# Understanding the Causal Impact of Bike Lane Installation on Urban Cycling Adoption*

**A Difference-in-Differences Analysis Shows Protected Bike Lanes Triple Bike Share Ridership in Toronto, 2017-2023**

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We examine the causal effect of cycling infrastructure improvements on Bike Share Toronto ridership by analyzing how different types of bikeways influence system usage between 2017-2023. Using a difference-in-differences design with over 7.4 million rides across 1,191 bikeways, we find that infrastructure improvements led to significant increases in ridership, with post-implementation effects reaching 133.1 additional monthly rides per bikeway, translating to approximately 300,000 additional annual rides across all treated segments. Protected lanes demonstrate the strongest impact, generating 381.9 additional monthly rides - more than double the effect of on-road lanes (169.2 rides) and triple that of shared roadways (111.7 rides), while upgrades to existing infrastructure showed more immediate benefits than new installations. Our findings suggest that strategic implementation of protected infrastructure can substantially increase cycling activity, with implications for Toronto's planned addition of 100 kilometers of cycling infrastructure between 2025-2027. These results provide evidence-based guidance for cities working to encourage sustainable transportation through cycling infrastructure development.

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*Code and data are available at: https://github.com/stevenli-uoft/Toronto_BikeShare_Causality.

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# 1 Introduction

Cycling infrastructure plays an essential role in urban transportation, yet quantifying its impact on cycling adoption remains challenging. While previous research demonstrates that protected bike lanes can reduce cycling injuries by up to 89% (Harris et al. 2020) and increase ridership by up to 171% on specific routes (City Transportation Officials 2016), less is known about how different types of infrastructure improvements affect bike share system utilization. This knowledge gap is particularly relevant for Toronto, where the city previously committed to significant cycling infrastructure expansion while simultaneously growing its bike share network from 2,854 stations in 2016 to over 6,850 stations in 2020 (Toronto 2020). Understanding this relationship is essential as cities increasingly rely on bike share systems to complement public transit and provide sustainable transportation options.

Our estimand is the causal effect of cycling infrastructure improvements on monthly Bike Share Toronto ridership, measured as the difference in average monthly rides between treated and control bikeways before and after infrastructure changes during 2017-2023. Specifically, we estimate how the installation of three infrastructure types (protected lanes, on-road lanes, and shared roadways) and two implementation approaches (new installations versus upgrades) affect the number of Bike Share trips originating within 100 meters of improved bikeways. Using a difference-in-differences design that combines ridership data with infrastructure locations, we isolate these treatment effects while controlling for broader trends in cycling adoption.

Our analysis indicates that infrastructure improvements significantly increase bike share ridership, with effects varying substantially by implementation approach. While we observe modest initial increases of 32.4 rides per month during the treatment year, post-implementation effects grow substantially to 133.1 additional monthly rides per bikeway ($p < 0.01$). In aggregate, this translates to approximately 300,000 additional annual rides across all 186 treated segments - a significant impact given that these improvements represent only 12.6% of Toronto's total bikeways. Protected bike lanes show particularly strong effects, generating 381.9 additional monthly rides post-implementation ($p < 0.001$) - more than twice the effect of on-road lanes (169.2 rides, $p < 0.001$) and triple that of shared roadways (111.7 rides, $p < 0.001$). Notably, these gains occurred despite treated bikeways having higher initial ridership at 209.03 monthly rides, compared to control bikeways 85.59 monthly rides pre-treatment. This suggests infrastructure improvements can substantially increase cycling activity even on popular routes.

These findings have important implications for urban transportation policy as cities work to expand sustainable mobility options. Toronto's commitment to add 100 kilometers of new cycling infrastructure between 2025 and 2027 (City of Toronto 2024) represents a significant opportunity to enhance cycling adoption, particularly if implemented with attention to the differential impacts of various infrastructure types. The substantial ridership gains observed from improving just 12.6% of the network suggest that targeted infrastructure investments can have outsized impacts on system utilization. Furthermore, our finding that improvements to already-popular routes generated significant additional ridership challenges the assumption

that infrastructure investments should prioritize underserved areas, highlighting the complex trade-offs cities face when allocating limited resources for cycling infrastructure.

The remainder of this paper proceeds as follows. Section 2 describes our data sources and measurement approach. Section 3 outlines our difference-in-differences methodology and identification strategy. Section 4 presents our main results and robustness checks. Section 5 discusses the implications of our findings and potential directions for future research. Section A introduces an idealized survey methodology designed to directly address our research question. The appendices provide supplementary materials, including detailed data processing steps in Section B and additional figures and analysis in Section C.

# 2 Data

## 2.1 Overview

This study draws on three datasets from the City of Toronto's Open Data Portal (Gelfand 2022): the Cycling Network (Bikeways) data (Transportation Services 2024), and both Bike Share Ridership and Stations data (Toronto Parking Authority 2024). Together, these datasets provide a detailed view of Toronto's cycling landscape, capturing infrastructure development from 2001-2023 and ridership patterns from 2017-2023. While alternative cycling metrics exist, such as manual traffic counts and automated counter data, these sources suffer from inconsistent maintenance and ceased updates after 2019. Our selected datasets offer better temporal coverage and data quality, with regular updates ensuring current, reliable measurements of both infrastructure changes and system usage.

All data cleaning and analysis was conducted using R (R Core Team 2023), with key packages including `tidyverse` (Wickham et al. 2019), `dplyr` (Wickham et al. 2023), `readr` (Wickham, Hester, and Bryan 2024), `jsonlite` (Ooms 2014), `arrow` (Richardson et al. 2024), and `sf` (Pebesma and Bivand 2023) for spatial analysis.

## 2.2 Measurement and Limitations

### 2.2.1 Cycling Infrastructure Measurement

The Cycling Network data captures two distinct types of infrastructure changes recorded by the City's Transportation Services division (Transportation Services 2024):

1. **New Installation**: The construction of new bikeway segments that expand the network's reach
2. **Upgrades**: Modifications to existing segments that enhance their safety or functionality

When either change occurs, the location, infrastructure type, and year of modification are documented. A key limitation of this measurement process is its temporal granularity - while the year of each change is recorded, the specific month and day are not, constraining our ability to pinpoint exact implementation dates.

### 2.2.2 Ridership and Stations Measurement

Bike Share ridership is measured through an automated system that anonymously records every trip's start and end points, time, and associated station IDs. The measurement process follows these steps:

1. A user unlocks a bike using their membership card, mobile app, or payment kiosks located at each station
2. The system logs the start time and station information
3. Upon return, the end time and station information are recorded
4. This data is automatically transmitted to Bike Share Toronto's database

The Public Bicycle System Company (PBSC) and City of Toronto also maintains detailed Bike Share stations records, documenting each station's location and capacity metrics (Transportation Services 2024).

### 2.2.3 Limitations and Potential Biases

Our analysis faces two primary measurement challenges that could affect causal inference. First, the Bike Share system cannot track actual route choices between endpoints. To address this, we focus on trips originating from stations within 100 meters of bikeways, assuming proximity indicates usage. While this provides a reasonable proxy, it may introduce selection bias by excluding riders who use bikeways despite starting from more distant stations.

Second, our measure of infrastructure changes may suffer from reverse causality bias. The city might prioritize upgrades for routes that already show high cycling traffic, potentially overstating the causal effect of infrastructure improvements on usage. We attempt to mitigate this through our difference-in-differences design and by examining pre-treatment trends, but this limitation should be considered when interpreting our results.

