# Structural and Geographic Influences on Residential Parking Availability in Toronto*

**Parking Type Strongly Predicts Multi-space Properties; Geographic Differences Are Modest.**

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We analyzed residential parking data from Toronto to understand factors influencing the availability of more than one parking space. Our findings show that parking type, such as boulevard or front yard parking, strongly predicts the likelihood of multiple spaces, while geographic differences across wards are less significant. This highlights how structural factors play a critical role in shaping parking availability. These insights can inform urban planning policies to better address parking demand in residential areas.

## 1 Introduction

Residential parking availability is a critical aspect of urban planning, particularly in dense metropolitan areas like Toronto. The rise in vehicle ownership and the increasing demand for parking spaces have created challenges for both homeowners and city planners. This paper examines the factors influencing the availability of more than one parking space in residential properties, using a dataset from Toronto's Open Data Portal that documents front yard parking permits and related attributes. While parking availability has been explored in terms of policy and infrastructure, few studies have systematically analyzed how structural and geographic factors combine to affect the likelihood of multiple parking spaces at a property. This paper addresses this gap by applying a logistic regression framework to examine how location and parking type impact this outcome.

The primary estimand of interest is the conditional probability of a residential property having more than one parking space, given specific predictors such as geographic location (ward) and

*Code and data are available at: https://github.com/JessLiang02/Residential-Front-Yard-Parking-Toronto.git.

parking type. This estimand is operationalized through a binary outcome ("Yes" for more than one space, "No" otherwise) and modeled using predictors derived from administrative data on residential parking in Toronto. The goal is to understand how these factors jointly influence the likelihood of additional parking capacity while controlling for variability in urban layouts and zoning practices across the city.

The analysis reveals several key findings. First, parking type plays a significant role in determining whether a property has more than one parking space. Properties with boulevard parking show a higher likelihood of accommodating additional spaces compared to those with front yard or widened driveway parking, which are typically more constrained. Second, geographic location also emerges as a modest predictor, with some wards exhibiting slightly higher probabilities of multiple parking spaces, likely due to differences in zoning regulations and residential design. However, across all wards, the prevalence of properties with more than one parking space remains low, underscoring the challenges of expanding parking availability in a densely populated urban environment.

Understanding the factors influencing residential parking availability is crucial for informing urban planning and policy decisions. Insights from this analysis can guide city planners in identifying areas where parking demand is mismatched with supply and in revising zoning regulations to address these disparities. Moreover, this study highlights the importance of structural considerations, such as parking type, in determining parking capacity, offering practical implications for property design and development. By filling a critical gap in the literature on parking availability, this paper contributes to broader discussions on urban sustainability and equitable access to resources in growing metropolitan regions. The findings also provide a foundation for future research into the interplay between urban infrastructure, residential design, and municipal regulations.

The structure of this paper is organized as follows. Section 2 provides an overview of the data sources and key variables used in our analysis, offering a detailed description of the dataset on residential front yard parking in Toronto and the criteria used for variable selection. Section 3 describes the modeling approach, focusing on the Bayesian logistic regression framework. This section outlines the rationale for including predictors such as ward and parking type and discusses the assumptions underpinning the model. Section 4 presents the findings, highlighting the key factors influencing the likelihood of having more than one parking space and examining diagnostic checks such as model fit and residual behavior. Section 5 interprets the broader implications of the results, exploring their relevance to urban planning and parking policy in Toronto. This section also addresses potential limitations of the study and suggests areas for future research to improve the understanding of parking trends and availability in residential areas.

# 2 Data

## 2.1 Overview

For this analysis, we used the R programming language (R Core Team 2023) to explore data on residential front yard parking in Toronto. The dataset, sourced from Toronto's Open Data Portal (Gelfand 2022; Toronto 2024), provides detailed information on parking permissions and associated attributes across various residential areas in the city. Key aspects analyzed include the type of parking (e.g., front yard, boulevard, or widened driveway), the presence of more than one parking space, and geographic differences across city wards.

