *6*, 100150. https://doi.org/10.1016/j.trip.2020.100150

De Vos, J. (2020). The effect of COVID-19 and subsequent social distancing on travel behavior. *Transportation Research Interdisciplinary Perspectives*, *5*, 100121. https://doi.org/10.1016/j.trip.2020.100121

Dharmowijoyo, D. B. E., Susilo, Y. O., & Karlström, A. (2018). On complexity and variability of individuals' discretionary activities. *Transportation*, *45*(1), 177–204. https://doi.org/10.1007/s11116-016-9731-5

Douglas, M., Katikireddi, S. V., Taulbut, M., McKee, M., & McCartney, G. (2020). Mitigating the wider health effects of covid-19 pandemic response. *BMJ*. https://doi.org/10.1136/bmj.m1557

Ehlert, A., & Wedemeier, J. (2022). Which factors influence mobility change during COVID-19 in Germany? Evidence from German county data. *Regional Science Policy &Amp; Practice*. https://doi.org/10.1111/rsp3.12537

Ehsani, J. P., Michael, J. P., Duren, M. L., Mui, Y., & Porter, K. M. P. (2021). Mobility Patterns Before, During, and Anticipated After the COVID-19 Pandemic: An Opportunity to Nurture Bicycling. *American Journal of Preventive Medicine*, *60*(6), e277–e279. https://doi.org/10.1016/j.amepre.2021.01.011

Fairos, W., Wan Yaacob, W. F., Lazim, M., & Yap, B. (2010). A Practical Approach in Modelling Count Data. *RCSS*, *7*. http://instatmy.org.my/downloads/rcss'10/proceedings/17p.pdf

Ferguson, N. M., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cuncunubá, Z., Cuomo-Dannenburg, G., Dighe, A., Dorigatti, I., Fu, H., Gaythorpe, K., Green, W., Hamlet, A., Hinsley, W., Okell, L. C., Van Elsland, S., . . . Ghani, A. C. (2020). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID- 19 mortality and healthcare demand. *Imperial College COVID-19 Response Team*. https://doi.org/10.25561/77482

Figueroa, M. J., Nielsen, T. A. S., & Siren, A. (2014). Comparing urban form correlations of the travel patterns of older and younger adults. *Transport Policy*, *35*, 10–20. https://doi.org/10.1016/j.tranpol.2014.05.007

Floyd, D. L., Prentice-Dunn, S., & Rogers, R. W. (2000). A Meta-Analysis of Research on Protection Motivation Theory. *Journal of Applied Social Psychology*, *30*(2), 407–429. https://doi.org/10.1111/j.1559-1816.2000.tb02323.x

Gardner, W., Mulvey, E. P., & Shaw, E. C. (1995). Regression analyses of counts and rates: Poisson, overdispersed Poisson, and negative binomial models. *Psychological Bulletin*, *118*(3), 392–404. https://doi.org/10.1037/0033-2909.118.3.392

Gelo, O., Braakmann, D., & Benetka, G. (2008). Quantitative and Qualitative Research: Beyond the Debate. *Integrative Psychological and Behavioral Science*, *42*(3), 266–290. https://doi.org/10.1007/s12124-008-9078-3

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

Greene, M., Ellsworth-Krebs, K., Volden, J., Fox, E., & Anantharaman, M. (2022). Practic-ing culture: exploring the implications of pre-existing mobility cultures on (post-) pandemic practices in Norway, Ireland, and the United States. *Sustainability: Science, Practice and Policy*, *18*(1), 483–499. https://doi.org/10.1080/15487733.2022.2091328

Griffiths, S., Furszyfer Del Rio, D., & Sovacool, B. (2021). Policy mixes to achieve sustainable mobility after the COVID-19 crisis. *Renewable and Sustainable Energy Reviews*, *143*, 110919. https://doi.org/10.1016/j.rser.2021.110919

Ha, J., Lee, S., & Ko, J. (2020). Unraveling the impact of travel time, cost, and transit burdens on commute mode choice for different income and age groups. *Transportation Research Part A: Policy and Practice*, *141*, 147–166. https://doi.org/10.1016/j.tra.2020.07.020

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529–538. https://doi.org/10.1038/s41562-021-01079-8

Hall, C. M. (2002). Travel Safety, Terrorism and the Media: The Significance of the Issue-Attention Cycle. *Current Issues in Tourism*, *5*(5), 458–466. https://doi.org/10.1080/13683500208667935

Harper, C. A., Satchell, L. P., Fido, D., & Latzman, R. D. (2020). Functional Fear Predicts Public Health Compliance in the COVID-19 Pandemic. *International Journal of Mental Health and Addiction*, *19*(5), 1875–1888. https://doi.org/10.1007/s11469-020-00281-5

Hawkins, J., Ahmed, U., Roorda, M., & Habib, K. N. (2022). Measuring the process of urban gentrification: A composite measure of the gentrification process in Toronto. *Cities*, *126*, 103708. https://doi.org/10.1016/j.cities.2022.103708

Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. *Evidence Based Nursing*, *18*(3), 66–67. https://doi.org/10.1136/eb-2015-102129

Hilbe, J. M. (2011). *Negative Binomial Regression*. Cambridge University Press.

Hörcher, D., Singh, R., & Graham, D. J. (2021). Social distancing in public transport: mobilising new technologies for demand management under the Covid-19 crisis. *Transportation*, *49*(2), 735–764. https://doi.org/10.1007/s11116-021-10192-6

Hussain, A. H. M. B. (2020). Stringency in Policy Responses to Covid-19 Pandemic and Social Distancing Behavior in Selected Countries. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3586319

International Monetary Fund. (2020). *World Economic Outlook, October 2020: A Long and Difficult Ascent*. IMF. https://www.imf.org/en/Publications/WEO/Issues/2020/09/30/world-economic-outlook-october-2020

Iyanda, A. E., Boakye, K. A., Lu, Y., & Oppong, J. R. (2022). Racial/Ethnic Heterogeneity and Rural-Urban Disparity of COVID-19 Case Fatality Ratio in the USA: a Negative Binomial and GIS-Based Analysis. *Journal of Racial and Ethnic Health Disparities*, *9*(2), 708–721. https://doi.org/10.1007/s40615-021-01006-7

Jasiński, A. (2022). COVID-19 pandemic is challenging some dogmas of modern urbanism. *Cities*, *121*, 103498. https://doi.org/10.1016/j.cities.2021.103498

Jenelius, E., & Cebecauer, M. (2020). Impacts of COVID-19 on public transport ridership in Sweden: Analysis of ticket validations, sales and passenger counts. *Transportation Research Interdisciplinary Perspectives*, *8*, 100242. https://doi.org/10.1016/j.trip.2020.100242

Jong, P. de, Heller, G. Z., & de Jong, P. (2008). *Generalized Linear Models for Insurance Data*. Cambridge University Press.

Kellerman, A. (2022). Personal Spatial Mobilities after the COVID-19 Pandemic: A Speculative View. *Journal of Urban Technology*, 1–14. https://doi.org/10.1080/10630732.2022.2044743

Kim, E. E. K., Seo, K., & Choi, Y. (2021). Compensatory Travel Post COVID-19: Cognitive and Emotional Effects of Risk Perception. *Journal of Travel Research*, *61*(8), 1895–1909. https://doi.org/10.1177/00472875211048930

Kim, J. H. (2019). Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology*, *72*(6), 558–569. https://doi.org/10.4097/kja.19087

Kraemer, M. U. G., Yang, C. H., Gutierrez, B., Wu, C. H., Klein, B., Pigott, D. M., du Plessis, L., Faria, N. R., Li, R., Hanage, W. P., Brownstein, J. S., Layan, M., Vespignani, A., Tian, H., Dye, C., Pybus, O. G., & Scarpino, S. V. (2020). The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science*, *368*(6490), 493–497. https://doi.org/10.1126/science.abb4218

Lau, H., Khosrawipour, V., Kocbach, P., Mikolajczyk, A., Ichii, H., Zacharski, M., Bania, J., & Khosrawipour, T. (2020). The association between international and domestic air traffic and the coronavirus (COVID-19) outbreak. *Journal of Microbiology, Immunology and Infection*, *53*(3), 467–472. https://doi.org/10.1016/j.jmii.2020.03.026

Lee, K. S., & Eom, J. K. (2022). Systematic Literature Review on Impacts of Covid-19 Pandemic and Corresponding Measures on Mobility. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4062876

Leung, L. (2015). Validity, reliability, and generalizability in qualitative research. *Journal of Family Medicine and Primary Care*, *4*(3), 324. https://doi.org/10.4103/2249-4863.161306

Li, S., Blake, A., & Cooper, C. (2010). China's tourism in a global financial crisis: a computable general equilibrium approach. *Current Issues in Tourism*, *13*(5), 435–453. https://doi.org/10.1080/13683500.2010.491899

Liu, D., & Lam, W. H. K. (2014). Modeling the Effects of Population Density on Prospect Theory-Based Travel Mode-Choice Equilibrium. *Journal of Intelligent Transportation Systems*, *18*(4), 379–392. https://doi.org/10.1080/15472450.2013.806745

Liu, W., Yue, X. G., & Tchounwou, P. B. (2020). Response to the COVID-19 Epidemic: The Chinese Experience and Implications for Other Countries. *International Journal of Environmental Research and Public Health*, *17*(7), 2304. https://doi.org/10.3390/ijerph17072304

Loa, P., Hossain, S., Mashrur, S. M., Liu, Y., Wang, K., Ong, F., & Habib, K. N. (2021). Exploring the impacts of the COVID-19 pandemic on modality profiles for non-mandatory trips in the Greater Toronto Area. *Transport Policy*, *110*, 71–85. https://doi.org/10.1016/j.tranpol.2021.05.028

Malecki, K. M. C., Keating, J. A., & Safdar, N. (2021). Crisis Communication and Public Perception of COVID-19 Risk in the Era of Social Media. *Clinical Infectious Diseases*, *72*(4), 697–702. https://doi.org/10.1093/cid/ciaa758

McGillivray, B. (2022). *Toronto | History, Population, Climate, & Facts*. Encyclopedia Britannica. https://www.britannica.com/place/Toronto

McKercher, B., & Chon, K. (2004). The Over-Reaction to SARS and the Collapse of Asian Tourism. *Annals of Tourism Research*, *31*(3), 716–719. https://doi.org/10.1016/j.annals.2003.11.002

Meloni, S., Perra, N., Arenas, A., Gómez, S., Moreno, Y., & Vespignani, A. (2011). Modeling human mobility responses to the large-scale spreading of infectious diseases. *Scientific Reports*, *1*(1). https://doi.org/10.1038/srep00062

Merriman, P. (2009). Mobility. *International Encyclopedia of Human Geography*, 134–143. https://doi.org/10.1016/B978-008044910-4.00300-X

