The Route 508 Streetcar and Congestion on Toronto's Shoreline, 2011 - 2020*

Examining Traffic Patterns Before and After Public Transit Improvements

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This study investigates the impact of enhanced public transit infrastructure on car congestion. It specifically focuses on the reintroduction of the Route 508 Lake Shore streetcar between 2011 and 2020. The data, sourced from the City of Toronto's Transportation Services Division, includes detailed traffic volumes for various modes at intersections across the city. The method of analysis includes comparing the negative binomial regression models of daily car traffic before and after transit upgrades. The results highlighted a significant reduction in the relationship between bus traffic and car congestion. Additionally, it was observed that car traffic decreased over time. These findings highlight the usefulness of public transit improvements in reducing urban congestion.

1 Introduction

Traffic congestion represents a significant challenge for urban cities. It is a non-productive activity which negatively affects economic efficiency, environmental sustainability and overall quality of life. To address this challenge, many cities like Toronto have undergone improvements to public transit infrastructure with the aim of reducing car dependency and mitigate traffic congestion. However, it is still highly debatable whether or not such improvements lead to a decrease in car congestion.

This study specifically investigates the 508 Lake Shore Streetcar route in Toronto. It utilizes two datasets provided by the City of Toronto's Transportation Services Division. These datasets capture traffic volumes for various modes at city intersections. To analyze this data, R Core Team (2023) was used along with several R packages. Through the use of a negative

*Code and data are available at: https://github.com/MariaMangru/Traffic-Congestion-on-Toronto-s-Shoreline.

binomial regression, we can assess daily car traffic relative to bus traffic, pedestrian, bicycle flows and a time trend. Models were created to investigate traffic patterns before and after public transit improvements.

The estimand of this study is quantitatively evaluated through the change in the relationship between daily bus traffic and daily car traffic, as well as the evolution of car traffic trends over time. The findings from this study indicates a significant reduction in the relationship between bus traffic and car congestion, following the transit improvements. Additionally, a reversal from an increasing to a decreasing trend in car traffic over time was noted.

This research begins with an in-depth exploration of the dataset and the analytical methods employed, highlighting the use of R Core Team (2023) for data analysis. It then goes on to explain the results of the regression model, comparing and contrasting traffic patterns prior to and following the installation of transportation upgrades. The discussion interprets these findings within the broader framework of managing urban congestion and the importance of public transit. Through this approach, I hope to illustrate the important role of public transit improvements in combating urban congestion, as well as its significance for promoting sustainable urban mobility and improving the standard of living in urban areas.

2 Data

2.1 Data Source

This research relies on traffic volume data sets from the City of Toronto's Transportation Services Division. It accessible through the Toronto OpenData portal and is titled "Traffic Volumes at Intersections for All Modes" which is free and accessible for public use. The information collected in the dataset are of two main types:

1. Automatic Traffic Recorder Counts (ATR): These are segment-level volumes which capture the total number of vehicles, cyclists, or pedestrians moving in a specific direction on a street.
2. Turning Movement Counts (TMCs): These detail the volume observed at each leg of an intersection, including the turning movement by mode (car, truck, bus, pedestrian, cyclist, other).

The data set covers various intersections across Toronto, providing a detailed view of the city's traffic dynamics. It includes data spanning 2010-2019 and 2020-2024 which was combined into one data set. The data set is segmented by direction of approach, turning movement, and mode, in 15-minute intervals. This level of detail allows for a thorough investigation of traffic patterns, which is especially important for analyzing how changes to public transport affect traffic congestion on the 508 Lake Shore route.

The data set was cleaned and prepared, with yearly data files combined, relevant date periods filtered, and traffic volumes aggregated to get daily totals for every mode of transportation. This pre-processing step made sure the data was suitable for analysis, with a particular emphasis on the time frame prior to and following the 508 Lake Shore route's streetcar upgrades.

2.2 Variables of Interest

In addition to a temporal trend variables, specific variables were chosen for this analysis, with an emphasis on the dynamics of car traffic in relation to bus, pedestrian, and bicycle traffic volumes:

- Daily Car Traffic (`daily_cars`): Total volume of car traffic recorded at selected intersections along the 508 Route.
- Daily Bus Traffic (`daily_bus`), Pedestrian Traffic (`daily_peds`) and Bicycle Traffic (`daily_bike`): Bus, pedestrian and bike traffic volumes used to indicate the presence and frequency of non personal car usage.
- Time Trend (time_trend): A constructed variable to analyze traffic pattern changes over time.