A range of `R` packages was employed for efficient data manipulation, modeling, and visualization. The `tidyverse` package suite formed the backbone of data processing, enabling seamless and reproducible workflows (Wickham et al. 2019). File path management was handled using `here`, ensuring reliable and consistent access to the dataset (Müller 2020). Data cleaning tasks were performed with `janitor`, which helped identify and rectify inconsistencies in the data (Firke 2023). Bayesian statistical modeling was conducted using `rstanarm`, allowing for robust inference and clear interpretation of results (Brilleman et al. 2018). The presentation of model outputs was streamlined using `modelsummary`, which facilitated the generation of concise and informative summaries (Arel-Bundock 2022). Additionally, `arrow` enabled fast and memory-efficient handling of the dataset, which was crucial for analyzing this spatially diverse data (Richardson et al. 2024). Lastly, `testthat` was used to test the validity and integrity of the simulated and analysis datasets (Wickham 2011).

To maintain clarity and reproducibility, we adhered to best practices in workflow organization and analysis, as outlined in Alexander (2023). These practices ensured that data manipulation, modeling, and visualization were seamlessly integrated into a coherent analytical pipeline. This approach supported an in-depth investigation of residential front yard parking trends and patterns across Toronto while ensuring transparency and replicability of results.

The dataset for this analysis, derived from Toronto's Open Data Portal, focuses on residential front yard parking permissions. To ensure the data was suitable for analysis, a thorough cleaning process was applied. Only relevant information, such as the type of parking and geographic details, was retained, while unrelated fields were removed. Entries representing properties without any licensed parking spaces were excluded, narrowing the focus to those with at least one space. A new classification was created to indicate whether a property had more than one parking space, simplifying the analysis of parking capacity. Geographic identifiers were transformed into meaningful names for better interpretability, and incomplete or invalid entries were removed to ensure consistency and accuracy. While alternative datasets on parking or zoning could have been used, this dataset was selected for its specificity to residential front yard parking and its relevance to understanding broader trends in urban parking infrastructure. The cleaning process ensured that the data was comprehensive, accurate, and ready for modeling and analysis.

## 2.2 Measurement

A thorough discussion of measurement, as it relates to the dataset on residential front yard parking, is provided in the data section. This section explains how real-world phenomena, such as parking infrastructure, city zoning regulations, and permissions granted by the municipal authorities, translate into structured data entries within the dataset. Specifically, it details the processes by which physical characteristics of parking spaces, such as front yard parking, boulevard parking, and widened driveways, are systematically documented and categorized. In addition, the dataset reflects administrative actions, including licensing and permits for additional parking spaces, capturing key decisions made to enforce zoning policies and maintain compliance across Toronto neighborhoods. This provides a snapshot of how parking infrastructure is managed and how residential properties interact with city policies.

The dataset reflects information meticulously collected and maintained by Toronto's municipal authorities, capturing instances of residential parking permissions and characteristics across the city's wards. These data entries stem from a series of systematic administrative processes, such as permit applications submitted by homeowners, inspections conducted by city officials, and approvals granted to ensure compliance with zoning and safety regulations. This formal documentation converts these processes into standardized data points, allowing for a consistent representation of real-world activities. For example, each property is classified by its parking type, geographic location (ward), and whether it has more than one licensed parking space. This standardization not only facilitates analysis but also ensures comparability across diverse neighborhoods with varying zoning and infrastructural constraints.

By focusing on these translated data points, we ensure that our analysis is grounded in how parking infrastructure and policies manifest in practice. This alignment enables us to investigate the relationships between geographical (ward-level) and structural (parking type) predictors and the likelihood of a property having more than one parking space. The dataset thus serves as a bridge between real-world urban phenomena and quantitative analysis, allowing for meaningful insights into residential parking dynamics. Additionally, the data section explores the implications of these measurement processes, highlighting potential limitations, such as the possibility of informal or unregistered parking arrangements that are not captured by the dataset. Such omissions could introduce biases or underreport the true extent of parking availability in some neighborhoods.

Furthermore, the data section underscores the importance of understanding the context in which the dataset was generated. For instance, while the dataset is robust in documenting licensed parking arrangements, it may not fully capture unlicensed modifications made by homeowners or discrepancies between zoning policies and actual usage. These gaps emphasize the need for cautious interpretation of the findings, as well as the importance of complementing administrative datasets with supplementary data sources, such as surveys or field observations, in future research. By addressing these nuances, the data section ensures a comprehensive understanding of the dataset's origins, its representational scope, and its role in analyzing Toronto's residential parking landscape.

