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

Examining Traffic Patterns Before and After Public Transit Access was Reinstated

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Abstract

This study investigates the impact of access to the Route 508 Lake Shore streetcar in Toronto on reducing urban car congestion from 2011 to 2020. By analyzing traffic volume data from the City of Toronto's Transportation Services Division and employing negative binomial regression models, we observed a notable shift in travel behaviour, highlighted by a significant decrease in the correlation between bus traffic and car congestion. Specifically, the coefficient for daily bus traffic reduced from 0.261 to 0.096 after access was reinstated, indicating a reduction in car traffic as more public transit options became available. This highlights the effectiveness of enhancing public transit infrastructure not only in easing car congestion but also in contributing to broader environmental and economic benefits. By improving public transit, cities can potentially achieve sustainable development goals by providing equitable access to essential services and reducing environmental impacts, thereby improving quality of life for all urban residents.

1 Introduction

Traffic congestion represents a significant challenge for urban areas, negatively affecting economic productivity, environmental sustainability, and quality of life. In cities like Toronto, public transit improvements are often implemented as a strategic response to reduce reliance on personal vehicles and mitigate congestion. This study centers on the Route 508 Lake Shore streetcar in Toronto, examining its impact on urban traffic dynamics, particularly in reducing car congestion.

The primary aim of this research is to evaluate the effect of the 508 Lake Shore streetcar enhancements on daily traffic patterns, focusing on how these changes influence the interaction between car traffic and other transportation modes such as buses, bicycles, and pedestrians. By employing traffic volume data collected by the City of Toronto's Transportation Services Division, we utilize negative binomial regression models to quantify the shifts in traffic patterns from 2011 to 2020. The estimand of this study is the change in the correlation between daily bus traffic and daily car traffic following transit improvements. For this research, the terms "improvements" and "reinstating of the streetcar" are used interchangeably. Both terms refer to the suite of upgrades and changes implemented along the 508 Lake Shore route, which included the restoration of streetcar services that had previously been discontinued or altered.'

The data source used is the Toronto OpenData portal, which provides comprehensive traffic counts across the city, making the analysis both robust and replicable. The data set, "Traffic Volumes at Intersections for All Modes," offers a granular view of the city's traffic flows at various intersections in the city.

This investigation not only sheds light on the specific case of Route 508 Lake Shore but aims to contribute to a broader understanding of how enhancing public transit infrastructure can significantly alter urban mobility patterns.

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

The remainder of this paper is structured as follows: Section 2 introduces the data used for analysis, detailing the sources, preparation, and specific variables considered, alongside initial descriptive statistics and visualizations. Section 3 presents the negative binomial regression model, justifying its use over other models and detailing the statistical methods employed to analyze the traffic volume data. Section 4 displays the results of the analysis, interpreting the changes in traffic patterns before and after the public transit improvements, with a focus on the correlation between different modes of transportation. Section 5 provides a discussion on the implications of the findings, considering the broader context of urban congestion management and the role of public transit in promoting sustainable urban mobility. This section also outlines the limitations of the current study and suggests areas for further research.

2 Data

2.1 Data Source

This research relies on traffic volume provided by the City of Toronto's Transportation Services Division, available through the Toronto OpenData portal. The dataset, titled "Traffic Volumes at Intersections for All Modes," is an open-access resource under the Open Government License - Toronto, ensuring broad usability and transparency. The data files for the years 2010-2019 and 2020-2029 were utilized, however, the data files are uploaded daily with data ranging from 1980 to present. The traffic volume data are cross-referenced with the City of Toronto's Street Centreline, Intersection File, and Street Traffic Signal datasets.

The data consist of two primary types of traffic counts, which capture detailed movement patterns across the city:

1. Automatic Traffic Recorder (ATR) Counts: These counts measure segment-level volumes, capturing the movement of vehicles, cyclists, and pedestrians in specific directions along city streets. For example, ATR data might include the total number of eastbound cyclists on Queen Street.
2. Turning Movement Counts (TMCs): These counts provide granular details at intersections, recording the volume of traffic movement (including turns) by various modes such as cars, trucks, buses, and bicycles. Each TMC includes data from eight non-continuous hours throughout a day, reported in 15-minute intervals.