Using R Core Team (2023), the dataset was processed by using tools like `ggplot2` for visualization, `dplyr` for data manipulation, and `lubridate` for date management. These packages made it easier to clean, aggregate, and analyze traffic volumes, which helped to provide a more complex picture of traffic patterns and flow.

Table 1: Summary statistics table for daily traffic volume

Transport Mode	Mean	Median
Daily Car Traffic	14169.85135	13291.5
Daily Bus Traffic	223.91441	190.5
Daily Pedestrian Traffic	686.05856	344.0
Daily Bicycle Traffic	50.48649	22.0

The summary table above provides a quantitative comparison across transportation modes by condensing the traffic data for each mode into average and median statistics. The data reveals that car traffic surpasses other modes in volume, with the mean and median values for daily car traffic being the highest.

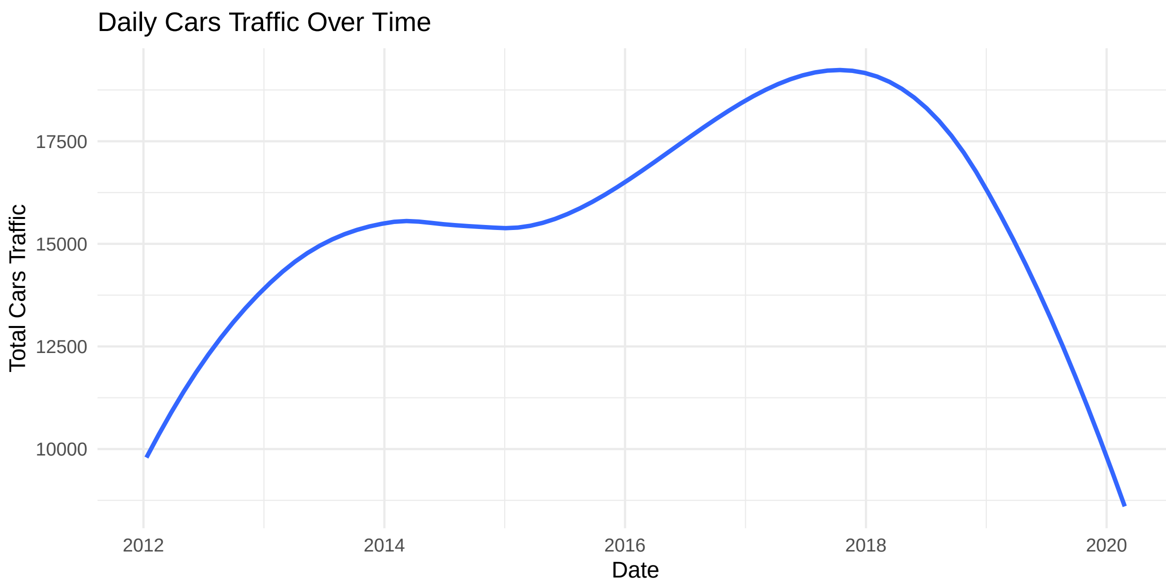

Figure 1: Daily Car Traffic Over Time. This graph displays the trend in number of cars within the area of interest between December 2011 to December 2014 and November 2018 to February 2020.

The daily variation in car traffic from 2011 to 2020 is shown in Figure 1. The traffic volume is depicted on a smooth line graph that first increases and peaks about 2016, after which it sharply declines. The fall that follows may point to the benefits of the Route 508 Lake Shore streetcar improvements on easing traffic congestion. The peak denotes a period of increased traffic.