## 2.3 Outcome variable

The outcome of interest in this analysis is whether a residential property has more than one parking space, categorized as "Yes" or "No." "Yes" indicates that the property offers more than one parking space, while "No" signifies a single parking space. The data shows that most properties fall under the "No" category, suggesting that having multiple parking spaces is relatively uncommon. This highlights the limited availability of properties equipped with additional parking capacity and underscores the need to explore factors that may influence this outcome.

## 2.4 Predictor variables

### 2.4.1 Ward

One of the key factors examined is the geographical location of the property, represented by different city wards. Each ward reflects unique characteristics, including zoning regulations, population density, and residential designs, which may affect parking availability. The analysis reveals that while the majority of properties in all wards have only one parking space, there are slight differences in the proportions of properties with more than one space across wards. These variations could be attributed to differing urban layouts or local policies influencing parking infrastructure.

### 2.4.2 Type of parking

Another important factor is the type of parking available on the property, such as street-side, front yard, or widened driveway parking. This structural characteristic appears to have a more pronounced impact on the availability of multiple parking spaces compared to location. For instance, properties with street-side parking are more likely to have multiple spaces than those with front yard or driveway parking, which are often constrained by property size or design. This finding suggests that the physical configuration of the parking area plays a critical role in determining whether a property can accommodate additional vehicles, providing valuable insights into the relationship between parking types and space availability.

## 2.5 Associations between variables

Figure 1 illustrates the proportion of responses for "more than 1 parking space" across the three parking types: Boulevard Parking, Front Yard, and Widened Driveway. The y-axis represents the percentage, scaled from 0% to 100%, while the x-axis shows the parking types. For Boulevard Parking, a larger proportion of "Yes" responses (blue) is observed compared to the other parking types, where "No" responses (red) dominate overwhelmingly. Front Yard and Widened Driveway parking types show minimal "Yes" responses, highlighting the disparity in the availability of additional parking spaces based on parking type. This visualization highlights how parking type correlates with the likelihood of having more than one parking space.

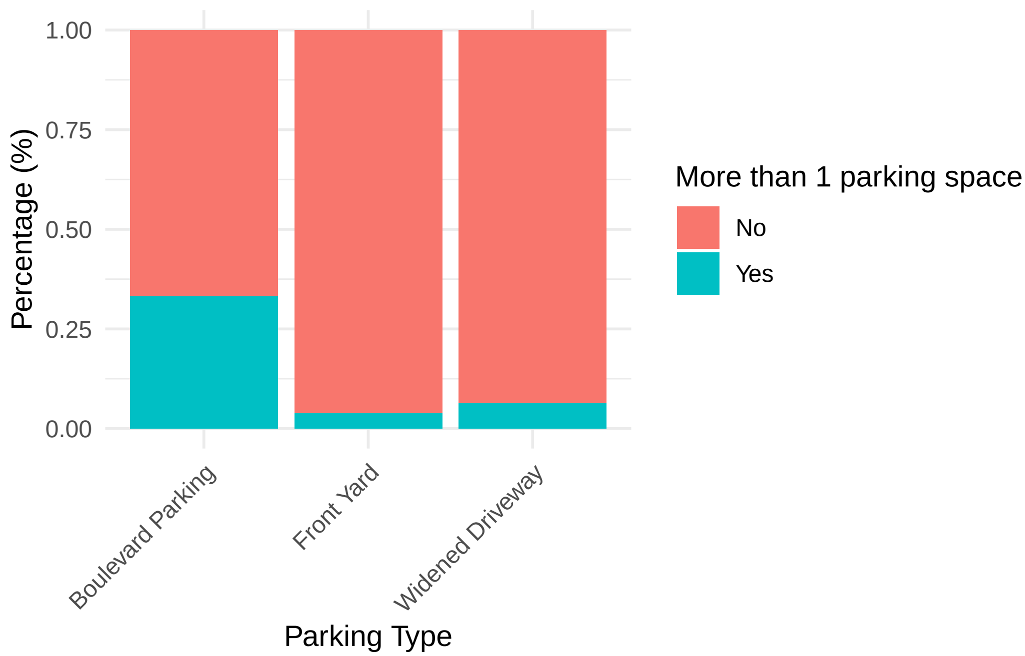
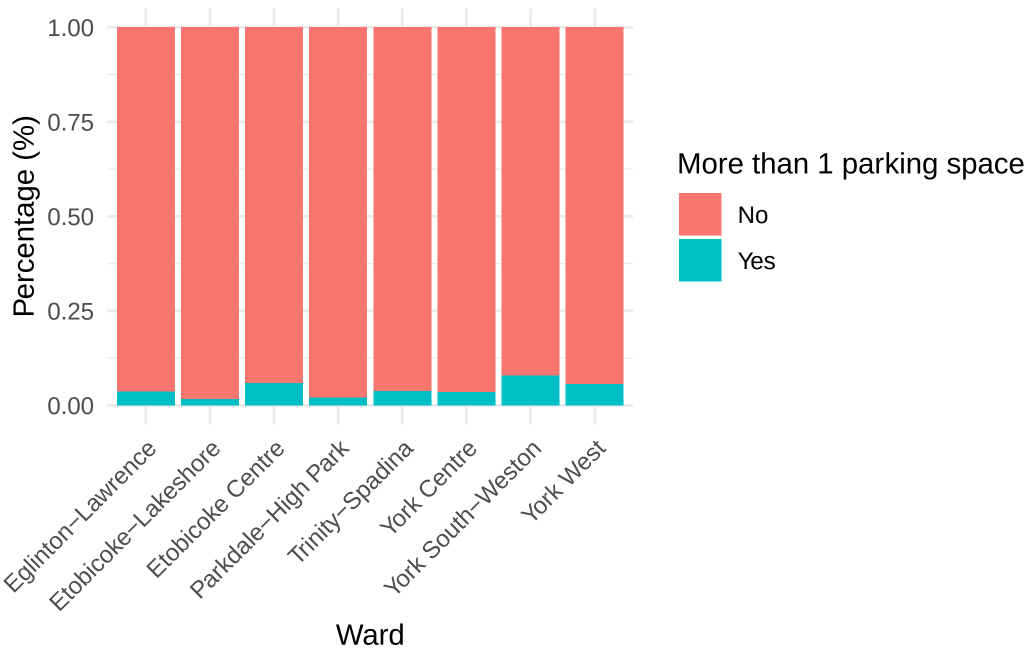