Meurs, H., & Haaijer, R. (2001). Spatial structure and mobility. *Transportation Research Part D: Transport and Environment*, *6*(6), 429–446. https://doi.org/10.1016/s1361-9209(01)00007-4

Miaou, S. P., & Lum, H. (1993). Modeling vehicle accidents and highway geometric design relationships. *Accident Analysis &Amp; Prevention*, *25*(6), 689–709. https://doi.org/10.1016/0001-4575(93)90034-t

Midi, H., Sarkar, S., & Rana, S. (2010). Collinearity diagnostics of binary logistic regression model. *Journal of Interdisciplinary Mathematics*, *13*(3), 253–267. https://doi.org/10.1080/09720502.2010.10700699

Moreira, P. (2008). Stealth Risks and Catastrophic Risks. *Journal of Travel &Amp; Tourism Marketing*, *23*(2–4), 15–27. https://doi.org/10.1300/j073v23n02_02

Moreno, C., Allam, Z., Chabaud, D., Gall, C., & Pratlong, F. (2021). Introducing the "15-Minute City": Sustainability, Resilience and Place Identity in Future Post-Pandemic Cities. *Smart Cities*, *4*(1), 93–111. https://doi.org/10.3390/smartcities4010006

Muñoz, B., Monzon, A., & Daziano, R. A. (2016). The Increasing Role of Latent Variables in Modelling Bicycle Mode Choice. *Transport Reviews*, *36*(6), 737–771. https://doi.org/10.1080/01441647.2016.1162874

Neuburger, L., & Egger, R. (2021). Travel risk perception and travel behaviour during the COVID-19 pandemic 2020: a case study of the DACH region. *Current Issues in Tourism*, *24*(7), 1003–1016. https://doi.org/10.1080/13683500.2020.1803807

Nguyen, H., & Nguyen, A. (2020). Covid-19 Misinformation and the Social (Media) Amplification of Risk: A Vietnamese Perspective. *Media and Communication*, *8*(2), 444–447. https://doi.org/10.17645/mac.v8i2.3227

Nielsen, K. (2021). *A timeline of COVID-19 in Ontario*. Global News. https://globalnews.ca/news/6859636/ontario-coronavirus-timeline/

Niresh, J. A., & Velnampy, T. (2014). Firm Size and Profitability: A Study of Listed Manufacturing Firms ed Manufacturing Firms in Sri Lanka. *International Journal of Business and Management*, *9*(4). https://doi.org/10.5539/ijbm.v9n4p57

Novelli, M., Gussing Burgess, L., Jones, A., & Ritchie, B. W. (2018). 'No Ebola. . .still doomed' – The Ebola-induced tourism crisis. *Annals of Tourism Research*, *70*, 76–87. https://doi.org/10.1016/j.annals.2018.03.006

Oka, T., Wei, W., & Zhu, D. (2021). The effect of human mobility restrictions on the COVID-19 transmission network in China. *PLOS ONE*, *16*(7), e0254403. https://doi.org/10.1371/journal.pone.0254403

Ontario COVID-19 Science Advisory Table. (2022). *Ontario Dashboard*. https://covid19-sciencetable.ca/ontario-dashboard/#stringencyandmobility

Ontario Data Catalogue. (2022). *Status of COVID-19 cases in Ontario*. Data.Ontario. https://data.ontario.ca/dataset/status-of-covid-19-cases-in-ontario

Ontario Newsroom. (2020). *Ontario Confirms First Case of Wuhan Novel Coronavirus*. https://news.ontario.ca/en/release/55486/ontario-confirms-first-case-of-wuhan-novel-coronavirus

Osorio, C. & Reuters. (2020). *A fox carries a squirrel in its mouth during a phased reopening from coronavirus restrictions in Toronto, Ontario, Canada May 19, 2020* [Photo]. https://www.reuters.com/news/picture/nature-reclaims-public-spaces-during-loc-idUSRTX7EJ1H

Our World In Data. (2020). *COVID-19: Google Mobility Trends* [Graph]. https://ourworldindata.org/covid-google-mobility-trends

Vatcheva, K., & Lee, M. (2016). Multicollinearity in Regression Analyses Conducted in Epidemiologic Studies. *Epidemiology: Open Access*, *06*(02). https://doi.org/10.4172/2161-1165.1000227

Pan, H., Geertman, S., Deal, B., Jiao, J., & Wang, B. (2022). Planning Support for Smart Cities in the Post-COVID Era. *Journal of Urban Technology*, *29*(2), 1–5. https://doi.org/10.1080/10630732.2022.2069938

Papagiannakis, A., Baraklianos, I., & Spyridonidou, A. (2018). Urban travel behaviour and household income in times of economic crisis: Challenges and perspectives for sustainable mobility. *Transport Policy*, *65*, 51–60. https://doi.org/10.1016/j.tranpol.2016.12.006

Parady, G., Taniguchi, A., & Takami, K. (2020). Analyzing Risk Perception and Social Influence Effects on Self-Restriction Behavior in Response to the COVID-19 Pandemic in Japan: First Results. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3618769

Paul, T., Chakraborty, R., & Anwari, N. (2022). Impact of COVID-19 on daily travel behaviour: a literature review. *Transportation Safety and Environment*, *4*(2). https://doi.org/10.1093/tse/tdac013

Poch, M., & Mannering, F. L. (1996). Negative Binomial Analysis of Intersection-Accident Frequencies. *Journal of Transportation Engineering*, *122*(2), 105–113. https://doi.org/10.1061/(asce)0733-947x(1996)122:2(105

Public Health Ontario. (2022). *Ontario COVID-19 Data Tool*. https://www.publichealthontario.ca/en/data-and-analysis/infectious-disease/covid-19-data-surveillance/covid-19-data-tool?tab=notes

Pucher, J., & Renne, J. L. (2005). Rural mobility and mode choice: Evidence from the 2001 National Household Travel Survey. *Transportation*, *32*(2), 165–186. https://doi.org/10.1007/s11116-004-5508-3

Rahman, M. M., & Thill, J. C. (2022). Associations between COVID-19 Pandemic, Lockdown Measures and Human Mobility: Longitudinal Evidence from 86 Countries. *International Journal of Environmental Research and Public Health*, *19*(12), 7317. https://doi.org/10.3390/ijerph19127317

Retallack, A. E., & Ostendorf, B. (2020). Relationship Between Traffic Volume and Accident Frequency at Intersections. *International Journal of Environmental Research and Public Health*, *17*(4), 1393. https://doi.org/10.3390/ijerph17041393

Ritchie, H., Mathieu, E., Rodés-Guirao, L., Appel, C., Giattino, C., Ortiz-Ospina, E., Hasell, J., Macdonald, B., Beltekian, D., & Roser, M. (2022). *Coronavirus Pandemic (COVID-19)*. Our World in Data. https://ourworldindata.org/coronavirus

Robinson, P. (1999). The CNN effect: can the news media drive foreign policy? *Review of International Studies*, *25*(2), 301–309. https://doi.org/10.1017/s0260210599003010

Robinson, P. (2000). The Policy-Media Interaction Model: Measuring Media Power during Humanitarian Crisis. *Journal of Peace Research*, *37*(5), 613–633. https://doi.org/10.1177/0022343300037005006

Robinson, P. (2001). Theorizing the Influence of Media on World Politics. *European Journal of Communication*, *16*(4), 523–544. https://doi.org/10.1177/0267323101016004005

Robinson, P. (2002). *The CNN Effect: The Myth of News, Foreign Policy and Intervention*. Routledge.

Robinson, P. (2005). The CNN Effect Revisited. *Critical Studies in Media Communication*, *22*(4), 344–349. https://doi.org/10.1080/07393180500288519

Rocklöv, J., & Sjödin, H. (2020). High population densities catalyse the spread of COVID-19. *Journal of Travel Medicine*, *27*(3). https://doi.org/10.1093/jtm/taaa038

SenicPhoto. (2020). *Toronto, Canada during Covid-19 pandemic - Empty city streets* [Photo]. https://stock.adobe.com/images/toronto-canada-during-covid-19-pandemic-empty-city-streets/336186701

Schafer, A., & Victor, D. G. (2000). The future mobility of the world population. *Transportation Research Part A: Policy and Practice*, *34*(3), 171–205. https://doi.org/10.1016/s0965-8564(98)00071-8

Scheepers, P. L. H., & Tobi, H. (2021). *Onderzoeksmethoden*. Boom Lemma.

Scheiner, J. (2010). Interrelations between travel mode choice and trip distance: trends in Germany 1976–2002. *Journal of Transport Geography*, *18*(1), 75–84. https://doi.org/10.1016/j.jtrangeo.2009.01.001

Scheiner, J. (2018). Why is there change in travel behaviour? In search of a theoretical framework for mobility biographies. *Erdkunde*, *72*(1), 41–62. https://doi.org/10.3112/erdkunde.2018.01.03

Schepers, J., & Heinen, E. (2013). How does a modal shift from short car trips to cycling affect road safety? *Accident Analysis &Amp; Prevention*, *50*, 1118–1127. https://doi.org/10.1016/j.aap.2012.09.004

Senaviratna, N. A. M. R., & A. Cooray, T. M. J. (2019). Diagnosing Multicollinearity of Logistic Regression Model. *Asian Journal of Probability and Statistics*, 1–9. https://doi.org/10.9734/ajpas/2019/v5i230132

Shaer, A., & Haghshenas, H. (2021). Evaluating the effects of the COVID-19 outbreak on the older adults' travel mode choices. *Transport Policy*, *112*, 162–172. https://doi.org/10.1016/j.tranpol.2021.08.016

Shortall, R., Mouter, N., & Van Wee, B. (2022). COVID-19 passenger transport measures and their impacts. *Transport Reviews*, *42*(4), 441–466. https://doi.org/10.1080/01441647.2021.1976307

Shrestha, N. (2020). Detecting Multicollinearity in Regression Analysis. *American Journal of Applied Mathematics and Statistics*, *8*(2), 39–42. https://doi.org/10.12691/ajams-8-2-1

Shrestha, N., Shad, M. Y., Ulvi, O., Khan, M. H., Karamehic-Muratovic, A., Nguyen, U. S. D., Baghbanzadeh, M., Wardrup, R., Aghamohammadi, N., Cervantes, D., Nahiduzzaman, K. M., Zaki, R. A., & Haque, U. (2020). The impact of COVID-19 on globalization. *One Health*, *11*, 100180. https://doi.org/10.1016/j.onehlt.2020.100180

Sigler, T., Mahmuda, S., Kimpton, A., Loginova, J., Wohland, P., Charles-Edwards, E., & Corcoran, J. (2021). The socio-spatial determinants of COVID-19 diffusion: the impact of globalisation, settlement characteristics and population. *Globalization and Health*, *17*(1). https://doi.org/10.1186/s12992-021-00707-2