The analysis in this paper was conducted using the R programming language R Core Team (2023), which facilitated the statistical computations and data visualization. Further, a suite of R packages, including several from the tidyverse collection were utilized. The Wickham et al. (2023) package was used for the transformation and summarization of traffic data. For importing and processing string data, Wickham, Hester, et al. (2024) and Wickham and RStudio (2023a) were utilized. The handling of date and time variables was done using Spinu et al. (2023) and data visualization was achieved with Wickham, Chang, et al. (2024), allowing us to explore and reveal traffic patterns visually. Additionally, Wickham and RStudio (2023b) assisted in reshaping the data to ensure it was structured appropriately for analysis. File path management was handled using the Müller and Bryan (2023) package, which was essential for ensuring reproducibility across different computing environments.

The dataset was refined to aggregate daily totals for each mode of transportation, with the data aligned and merged based on date, location, and traffic mode specifics. While the dataset was merged from two data files which span from 2010 to 2019 and 2020 to 2029, this research will focus on December 2011 to December 2014 and November 2018 to February 2020. These years were chosen to provide a comprehensive view of traffic patterns before, during, and following the enhancement of the 508 Lake Shore route. The data collection period was intentionally concluded in February 2020 to ensure that the results were not influenced by the disruptions caused by the COVID-19 pandemic.

2.2 Variables of Interest

In this study, the examination of traffic dynamics is conducted by analyzing interactions among various modes of transportation at various intersections. As such, traffic counts for each mode of transit were aggregated to daily totals to allow for better analysis. For example, car traffic variables such as `sb_cars_l`, `nb_cars_r`, `eb_cars_t`, among others, representing different directions and types of car movements at intersections, were combined to form the Daily Car Traffic (`daily_cars`). This variable captures the total volume of car traffic and serves as a primary indicator of vehicular congestion. Similarly, this was done to create the variable Daily Bus Traffic (`daily_bus`), which helps in evaluating the volume and effectiveness of bus transit in relation to car traffic. Furthermore, Daily Pedestrian Traffic (`daily_peds`) and Daily Bicycle Traffic (`daily_bike`) were created to aid in understanding the prevalence and trends of non-vehicular traffic modes. A Time Trend variable (`time_trend`) was constructed to analyze the longitudinal changes in traffic patterns over time, providing insights into the temporal effects of transit improvements.

Table 1: Summary statistics of Daily Traffic Volume by mode of transportation. This table displays the mean and median counts of cars, buses, pedestrians, and bicycles

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 statistics presented in Table 1 offer a quantitative comparison across different modes of transportation, capturing the daily traffic volumes on the 508 Lake Shore route. Notably, **Daily Car Traffic** significantly surpasses other modes of transit, with mean and median values at 14,169.85 and 13,291.5, respectively. This highlights the predominant use of cars in the area, highlighting the challenges of reducing vehicular congestion.

In contrast, **Daily Bus Traffic** shows much lower volumes, with a mean of 223.91 and a median of 190.5, reflecting less frequent usage but indicating a critical focus area for transit improvements. **Daily Pedestrian Traffic** and **Daily Bicycle Traffic** also exhibit considerably lower traffic volumes, with means of 686.06 and 50.49, respectively. The pedestrian traffic presents a median significantly lower than its mean, at 344, suggesting a skewed distribution with potentially high traffic on certain days or specific intersections. Similarly, the median for bicycle traffic stands at 22, indicating that on many days, bicycle usage is quite low despite a higher average, which might reflect seasonal variations or special events influencing bike use.