Figure 1: The figure illustrates the distribution of "More than 1 parking space" (Yes/No) as a percentage across various wards. Each bar represents a ward, and the height of the stacked segments within each bar corresponds to the proportion of responses for "Morespace." The responses "No" (red) and "Yes" (blue) sum to 100% for each ward.

Figure 2 provides a visual comparison of the proportion of residential addresses with more than one parking space across wards in the city of Toronto. The y-axis represents the percentage, scaled from 0% to 100%, while the x-axis shows the wards under study. The red portion of each bar indicates the percentage of "No" responses, whereas the blue portion indicates the percentage of "Yes" responses. From the chart, it is evident that "No" dominates the responses in all wards, with "Yes" contributing only a small proportion across the board. The distribution highlights the consistency in the prevalence of "No" responses irrespective of ward, with slight variations in the proportion of "Yes" responses between different wards. This visualization underscores potential patterns or uniformity in the proportion of more than 1 parking space within the study area.

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# 3 Model

The objective of our modeling strategy is twofold. First, we aim to understand the factors that influence whether a residential property has more than one parking space. Second, we seek to quantify the relative importance of structural factors, such as parking type, and geographic factors, such as ward, in predicting the likelihood of multiple parking spaces. To achieve these objectives, we employ a Bayesian logistic regression model that allows for probabilistic interpretation of the predictors' effects while incorporating prior information in a transparent manner. Background details and additional diagnostics are provided in Appendix B.

## 3.1 Model set-up

Define $y_i$ as an indicator of whether a property has more than one parking space, where $y_i = 1$ for properties with more than one space and $y_i = 0$ otherwise. The predictors include $x_{1i}$, the type of parking available on the property, and $x_{2i}$, the geographic location (ward). Parking type is included as categorical variables for "Front Yard" and "Widened Driveway," with "Boulevard Parking" serving as the reference category. Wards are included as a set of dummy variables, with Etobicoke-Lakeshore as the reference group.

The model is specified as:

$$y_i \mid \pi_i \sim \text{Bernoulli}(\pi_i)$$

$$\text{logit}(\pi_i) = \alpha + \beta_1 \text{ FrontYard}_i + \beta_2 \text{ WidenedDriveway}_i + \gamma_1 \text{ EtobicokeCentre}_i + \gamma_2 \text{ ParkdaleHighPark}_i + \gamma_3 \text{ Trinity}$$

Here, $\pi_i$ represents the probability that property $i$ has more than one parking space. The intercept $\alpha$ captures the baseline log-odds for properties in Etobicoke-Lakeshore with Boulevard Parking.