## 2.3 Data Cleaning

The data cleaning process involved several key steps to create our final analysis panel dataset (detailed methodology available in Appendix Section B):

1. Spatial filtering to identify stations proximate to bikeways (within 100 meters)

2. Extract relevant Bike Share trips based on filtered station locations

3. Aggregating total monthly rides for each bikeway, adjusting for seasonality

4. Creating treatment and control groups:

  - **Treatment group**: Bikeways upgraded or constructed between 2019-2021
  - **Control group** : Bikeways unmodified since before 2017

A vital methodological choice was the use of relative timing rather than calendar years. Due to bikeways having different upgrade or installation years, we align their treatment event year using a relative period. For treated bikeways, this creates a 60-month window: 24 months pre-treatment, 12 months during the treatment year, and 24 months post-treatment. Control bikeways receive randomly assigned pseudo-treatment years (2019, 2020, or 2021) to enable parallel analysis. This approach allows us to facilitate direct comparison between treatment and control groups while accounting for the temporal distribution of infrastructure changes.

Table 5 in Appendix Section C provides a sample of our processed dataset.

## 2.4 Outcome Variables

Our primary outcome variable is seasonally-adjusted monthly ridership for each bikeway (`monthly_rides_adj`). Figure 1 shows several important patterns in ridership behavior. The raw ridership (black line) displays pronounced seasonal fluctuations, with consistent peaks during summer months and troughs in winter, reflecting Toronto's strong cycling seasonality. After applying seasonal adjustments (blue line), these cyclical patterns are smoothed while preserving the underlying growth trends. Both treatment and control groups show a general upward trend in ridership over the observation period, suggesting broader growth in cycling activity across Toronto's network.

The notable unadjusted ridership activity during the treatment period (relative month 0) reflects both the granularity of our data and real-world implementation patterns. Since we observe only the year of infrastructure changes due to data limitations, all twelve months of the treatment year are assigned to relative month 0. This ridership activity captures both partial-year effects (as changes may occur at different points throughout the year) and continued system usage during implementation.

## 2.5 Treatment Variables

Our main treatment variable (`treatment`) indicates whether a bikeway received an infrastructure change (either an upgrade or new installation) during our study period 2019-2021. Figure 2 presents the distribution of bikeways between treatment and control groups, showing a larger pool of control bikeways to enable robust comparison with treated segments.
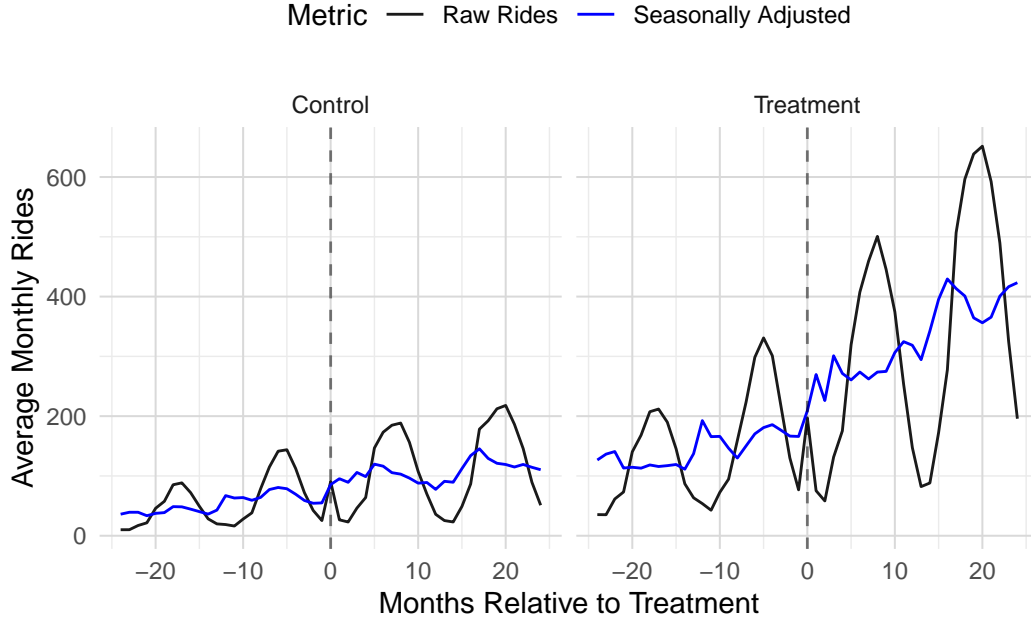
Figure 1: Average ridership by relative months to treatment

Appendix Section C provides a further breakdown on types of bikeways installed and upgraded throughout the years. Figure 6 in the appendix shows consistent bikeway installations every year after 2010, with protected lanes most commonly installed. Figure 7 presents yearly bikeway upgrades, showing an increase during our treatment period (2019-2021), especially with protected bike lanes.

To explore treatment effect heterogeneity, we examine two additional dimensions of infrastructure changes:

- **Bikeway Type**:

    - *Protected Lanes*: Physically separated cycling infrastructure
    - *On-Road Lanes*: Dedicated but unprotected bike lanes
    - *Shared Roadways*: Designated shared-use routes

- **Installation Type**:

    - *Upgrades*: Improvements to existing infrastructure
    - *New Installations*: Addition of new cycling routes

Figure 3 presents distinct infrastructure patterns between groups. While protected lanes dominate both treatment and control groups, comprising 50% and 54% respectively, the distribution of other types differs notably. The treatment group shows a higher proportion of on-road lanes
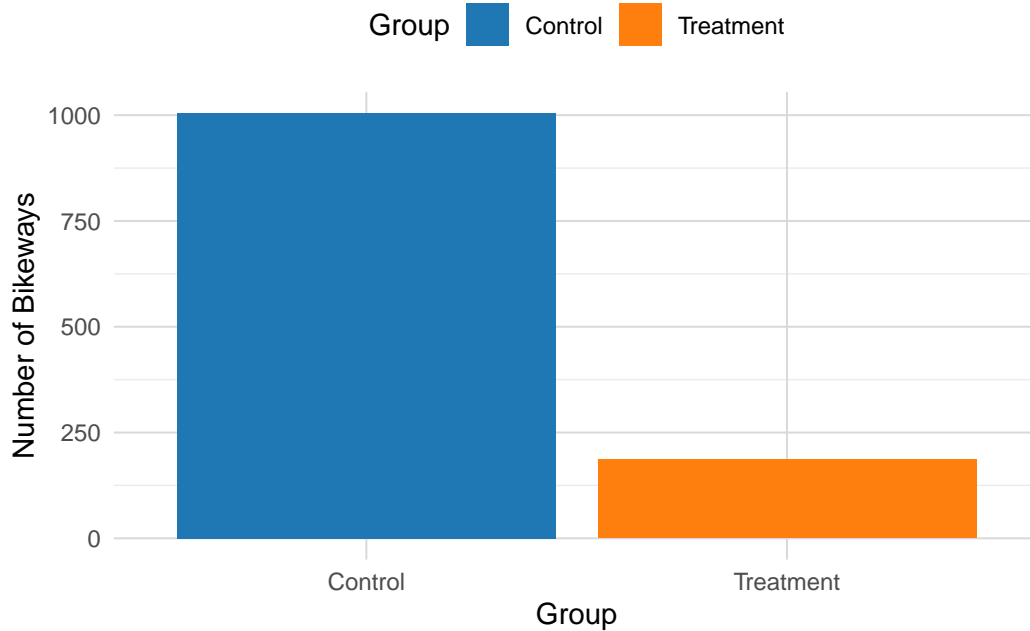
Figure 2: Total Bikeway Count in Control Vs. Treatment Group

relative to shared roadways, suggesting a deliberate strategy of upgrading less protected infrastructure. This aligns with Toronto's broader policy goal of enhancing cyclist safety through infrastructure improvements (City of Toronto Council 2019).