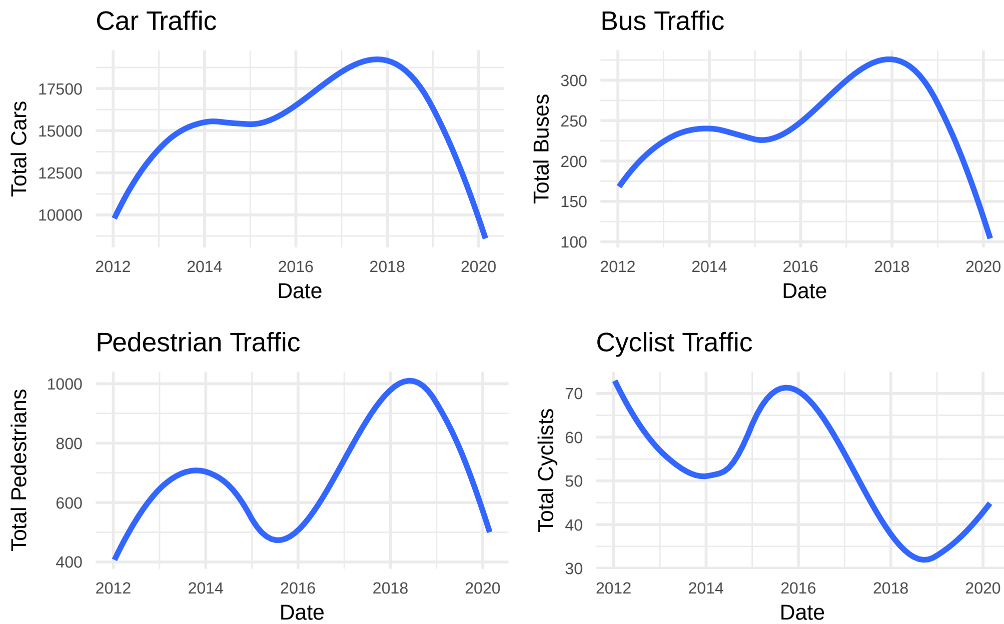

Figure 1: Traffic Trends by Mode along the 508 Lakeshore Route from December 2011 to December 2014 and November 2018 to February 2020.

Figure 1 presents a visual analysis of the various modes of traffic from 2011 to 2020, demonstrating their respective trends and allowing for comparative insights. The car traffic graph illustrates an initial uptrend in volume, reaching a peak around 2016, followed by a pronounced decline that coincides with the reintroduction of the Route 508 Lake Shore streetcar, suggesting a potential correlation with improved public transit and a reduction in car use. Concurrently, bus traffic mirrors this pattern to a degree, with a rise and subsequent fall post-2016, hinting at an adaptive response in public transport usage. The pedestrian traffic trendline depicts a mid-period dip followed by a recovery and then a decline again. Cyclist traffic, on the other hand, displays a waveform pattern with significant ups and downs, possibly reflecting the impact of varied factors including public attitudes towards cycling, the introduction or enhancement of cycling infrastructure, and seasonal changes that affect cycling prevalence.

The scatter plot in Figure 2, representing daily car traffic counts over time against a time trend, offers a granular view of the data. Each dot signifies the traffic volume on a single day, while the trend line captures the general trajectory over the entire data collection period. An initial increase in traffic volume is apparent, eventually giving way to a downward trend.

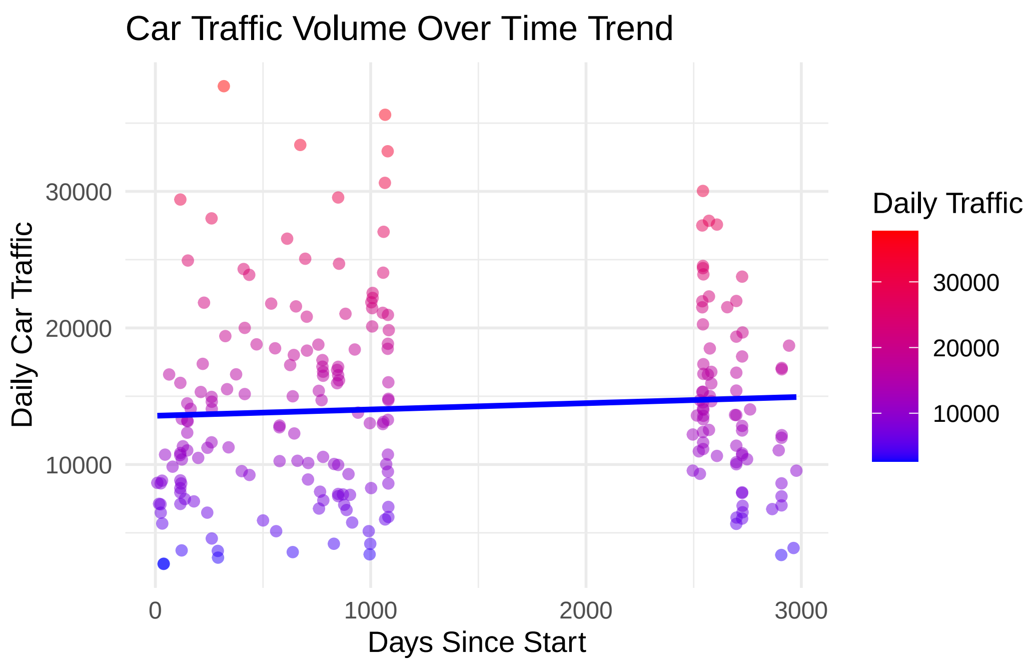

Figure 2: Daily Car Traffic Over Time. This graph displays the general trend in number of cars from the beginning of data collection period.