Siksna, A. (1996). The evolution of block size and form in North American and Australian city centres. *Urban Morphology*, *1*(1), 19–33. https://doi.org/10.51347/jum.v1i1.4048

Sjöberg, L., Moen, B. E., & Rundmo, T. (2004). Explaining risk perception. An evaluation of the psychometric paradigm in risk perception research. *Rotunde Publikasjoner Rotunde*, *84*, 55–76. https://www.yumpu.com/s/NtPH1ARD3QprBxN5

Statistics Canada. (2022a). *Profile table, Census Profile, 2021 Census of Population - Toronto, City (C) [Census subdivision], Ontario*. StatCan. https://www12.statcan.gc.ca/census-recensement/2021/dp-pd/prof/index.cfm?Lang=E

Statistics Canada. (2022b). *Census Profile, 2021 Census of Population, Aggregate dissemination areas (ADAs))*. StatCan. https://www12.statcan.gc.ca/census-recensement/2021/dp-pd/prof/details/download-telecharger.cfm?Lang=E

Statistics Canada. (2022c). *Road network files (census year 2021)*. StatCan. https://www12.statcan.gc.ca/census-recensement/2011/geo/RNF-FRR/index-eng.cfm

Taylor, C. (2022). *Some European countries are scrapping all Covid rules despite scientists warning it's too soon*. CNBC. https://www.cnbc.com/2022/02/11/european-countries-scrap-covid-rules-despite-warnings-its-too-soon.html

Thøgersen, J. (2006). Understanding repetitive travel mode choices in a stable context: A panel study approach. *Transportation Research Part A: Policy and Practice*, *40*(8), 621–638. https://doi.org/10.1016/j.tra.2005.11.004

Ton, D., Duives, D. C., Cats, O., Hoogendoorn-Lanser, S., & Hoogendoorn, S. P. (2019). Cycling or walking? Determinants of mode choice in the Netherlands. *Transportation Research Part A: Policy and Practice*, *123*, 7–23. https://doi.org/10.1016/j.tra.2018.08.023

Toronto Information & Technology. (2019). *Regional Municipal Boundary*. City of Toronto Open Data Portal. https://open.toronto.ca/dataset/regional-municipal-boundary/

Toronto Police Services & City of Toronto. (n.d.). *Reducing Traffic Congestion*. Reducing Traffic Congestion. https://www.toronto.ca/services-payments/tickets-fines-penalties/reducing-traffic-congestion-parking-regulations-program/

Toronto Public Health. (2019). T.O. Health Check An Overview of Toronto's Population Health Status. In *toronto.ca* (416.338.7600). https://www.toronto.ca/wp-content/uploads/2019/11/92ef-TOHealthCheck_2019.pdf

Toronto Transportation Services. (2022). *Traffic Volumes at Intersections for All Modes*. City of Toronto Open Data Portal. https://open.toronto.ca/dataset/traffic-volumes-at-intersections-for-all-modes/

Transportation Tomorrow Survey. (2016). *TTS 2016: 2016, 2011, 2006, 1996 AND 1986 TRAVEL SUMMARIES FOR THE GREATER TORONTO & HAMILTON AREA MARCH 2018*. http://www.dmg.utoronto.ca/pdf/tts/2016/2016TTS_Summaries_TTSarea.pdf

Tsoy, D., Tirasawasdichai, T., & Ivanovich Kurpayanidi, K. (2021). Role of Social Media in Shaping Public Risk Perception during COVID-19 Pandemic: A Theoretical Review. *THE INTERNATIONAL JOURNAL OF MANAGEMENT SCIENCE AND BUSINESS ADMINISTRATION*, *7*(2), 35–41. https://doi.org/10.18775/ijmsba.1849-5664-5419.2014.72.1005

Urry, J. (2002). Mobility and Proximity. *Sociology*, *36*(2), 255–274. https://doi.org/10.1177/0038038502036002002

Van der Drift, S., Wismans, L., & Olde Kalter, M. J. (2021). Changing mobility patterns in the Netherlands during COVID-19 outbreak. *Journal of Location Based Services*, *16*(1), 1–24. https://doi.org/10.1080/17489725.2021.1876259

Ver Hoef, J. M., & Boveng, P. L. (2007). QUASI-POISSON VS. NEGATIVE BINOMIAL REGRESSION: HOW SHOULD WE MODEL OVERDISPERSED COUNT DATA? *Ecology*, *88*(11), 2766–2772. https://doi.org/10.1890/07-0043.1

Visual Crossing Corporation. (n.d.). *Historical weather data for any location*. Visual Crossing. https://www.visualcrossing.com/weather-history

Vrieze, S. I. (2012). Model selection and psychological theory: A discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological Methods*, *17*(2), 228–243. https://doi.org/10.1037/a0027127

Wahlberg, A. A. F., & Sjoberg, L. (2000). Risk perception and the media. *Journal of Risk Research*, *3*(1), 31–50. https://doi.org/10.1080/136698700376699

Wang, C., & Han, J. (2022). Will the COVID-19 pandemic end with the Delta and Omicron variants? *Environmental Chemistry Letters*. https://doi.org/10.1007/s10311-021-01369-7

Wang, F., Ge, X., & Huang, D. (2022). Government Intervention, Human Mobility, and COVID-19: A Causal Pathway Analysis from 121 Countries. *Sustainability*, *14*(6), 3694. https://doi.org/10.3390/su14063694

Weather Atlas. (n.d.). *March weather forecast Toronto, Canada*. https://www.weather-atlas.com/en/canada/toronto-weather-march

Winters, M., Teschke, K., Grant, M., Setton, E. M., & Brauer, M. (2010). How Far Out of the Way Will We Travel? *Transportation Research Record: Journal of the Transportation Research Board*, *2190*(1), 1–10. https://doi.org/10.3141/2190-01

Yue, R. P. H., Lau, B. H. P., Chan, C. L. W., & Ng, S. M. (2021). Risk perception as a double-edged sword in policy compliance in COVID-19 pandemic? A two-phase evaluation from Hong Kong. *Journal of Risk Research*, *25*(9), 1131–1145. https://doi.org/10.1080/13669877.2021.1936612

Zafri, N. M., Khan, A., Jamal, S., & Alam, B. M. (2022). Risk perceptions of COVID-19 transmission in different travel modes. *Transportation Research Interdisciplinary Perspectives*, *13*, 100548. https://doi.org/10.1016/j.trip.2022.100548

Zhang, J., Hayashi, Y., & Frank, L. D. (2021). COVID-19 and transport: Findings from a world-wide expert survey. *Transport Policy*, *103*, 68–85. https://doi.org/10.1016/j.tranpol.2021.01.011

Zhao, S., Zhuang, Z., Cao, P., Ran, J., Gao, D., Lou, Y., Yang, L., Cai, Y., Wang, W., He, D., & Wang, M. H. (2020). Quantifying the association between domestic travel and the exportation of novel coronavirus (2019-nCoV) cases from Wuhan, China in 2020: a correlational analysis. *Journal of Travel Medicine*, *27*(2). https://doi.org/10.1093/jtm/taaa022

Zimmermann, K. F., Karabulut, G., Bilgin, M. H., & Doker, A. C. (2020). Inter-country distancing, globalisation and the coronavirus pandemic. *The World Economy*, *43*(6), 1484–1498. https://doi.org/10.1111/twec.12969

Zubair, H., Karoonsoontawong, A., & Kanitpong, K. (2022). Effects of COVID-19 on Travel Behavior and Mode Choice: A Case Study for the Bangkok Metropolitan Area. *Sustainability*, *14*(15), 9326. https://doi.org/10.3390/su14159326

Appendix

3.1 List of followed cities to be potentially analyzed based on their data-availability and quality

Amsterdam	Chicago	Madrid	Rotterdam
Antwerp	Cologne	Manchester	San Francisco
Barcelona	Copenhagen	Melbourne	Seattle
Berlin	Düsseldorf	Miami	Seoul
Birmingham	Hamburg	Milan	Sydney
Boston	Hong Kong	Montreal	Toronto
Bristol	Houston	Munich	Tokio
Brussels	London	New York	Vancouver
Calcary	Los Angeles	Paris	

3.2 Statistics of selected independent variables (total)

		Daily new COVID-19 cases Canada	Stringency Index Ontario	Temperature	Precipitation	Windspeed	Population density	Females%	Age weighted average	Income 2020 weighted average
N	Valid	146	146	146	146	146	146	146	146	146
	Missing	0	0	0	0	0	0	0	0	0
Mean		3686.79	16.7824	.382	.7019	26.270	7372.1383	51.8595%	42.2912	75398.0172
Variance		15044123.162	271.303	15.057	5.632	57.165	28719280.012	3.521	12.080	1108744109.652
Skewness		.456	.051	-.698	7.040	.844	1.682	-1.107	-.074	1.935
Std. Error of Skewness		.201	.201	.201	.201	.201	.201	.201	.201	.201
Kurtosis		-1.196	-1.888	.975	57.010	.803	2.700	1.704	-.168	4.792
Std. Error of Kurtosis		.399	.399	.399	.399	.399	.399	.399	.399	.399
Minimum		0	.00	-10.2	.00	16.7	523.61	44.74%	33.40	30767.12
Maximum		10976	35.19	9.4	22.16	51.4	27040.91	54.59%	48.49	195600.00

3.3 Statistics of selected independent variables (by counting year)

year			Daily new COVID-19 cases Canada	Stringency Index Ontario	Temperature	Precipitation	Windspeed	Population density	Females%	Age weighted average	Income 2020 weighted average
2019	N	Valid	69	69	69	69	69	69	69	69	69
		Missing	0	0	0	0	0	0	0	0	0
	Mean		.00	.0000	.823	1.3675	22.375	8138.5253	51.1303%	41.0394	58622.6138
	Variance		.000	.000	22.343	10.958	52.060	29963656.084	3.844	11.298	218404448.772
	Std. Error of Skewness		.289	.289	.289	.289	.289	.289	.289	.289	.289
	Std. Error of Kurtosis		.570	.570	.570	.570	.570	.570	.570	.570	.570
	Minimum		0	.00	-10.2	.00	16.7	523.61	44.74%	33.40	30767.12
	Maximum		0	.00	6.2	22.16	40.4	26254.08	54.12%	47.33	93212.09
	Skewness				-.996	4.993	1.449	1.230	-.965	-.411	.099
	Kurtosis				.386	27.791	.906	.886	1.332	-.361	-.947
2022	N	Valid	77	77	77	77	77	77	77	77	77
		Missing	0	0	0	0	0	0	0	0	0
	Mean		6990.53	31.8212	-.013	.1055	29.760	6685.3758	52.5129%	43.4129	90430.5214
	Variance		5303787.410	32.770	8.402	.178	36.375	26972676.480	2.363	10.242	1435508556.737
	Std. Error of Skewness		.274	.274	.274	.274	.274	.274	.274	.274	.274
	Std. Error of Kurtosis		.541	.541	.541	.541	.541	.541	.541	.541	.541
	Minimum		3197	22.22	-6.3	.00	22.2	1123.47	47.29%	37.08	35959.89
	Maximum		10976	35.19	9.4	2.58	51.4	27040.91	54.59%	48.49	195600.00
	Skewness		.541	-1.118	-.080	5.483	1.813	2.241	-1.269	.362	1.512
	Kurtosis		-1.100	-.771	2.428	30.748	4.115	5.615	2.681	-1.189	2.335