Figure 4 demonstrates a nearly even split in treatment approaches, with 98 new installations and 88 upgrades among the 186 treated bikeways. This balanced distribution enables us to examine whether infrastructure expansion (new installations) versus enhancement (upgrades) generates different effects on ridership patterns. Further categorization into bikeway types, and sub-treatment groups allow us to examine whether certain types of infrastructures and types of changes yield different impacts on ridership patterns.

Table 7 in the Appendix provides detailed quantitative breakdowns of both our outcome variables (showing pre/post/treatment period ridership counts and adjusted means) and treatment variables (showing the distribution of protected lanes, on-road lanes, and shared roadways across treatment and control groups).

## 3 Model

### 3.1 Assumptions

Our model implementation and interpretation rests on two key assumptions. First, we assume Bike Share rides that start within 100 meters of a bikeway indicate usage of that infrastruc-
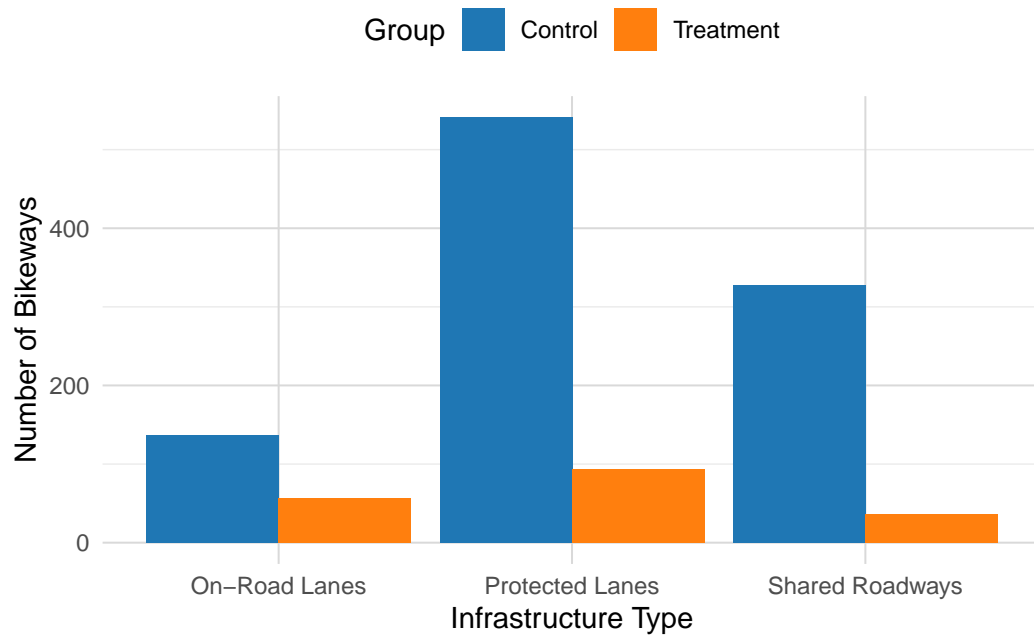
Figure 3: Infrastrucutre Type Distribution between Control and Treatment Group
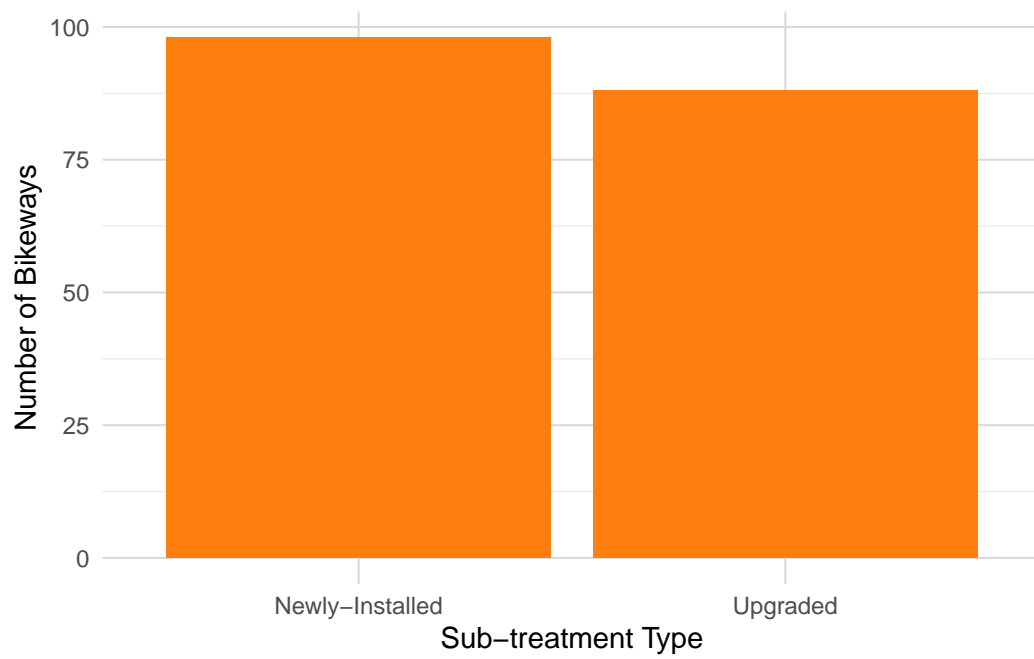


Figure 4: Number of New-Installations Vs Upgrades in Treatment Group

ture, as cyclists typically choose the most direct route to their destination and are unlikely to travel significant distances to access a bikeway. Second, we treat the year of bikeway construction or upgrade as generating a sharp treatment effect, though we account for potential construction overlap by excluding six months of pre-treatment data in our parallel trend test to mitigate anticipatory affects. Our 24-month post-treatment window allows sufficient time to observe behavioral adaptation while minimizing contamination from other infrastructure changes. Additionally, our use of seasonally adjusted ridership helps isolate infrastructure effects from weather-related variation in cycling patterns, as Toronto's distinct seasonal climate significantly influences cycling behavior.

## 3.2 Model justification

To estimate the causal effect of bikeway infrastructure changes on Bike Share ridership, we employ a difference-in-differences (DiD) approach. This methodology is particularly well-suited for our research question as it allows us to exploit the temporal variation in bikeway upgrades and installations while controlling for unobserved confounders. The staggered implementation of bikeway improvements across Toronto from 2019 to 2021 provides a natural experiment setting where we can compare ridership changes between treated and untreated bikeways before and after infrastructure improvements.

While Regression Discontinuity Design (RDD) was considered as an alternative approach, our data's temporal granularity (only observing treatment years rather than specific dates) and the gradual nature of infrastructure effects made DiD more appropriate for capturing the full impact of these changes. Moreover, the lack of a clear "forcing variable" that determines treatment status and the potential anticipation effects during construction periods would violate key RDD assumptions, making it unsuitable for our analysis.

Our DiD analysis is ran in R (R Core Team 2023) using the `fixest` package (Bergé 2018), which provides estimation methods for fixed effects models. This package is particularly suitable for our analysis as it handles multiple fixed effects efficiently and provides robust standard errors clustered at the bikeway level.