3 Model

Modelling traffic dynamics poses unique challenges, particularly with count data that often exhibit over-dispersion—where the variance exceeds the mean—making conventional regression models like Poisson unsuitable. To address this, this study employs a negative binomial regression model to handle over-dispersion and is more aligned with the distribution characteristics of traffic counts.

We define our model with the daily car traffic count as the dependent variable, hypothesizing its dependence on several factors: temporal trends and daily counts of alternative transport modes—buses, pedestrians, and bicycles.

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

The rationale for selecting the negative binomial model is based on two primary areas. Firstly, traffic data are prone to clustering in both spatial and temporal dimensions, leading to overdispersion. Secondly, traffic count data typically skew away from a normal distribution, and the negative binomial model is equipped to address this skewness.

To capture the effects of the Route 508 Lake Shore streetcar service reinstatement, the analysis dives into two temporal segments: pre-improvement (`model_before`) and post-improvement (`model_after`). This segmentation enables a nuanced understanding of the relationships between car traffic and alternative transport modes before and after the streetcar was reinstated. The `model_before` sets the baseline, showcasing the original dynamics between cars and other transport forms. The `model_after` reveals the traffic landscape streetcar service has resumed. This offers a comparative view to measure the efficacy of these public transit access improvements in mitigating car congestion.

This modelling approach not only provides insights into the immediate effects of transit policy changes but also establishes a methodological framework for future studies examining the longitudinal impact of urban transit interventions.

4 Results

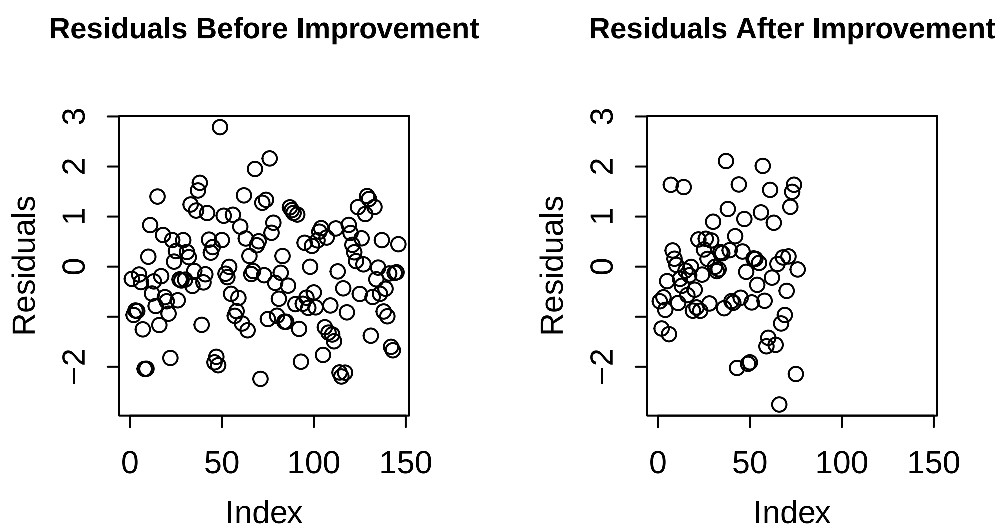

Figure 3: Residuals of the negative binomial regression model before and after the transit improvement. This plot helps to visualize if there are any patterns or systematic deviations unexplained by the model.

The residual plots depicted in Figure 3 serve as a diagnostic tool to evaluate the adequacy of the negative binomial regression models used in this study, both before and after the implementation of public transit improvements. The left panel of the figure illustrates the residuals for the model before the reinstatement of the Route 508 Lake Shore streetcar, showing a random dispersion of data points around the zero line. This lack of systematic pattern suggests that the model assumptions are met, indicating a good fit for the pre-improvement traffic data.

Similarly, the right panel of the figure, representing the residuals post-improvement, exhibits a scatter of data points without discernible trends or biases. The randomness observed in the distribution of these residuals supports the conclusion that the post-improvement model is also well-fitted to the data, capturing the essential variability in daily car counts without leaving unexplained structure in the residuals.