Coefficients $\beta_1$ and $\beta_2$ measure the effect of "Front Yard" and "Widened Driveway" parking types relative to the reference category. The coefficients $\gamma_1, \ldots, \gamma_6$ capture the effects of specific wards compared to the baseline (Etobicoke-Lakeshore), explicitly:

- $\gamma_1$ : Etobicoke Centre
- $\gamma_2$ : Parkdale-High Park
- $\gamma_3$ : Trinity-Spadina
- $\gamma_4$ : York Centre
- $\gamma_5$ :York South-Weston
- $\gamma_6$ : York West

The priors for the intercept and coefficients are weakly informative and specified as follows:

$$
\begin{aligned}
\alpha &\sim \text{Normal}(0, 10) \\
\beta_1, \beta_2 &\sim \text{Normal}(0, 10) \\
\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6 &\sim \text{Normal}(0, 10)
\end{aligned}
$$

These priors reflect minimal prior knowledge, allowing the data to influence the posterior estimates while discouraging extreme values. The model estimates how parking type and geographic location jointly predict the likelihood of a property having more than one parking space, with the logistic link function ensuring predictions are appropriately bounded between 0 and 1.

We fit the model in R (R Core Team 2023) using the `rstanarm` package from Brilleman et al. (2018). These priors ensure flexibility in the modeling process while allowing the data to drive the posterior estimates.

### 3.1.1 Model justification

This model is well-suited to the research question because the outcome variable, whether a property has more than one parking space, is binary. A logistic regression framework naturally models the relationship between this binary outcome and the predictors. Parking type and geographic location are included as predictors because they capture structural and locational influences on parking availability. Weakly informative priors ensure that the model is not overly constrained by prior beliefs, allowing the observed data to guide the estimates while guarding against overfitting.

## 4 Results

Our results are summarized in Table 1. The model results provide insights into the factors influencing the likelihood of a property having more than one parking space. The intercept represents the baseline log-odds for properties with boulevard parking in wards not explicitly listed in the model. Among parking types, properties with front yard parking and widened driveway parking show significantly lower likelihoods of having more than one parking space compared to boulevard parking, as indicated by their strongly negative coefficients (-2.57 and -2.12, respectively). This suggests that the physical and spatial constraints associated with these parking types limit the capacity for additional parking. These results highlight the critical role of parking type in determining parking space availability, with boulevard parking offering more flexibility for accommodating additional spaces.

The geographic location, as captured by the ward variable, also exhibits notable effects. Properties in York South-Weston have the highest positive association (0.90) with the likelihood of more than one parking space, followed by Etobicoke Centre (0.54) and York West (0.44). Conversely, properties in Etobicoke-Lakeshore (-0.64) and Parkdale-High Park (-0.57) show lower likelihoods of multiple parking spaces, while other wards exhibit smaller or non-significant effects. These geographic variations likely reflect differences in zoning regulations, property sizes, and urban layouts across Toronto. Although the model explains only a modest proportion of the variability in the outcome ($R^2 = 0.029$), the significant predictors offer valuable insights into structural and locational influences on residential parking availability. The model diagnostics, including log-likelihood, ELPD, and RMSE, indicate reasonable fit but suggest opportunities for further refinement, such as incorporating additional predictors, not included in the analysis dataset, to better capture complex relationships.

# 5 Discussion

## 5.1 The influence of structural and geographic factors on parking availability

This paper provides a detailed examination of the factors that influence whether a residential property in Toronto has more than one parking space. By employing a Bayesian logistic regression model, we uncover critical insights into how parking type and geographic location shape parking availability. One key finding is that structural factors, such as parking type, exert a strong influence on whether properties can accommodate multiple parking spaces. Specifically, properties with boulevard parking are more likely to have additional spaces compared to those with front yard or widened driveway parking, which tend to be more spatially constrained. This emphasizes the importance of physical characteristics in determining parking capacity and provides practical implications for urban planning and residential design.