## 3.3 Model Setup

Following the framework of Cuborican (2024), let $y_{it}$ represent the seasonally-adjusted monthly Bike Share rides for bikeway $i$ in month $t$. Our main DiD specification is:

$$y_{it} = \alpha_i + \gamma_t + \sum_{p \in \{treatment, post\}} \beta_p (Treatment_i \times Period_{p,it}) + \epsilon_{it}$$

where:

- $\alpha_i$ represents bikeway fixed effects
- $\gamma_t$ represents relative-month fixed effects
- $Treatment_i$ is an indicator equal to 1 if bikeway $i$ received an upgrade or was newly installed during 2019-2021
- $Period_{p,it}$ are indicators for treatment period and post-treatment period (The pre-treatment period serves as the reference category)
- $\epsilon_{it}$ is the error term

The coefficients of interest are $\beta_{treatment}$ and $\beta_{post}$, which capture the average treatment effects during and after the infrastructure changes, respectively.

## 3.4 Robustness Checks

### 3.4.1 Parallel Trends Test

An important assumption of the DiD design is that treated and control bikeways would have followed parallel trends in the absence of treatment (Cuborican 2024). While this counterfactual cannot be directly tested, we can examine pre-treatment trends to assess the plausibility of this assumption. We implement this test by estimating:

$$y_{it} = \alpha_i + \gamma_t + \sum_{k=-24}^{-6} \delta_k (Treatment_i \times 1[t = k]) + \epsilon_{it}$$

where $k$ indexes months relative to treatment. Due to data limitations that only specify the year of infrastructure changes, we conservatively exclude the six months immediately preceding treatment to account for potential construction overlap from the previous year that could affect ridership patterns. This approach helps isolate the true pre-treatment period from any anticipation effects or early construction impacts. The coefficients $\delta_k$ should not be statistically different from zero if the parallel trends assumption holds.

### 3.4.2 Placebo Tests

To further validate our results, we conduct a placebo test by randomly reassigning treatment status among bikeways while maintaining the original proportion of treated units. This approach helps ensure our findings are not driven by spurious correlations or systematic differences unrelated to the actual infrastructure changes. The specification mirrors our main DiD model but uses the randomly assigned treatment status:

$$y_{it} = \alpha_i + \gamma_t + \sum_{p \in \{treatment, post\}} \beta_p (PlaceboTreatment_i \times Period_{p,it}) + \epsilon_{it}$$

### 3.4.3 Heterogeneity Analysis

We extend our analysis to examine treatment effect heterogeneity across different types of infrastructure changes. This investigation is necessary for understanding which interventions are most effective at increasing ridership. We estimate two separate models:

1. **Bikeway Type Effects**:

$$y_{it} = \alpha_i + \gamma_t + \sum_{p \in \{treatment, post\}} \sum_{j \in J} \beta_{pj}(Treatment_{ij} \times Period_{p,it}) + \epsilon_{it}$$

where $J = \{\text{Protected Lanes, On-Road Lanes, Shared Roadways}\}$

2. **Installation Type Effects**:

$$y_{it} = \alpha_i + \gamma_t + \sum_{p \in \{treatment, post\}} \sum_{k \in K} \beta_{pk}(Treatment_{ik} \times Period_{p,it}) + \epsilon_{it}$$

where $K = \{\text{Upgraded, Newly-Installed}\}$

These specifications allow us to identify which types of infrastructure improvements and implementation strategies are most effective at increasing Bike Share utilization. For both heterogeneity analyses, we cluster standard errors at the bikeway level to account for serial correlation within bikeways over time.

## 4 Results

### 4.1 Parallel Trends Analysis

A key assumption of our difference-in-differences design is that treated and control bikeways would have followed parallel trends in the absence of treatment. Figure 5 visualizes this assumption by plotting the seasonally adjusted monthly rides for both treated and control bikeways during the pre-treatment period. While the treatment group consistently shows higher monthly average ridership levels than the control group, the trends between the two groups appear to move in parallel before treatment, particularly in the period from month -20 to month -10. We exclude the six months immediately preceding treatment from this visual analysis due to possible overlap in construction, avoiding potential anticipation effects.

The full results of the parallel trends test are provided in Table 6 in the appendix. The coefficients show no clear trend and are generally not statistically different from zero in the pre-treatment period, supporting the parallel trends assumption. While we observe slightly negative coefficients in months -8 and -7 (significant at the 10% and 5% levels respectively), the
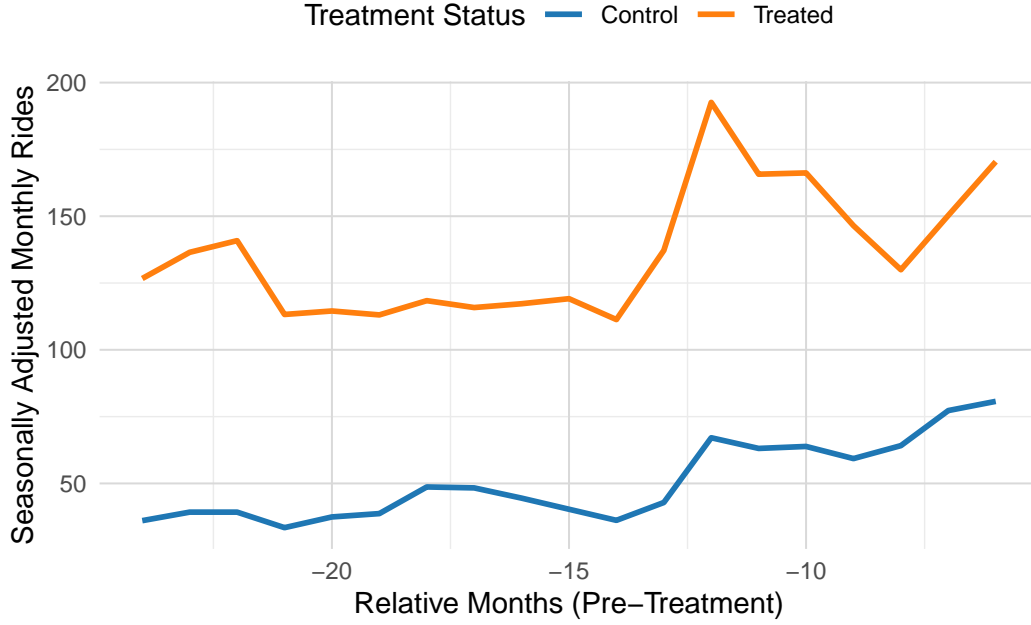
Figure 5: Parallel Trends Test: Average Monthly Rides in Pre-Treatment Period

magnitudes are small relative to our main treatment effects and may reflect normal variation rather than systematic differences.

## 4.2 Difference-in-Differences Model Estimates

Table 1 presents the results from our main difference-in-differences model. The model estimates that infrastructure improvements led to a significant increase in Bike Share ridership. During the treatment year, we observe a marginally significant increase of 32.4 rides per month (p < 0.10). The effect becomes substantially larger in the post-treatment period, with an estimated increase of 133.1 rides per month (p < 0.01), compared to the pre-treatment period.

The high R-squared value of 0.785 indicates that our model explains a substantial portion of the variation in ridership. The inclusion of bikeway and time fixed effects helps control for unobserved confounders that might affect ridership patterns.

## 4.3 Robustness Checks

### 4.3.1 Placebo Test Results

To verify that our results are not driven by spurious correlations, we conduct a placebo test by randomly reassigning treatment status across bikeways. As shown in Table 2, when using

Table 1: Main Difference-in-Difference Results

|  | Main DiD Model |
| --- | --- |
| period = post × treatment | 133.132** |
|  | (41.883) |
| period = treatment × treatment | 32.411+ |
|  | (16.811) |
| Num.Obs. | 71 460 |
| R2 | 0.785 |
| R2 Adj. | 0.781 |

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table 2: Placebo Test Results - Random Treatment Assignment

|  | Placebo Test - Random Assignment |
| --- | --- |
| period = post × placebo_treatment | 0.107 |
|  | (25.720) |
| period = treatment × placebo_treatment | 4.039 |
|  | (13.943) |
| Num.Obs. | 71 460 |
| R2 | 0.783 |
| R2 Adj. | 0.779 |

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

this random assignment, we find near-zero effects in both the treatment period (4.0 rides) and post-treatment period (0.1 rides), with neither coefficient being statistically significant. These null results, compared to the significant effects found in our main analysis, support the validity of our findings by demonstrating that randomly assigned "fake" treatments do not generate the ridership increases we observe with actual infrastructure improvements.