3.4 Statistics of selected independent variables (by crossing type)

Statistics

CrossingType			Daily new COVID-19 cases Canada	Stringency Index Ontario	Temperature	Precipitation	Windspeed	Population density	Females %	Age weighted average	Income 2020 weighted average
Arterial dominant crossing	N	Valid	84	84	84	84	84	84	84	84	84
		Missing	0	0	0	0	0	0	0	0	0
	Mean		3233.45	12.1920	.175	1.1074	25.732	7462.7557	51.8055%	42.5959	77454.3691
	Variance		17520481.962	228.215	16.979	9.243	79.323	29928779.176	3.741	15.827	1565302263.413
	Skewness		.784	.567	-.621	5.499	1.055	1.710	-.769	-.187	1.588
	Std. Error of Skewness		.263	.263	.263	.263	.263	.263	.263	.263	.263
	Kurtosis		-1.003	-1.480	1.110	33.874	.480	2.756	.398	-.636	2.463
	Std. Error of Kurtosis		.520	.520	.520	.520	.520	.520	.520	.520	.520
	Minimum		0	.00	-10.2	.00	16.7	1123.47	45.57%	33.40	30767.12
	Maximum		10976	35.19	9.4	22.16	51.4	27040.91	54.17%	48.49	195600.00
Collector dominant crossing	N	Valid	30	30	30	30	30	30	30	30	30
		Missing	0	0	0	0	0	0	0	0	0
	Mean		3939.30	19.3847	1.347	.2127	27.123	9140.6586	51.2950%	41.0050	65081.7787
	Variance		14072763.528	277.195	11.785	.378	34.982	37264645.005	4.558	7.164	253756494.735
	Skewness		.360	-.257	-.416	3.488	.049	1.085	-1.518	-.375	-.057
	Std. Error of Skewness		.427	.427	.427	.427	.427	.427	.427	.427	.427
	Kurtosis		-1.107	-1.919	-.090	11.328	.040	1.114	2.519	.784	-1.341
	Std. Error of Kurtosis		.833	.833	.833	.833	.833	.833	.833	.833	.833
	Minimum		0	.00	-6.3	.00	16.7	523.61	44.74%	34.33	40500.00
	Maximum		10561	35.19	6.2	2.44	40.4	27040.91	53.99%	46.99	93212.09
Local dominant crossing	N	Valid	32	32	32	32	32	32	32	32	32
		Missing	0	0	0	0	0	0	0	0	0
	Mean		4640.06	26.3925	.022	.0963	26.881	5476.2796	52.5303%	42.6970	79671.5668
	Variance		8736525.931	239.678	12.795	.186	20.405	12580502.486	1.409	5.405	624403295.371
	Skewness		-.660	-1.212	-1.180	5.519	-.615	2.717	-.274	.445	3.225
	Std. Error of Skewness		.414	.414	.414	.414	.414	.414	.414	.414	.414
	Kurtosis		-.877	-.570	.687	30.879	-.392	9.421	.865	.401	15.217
	Std. Error of Kurtosis		.809	.809	.809	.809	.809	.809	.809	.809	.809
	Minimum		0	.00	-9.0	.00	16.7	1123.47	49.07%	37.34	43686.52
	Maximum		8355	35.19	6.2	2.44	33.2	20109.43	54.59%	47.53	195600.00

3.5 Road classification statistics by year

year			Arterial dominant crossings	Local dominant crossings	CrossingType
2019	N	Valid	69	69	69
		Missing	0	0	0
	Mean		.71	.12	1.41
	Variance		.209	.104	.480
	Skewness		-.947	2.453	1.442
	Std. Error of Skewness		.289	.289	.289
	Kurtosis		-1.137	4.136	.663
	Std. Error of Kurtosis		.570	.570	.570
	Minimum		0	0	1
	Maximum		1	1	3
2022	N	Valid	77	77	77
		Missing	0	0	0
	Mean		.45	.31	1.86
	Variance		.251	.217	.756
	Skewness		.186	.829	.285
	Std. Error of Skewness		.274	.274	.274
	Kurtosis		-2.018	-1.348	-1.630
	Std. Error of Kurtosis		.541	.541	.541
	Minimum		0	0	1
	Maximum		1	1	3

Arterial dominant crossings

year			Frequency	Percent	Valid Percent	Cumulative Percent
2019	Valid	0	20	29.0	29.0	29.0
		1	49	71.0	71.0	100.0
		Total	69	100.0	100.0	
2022	Valid	0	42	54.5	54.5	54.5
		1	35	45.5	45.5	100.0
		Total	77	100.0	100.0	

Local dominant crossings

year			Frequency	Percent	Valid Percent	Cumulative Percent
2019	Valid	0	61	88.4	88.4	88.4
		1	8	11.6	11.6	100.0
		Total	69	100.0	100.0	
2022	Valid	0	53	68.8	68.8	68.8
		1	24	31.2	31.2	100.0
		Total	77	100.0	100.0	

CrossingType

year			Frequency	Percent	Valid Percent	Cumulative Percent
2019	Valid	Arterial dominant crossing	49	71.0	71.0	71.0
		Collector dominant crossing	12	17.4	17.4	88.4
		Local dominant crossing	8	11.6	11.6	100.0
		Total	69	100.0	100.0	
2022	Valid	Arterial dominant crossing	35	45.5	45.5	45.5
		Collector dominant crossing	18	23.4	23.4	68.8
		Local dominant crossing	24	31.2	31.2	100.0
		Total	77	100.0	100.0	

4.1 Comparison of AIC and BIC values among models including both COVID-19 dependent variables, only COVID-19 cases and only Stringency Index.

Counting category	AIC	AIC difference to model with both COVID-19 variables	BIC	BIC difference to model with both COVID-19 variables
Total all modes (both C19 variables)	2980.223		3019.010	
Total all modes (cases)	2983.522	+3.299	3019.326	+0.316
Total all modes (stringency)	2984.270	+4.047	3020.073	+1.063
AM total (both C19 variables)	2562.198		2600.985	
AM total (cases)	2567.743	+5.545	2603.546	+2.561
AM total (stringency)	2565.738	+3.540	2601.538	+0.553
IB total (both C19 variables)	2757.491		2757.491	
IB total (cases)	2759.060	+1.569	2794.863	+37.372
IB total (stringency)	2761.710	+4.219	2797.514	+40.023
PM total (both C19 variables)	2628.335		2667.122	
PM total (cases)	2632.650	+4.315	2668.454	+1.332
PM total (stringency)	2631.444	+3.109	2667.248	+0.126
Cars total (both C19 variables)	2918.416		2957.202	
Cars total (cases)	2917.055	-1.361	2952.859	-4.343
Cars total (stringency)	2929.830	+11.414	2965.633	+8.431
Cars AM (both C19 variables)	2509.469		2548.255	
Cars AM (cases)	2509.425	-0.044	2545.228	-3.027
Cars AM (stringency)	2518.472	+9.003	2554.276	+6.021
Cars IB (both C19 variables)	2697.311		2736.097	
Cars IB (cases)	2695.654	-1.657	2731.457	-4.640
Cars IB (stringency)	2708.492	+11.181	2744.295	+8.198
Cars PM (both C19 variables)	2556.446		2595.233	
Cars PM (cases)	2554.859	-1.587	2590.662	-4.571
Cars PM (stringency)	2568.736	+12.290	2604.540	+9.307
Peds total (both C19 variables)	2471.309		2510.096	
Peds total (cases)	2501.839	+30.530	2537.642	+27.546
Peds total (stringency)	2481.896	+10.587	2517.700	+7.604
Peds AM (both C19 variables)	2018.342		2057.129	
Peds AM (cases)	2050.532	+32.190	2086.336	+29.207
Peds AM (stringency)	2026.875	+8.533	2062.678	+5.549
Peds IB (both C19 variables)	2238.495		2277.282	
Peds IB (cases)	2266.191	+27.696	2301.994	+24.712
Peds IB (stringency)	2248.905	+10.410	2284.709	+7.427
Peds PM (both C19 variables)	2142.363		2181.149	
Peds PM (cases)	2172.883	+30.520	2208.686	+27.537
Peds PM (stringency)	2153.034	+10.671	2188.837	+7.688
Bike total (both C19 variables)	1538.119		1576.906	
Bike total (cases)	1562.593	+24.474	1598.396	+21.490
Bike total (stringency)	1575.091	+36.972	1610.894	+33.988
Bike AM (both C19 variables)	1112.028		1150.814	
Bike AM (cases)	1141.510	+29.482	1177.313	+26.499
Bike AM (stringency)	1143.133	+31.105	1178.936	+28.122
Bike IB (both C19 variables)	1296.739		1335.526	
Bike IB (cases)	1314.249	+17.510	1350.052	+14.526
Bike IB (stringency)	1327.192	+30.453	1362.995	+27.469
Bike PM (both C19 variables)	1219.144		1257.931	
Bike PM (cases)	1242.666	+23.522	1278.469	+20.538
Bike PM (stringency)	1259.278	+40.134	1295.081	+37.150

4.2 Total all modes negative binomial regression SPSS output

Model Information

Dependent Variable	Total all modes
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Total all modes	146	276	44240	13415.61	9721.969
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	154.511	133	1.162
Scaled Deviance	154.511	133	
Pearson Chi-Square	146.436	133	1.101
Scaled Pearson Chi-Square	146.436	133	
Log Likelihood[b]	-1477.111		
Akaike's Information Criterion (AIC)	2980.223		
Finite Sample Corrected AIC (AICC)	2982.980		
Bayesian Information Criterion (BIC)	3019.010		
Consistent AIC (CAIC)	3032.010		

Dependent Variable: Total all modes
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
95.884	11	<.001

Dependent Variable: Total all modes
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	14.640	1	<.001
Daily COVID-19 cases Canada (in thousands)	6.312	1	.012
Stringency Index Ontario	5.368	1	.021
Temperature	.007	1	.933
Precipitation	1.569	1	.210
Windspeed	.870	1	.351
Population density (thousand people / square km)	1.341	1	.247
Females%	.819	1	.365
Age weighted average	.077	1	.781
Income 2020 weighted average (in thousands CAN$)	2.547	1	.110
Arterial dominant crossings	6.864	1	.009
Local dominant crossings	15.235	1	<.001