## 5.2 Geographic variations in parking capacity

Another important finding relates to the role of geographic location, captured through ward-level data. While the likelihood of a property having more than one parking space is generally low across all wards, certain areas, such as York South-Weston and Etobicoke Centre, exhibit slightly higher probabilities. These differences may reflect variations in zoning regulations, housing density, and property size across Toronto's diverse neighborhoods. By highlighting these geographic disparities, this paper contributes to our understanding of how local policies and urban layouts affect parking availability. These insights could inform targeted zoning reforms and development strategies in areas where parking demand outstrips supply.

## 5.3 Broader implications for urban planning

Beyond the specific findings, this analysis sheds light on broader urban planning challenges associated with residential parking. The increasing demand for parking in growing metropoli-

Table 1: Explanatory models of having more than parking space based on parking type and city ward.

| | Logistic regression model |
|---|---|
| (Intercept) | −0.95 |
| | (0.23) |
| parking_typeFront Yard | −2.57 |
| | (0.19) |
| parking_typeWidened Driveway | −2.12 |
| | (0.20) |
| wardEtobicoke-Lakeshore | −0.64 |
| | (0.31) |
| wardEtobicoke Centre | 0.54 |
| | (0.17) |
| wardParkdale-High Park | −0.57 |
| | (0.19) |
| wardTrinity-Spadina | 0.15 |
| | (0.17) |
| wardYork Centre | 0.01 |
| | (0.18) |
| wardYork South-Weston | 0.90 |
| | (0.15) |
| wardYork West | 0.44 |
| | (0.16) |
| Num.Obs. | 17 527 |
| R2 | 0.029 |
| Log.Lik. | −3120.955 |
| ELPD | −3130.9 |
| ELPD s.e. | 81.6 |
| LOOIC | 6261.8 |
| LOOIC s.e. | 163.3 |
| WAIC | 6261.8 |
| RMSE | 0.21 |

tan areas like Toronto underscores the need for innovative solutions that balance parking availability with land use efficiency. Our results suggest that policymakers should consider both structural and locational factors when addressing parking shortages. For example, incentivizing the adoption of space-efficient parking designs, such as boulevard parking, or revising zoning policies to allow for greater parking capacity in underserved wards could help address these challenges. This study demonstrates how data-driven approaches can guide such policy decisions, offering a framework for similar analyses in other cities.

### 5.4 Weaknesses and next steps

While this study provides valuable insights, it is not without limitations. First, the dataset relies on administrative records, which may not capture informal or unlicensed parking arrangements. This could lead to an underestimation of the true availability of additional parking spaces. Second, the analysis focuses on a limited set of predictors, leaving out potentially relevant factors such as property size, household income, or neighborhood-level car ownership rates. Incorporating these variables in future research could enhance the explanatory power of the model. Finally, the geographic scale of analysis is restricted to wards, which may overlook finer-grained spatial patterns within neighborhoods. Future studies could explore these patterns at a more localized level, providing a deeper understanding of parking dynamics and informing more targeted interventions. These next steps would build on the findings of this paper, advancing our understanding of residential parking and its implications for urban policy.

# Appendix

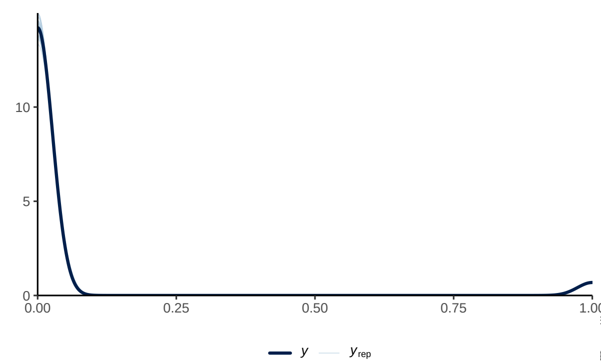
## A Additional data details

## B Model details

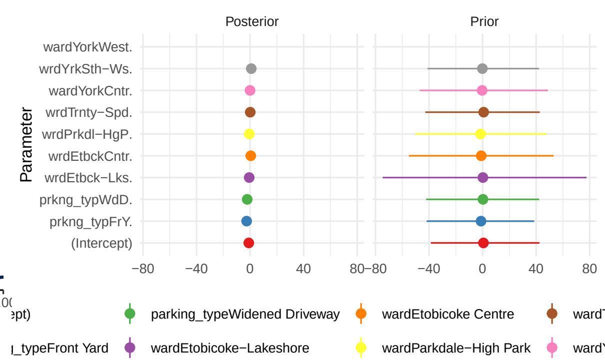
### B.1 Posterior predictive check

In Figure 3a we implement a posterior predictive check. The comparison between the observed outcomes ($y$) and the replicated outcomes ( $y_{\text{rep}}$ ) generated by the model demonstrates that the model performs reasonably well in capturing the general distribution of the observed data. However, deviations in the tail areas indicate that the model might have limitations in accounting for extreme values, suggesting potential areas for refinement.