### 4.3.2 Heterogeneous Effects

We examine treatment effect heterogeneity across different types of infrastructure and implementation strategies. Table 3 presents the results by bikeway type, with each coefficient representing the change in ridership compared to the pre-treatment period for that specific infrastructure type. Protected lanes show the most dramatic impact, generating an additional 381.9 rides per month post-treatment (p < 0.001) – more than twice the effect of on-road

Table 3: Heterogeneous Treatment Effects by Bikeway Type

|  | Heterogeneous Effects - Bikeway Type |
| --- | --- |
| Treatment x Control | −66.598+ |
|  | (37.416) |
| Treatment x Treated-OnRoad | −63.386 |
|  | (43.105) |
| Treatment x Treated-Protected | 2.445 |
|  | (18.722) |
| Treatment x Treated-Shared | −82.754* |
|  | (37.767) |
| Post x Control | 131.321*** |
|  | (29.446) |
| Post x Treated-OnRoad | 169.163*** |
|  | (27.240) |
| Post x Treated-Protected | 381.914*** |
|  | (102.174) |
| Post x Treated-Shared | 111.722*** |
|  | (33.621) |
| Num.Obs. | 71 460 |
| R2 | 0.786 |
| R2 Adj. | 0.782 |

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

lanes (169.2 rides, $p < 0.001$) and more than triple the effect of shared roadways (111.7 rides, $p < 0.001$). The substantially larger effect of protected lanes suggests that perceived safety significantly influences riders' willingness to use Bike Share.

Table 4 compares the effectiveness of upgrading existing infrastructure versus installing new bikeways. Upgrades to existing infrastructure generate larger and more immediate benefits, showing both a significant treatment-year effect (43.8 additional rides, $p < 0.10$) and a strong post-treatment effect (152.7 additional rides, $p < 0.01$). In contrast, newly-installed bikeways show no significant effect during the treatment year and a smaller post-treatment increase (115.5 rides, $p < 0.10$), suggesting that improvements to established cycling routes may be more effective at increasing ridership than creating entirely new routes.

These heterogeneity analyses shows important distinctions in the effectiveness of different in-

Table 4: Heterogeneous Treatment Effects by Implementation Strategy

|  | Heterogeneous Effects - Treatment Type |
| --- | --- |
| Treatment x Upgraded | 43.784+ |
|  | (25.777) |
| Treatment x Newly Installed | 22.198 |
|  | (20.547) |
| Post x Upgraded | 152.739** |
|  | (52.024) |
| Post x Newly Installed | 115.526+ |
|  | (63.181) |
| Num.Obs. | 71 460 |
| R2 | 0.785 |
| R2 Adj. | 0.781 |

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

frastructure strategies. The particularly strong effect of protected lanes suggests that safety and separation from vehicle traffic may be key factors in encouraging Bike Share usage. Additionally, the stronger effects of upgrades compared to new installations may indicate the importance of improving infrastructure in areas where cycling activity already exists.

# 5 Discussion

Our difference-in-differences analysis of Toronto's cycling infrastructure changes between 2019-2021 demonstrates how different types of cycling infrastructure improvements influence Bike Share utilization. The results demonstrate that while infrastructure investments broadly increase cycling adoption, the magnitude and timing of these effects vary substantially by implementation approach and infrastructure type.

## 5.1 Key Empirical Findings and Their Implications

The evolution of treatment effects over time tells an important story about behavior change and infrastructure adoption. During the treatment year, we observe a modest but marginally significant increase of 32.4 rides per month ($p < 0.10$). This relatively small initial effect likely reflects several factors. First, infrastructure improvements often cause temporary disruption during construction, potentially suppressing immediate usage of bike share in the surrounding

areas. Second, the treatment year impacts may be diluted because we only observe the year of changes, not precise implementation dates. Most importantly, the minor initial increase suggests that behavioral adaptation to new infrastructure takes time as users adjust their travel patterns and routine to new routes.

The significant increase in the post-treatment period – to 133.1 additional rides per month (p < 0.01) – shows the true potential of infrastructure improvements once fully integrated into the transportation network. This impact from pre-treatment to post-treatment periods aligns with research from the University of Colorado Denver showing that "building safe facilities for cyclists is one of the biggest factors in road safety for everyone" (Marshall and Ferenchak 2019). The magnitude of this change suggests that infrastructure improvements don't just make existing cyclists' trips safer, they also alter the decisions behind mode of transportation for many residents.

To put these effects in perspective, our treatment estimate of 133.1 additional monthly rides per bikeway translates to approximately 24,757 additional monthly rides across all 186 treated segments, or nearly 300,000 additional rides annually. This substantial increase is reflected in the raw data (see Table 7 in Appendix Section C) - treated segments averaged 331.92 monthly rides post-treatment compared to 209.03 pre-treatment, while control segments saw a more modest increase from 85.59 to 107.77 monthly rides over the same period. The magnitude of this effect is particularly notable given that treated segments represent only about 16% of Toronto's total bikeways (186 out of 1,191 total segments) but generated significant ridership gains, suggesting that targeted infrastructure improvements can have outsized impacts on system utilization.

The dramatic difference in baseline ridership between treatment and control groups (209.03 versus 85.59 average monthly rides pre-treatment, as shown in Table 7) also provides important context for interpreting our heterogeneous effects. This pattern suggests that the city prioritized improvements on already-popular routes, which may partially explain why upgrades to existing infrastructure showed more immediate effects than new installations. However, the fact that treated segments still demonstrated substantial gains in ridership despite starting from a higher baseline suggests that infrastructure improvements can drive meaningful increases in cycling activity even on already-established routes.

This substantial increase in post-treatment ridership may also be partially driven by strategic expansion of the Bike Share network itself. Following infrastructure improvements, Bike Share Toronto can coordinate with the city to place new stations near cycling infrastructure. This complementary expansion of both infrastructure and Bike Share access could create a multiplier effect, where improved infrastructure attracts more stations, which in turn enables more riders to access the enhanced bike lanes. While this interaction between infrastructure and system expansion complicates our causal interpretation, it reflects the real-world synergy between cycling infrastructure and bike share system development.

### 5.1.1 Heterogenous Effect Findings

Our heterogeneous effects analysis show which interventions most effectively promote cycling. Protected lanes show remarkably strong effects, generating 381.9 additional monthly rides post-treatment ($p < 0.001$) – more than twice the impact of on-road lanes (169.2 rides, $p < 0.001$) and more than triple the effect of shared roadways (111.7 rides, $p < 0.001$). This substantial difference in effectiveness likely stems from:

- **Safety perceptions**: The physical separation from traffic provided by protected lanes addresses the concerns of what City Transportation Officials (2016) research identifies as the "interested but concerned" majority of potential cyclists.
- **User confidence**: Protected infrastructure may encourage less experienced cyclists to try Bike Share, expanding the user base beyond confident urban cyclists.
- **Urban density patterns**: Protected lanes are more commonly implemented in denser, high-traffic areas like downtown Toronto, where higher population density and concentration of destinations naturally generate more cycling trips. This geographic distribution may partially explain their stronger treatment effects compared to other infrastructure types.