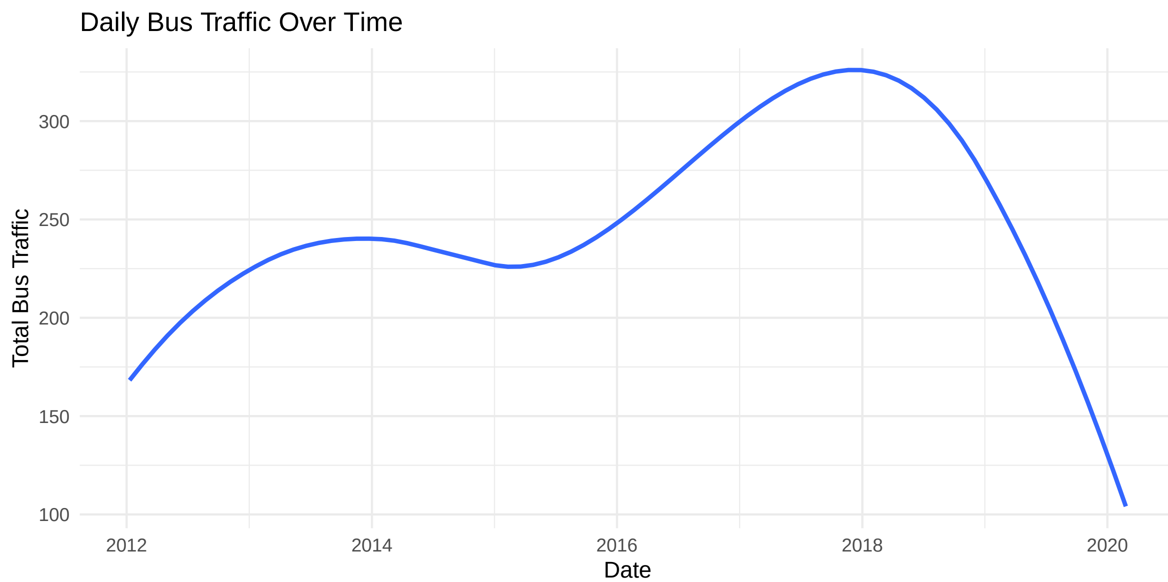

Figure 2: Daily Bus Traffic Over Time. This graph displays the trend in number of buses within the area of interest between December 2011 to December 2014 and November 2018 to February 2020.

Figure 2 depicts the daily patterns in bus traffic, which follow a similar pattern to that of car traffic. It is a smooth line graph that rises to a high around in 2016, then declines. This pattern might be an indication of how bus utilization has changed, which could be related to the streetcar route's service modifications and other improvements to public transportation.

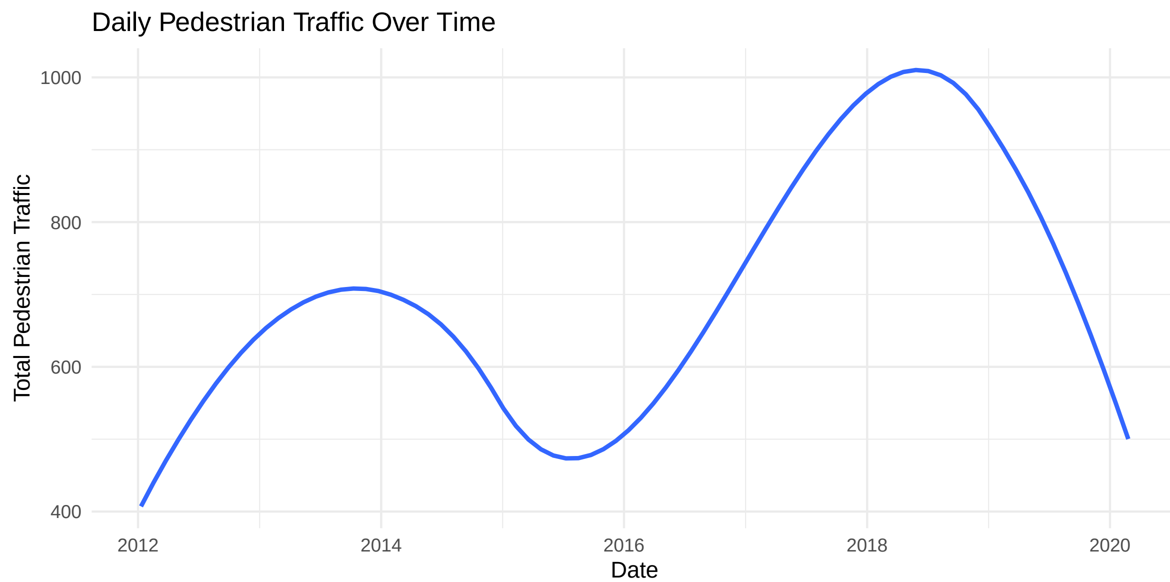

Figure 3: Daily Pedestrian Traffic Over Time. This graph displays the trend in number of pedestrian within the area of interest between December 2011 to December 2014 and November 2018 to February 2020.