Dependent Variable: Total all modes
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	7.155	1.8700	3.490	10.820	14.640	1	<.001	1280.615	32.782	50026.714
Daily COVID-19 cases Canada (in thousands)	-.064	.0254	-.113	-.014	6.312	1	.012	.938	.893	.986
Stringency Index Ontario	-.014	.0059	-.025	-.002	5.368	1	.021	.986	.975	.998
Temperature	.001	.0135	-.025	.028	.007	1	.933	1.001	.975	1.028
Precipitation	-.028	.0225	-.072	.016	1.569	1	.210	.972	.930	1.016
Windspeed	.008	.0084	-.009	.024	.870	1	.351	1.008	.991	1.024
Population density (thousand people / square km)	.016	.0136	-.011	.042	1.341	1	.247	1.016	.989	1.043
Females%	.034	.0380	-.040	.109	.819	1	.365	1.035	.961	1.115
Age weighted average	.006	.0229	-.039	.051	.077	1	.781	1.006	.962	1.053
Income 2020 weighted average (in thousands CAN$)	.003	.0019	-.001	.007	2.547	1	.110	1.003	.999	1.007
Arterial dominant crossings	.364	.1390	.092	.637	6.864	1	.009	1.439	1.096	1.890
Local dominant crossings	-.638	.1635	-.958	-.318	15.235	1	<.001	.528	.384	.728
(Scale)	1[a]									
(Negative binomial)	.353	.0391	.284	.438						

Dependent Variable: Total all modes
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.3 AM total negative binomial regression SPSS output

Model Information

Dependent Variable	AM total
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	AM total	146	60	11968	3135.51	2441.414
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	154.691	133	1.163
Scaled Deviance	154.691	133	
Pearson Chi-Square	146.134	133	1.099
Scaled Pearson Chi-Square	146.134	133	
Log Likelihood[b]	-1268.099		
Akaike's Information Criterion (AIC)	2562.198		
Finite Sample Corrected AIC (AICC)	2564.955		
Bayesian Information Criterion (BIC)	2600.985		
Consistent AIC (CAIC)	2613.985		

Dependent Variable: AM total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
86.991	11	<.001

Dependent Variable: AM total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	10.409	1	.001
Daily COVID-19 cases Canada (in thousands)	5.762	1	.016
Stringency Index Ontario	7.689	1	.006
Temperature	1.173	1	.279
Precipitation	13.371	1	<.001
Windspeed	4.949	1	.026
Population density (thousand people / square km)	.149	1	.700
Females%	1.051	1	.305
Age weighted average	.193	1	.661
Income 2020 weighted average (in thousands CAN$)	5.283	1	.022
Arterial dominant crossings	4.645	1	.031
Local dominant crossings	10.425	1	.001

Dependent Variable: AM total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	6.024	1.8672	2.365	9.684	10.409	1	.001	413.331	10.640	16057.148
Daily COVID-19 cases Canada (in thousands)	-.062	.0258	-.113	-.011	5.762	1	.016	.940	.894	.989
Stringency Index Ontario	-.017	.0060	-.029	-.005	7.689	1	.006	.983	.972	.995
Temperature	.015	.0139	-.012	.042	1.173	1	.279	1.015	.988	1.043
Precipitation	-.075	.0205	-.115	-.035	13.371	1	<.001	.928	.891	.966
Windspeed	.020	.0089	.002	.037	4.949	1	.026	1.020	1.002	1.038
Population density (thousand people / square km)	-.005	.0138	-.032	.022	.149	1	.700	.995	.968	1.022
Females%	.038	.0374	-.035	.112	1.051	1	.305	1.039	.966	1.118
Age weighted average	-.010	.0227	-.055	.035	.193	1	.661	.990	.947	1.035
Income 2020 weighted average (in thousands CAN$)	.004	.0020	.001	.008	5.283	1	.022	1.004	1.001	1.008
Arterial dominant crossings	.304	.1409	.028	.580	4.645	1	.031	1.355	1.028	1.786
Local dominant crossings	-.535	.1657	-.860	-.210	10.425	1	.001	.586	.423	.810
(Scale)	1[a]									
(Negative binomial)	.357	.0397	.288	.444						

Dependent Variable: AM total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.4 IB total negative binomial regression SPSS output

Model Information

Dependent Variable	IB total
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	IB total	146	142	20658	6237.53	4651.462
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	155.017	133	1.166
Scaled Deviance	155.017	133	
Pearson Chi-Square	147.633	133	1.110
Scaled Pearson Chi-Square	147.633	133	
Log Likelihood[b]	-1365.746		
Akaike's Information Criterion (AIC)	2757.491		
Finite Sample Corrected AIC (AICC)	2760.249		
Bayesian Information Criterion (BIC)	2796.278		
Consistent AIC (CAIC)	2809.278		

Dependent Variable: IB total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
99.514	11	<.001

Dependent Variable: IB total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	10.171	1	.001
Daily COVID-19 cases Canada (in thousands)	6.502	1	.011
Stringency Index Ontario	3.596	1	.058
Temperature	.215	1	.643
Precipitation	.054	1	.816
Windspeed	.086	1	.769
Population density (thousand people / square km)	2.872	1	.090
Females%	.537	1	.464
Age weighted average	.737	1	.391
Income 2020 weighted average (in thousands CAN$)	1.432	1	.231
Arterial dominant crossings	8.030	1	.005
Local dominant crossings	16.446	1	<.001

Dependent Variable: IB total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	6.151	1.9286	2.371	9.931	10.171	1	.001	469.179	10.707	20559.237
Daily COVID-19 cases Canada (in thousands)	-.066	.0260	-.117	-.015	6.502	1	.011	.936	.889	.985
Stringency Index Ontario	-.012	.0061	-.023	.000	3.596	1	.058	.989	.977	1.000
Temperature	-.006	.0139	-.034	.021	.215	1	.643	.994	.967	1.021
Precipitation	-.006	.0245	-.054	.042	.054	1	.816	.994	.948	1.043
Windspeed	.002	.0084	-.014	.019	.086	1	.769	1.002	.986	1.019
Population density (thousand people / square km)	.024	.0139	-.004	.051	2.872	1	.090	1.024	.996	1.052
Females%	.029	.0394	-.048	.106	.537	1	.464	1.029	.953	1.112
Age weighted average	.020	.0236	-.026	.067	.737	1	.391	1.021	.974	1.069
Income 2020 weighted average (in thousands CAN$)	.002	.0020	-.002	.006	1.432	1	.231	1.002	.998	1.006
Arterial dominant crossings	.405	.1430	.125	.686	8.030	1	.005	1.500	1.133	1.985
Local dominant crossings	-.680	.1678	-1.009	-.352	16.446	1	<.001	.506	.364	.704
(Scale)	1[a]									
(Negative binomial)	.373	.0413	.300	.463						

Dependent Variable: IB total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.5 PM total negative binomial regression SPSS output

Model Information

Dependent Variable	PM total
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	PM total	146	74	14124	4042.58	2943.784
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	154.601	133	1.162
Scaled Deviance	154.601	133	
Pearson Chi-Square	144.659	133	1.088
Scaled Pearson Chi-Square	144.659	133	
Log Likelihood[b]	-1301.168		
Akaike's Information Criterion (AIC)	2628.335		
Finite Sample Corrected AIC (AICC)	2631.093		
Bayesian Information Criterion (BIC)	2667.122		
Consistent AIC (CAIC)	2680.122		

Dependent Variable: PM total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
98.650	11	<.001

Dependent Variable: PM total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	10.264	1	.001
Daily COVID-19 cases Canada (in thousands)	5.307	1	.021
Stringency Index Ontario	6.415	1	.011
Temperature	.110	1	.740
Precipitation	1.986	1	.159
Windspeed	1.152	1	.283
Population density (thousand people / square km)	2.064	1	.151
Females%	1.035	1	.309
Age weighted average	.001	1	.977
Income 2020 weighted average (in thousands CAN$)	2.192	1	.139
Arterial dominant crossings	6.305	1	.012
Local dominant crossings	16.760	1	<.001

Dependent Variable: PM total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	5.994	1.8711	2.327	9.662	10.264	1	.001	401.188	10.249	15704.451
Daily COVID-19 cases Canada (in thousands)	-.058	.0253	-.108	-.009	5.307	1	.021	.943	.898	.991
Stringency Index Ontario	-.015	.0060	-.027	-.003	6.415	1	.011	.985	.974	.997
Temperature	.004	.0135	-.022	.031	.110	1	.740	1.004	.978	1.031
Precipitation	-.032	.0224	-.075	.012	1.986	1	.159	.969	.927	1.012
Windspeed	.009	.0084	-.007	.025	1.152	1	.283	1.009	.993	1.026
Population density (thousand people / square km)	.020	.0136	-.007	.046	2.064	1	.151	1.020	.993	1.047
Females%	.039	.0382	-.036	.114	1.035	1	.309	1.040	.965	1.120
Age weighted average	-.001	.0231	-.046	.045	.001	1	.977	.999	.955	1.046
Income 2020 weighted average (in thousands CAN$)	.003	.0019	-.001	.007	2.192	1	.139	1.003	.999	1.007
Arterial dominant crossings	.348	.1385	.076	.619	6.305	1	.012	1.416	1.079	1.858
Local dominant crossings	-.669	.1634	-.989	-.349	16.760	1	<.001	.512	.372	.706
(Scale)	1[a]									
(Negative binomial)	.353	.0392	.284	.438						

Dependent Variable: PM total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.6 Cars total negative binomial regression SPSS output

Model Information

Dependent Variable	Cars total
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Cars total	146	148	37920	10710.22	8066.815
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	154.860	134	1.156
Scaled Deviance	154.860	134	
Pearson Chi-Square	138.104	134	1.031
Scaled Pearson Chi-Square	138.104	134	
Log Likelihood[b]	-1446.528		
Akaike's Information Criterion (AIC)	2917.055		
Finite Sample Corrected AIC (AICC)	2919.401		
Bayesian Information Criterion (BIC)	2952.859		
Consistent AIC (CAIC)	2964.859		

Dependent Variable: Cars total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
92.392	10	<.001

Dependent Variable: Cars total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	9.246	1	.002
Daily COVID-19 cases Canada (in thousands)	32.364	1	<.001
Temperature	.163	1	.687
Precipitation	.564	1	.453
Windspeed	.470	1	.493
Population density (thousand people / square km)	.010	1	.920
Females%	.976	1	.323
Age weighted average	2.721	1	.099
Income 2020 weighted average (in thousands CAN$)	.446	1	.504
Arterial dominant crossings	8.547	1	.003
Local dominant crossings	15.158	1	<.001