The comparison between upgrades and new installations provides equally important discoveries for implementation strategy. Upgrades to existing infrastructure generate more monthly ridership (152.7 adjusted rides), compared to newly-installing bike lanes (115.5 adjusted rides) post-treatment. Additionally, during the treatment period, upgrades to existing infrastructure show immediate effect to ridership (43.8 rides, $p < 0.10$), whereas new installations show no significant treatment-year effect. This pattern suggests that improving existing cycling routes may be more effective than expanding into new areas, particularly for short-term ridership gains. This finding aligns with Toronto's strategic focus during the same period as our study, on upgrading existing infrastructure to "higher-order" facilities, as outlined in the 2019-2021 Cycling Network Plan Update (City of Toronto Council 2019).

## 5.2 Infrastucture Development and Policy Implications

Our findings have substantial implications for cycling infrastructure development strategies. The strong performance of protected lanes, combined with the effectiveness of upgrades, suggests a coupled approach:

- Systematically upgrade existing high-traffic routes to protected infrastructure where feasible
- Strategically expand the network through new protected lanes in high-potential corridors

This approach is particularly relevant given Toronto's commitment to add 100 kilometers of new cycling infrastructure between 2025 and 2027 (City of Toronto 2024). The significant post-treatment effects we observe – especially for protected lanes – suggest these investments

could substantially increase Bike Share ridership if properly implemented. These findings and implications align with historical actions, as in 2020, the City of Toronto worked to expand Bike Share coverage to 20 of the city's 25 wards (Toronto Parking Authority 2020), further suggesting opportunities for coordinated deployment of infrastructure improvements and system expansion.

The timing of effects also has important implications for policy evaluation. The delay between implementation and peak impact suggests that infrastructure evaluations should maintain longer time horizons. Short-term metrics may significantly underestimate the full benefits of cycling investments, particularly for new installations which show no significant treatment-year effects but meaningful long-term impacts. This delayed-benefit pattern aligns with experiences in other cities; for instance, Portland saw a 75% reduction in road fatality rates over a 20-year period of sustained infrastructure investment, highlighting the importance of maintaining long-term commitment to cycling infrastructure development (Marshall and Ferenchak 2019).

## 5.3 Methodological Strengths and Limitations

Our difference-in-differences design, supported by robust parallel trends in the pre-treatment period and null results in placebo tests, provides strong causal evidence for the effectiveness of cycling infrastructure. The robustness of our results is particularly noteworthy given Toronto's challenging research context, where multiple infrastructure projects and transportation initiatives often overlap temporally and spatially. However, several limitations merit discussion:

- **Temporal precision**: Our inability to observe exact implementation dates within treatment years likely diminishes treatment-year effects and may understate immediate post-implementation impacts.
- **Spatial relationships**: While we control for station proximity to bikeways, we cannot observe actual route choices. This may lead us to underestimate infrastructure usage if riders access lanes from more distant starting points, or even overestimate usage if riders don't use bike lanes, despite starting near one. This limitation is particularly significant in downtown areas where the density of both bike lanes and stations makes it difficult to isolate specific infrastructure effects.
- **Station placement effects**: Our results may partially reflect strategic placement of new Bike Share stations near improved infrastructure rather than purely infrastructure-driven changes in behavior. While this interaction makes it harder to isolate the direct effect of infrastructure improvements, it captures the realistic policy dynamic where bike share systems expand in tandem with cycling infrastructure.

## 5.4 Future Research Directions

Several promising avenues for future research emerge from these findings:

- **User surveys**: Qualitative research could help explain the mechanisms behind the stronger effects of protected lanes and how infrastructure influences mode choice decisions. Such research could particularly focus on understanding the "interested but concerned" demographic identified by City Transportation Officials (2016) as vital for expanding cycling adoption.
- **Network effects**: Future studies could examine how the benefits of infrastructure improvements spill over onto connecting routes and affect system-wide ridership patterns. This could help inform Toronto's goal of creating a more connected cycling network, as outlined in the city's 2025-2027 implementation program (City of Toronto 2024).
- **Neighborhood-level analysis**: Future research could examine how infrastructure effects vary across Toronto's diverse neighborhoods. Such analysis would be particularly beneficial as Toronto expands Bike Share into new areas, helping identify where different types of infrastructure improvements might have the greatest impact. This geographic heterogeneity analysis could also inform equity considerations in infrastructure deployment, ensuring benefits are distributed across the city's diverse communities.
- **Integration with public transit**: Studies could investigate how cycling infrastructure near transit hubs affects multi-modal trip patterns, particularly relevant given Toronto's efforts to integrate Bike Share with the TTC system ("Bike Access and Amenities - Toronto Transit Commission" 2024).

This research contributes to our understanding of how cycling infrastructure influences urban mobility patterns. The clear relationship between infrastructure quality and ridership, particularly the strong effect of protected lanes, provides evidence-based guidance for cities working to encourage sustainable transportation. As Toronto continues expanding its cycling network, these findings can help inform investment priorities and implementation strategies to maximize the impact of infrastructure improvements.

# Appendix

# A Idealized Survey Methodology

## A.1 Survey Objectives

Following Stantcheva's (2023) framework, we recognize that surveys are not merely for data colletion, but rather "creating the process that will generate the data." The goal of our idealized survey is to measure otherwise "invisible factors" regarding cycling infrastructures influence on bike share usage, specifically:

- Causal relationship between infrastructure changes and ridership
- Mental processes behind route selection with/without bike lanes
- Perception of safety and convenience
- Counterfactual behavior (would people use bike share if infrastructure improves)

Having this idealized survey would help us directly answer our research question by creating controlled variation in our sampling strategy, comparing treatment areas with new or upgraded bike lanes against control areas without changes. This design allows us to measure both first-stage effects of infrastructure changes on perceptions and intended behavior, and second-stage effects on actual ridership through follow-up surveys, while controlling for demographic and geographic factors. Through carefully designed questions about safety perceptions, route preferences, and time-value tradeoffs, we can identify the specific mechanisms through which infrastructure improvements affect ridership patterns. Additionally, our sampling of different user types enables analysis of heterogeneous effects across current, former, and potential users in various neighborhoods, providing a extensive understanding of how infrastructure changes influence Bike Share adoption.

## A.2 Implementation Strategy

### A.2.1 Sample Size and Target Audience

Our survey will be targeted towards: current and former (In-active user for over 6 months) Bike Share members, and non-bike share users living within 200 meters of Bike Share Station. Our target sample size will be 3,000 respondents:

- 1,000 treatment area residents
- 1,000 control area residents
- 1,000 current Bike Share users

### A.2.2 Recruitment Channels

- **Digital Targeting:** Instagram/Facebook/X (Twitter) ads geo-targeting users within 200 meters to a bike share station. This method will target our entire audience group, and allow us to differentiate between treatment and control groups.
- **Direct Outreach**: Email distribution or SMS notifications to current and former bike share users living within 200 meters of a Bike Share station, identified through Bike Share Toronto's database.
- **Incentive Structure**: $20 Bike Share gift card for completed surveys, with a bonus $10 for follow-up survey completion

### A.2.3 Budget Allocation

Our allocation of a $100,000 budget, will be:

- $15,000 to digital targeting costs of placing ads on social media platforms.
- $10,000 to Bike Share Toronto to distribute Emails and SMS notifications, taking advantage of their existing digital platform and data.
- $75,000 to incentives, ensuring that all respondents receive their $20 Bike Share Toronto gift card, and the bonus $10 gift card.