Variations in pedestrian traffic over is shown in Figure 3's line graph. The middle of the time period has a noteworthy decrease, which is followed by a rise and another decline. This could be attributed to a number of things, such as changes in walkability, urban development, and perhaps the availability of better public transportation alternatives that encourage walking as a mode of transportation.

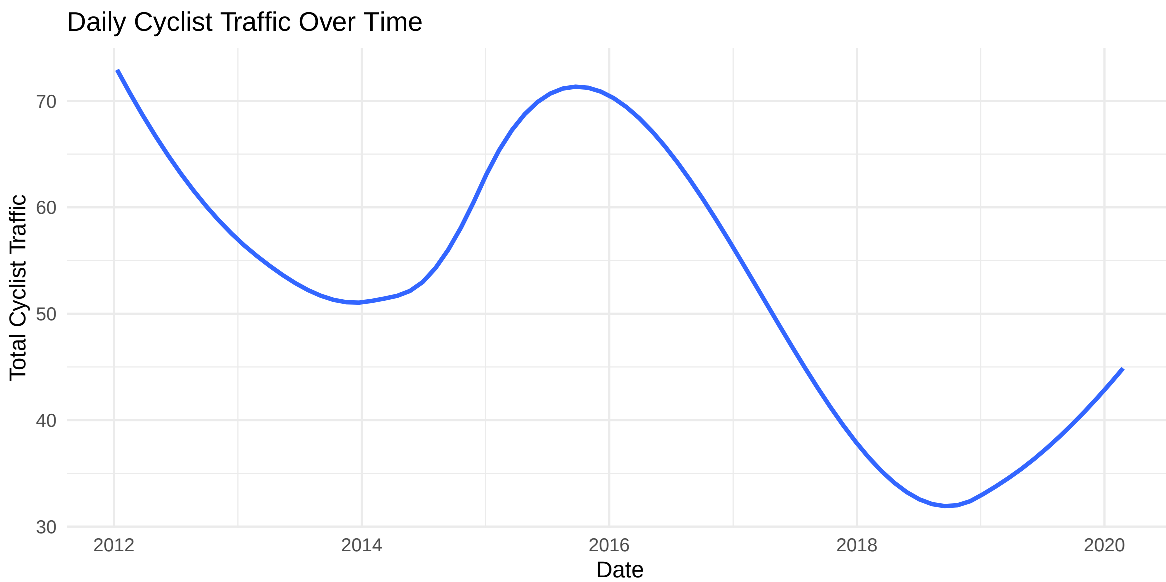

Figure 4: Daily Bike Traffic Over Time. This graph displays the trend in number of bikes within the area of interest between December 2011 to December 2014 and November 2018 to February 2020.

The pattern of bicycle traffic over time is depicted in Figure 4, where a notable rise and fall are shown on the line graph, indicating huge variations. The variations may be attributed to changing public opinions on riding, the implementation of bike infrastructure, or seasonal variations in weather patterns, which may be exacerbated by changes made to the transit system.