Dependent Variable: Cars total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.	Exp(B)	95% Wald Confidence Interval for Exp(B) Lower	95% Wald Confidence Interval for Exp(B) Upper
(Intercept)	5.681	1.8685	2.019	9.344	9.246	1	.002	293.369	7.533	11424.808
Daily COVID-19 cases Canada (in thousands)	-.111	.0195	-.149	-.073	32.364	1	<.001	.895	.861	.930
Temperature	-.006	.0137	-.032	.021	.163	1	.687	.995	.968	1.022
Precipitation	-.017	.0223	-.060	.027	.564	1	.453	.983	.941	1.027
Windspeed	.005	.0079	-.010	.021	.470	1	.493	1.005	.990	1.021
Population density (thousand people / square km)	.001	.0134	-.025	.028	.010	1	.920	1.001	.975	1.028
Females%	.038	.0383	-.037	.113	.976	1	.323	1.039	.964	1.119
Age weighted average	.037	.0223	-.007	.081	2.721	1	.099	1.037	.993	1.084
Income 2020 weighted average (in thousands CAN$)	.001	.0019	-.003	.005	.446	1	.504	1.001	.997	1.005
Arterial dominant crossings	.413	.1412	.136	.689	8.547	1	.003	1.511	1.146	1.993
Local dominant crossings	-.632	.1622	-.949	-.314	15.158	1	<.001	.532	.387	.731
(Scale)	1[a]									
(Negative binomial)	.367	.0406	.295	.456						

Dependent Variable: Cars total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.7 Cars AM negative binomial regression SPSS output

Model Information

Dependent Variable	CarsAM
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	CarsAM	146	25	9466	2606.08	2016.546
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	155.160	134	1.158
Scaled Deviance	155.160	134	
Pearson Chi-Square	136.326	134	1.017
Scaled Pearson Chi-Square	136.326	134	
Log Likelihood[b]	-1242.713		
Akaike's Information Criterion (AIC)	2509.425		
Finite Sample Corrected AIC (AICC)	2511.771		
Bayesian Information Criterion (BIC)	2545.228		
Consistent AIC (CAIC)	2557.228		

Dependent Variable: CarsAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
86.358	10	<.001

Dependent Variable: CarsAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	4.525	1	.033
Daily COVID-19 cases Canada (in thousands)	33.077	1	<.001
Temperature	.109	1	.742
Precipitation	8.540	1	.003
Windspeed	2.910	1	.088
Population density (thousand people / square km)	.533	1	.465
Females%	1.652	1	.199
Age weighted average	1.212	1	.271
Income 2020 weighted average (in thousands CAN$)	1.584	1	.208
Arterial dominant crossings	7.749	1	.005
Local dominant crossings	12.126	1	<.001

Dependent Variable: CarsAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	4.018	1.8888	.316	7.720	4.525	1	.033	55.581	1.371	2252.644
Daily COVID-19 cases Canada (in thousands)	-.113	.0196	-.151	-.074	33.077	1	<.001	.893	.860	.928
Temperature	.005	.0139	-.023	.032	.109	1	.742	1.005	.978	1.032
Precipitation	-.060	.0207	-.101	-.020	8.540	1	.003	.941	.904	.980
Windspeed	.014	.0083	-.002	.031	2.910	1	.088	1.014	.998	1.031
Population density (thousand people / square km)	-.010	.0139	-.037	.017	.533	1	.465	.990	.963	1.017
Females%	.049	.0380	-.026	.123	1.652	1	.199	1.050	.975	1.131
Age weighted average	.024	.0222	-.019	.068	1.212	1	.271	1.025	.981	1.070
Income 2020 weighted average (in thousands CAN$)	.002	.0020	-.001	.006	1.584	1	.208	1.002	.999	1.006
Arterial dominant crossings	.400	.1436	.118	.681	7.749	1	.005	1.491	1.126	1.976
Local dominant crossings	-.576	.1654	-.900	-.252	12.126	1	<.001	.562	.406	.777
(Scale)	1[a]									
(Negative binomial)	.373	.0414	.300	.464						

Dependent Variable: CarsAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.8 Cars IB negative binomial regression SPSS output

Model Information

Dependent Variable	CarsIB
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	CarsIB	146	87	18353	4995.14	3920.239
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	155.364	134	1.159
Scaled Deviance	155.364	134	
Pearson Chi-Square	143.190	134	1.069
Scaled Pearson Chi-Square	143.190	134	
Log Likelihood[b]	-1335.827		
Akaike's Information Criterion (AIC)	2695.654		
Finite Sample Corrected AIC (AICC)	2698.000		
Bayesian Information Criterion (BIC)	2731.457		
Consistent AIC (CAIC)	2743.457		

Dependent Variable: CarsIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
94.956	10	<.001

Dependent Variable: CarsIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	6.693	1	.010
Daily COVID-19 cases Canada (in thousands)	29.246	1	<.001
Temperature	.526	1	.468
Precipitation	.010	1	.920
Windspeed	.025	1	.876
Population density (thousand people / square km)	.191	1	.662
Females%	.742	1	.389
Age weighted average	3.276	1	.070
Income 2020 weighted average (in thousands CAN$)	.313	1	.576
Arterial dominant crossings	8.833	1	.003
Local dominant crossings	16.386	1	<.001

Dependent Variable: CarsIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	4.970	1.9213	1.205	8.736	6.693	1	.010	144.075	3.336	6222.643
Daily COVID-19 cases Canada (in thousands)	-.109	.0202	-.149	-.070	29.246	1	<.001	.896	.862	.933
Temperature	-.010	.0140	-.038	.017	.526	1	.468	.990	.963	1.017
Precipitation	.002	.0240	-.045	.049	.010	1	.920	1.002	.956	1.051
Windspeed	.001	.0080	-.014	.017	.025	1	.876	1.001	.986	1.017
Population density (thousand people / square km)	.006	.0137	-.021	.033	.191	1	.662	1.006	.979	1.033
Females%	.034	.0396	-.043	.112	.742	1	.389	1.035	.957	1.118
Age weighted average	.041	.0229	-.003	.086	3.276	1	.070	1.042	.997	1.090
Income 2020 weighted average (in thousands CAN$)	.001	.0020	-.003	.005	.313	1	.576	1.001	.997	1.005
Arterial dominant crossings	.430	.1447	.146	.714	8.833	1	.003	1.537	1.158	2.041
Local dominant crossings	-.673	.1661	-.998	-.347	16.386	1	<.001	.510	.369	.707
(Scale)	1[a]									
(Negative binomial)	.386	.0427	.311	.480						

Dependent Variable: CarsIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.9 Cars PM negative binomial regression SPSS output

Model Information

Dependent Variable	CarsPM
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	CarsPM	146	36	10479	3109.00	2302.709
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	154.916	134	1.156
Scaled Deviance	154.916	134	
Pearson Chi-Square	131.964	134	.985
Scaled Pearson Chi-Square	131.964	134	
Log Likelihood[b]	-1265.429		
Akaike's Information Criterion (AIC)	2554.859		
Finite Sample Corrected AIC (AICC)	2557.204		
Bayesian Information Criterion (BIC)	2590.662		
Consistent AIC (CAIC)	2602.662		

Dependent Variable: CarsPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
93.105	10	<.001

Dependent Variable: CarsPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	5.948	1	.015
Daily COVID-19 cases Canada (in thousands)	33.386	1	<.001
Temperature	.111	1	.739
Precipitation	.622	1	.430
Windspeed	.672	1	.412
Population density (thousand people / square km)	.064	1	.801
Females%	.834	1	.361
Age weighted average	3.080	1	.079
Income 2020 weighted average (in thousands CAN$)	.074	1	.786
Arterial dominant crossings	7.972	1	.005
Local dominant crossings	15.213	1	<.001

Dependent Variable: CarsPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	4.517	1.8522	.887	8.148	5.948	1	.015	91.603	2.428	3455.531
Daily COVID-19 cases Canada (in thousands)	-.111	.0192	-.148	-.073	33.386	1	<.001	.895	.862	.929
Temperature	-.005	.0136	-.031	.022	.111	1	.739	.995	.969	1.022
Precipitation	-.017	.0221	-.061	.026	.622	1	.430	.983	.941	1.026
Windspeed	.006	.0079	-.009	.022	.672	1	.412	1.007	.991	1.022
Population density (thousand people / square km)	.003	.0133	-.023	.029	.064	1	.801	1.003	.978	1.030
Females%	.035	.0381	-.040	.109	.834	1	.361	1.035	.961	1.116
Age weighted average	.039	.0224	-.005	.083	3.080	1	.079	1.040	.995	1.087
Income 2020 weighted average (in thousands CAN$)	.001	.0019	-.003	.004	.074	1	.786	1.001	.997	1.004
Arterial dominant crossings	.396	.1401	.121	.670	7.972	1	.005	1.485	1.129	1.955
Local dominant crossings	-.628	.1610	-.943	-.312	15.213	1	<.001	.534	.389	.732
(Scale)	1[a]									
(Negative binomial)	.362	.0403	.291	.450						

Dependent Variable: CarsPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.10 Pedestrians total negative binomial regression SPSS output

Model Information

Dependent Variable	Pedestrians total
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Pedestrians total	146	7	25798	2593.07	4127.960
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	166.238	133	1.250
Scaled Deviance	166.238	133	
Pearson Chi-Square	135.219	133	1.017
Scaled Pearson Chi-Square	135.219	133	
Log Likelihood[b]	-1222.654		
Akaike's Information Criterion (AIC)	2471.309		
Finite Sample Corrected AIC (AICC)	2474.066		
Bayesian Information Criterion (BIC)	2510.096		
Consistent AIC (CAIC)	2523.096		

Dependent Variable: Pedestrians total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
115.275	11	.000

Dependent Variable: Pedestrians total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	12.217	1	<.001
Daily COVID-19 cases Canada (in thousands)	13.443	1	<.001
Stringency Index Ontario	36.094	1	<.001
Temperature	1.319	1	.251
Precipitation	1.732	1	.188
Windspeed	1.756	1	.185
Population density (thousand people / square km)	9.203	1	.002
Females%	.152	1	.697
Age weighted average	10.244	1	.001
Income 2020 weighted average (in thousands CAN$)	.371	1	.542
Arterial dominant crossings	1.375	1	.241
Local dominant crossings	2.885	1	.089