## A.3 Survey Design Elements

### Opening Module

"Welcome! Thank you for participating in our survey about bike lane infrastructure and its effects on Bike Share ridership in Toronto. This survey is being conducted as part of research to better understand how infrastructure upgrades influence biking habits.

Your responses will help shape future urban transportation decisions. The survey will take approximately 5 minutes to complete. As a thank-you for your time, you will receive a $20 Bike Share Toronto gift card, with an additional $10 gift card for completing a follow-up survey in 3 months.

Your participation is completely voluntary, and all responses will remain confidential and anonymous.

For any questions or concerns, contact us at: stevency.li@mail.utoronto.ca"

### Key Questions

1. **Time-Based Preference**: "Consider two possible routes for a 15-minute trip. Route A: 15 minutes using regular streets with cars. Route B: 20-minutes using protected bike lanes. Which would you choose for a Bike Share trip?

- Route A (shorter, regular streets)
- Not sure
- Route B (longer, protected lanes)"

2. **Route Selection Experiment** (Map showing City of Toronto's neighbourhoods): "Which areas of Toronto do you typically commute through? Please type in the neighbourhood(s) in the text box below."

3. **Attention Check**: "Select the option 'Green'

   - Red
   - Elephant
   - Green
   - Circle
   - Rain

4. **Visual Choice Experiment** (Show side-by-side images of the same bike lane before and after upgrades) : "If you needed to travel along this route, which version would make you more likely to use Bike Share?

   - Much more likely with the upgraded lane
   - Somewhat more likely with the upgraded lane
   - No difference
   - Less likely with the upgraded lane"

5. **Behavioral Scenarios**: "Imagine a Bike Share station gets installed near your workplace, and the city adds protected bike lanes on your route to work. What would you do?

   - Definitely try biking to work
   - Might try biking occasionally
   - Probably wouldn't change my commuting method
   - Definitely wouldn't change my commuting method"

**Confirmation Message**

"Thank you for your time and participation…"Thank you for completing this survey! Your responses will help us better understand how bike infrastructure influences transportation choices in Toronto.

Your $20 Bike Share Toronto gift card will be sent to your provided contact information within 5 business days. In approximately 3 months, we will send you an invitation for a brief follow-up survey, where you can earn an additional $10 gift card.

For any questions about the survey or your gift card, please contact: stevency.li@mail.utoronto.ca"

**Idealized Survey — Opening Module can be found at**: First Survey Link

**Follow-up Module**

As recommended by Stantcheva (2023) for testing persistence of effects, we will implement a three-month follow-up survey. The key objective is to assess whether the stated preferences and intentions from the initial survey translate into actual behavioral changes, while also measuring any infrastructure-induced effects on ridership patterns. To maximize response rates, we will offer an additional $10 gift card incentive and keep the follow-up survey brief (under 3 minutes).

The follow-up survey will focus on concrete behavioral measures rather than attitudes, asking respondents about their actual Bike Share usage patterns over the past three months, including:

- Frequency of Bike Share trips
- Use of routes with new or upgraded infrastructure
- Reasons for any deviations from stated intentions

To minimize attrition bias, which Stantcheva (2023) identifies as a key concern in follow-up surveys, we will:

- Send reminder notifications through multiple channels (email, SMS, app notifications)
- Track and analyze patterns of non-response
- Apply appropriate statistical corrections for differential attrition

This approach allows us to not only validate initial survey responses but also capture how seasonal changes and growing familiarity with new infrastructure might influence ridership patterns. The combination of initial intentions and realized behaviors provides a more robust foundation for establishing the causal relationship between infrastructure improvements and Bike Share adoption.

**Idealized Survey** — **Follow-up Module can be found at**: Follow-up Survey Link

## A.4 Bias Mitigation Strategies

We implement several strategies to mitigate potential biases in our survey design. To reduce social desirability bias, we emphasize complete anonymity of responses, employ indirect questioning techniques, and carefully avoid leading questions about environmental benefits that might prompt respondents to present themselves as more environmentally conscious. Survey fatigue is addressed by keeping the total length to 5 minutes, and varying question formats to maintain engagement. Selection bias poses a particular challenge in transportation surveys, so we collect detailed non-response data, and carefully document and analyze attrition patterns. This approach to bias mitigation helps ensure our results accurately reflect the relationship between cycling infrastructure and Bike Share usage, rather than capturing respondent's desires to appear environmentally conscious or systematic differences between those who complete versus abandon the survey.

## A.5 Tradeoffs and Limitations

Our survey methodology faces several important limitations that could affect the validity of our results. First, self-selection and non-response bias may skew our sample toward respondents who are already interested in cycling or have strong opinions about infrastructure, while our incentive structure might attract particular demographic groups, potentially missing key segments of the population. Our reliance on hypothetical scenarios and stated preferences introduces additional uncertainty, as actual behavior may differ significantly from reported intentions, especially regarding route selection and infrastructure usage. Despite careful design to minimize social desirability bias, respondents may still feel pressure to express support for sustainable transportation initiatives or understate safety concerns. Furthermore, temporal limitations of our three-month follow-up period may inadequately capture seasonal variations in cycling behavior and long-term adaptation to infrastructure changes, while the results may not generalize well to other urban contexts or represent the full diversity of potential users. These limitations suggest that while our survey can provide imporant findings into the relationship between infrastructure and ridership, findings should be interpreted alongside other data sources and methodologies.

# B Data Processing Methodology

This appendix section provides a detailed overview of our data processing methodology, explaining how we construct the final analysis dataset from raw Bike Share and cycling infrastructure data.

## B.1 Spatial Filtering

We begin by identifying bike stations near cycling infrastructure:

1. Calculate distances between each Bike Share station and nearby bikeways
2. Retain only stations within 100 meters of a bikeway
3. Tag each retained station with its nearest bikeway ID

This spatial filtering reduces our dataset from 21.8 million total rides to 13.8 million rides starting near bikeways, creating a focused sample of trips most likely to utilize cycling infrastructure.

## B.2 Monthly Ridership Aggregation and Adjustment

To prepare for our difference-in-differences analysis, we:

1. Aggregate rides by bikeway and month
2. Create seasonal adjustment factors based on monthly patterns
3. Apply these adjustments to normalize seasonal variation in ridership

## B.3 Treatment and Control Groups

**Treatment Group**

- Identify bikeways upgraded or constructed in 2019-2021
- Create 60-month windows for each:
    - 24 months pre-treatment
    - 12 months treatment year
    - 24 months post-treatment

**Control Group**

- Select bikeways unchanged since pre-2017
- Randomly assign pseudo-treatment years (2019-2021)
- Create matching 60-month observation windows

This approach yields our final analysis dataset of approximately 8 million rides, capturing ridership patterns around infrastructure changes while controlling for broader trends through our comparison group.

## B.4 Key Methodological Decisions

1. **100-meter Threshold**: Balances capturing relevant rides while maintaining confidence in infrastructure usage
2. **60-month Window**: Provides sufficient pre/post data while maintaining balanced observations
3. **Seasonal Adjustment**: Addresses Toronto's strong cycling seasonality to better isolate infrastructure effects

These processing steps create a dataset structured to identify the causal impact of infrastructure changes on ridership patterns.