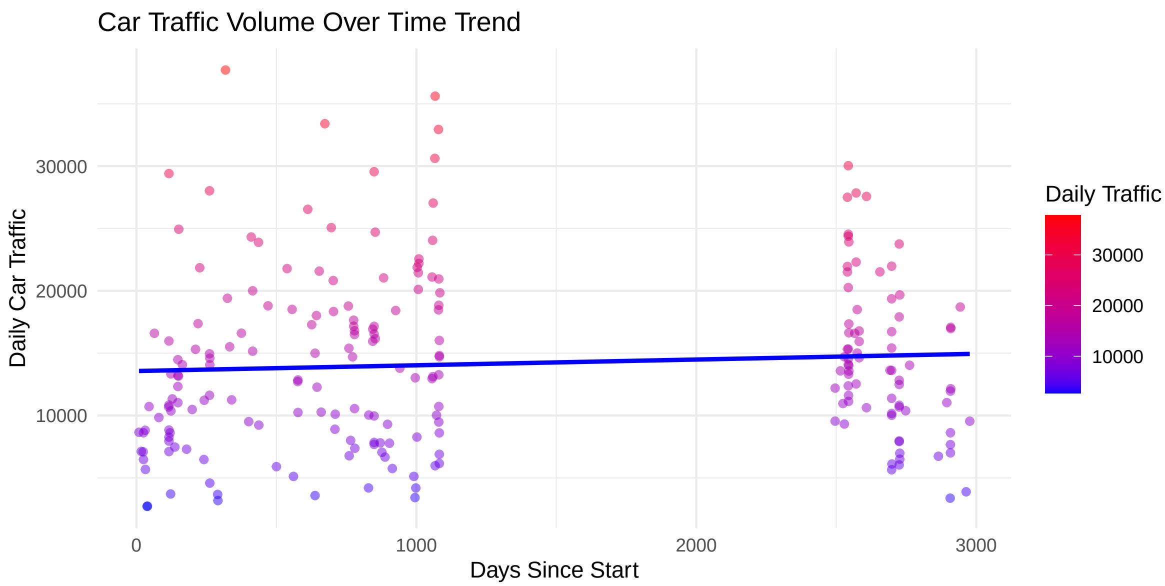

Figure 5: Daily Car Traffic Over Time. This graph displays the general trend in number of cars from the beginning of data collection period.

The scatter plot illustrates the fluctuating daily car counts over time, with a trend line suggesting an initial increase in traffic followed by a decline.

3 Model

This study uses negative binomial regression to address the problem of over-dispersion, which occurs when observed variance is greater than the mean and is frequently seen in count data. The dependent variable in the model is the daily count of cars, which is assumed to be impacted by temporal variations and the counts of alternative transportation modes (such as buses, bicycles, and pedestrians).

As such, we estimate the following model:

$$
\begin{aligned}
\log(\text{Count\_Cars}) &= \beta_0 + \beta_1 \times \text{Bus} + \beta_2 \times \text{Pedestrians} + \beta_3 \times \text{Bike} + \text{time\_trend} \\
\text{where} & \\
\log(\text{Count\_Cars}) &\text{ is the natural logarithm of the count of cars,} \\
\beta_0 &\text{ is the intercept of the model,} \\
\beta_1, \beta_2, \beta_3 &\text{ are the coefficients for the counts of buses, pedestrians, and bicycles,} \\
\text{time\_trend} &\text{ is the variable capturing the longitudinal changes.}
\end{aligned}
$$

3.1 Model justification

There are two reasons for using negative binomial regression. First, since events tend to cluster together in both place and time, traffic count data usually show overdispersion. For such data, the negative binomial model makes sense since it allows the variance to surpass the mean. Second, given that traffic counts frequently deviate from a normal distribution, this model can account for their skewed nature.

The analysis is divided into two temporal models in order to evaluate the effects of the Route 508 Lake Shore streetcar service upgrades: `model_before`, which is the model before the improvements, and `model_after`, which is the model after the improvements. This method clarifies the relationship that existed before and after the policy intervention between the independent and dependent variables.

Together with a temporal trend, the `model_before` captures the baseline relationship between automobile traffic and other modes of transportation. As an illustration of possible changes in traffic patterns brought about by the improved streetcar service, the `model_after`, on the other hand, depicts the altered dynamics following the enhancement. By use of comparative analysis, these models demonstrate the effectiveness of the Route 508 enhancements in mitigating car congestion.