Table 2: Model Summary of Traffic Patterns Before Improvement on the 508 Lakeshore Route

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: Model Summary of Traffic Patterns After Improvement on the 508 Lakeshore Route

term	estimate	std.error	statistic	p.value
(Intercept)	12.2741496	0.8463970	14.5016460	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

The pre-improvement model, as detailed in Table 2, reveals significant coefficients for both the intercept and daily bus traffic, alongside a temporal trend. With a coefficient of 9.34, the model showcases a high baseline volume of car traffic, independent of other variables. Bus traffic, represented by a coefficient of 0.261, appears to move in tandem with car traffic, implying that increases in bus usage were historically linked to increases in car traffic. However, the coefficients for pedestrian and bicycle traffic do not present a significant association with car traffic, reflecting a p-value greater than 0.05 for both.

Conversely, the post-improvement model shown in Table 3 exhibits a marked change in these dynamics. The increase in the intercept to 12.283 suggests an elevated baseline of car traffic, potentially as a result of external influences not accounted for in the model. The coefficient for daily bus traffic experiences a considerable reduction to 0.096, signalling a weakened relationship between bus and car traffic in the wake of the transit improvements. This could indicate a disconnect between these modes of transport, possibly due to more passengers opting for the improved public transit system over personal vehicles. The time trend coefficient inverses to -0.001033, denoting a statistically significant decline in car traffic over time post-improvement, showcasing the potential efficacy of the public transit enhancements in reducing car traffic.

These findings show that following the public transit improvements, the relationship between bus traffic and car congestion significantly diminished, potentially reflective of the transit system's capacity to alleviate car congestion. Additionally, the persistent non-significance of pedestrian and bicycle traffic variables implies these modes have not impacted car traffic volumes in the models considered.

5 Discussion

5.1 Reducing urban congestion and advancing sustainability through public transit

This study's analysis, centred 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 (2019) 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 do not stop at decreased car congestion. Insights from the American Public Transportation Association (2023), 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. 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 (Lachman et al. (2013)). 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 support not only the movement of people from place to place but also act as 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, Quamie (2011) research 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 and 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, concentrating 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.

References

American Public Transportation Association. 2023. "Public Transportation Facts." https://www.apta.com/news-publications/public-transportation-facts/.

Lachman, Beth E., Agnes Gereben Schaefer, Nidhi Kalra, Scott Hassell, Kimberly Curry Hall, Aimee E. Curtright, and David E. Mosher. 2013. "Sustainability: Communities, Transportation, and Agriculture Trends." In *Key Trends That Will Shape Army Installations of Tomorrow*, 59–110. RAND Corporation. https://doi.org/10.7249/j.ctt5hhv93.11.

Müller, Kirill, and Jennifer Bryan. 2023. *Here: A Simpler Way to Find Your Files*. https://CRAN.R-project.org/package=here.

Quamie, Lexer. 2011. "Transportation Equity a Key to Winning Full Civil Rights." *Race, Poverty & the Environment* 18 (2): 59–60. https://www.jstor.org/stable/41554788.

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

Spinu, Vitalie, Garrett Grolemund, Hadley Wickham, et al. 2023. *Lubridate: Make Dealing with Dates a Little Easier*. https://CRAN.R-project.org/package=lubridate.

Verbavatz, Vincent, and Marc Barthelemy. 2019. "Critical Factors for Mitigating Car Traffic in Cities." *PLOS ONE* 14 (7): e0219559. https://doi.org/10.1371/journal.pone.0219559.

Wickham, Hadley, Winston Chang, Lionel Henry, Thomas Lin Pedersen, Kohske Takahashi, Claus Wilke, Kara Woo, et al. 2024. *Ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics*. https://CRAN.R-project.org/package=ggplot2.

Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Wickham, Hadley, Jim Hester, Romain Francois, Jennifer Bryan, Shelby Bearrows, et al. 2024. *Readr: Read Rectangular Text Data*. https://CRAN.R-project.org/package=readr.

Wickham, Hadley, and RStudio. 2023a. *Stringr: Simple, Consistent Wrappers for Common String Operations*. https://CRAN.R-project.org/package=stringr.

———. 2023b. *Tidyverse: Easily Install and Load the 'Tidyverse'*. https://CRAN.R-project.org/package=tidyverse.