# C  Additional Tables & Figures

Table 5: Sample of processed dataset for DiD Model

| bikeway_id | 1268 | 744 | 273 | 166 | 788 |
|---|---|---|---|---|---|
| construct_year | 2020 | NA | 2019 | NA | NA |
| period | pre | pre | post | post | treatment |
| treatment | TRUE | FALSE | TRUE | FALSE | FALSE |
| year_month | 2018-06-01 | 2018-12-01 | 2020-09-01 | 2021-05-01 | 2021-12-01 |
| calendar_year | 2018 | 2018 | 2020 | 2021 | 2021 |
| relative_month | -19 | -13 | 9 | 17 | 0 |
| bikeway_type | Protected Lanes | Protected Lanes | On-Road Lanes | Shared Roadways | Shared Roadways |
| sub_treatment_type | Upgraded | No Treatment | Upgraded | No Treatment | No Treatment |
| monthly_rides | 2343 | 0 | 0 | 657 | 0 |
| monthly_rides_adj | 1574.6593 | 0.0000 | 0.0000 | 535.8687 | 0.0000 |
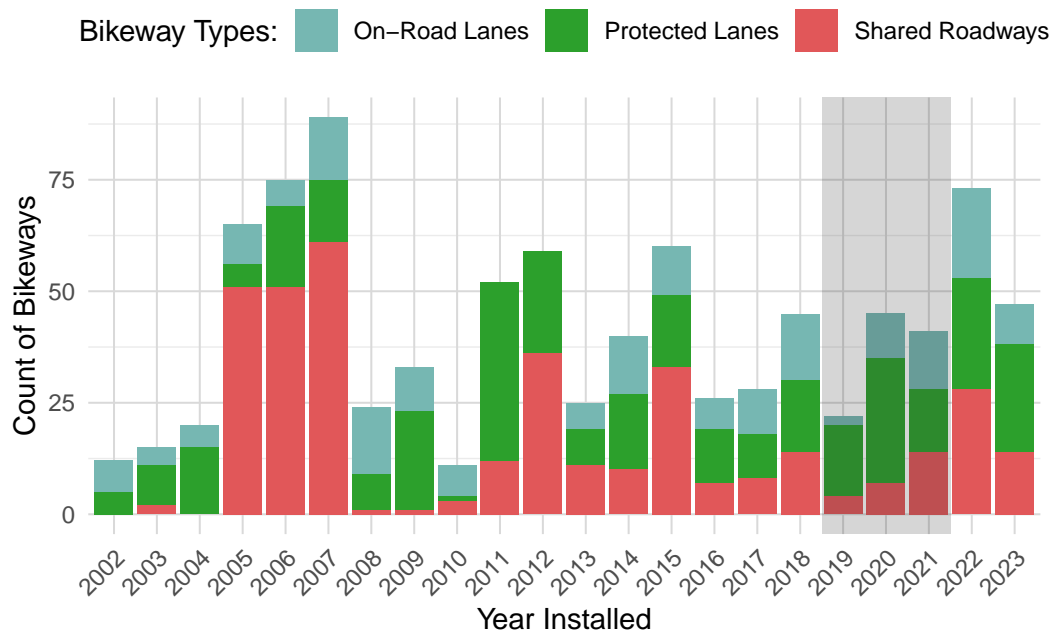
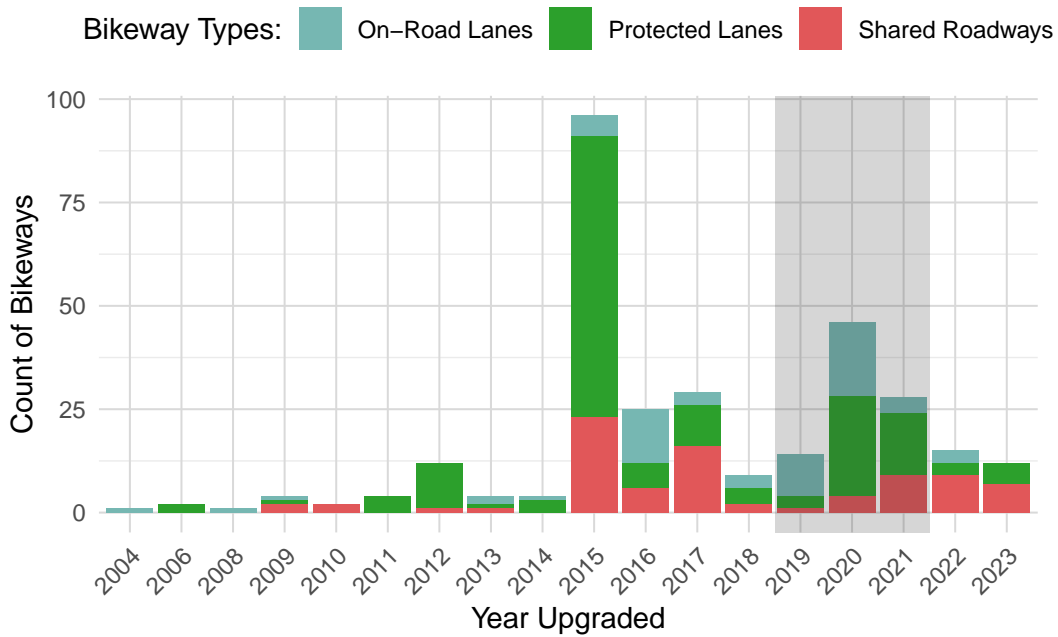Figure 6: Breakdown of Bikeway Types by Installation Year (2002-2023)



Figure 7: Breakdown of Bikeway Types by Upgraded Year (2002-2023)

Table 6: Parallel Trends Test Results - Monthly Treatment Effects

|  | Coefficient (std.error) |
| --- | --- |
| relative_month = -24 × treatment | 0.920 (20.060) |
| relative_month = -23 × treatment | 7.540 (20.866) |
| relative_month = -22 × treatment | 11.895 (21.638) |
| relative_month = -21 × treatment | $-9.911$ (19.689) |
| relative_month = -20 × treatment | $-12.619$ (18.818) |
| relative_month = -19 × treatment | $-15.337$ (18.747) |
| relative_month = -18 × treatment | $-19.975$ (16.063) |
| relative_month = -17 × treatment | $-22.196$ (16.127) |
| relative_month = -16 × treatment | $-16.942$ (14.914) |
| relative_month = -15 × treatment | $-10.895$ (15.945) |
| relative_month = -14 × treatment | $-14.561$ (16.953) |
| relative_month = -13 × treatment | 4.645 (14.737) |
| relative_month = -12 × treatment | 35.805 (22.597) |
| relative_month = -11 × treatment | 12.924 (22.307) |
| relative_month = -10 × treatment | 12.668 (14.822) |
| relative_month = -9 × treatment | $-2.516$ (15.044) |
| relative_month = -8 × treatment | $-23.866+$ (13.254) |
| relative_month = -7 × treatment | $-16.656$* (8.449) |
| Num.Obs. | 22 629 |
| R2 | 0.848 |
| R2 Adj. | 0.839 |

## C.1 Summary Statistics

Table 7 is a summary statistics table comparing the control and treatment groups ridership and bikeway details. The Pre-period is 24 relative months before the treatment period, and Post-period is 24 relative months after the treatment period, while the Treatment-period spans 12 months.

Table 7: Summary Statistics between treatment and control groups

| Metric | Control Group | Treatment Group |
|---|---|---|
| Total Rides (Post) | 2,693,201.00 | 1,481,495.00 |
| Total Rides (Pre) | 1,344,689.00 | 635,865.00 |
| Total Rides (Treatment) | 1,093,183.00 | 440,216.00 |
| Mean Rides Adjusted (Post) | 107.77 | 331.92 |
| Mean Rides Adjusted (Pre) | 53.20 | 144.23 |
| Mean Rides Adjusted (Treatment) | 85.59 | 209.03 |
| Number of Bikeways | 1,005.00 | 186.00 |
| Protected Lanes | 0.54 | 0.50 |
| On-Road Lanes | 0.14 | 0.31 |
| Shared Roadways | 0.33 | 0.19 |

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