4 Results

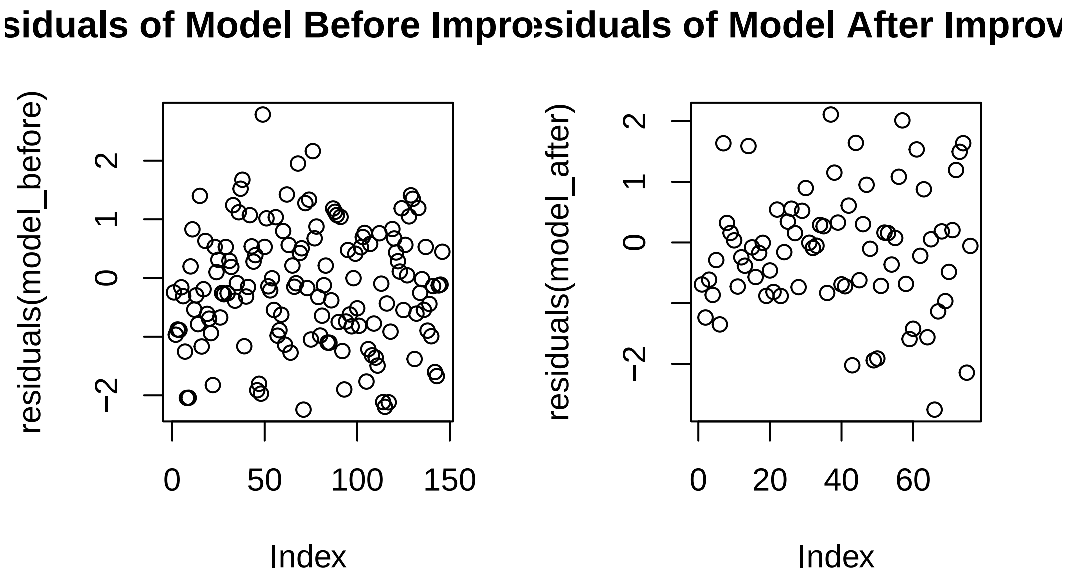

Figure 6: Residuals of the negative binomial regression model before and after the transit improvement. This plot helps to visualize if there are any patterns or systematic deviations unexplained by the model.

Figures 6 and 7 show an examination of residuals from the negative binomial regression models before and after the public transit improvement. For the model before improvements, the residuals plot does not indicate any apparent patterns or systemic deviations, suggesting that the model's assumptions may be adequate for the data. After the transit improvements, the residuals' plot again shows no obvious patterns, which suggests a random scatter.

Table 2: Negative Binomial Regression Model - Before Improvement

term	estimate	std.error	statistic	p.value
(Intercept)	**9.3403806**	0.0723649	129.0733096	0.0000000
daily_bus	**0.2614418**	0.0444629	5.8800049	0.0000000
daily_peds	**0.0217789**	0.0548485	0.3970727	0.6913139
daily_bike	**0.0624382**	0.0370956	1.6831701	0.0923422
time_trend	**0.0002870**	0.0001033	2.7787750	0.0054564

Table 3: Negative Binomial Regression Model - After Improvement

term	estimate	std.error	statistic	p.value
(Intercept)	**12.2834426**	0.8492461	14.4639382	0.0000000
daily_bus	**0.0964609**	0.0372417	2.5901303	0.0095940
daily_peds	**0.0235839**	0.0320754	0.7352644	0.4621785
daily_bike	**-0.0862823**	0.0549651	-1.5697648	0.1164698
time_trend	**-0.0010326**	0.0003170	-3.2574524	0.0011242

Table 2 represents the traffic patterns before the improvement. These results produced significant coefficients for both the intercept and daily bus traffic, as well as the time trend variable. The intercept, representing the baseline log-count of cars when all other variables are zero, was significant with an estimate of 9.340 and a standard error of 0.072, indicating a high baseline traffic volume. Daily bus traffic had a positive and significant relationship with car traffic, with a coefficient of 0.261, suggesting that increases in bus traffic were associated with increases in car traffic. The time trend also showed a significant, albeit small, positive effect on car traffic `( = 0.000287)`, indicating a gradual increase in car traffic over time.

Pedestrian and bicycle traffic, however, were not significantly associated with car traffic before the improvements ($p > 0.05$ for both).

Post-improvement, the model exhibits significant changes in the dynamics of traffic patterns. The intercept remains significant but increases to 12.283, reflecting an overall higher baseline of car traffic possibly due to other factors. The coefficient for daily bus traffic notably decreases to 0.096, indicating a diminished relationship between bus and car traffic after the public transit improvements.

The time trend shifts from a slight increase to a significant decrease `( = -0.001033)`, reflecting a reversal in the car traffic trend, which now shows a significant decline over time post-improvement.

Variables for pedestrian and bicycle traffic remained non-significant, suggesting that these modes of transport did not have a substantial impact on car traffic volumes in either model.