Dependent Variable: Pedestrians total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	10.568	3.0235	4.642	16.494	12.217	1	<.001	38869.646	103.760	14561066.704
Daily COVID-19 cases Canada (in thousands)	.164	.0449	.077	.252	13.443	1	<.001	1.179	1.080	1.287
Stringency Index Ontario	-.066	.0110	-.088	-.045	36.094	1	<.001	.936	.916	.956
Temperature	.025	.0213	-.017	.066	1.319	1	.251	1.025	.983	1.069
Precipitation	-.057	.0432	-.141	.028	1.732	1	.188	.945	.868	1.028
Windspeed	.018	.0136	-.009	.045	1.756	1	.185	1.018	.991	1.046
Population density (thousand people / square km)	.066	.0216	.023	.108	9.203	1	.002	1.068	1.023	1.114
Females%	.025	.0629	-.099	.148	.152	1	.697	1.025	.906	1.159
Age weighted average	-.121	.0377	-.195	-.047	10.244	1	.001	.886	.823	.954
Income 2020 weighted average (in thousands CAN$)	.002	.0036	-.005	.009	.371	1	.542	1.002	.995	1.009
Arterial dominant crossings	.276	.2350	-.185	.736	1.375	1	.241	1.317	.831	2.088
Local dominant crossings	-.460	.2707	-.990	.071	2.885	1	.089	.631	.372	1.073
(Scale)	1[a]									
(Negative binomial)	.890	.0929	.725	1.092						

Dependent Variable: Pedestrians total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.11 Pedestrians AM negative binomial regression SPSS output

Model Information

Dependent Variable	PedestriansAM
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	PedestriansAM	146	0	8942	504.62	1055.684
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	166.975	133	1.255
Scaled Deviance	166.975	133	
Pearson Chi-Square	152.727	133	1.148
Scaled Pearson Chi-Square	152.727	133	
Log Likelihood[b]	-996.171		
Akaike's Information Criterion (AIC)	2018.342		
Finite Sample Corrected AIC (AICC)	2021.099		
Bayesian Information Criterion (BIC)	2057.129		
Consistent AIC (CAIC)	2070.129		

Dependent Variable: PedestriansAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
99.009	11	<.001

Dependent Variable: PedestriansAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	11.014	1	<.001
Daily COVID-19 cases Canada (in thousands)	11.125	1	<.001
Stringency Index Ontario	38.962	1	<.001
Temperature	4.947	1	.026
Precipitation	10.195	1	.001
Windspeed	4.597	1	.032
Population density (thousand people / square km)	2.719	1	.099
Females%	.077	1	.781
Age weighted average	13.950	1	<.001
Income 2020 weighted average (in thousands CAN$)	1.656	1	.198
Arterial dominant crossings	.114	1	.735
Local dominant crossings	.262	1	.609

Dependent Variable: PedestriansAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	10.013	3.0170	4.100	15.926	11.014	1	<.001	22312.883	60.317	8254147.245
Daily COVID-19 cases Canada (in thousands)	.150	.0449	.062	.238	11.125	1	<.001	1.162	1.064	1.268
Stringency Index Ontario	-.068	.0108	-.089	-.046	38.962	1	<.001	.935	.915	.955
Temperature	.048	.0217	.006	.091	4.947	1	.026	1.050	1.006	1.095
Precipitation	-.113	.0355	-.183	-.044	10.195	1	.001	.893	.833	.957
Windspeed	.030	.0139	.003	.057	4.597	1	.032	1.030	1.003	1.059
Population density (thousand people / square km)	.036	.0220	-.007	.079	2.719	1	.099	1.037	.993	1.083
Females%	.017	.0616	-.104	.138	.077	1	.781	1.017	.902	1.148
Age weighted average	-.138	.0370	-.211	-.066	13.950	1	<.001	.871	.810	.936
Income 2020 weighted average (in thousands CAN$)	.005	.0036	-.002	.012	1.656	1	.198	1.005	.998	1.012
Arterial dominant crossings	.080	.2378	-.386	.546	.114	1	.735	1.084	.680	1.727
Local dominant crossings	-.138	.2694	-.666	.390	.262	1	.609	.871	.514	1.477
(Scale)	1[a]									
(Negative binomial)	.887	.0942	.720	1.092						

Dependent Variable: PedestriansAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.12 Pedestrians IB negative binomial regression SPSS output

Model Information

Dependent Variable	PedestriansIB
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	PedestriansIB	146	7	9284	1196.65	1760.526
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	166.688	133	1.253
Scaled Deviance	166.688	133	
Pearson Chi-Square	137.212	133	1.032
Scaled Pearson Chi-Square	137.212	133	
Log Likelihood[b]	-1106.248		
Akaike's Information Criterion (AIC)	2238.495		
Finite Sample Corrected AIC (AICC)	2241.253		
Bayesian Information Criterion (BIC)	2277.282		
Consistent AIC (CAIC)	2290.282		

Dependent Variable: PedestriansIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
117.005	11	.000

Dependent Variable: PedestriansIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	9.325	1	.002
Daily COVID-19 cases Canada (in thousands)	13.233	1	<.001
Stringency Index Ontario	32.200	1	<.001
Temperature	.251	1	.616
Precipitation	.224	1	.636
Windspeed	1.074	1	.300
Population density (thousand people / square km)	11.835	1	<.001
Females%	.048	1	.826
Age weighted average	6.166	1	.013
Income 2020 weighted average (in thousands CAN$)	.002	1	.963
Arterial dominant crossings	2.311	1	.128
Local dominant crossings	4.442	1	.035

Dependent Variable: PedestriansIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	9.438	3.0906	3.380	15.495	9.325	1	.002	12552.610	29.375	5364081.483
Daily COVID-19 cases Canada (in thousands)	.166	.0458	.077	.256	13.233	1	<.001	1.181	1.080	1.292
Stringency Index Ontario	-.064	.0113	-.086	-.042	32.200	1	<.001	.938	.918	.959
Temperature	.011	.0219	-.032	.054	.251	1	.616	1.011	.969	1.055
Precipitation	-.024	.0513	-.125	.076	.224	1	.636	.976	.883	1.079
Windspeed	.014	.0137	-.013	.041	1.074	1	.300	1.014	.987	1.042
Population density (thousand people / square km)	.075	.0219	.032	.118	11.835	1	<.001	1.078	1.033	1.125
Females%	.014	.0646	-.112	.141	.048	1	.826	1.014	.894	1.151
Age weighted average	-.098	.0393	-.174	-.021	6.166	1	.013	.907	.840	.980
Income 2020 weighted average (in thousands CAN$)	.000	.0038	-.008	.007	.002	1	.963	1.000	.993	1.007
Arterial dominant crossings	.365	.2404	-.106	.837	2.311	1	.128	1.441	.900	2.308
Local dominant crossings	-.578	.2744	-1.116	-.041	4.442	1	.035	.561	.328	.960
(Scale)	1[a]									
(Negative binomial)	.921	.0962	.751	1.130						

Dependent Variable: PedestriansIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.13 Pedestrians PM negative binomial regression SPSS output

Model Information

Dependent Variable	PedestriansPM
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	PedestriansPM	146	0	10206	891.79	1532.876
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	168.114	133	1.264
Scaled Deviance	168.114	133	
Pearson Chi-Square	132.179	133	.994
Scaled Pearson Chi-Square	132.179	133	
Log Likelihood[b]	-1058.181		
Akaike's Information Criterion (AIC)	2142.363		
Finite Sample Corrected AIC (AICC)	2145.120		
Bayesian Information Criterion (BIC)	2181.149		
Consistent AIC (CAIC)	2194.149		

Dependent Variable: PedestriansPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
120.432	11	.000

Dependent Variable: PedestriansPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	7.897	1	.005
Daily COVID-19 cases Canada (in thousands)	13.543	1	<.001
Stringency Index Ontario	36.168	1	<.001
Temperature	1.810	1	.178
Precipitation	2.266	1	.132
Windspeed	1.813	1	.178
Population density (thousand people / square km)	11.045	1	<.001
Females%	.426	1	.514
Age weighted average	11.172	1	<.001
Income 2020 weighted average (in thousands CAN$)	.765	1	.382
Arterial dominant crossings	1.266	1	.261
Local dominant crossings	4.223	1	.040

Dependent Variable: PedestriansPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	8.720	3.1031	2.638	14.802	7.897	1	.005	6123.189	13.985	2681043.313
Daily COVID-19 cases Canada (in thousands)	.171	.0464	.080	.262	13.543	1	<.001	1.186	1.083	1.299
Stringency Index Ontario	-.069	.0115	-.091	-.046	36.168	1	<.001	.933	.913	.955
Temperature	.029	.0219	-.013	.072	1.810	1	.178	1.030	.987	1.075
Precipitation	-.064	.0426	-.148	.019	2.266	1	.132	.938	.863	1.020
Windspeed	.019	.0143	-.009	.047	1.813	1	.178	1.019	.991	1.048
Population density (thousand people / square km)	.074	.0222	.030	.117	11.045	1	<.001	1.077	1.031	1.125
Females%	.042	.0648	-.085	.169	.426	1	.514	1.043	.919	1.184
Age weighted average	-.128	.0384	-.204	-.053	11.172	1	<.001	.880	.816	.948
Income 2020 weighted average (in thousands CAN$)	.003	.0037	-.004	.010	.765	1	.382	1.003	.996	1.010
Arterial dominant crossings	.270	.2404	-.201	.742	1.266	1	.261	1.311	.818	2.099
Local dominant crossings	-.577	.2808	-1.127	-.027	4.223	1	.040	.562	.324	.974
(Scale)	1[a]									
(Negative binomial)	.945	.0997	.769	1.162						

Dependent Variable: PedestriansPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.14 Cyclists total negative binomial regression SPSS output

Model Information

Dependent Variable	Cyclists total
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Cyclists total	146	0	1098	112.32	182.015
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	168.381	133	1.266
Scaled Deviance	168.381	133	
Pearson Chi-Square	191.731	133	1.442
Scaled Pearson Chi-Square	191.731	133	
Log Likelihood[b]	-756.059		
Akaike's Information Criterion (AIC)	1538.119		
Finite Sample Corrected AIC (AICC)	1540.876		
Bayesian Information Criterion (BIC)	1576.906		
Consistent AIC (CAIC)	1589.906		

Dependent Variable: Cyclists total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
119.458	11	.000

Dependent Variable: Cyclists total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	22.148	1	<.001
Daily COVID-19 cases Canada (in thousands)	46.546	1	<.001
Stringency Index Ontario	28.828	1	<.001
Temperature	19.335	1	<.001
Precipitation	13.134	1	<.001
Windspeed	.425	1	.515
Population density (thousand people / square km)	9.348	1	.002
Females%	10.580	1	.001
Age weighted average	.264	1	.607
Income 2020 weighted average (in thousands CAN$)	.097	1	.756
Arterial dominant crossings	1.889	1	.169
Local dominant crossings	.151	1	.698