In Figure 3b we compare the posterior with the prior. The shrinkage observed in the posterior distributions highlights the influence of the data in updating the initial beliefs (priors). For example, coefficients for parking type and ward display distinct shifts from the prior, reflecting the data's strong signal in identifying their effects. The comparison also shows that the priors were appropriately weakly informative, allowing the data to dominate the estimation process. This assessment ensures that the model outputs are data-driven and not overly influenced by prior assumptions.




(a) Posterior prediction check compares the observed data with the model's predictions, highlighting how well the model replicates the actual distribution and identifying areas where the fit could improve.



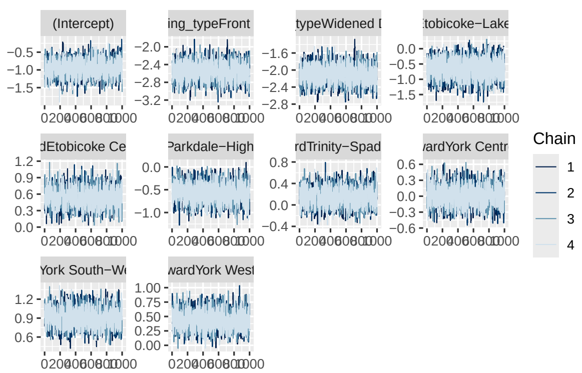

(b) Comparing the posterior with the prior shows the contrast between the prior and posterior distributions for each parameter, emphasizing how the data contribute to refining parameter estimates and reducing uncertainty.

Figure 3: Examining how well the model captures the observed data and how the data influence the parameter estimates.

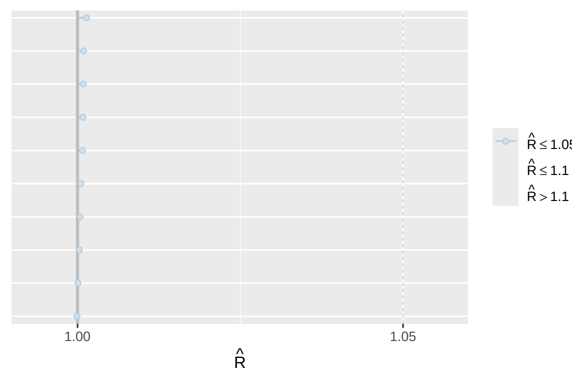
## B.2 Diagnostics

Figure 4a is a trace plot. It shows the sampling paths of the four Markov chains for each parameter in the model. The plot demonstrates that all chains mix well and explore the posterior distribution without noticeable patterns or divergences. The oscillations within a stable range indicate that the chains have reached convergence, suggesting that the samples are representative of the posterior distribution. This provides confidence in the reliability of the parameter estimates derived from the model.

Figure 4b is an Rhat plot. It shows the Gelman-Rubin diagnostic ($R$) for each parameter in the model, which measures the convergence of the chains. All parameters have $\hat{R}$ values very close to 1, indicating that the chains have converged well and there is no significant between-chain variation. This suggests that the model's posterior samples are valid and that the results can be interpreted with confidence. Additionally, the lack of any outliers in the $\hat{R}$ values further reinforces the robustness of the sampling process.




(a) Trace plot shows the sampling trajectories of four MCMC chains for each parameter in the model. The consistent oscillations across the chains, within a stable range, indicate good mixing and convergence, ensuring the samples are representative of the posterior distribution.




(b) Rhat plot illustrates the Gelman-Rubin diagnostic (Rhat) for each parameter. All Rhat values are close to 1, signifying that the chains have converged and there is minimal between-chain variability, confirming the reliability of the posterior estimates.

Figure 4: Checking the convergence of the MCMC algorith and ssessing the convergence of the Markov Chain Monte Carlo (MCMC) algorithm to ensure reliable parameter estimates.

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