The model results indicate a significant reduction in the relationship between bus traffic and car congestion following the transit improvements, as shown by the decrease in the coefficient of daily bus traffic from 0.261 to 0.096. This suggests that improvements in the public transit system might be effectively alleviating car congestion. Additionally, the significant negative time trend in the post-improvement model underscores a successful overall reduction in car traffic between 2012 to 2020.

5 Discussion

5.1 Reducing urban congestion and advancing sustainability through public transit

This study's analysis, centered on the Route 508 Lake Shore streetcar enhancements in Toronto, demonstrates a statistically significant divergence of bus traffic from car congestion trends, suggesting that improvements to public transit infrastructure can effectively reduce car congestion in urban areas. Specifically a decrease in the coefficient for `daily_bus` from 0.261 to 0.096 post-improvement, indicates a notable shift in travel behaviour.

These local findings align with research conducted by Verbavatz and Barthelemy `source` in which they found that urban area size and public transport density are pivotal in managing car traffic in cities, rather than urban density alone. The article further states that enhancing the density and accessibility of public transport is a viable path to mitigating traffic and its associated environmental impacts.

Moreover, the benefits of improved public transit does not stop at decreased car congestion. Insights from the American Public Transportation Association, which illustrate that public transit investments yield substantial congestion relief and economic benefits. Specifically, every dollar spent on public transportation generates 5 dollars in economic return and an associated creation of approximately 50,000 jobs for every billion dollars invested `source`. While on the individual level, households in America can save more than $13,000 per year by using public transit and owning one less car.

These advantages of public transportation investments are in alignment with the principles of sustainable development as defined by the UN's World Commission on Environment and Development: to meet current needs without compromising the ability of future generations to meet their own needs `source`. Together, these strands of evidence support the case for enhancing public transit as a strategic approach to improving urban traffic conditions and achieving broader sustainability goals.

5.2 Good public transit provides access to essential services and promotes social equity

Public transit systems supports not only the movement of people from place to place but also acts a vital channel for economic empowerment and social integration. Access to jobs, education, healthcare, and cultural institutions are fundamental rights, and equitable public transit policies are crucial to ensuring that these services are available to all individuals, regardless of their socioeconomic status.

Supporting this claim, Lexer Quamie's research (2011) `source` highlights the integral role of transportation policy in civil rights, particularly in periods of pronounced unemployment and income disparity. Quamie emphasizes that transportation decisions significantly affect who can access employment opportunities and essential services, positioning public transit as a pivotal tool in the fight for civil rights. By facilitating or hindering access to critical resources, transportation policies not only impact economic outcomes but also health and environmental conditions. This is evident as inadequate or unaffordable public transit disproportionately affects low-income populations, limiting their ability to reach jobs, healthcare, and thereby affecting their overall economic and health status. Additionally, prioritization of car travel over public transit can lead to increased emissions, affecting urban air quality and contributing to environmental degradation.

Moreover, the significance of social equity in public transit is underscored by the stigma associated with bus ridership, particularly among racial minorities and economically marginalized groups. This stigma can lead to policies that inadvertently reinforce social inequities. Actively combating such biases, transit policymakers can ensure that public transit remains an inclusive service that aligns with the broader goals of sustainable development.

5.3 Weaknesses and next steps

5.3.1 Weaknesses

While this research provides valuable insights, it acknowledges several limitations that could be addressed in future studies. The absence of detailed demographic and socioeconomic data limits the ability to deeply understand the differential impacts of public transit improvements across various population segments. Moreover, external factors like varying weather conditions and significant social shifts such as attitudes towards public transit, have not been considered. These elements have the potential to influence public transit usage patterns and public perception significantly. One of the study's primary limitations is its narrow analytical lens, concentrated on traffic volume data, which potentially overlooks the other factors that might influence traffic patterns. For instance, changes in the local economy or shifts in population density.

5.3.2 Next Steps

Future research directions should broaden the analytical framework to incorporate a comparative analysis of diverse urban settings, including multiple transit modes to identify best practices and the varying impacts these have across different population segments. Additionally, it would be beneficial to integrate granular demographic data, enabling a deeper exploration of how public transit enhancements affect population groups defined by age, income, race, and other socioeconomic factors.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

B.2 Diagnostics

References

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.