Dependent Variable: Cyclists total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	15.890	3.3763	9.272	22.507	22.148	1	<.001	7956964.921	10636.871	5952247475.040
Daily COVID-19 cases Canada (in thousands)	.327	.0479	.233	.421	46.546	1	<.001	1.387	1.262	1.523
Stringency Index Ontario	-.060	.0112	-.082	-.038	28.828	1	<.001	.942	.921	.962
Temperature	.102	.0233	.057	.148	19.335	1	<.001	1.108	1.058	1.159
Precipitation	-.126	.0347	-.194	-.058	13.134	1	<.001	.882	.824	.944
Windspeed	.010	.0149	-.019	.039	.425	1	.515	1.010	.981	1.040
Population density (thousand people / square km)	.071	.0232	.025	.117	9.348	1	.002	1.074	1.026	1.124
Females%	-.231	.0711	-.371	-.092	10.580	1	.001	.793	.690	.912
Age weighted average	-.021	.0415	-.103	.060	.264	1	.607	.979	.902	1.062
Income 2020 weighted average (in thousands CAN$)	.001	.0042	-.007	.009	.097	1	.756	1.001	.993	1.009
Arterial dominant crossings	.318	.2316	-.136	.772	1.889	1	.169	1.375	.873	2.165
Local dominant crossings	-.105	.2702	-.634	.425	.151	1	.698	.900	.530	1.529
(Scale)	1[a]									
(Negative binomial)	.935	.1040	.752	1.163						

Dependent Variable: Cyclists total
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.15 Cyclists AM negative binomial regression SPSS output

Model Information

Dependent Variable	CyclistsAM
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	CyclistsAM	146	0	365	24.80	52.330
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	168.124	133	1.264
Scaled Deviance	168.124	133	
Pearson Chi-Square	216.916	133	1.631
Scaled Pearson Chi-Square	216.916	133	
Log Likelihood[b]	-543.014		
Akaike's Information Criterion (AIC)	1112.028		
Finite Sample Corrected AIC (AICC)	1114.785		
Bayesian Information Criterion (BIC)	1150.814		
Consistent AIC (CAIC)	1163.814		

Dependent Variable: CyclistsAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
100.369	11	<.001

Dependent Variable: CyclistsAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	21.344	1	<.001
Daily COVID-19 cases Canada (in thousands)	36.810	1	<.001
Stringency Index Ontario	35.064	1	<.001
Temperature	17.919	1	<.001
Precipitation	12.393	1	<.001
Windspeed	.245	1	.621
Population density (thousand people / square km)	1.099	1	.294
Females%	13.654	1	<.001
Age weighted average	.141	1	.707
Income 2020 weighted average (in thousands CAN$)	.090	1	.764
Arterial dominant crossings	.213	1	.644
Local dominant crossings	.116	1	.733

Dependent Variable: CyclistsAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	16.880	3.6538	9.719	24.041	21.344	1	<.001	21425770.559	16628.248	27607457629.934
Daily COVID-19 cases Canada (in thousands)	.318	.0525	.216	.421	36.810	1	<.001	1.375	1.241	1.524
Stringency Index Ontario	-.071	.0121	-.095	-.048	35.064	1	<.001	.931	.909	.953
Temperature	.110	.0259	.059	.161	17.919	1	<.001	1.116	1.061	1.174
Precipitation	-.144	.0408	-.224	-.064	12.393	1	<.001	.866	.800	.938
Windspeed	.008	.0161	-.024	.040	.245	1	.621	1.008	.977	1.040
Population density (thousand people / square km)	.027	.0262	-.024	.079	1.099	1	.294	1.028	.976	1.082
Females%	-.269	.0727	-.411	-.126	13.654	1	<.001	.764	.663	.881
Age weighted average	-.018	.0467	-.109	.074	.141	1	.707	.983	.897	1.077
Income 2020 weighted average (in thousands CAN$)	.001	.0042	-.007	.009	.090	1	.764	1.001	.993	1.010
Arterial dominant crossings	.120	.2597	-.389	.629	.213	1	.644	1.127	.678	1.876
Local dominant crossings	-.103	.3011	-.693	.488	.116	1	.733	.903	.500	1.628
(Scale)	1[a]									
(Negative binomial)	1.063	.1317	.834	1.355						

Dependent Variable: CyclistsAM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.16 Cyclists IB negative binomial regression SPSS output

Model Information

Dependent Variable	CyclistsIB
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	CyclistsIB	146	0	327	45.74	65.341
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	168.088	133	1.264
Scaled Deviance	168.088	133	
Pearson Chi-Square	163.059	133	1.226
Scaled Pearson Chi-Square	163.059	133	
Log Likelihood[b]	-635.370		
Akaike's Information Criterion (AIC)	1296.739		
Finite Sample Corrected AIC (AICC)	1299.497		
Bayesian Information Criterion (BIC)	1335.526		
Consistent AIC (CAIC)	1348.526		

Dependent Variable: CyclistsIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
110.141	11	.000

Dependent Variable: CyclistsIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	14.309	1	<.001
Daily COVID-19 cases Canada (in thousands)	37.640	1	<.001
Stringency Index Ontario	20.734	1	<.001
Temperature	11.651	1	<.001
Precipitation	8.739	1	.003
Windspeed	.383	1	.536
Population density (thousand people / square km)	13.748	1	<.001
Females%	7.076	1	.008
Age weighted average	.339	1	.560
Income 2020 weighted average (in thousands CAN$)	.520	1	.471
Arterial dominant crossings	3.579	1	.059
Local dominant crossings	.100	1	.752

Dependent Variable: CyclistsIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	12.430	3.2860	5.990	18.870	14.309	1	<.001	250195.225	399.224	156798383.848
Daily COVID-19 cases Canada (in thousands)	.287	.0468	.196	.379	37.640	1	<.001	1.333	1.216	1.461
Stringency Index Ontario	-.050	.0110	-.072	-.029	20.734	1	<.001	.951	.931	.972
Temperature	.080	.0233	.034	.125	11.651	1	<.001	1.083	1.034	1.133
Precipitation	-.112	.0380	-.187	-.038	8.739	1	.003	.894	.830	.963
Windspeed	.009	.0146	-.020	.038	.383	1	.536	1.009	.981	1.038
Population density (thousand people / square km)	.083	.0224	.039	.127	13.748	1	<.001	1.087	1.040	1.135
Females%	-.185	.0695	-.321	-.049	7.076	1	.008	.831	.725	.953
Age weighted average	-.023	.0399	-.102	.055	.339	1	.560	.977	.903	1.057
Income 2020 weighted average (in thousands CAN$)	.003	.0041	-.005	.011	.520	1	.471	1.003	.995	1.011
Arterial dominant crossings	.425	.2246	-.015	.865	3.579	1	.059	1.530	.985	2.376
Local dominant crossings	-.086	.2725	-.620	.448	.100	1	.752	.918	.538	1.565
(Scale)	1[a]									
(Negative binomial)	.886	.1057	.702	1.120						

Dependent Variable: CyclistsIB
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.

4.17 Cyclists PM negative binomial regression SPSS output

Model Information

Dependent Variable	CyclistsPM
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	146	100.0%
Excluded	0	0.0%
Total	146	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	CyclistsPM	146	0	416	41.78	71.922
Covariate	Daily COVID-19 cases Canada (in thousands)	146	.00	10.98	3.6868	3.87868
	Stringency Index Ontario	146	.00	35.19	16.7824	16.47129
	Temperature	146	-10.2	9.4	.382	3.8804
	Precipitation	146	.00	22.16	.7019	2.37309
	Windspeed	146	16.7	51.4	26.270	7.5608
	Population density (thousand people / square km)	146	.52	27.04	7.3721	5.35904
	Females%	146	44.74%	54.59%	51.8595%	1.87650%
	Age weighted average	146	33.40	48.49	42.2912	3.47565
	Income 2020 weighted average (in thousands CAN$)	146	30.77	195.60	75.3980	33.29781
	Arterial dominant crossings	146	0	1	.58	.496
	Local dominant crossings	146	0	1	.22	.415

Goodness of Fit[a]

	Value	df	Value/df
Deviance	167.783	133	1.262
Scaled Deviance	167.783	133	
Pearson Chi-Square	189.150	133	1.422
Scaled Pearson Chi-Square	189.150	133	
Log Likelihood[b]	-596.572		
Akaike's Information Criterion (AIC)	1219.144		
Finite Sample Corrected AIC (AICC)	1221.902		
Bayesian Information Criterion (BIC)	1257.931		
Consistent AIC (CAIC)	1270.931		

Dependent Variable: CyclistsPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
119.891	11	.000

Dependent Variable: CyclistsPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	18.538	1	<.001
Daily COVID-19 cases Canada (in thousands)	51.672	1	<.001
Stringency Index Ontario	28.429	1	<.001
Temperature	22.773	1	<.001
Precipitation	10.610	1	.001
Windspeed	.250	1	.617
Population density (thousand people / square km)	7.995	1	.005
Females%	9.397	1	.002
Age weighted average	.706	1	.401
Income 2020 weighted average (in thousands CAN$)	.054	1	.817
Arterial dominant crossings	1.165	1	.280
Local dominant crossings	.735	1	.391

Dependent Variable: CyclistsPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	16.474	3.8263	8.975	23.974	18.538	1	<.001	14280478.468	7903.137	25803938804.463
Daily COVID-19 cases Canada (in thousands)	.395	.0550	.287	.503	51.672	1	<.001	1.485	1.333	1.654
Stringency Index Ontario	-.068	.0127	-.092	-.043	28.429	1	<.001	.935	.912	.958
Temperature	.122	.0255	.072	.172	22.773	1	<.001	1.129	1.074	1.187
Precipitation	-.133	.0408	-.213	-.053	10.610	1	.001	.876	.808	.948
Windspeed	.008	.0167	-.024	.041	.250	1	.617	1.008	.976	1.042
Population density (thousand people / square km)	.073	.0259	.022	.124	7.995	1	.005	1.076	1.023	1.132
Females%	-.247	.0805	-.405	-.089	9.397	1	.002	.781	.667	.915
Age weighted average	-.040	.0474	-.133	.053	.706	1	.401	.961	.876	1.055
Income 2020 weighted average (in thousands CAN$)	-.001	.0048	-.011	.008	.054	1	.817	.999	.990	1.008
Arterial dominant crossings	.279	.2584	-.228	.786	1.165	1	.280	1.322	.796	2.194
Local dominant crossings	-.259	.3016	-.850	.332	.735	1	.391	.772	.428	1.394
(Scale)	1[a]									
(Negative binomial)	1.092	.1306	.864	1.381						

Dependent Variable: CyclistsPM
Model: (Intercept), Daily COVID-19 cases Canada (in thousands), Stringency Index Ontario, Temperature, Precipitation, Windspeed, Population density (thousand people / square km), Females%, Age weighted average, Income 2020 weighted average (in thousands CAN$), Arterial dominant crossings, Local dominant crossings

a. Fixed at the displayed value.