Bay Wheels Stations and Muni Bus Ridership in San Francisco

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Between 2019 and 2025, the Bay Wheels bikeshare network expanded across the Bay Area. At the same time, San Francisco Muni's (SFMTA) average weekday ridership collapsed during the COVID-19 pandemic and has recovered unevenly. This joint variation is my motivation for testing whether the opening of a bikeshare station near a bus route changes that route's average weekday ridership.

Bikeshare stations can act as either substitutes or complements to bus ridership. For example, a student might ride a Bay Wheels bike to school, acting as a substitute for taking Muni. On the other hand, they might choose to bike to a Muni stop and continue by bus, acting as a complement. I hypothesize opening a bikeshare station near a bus route reduces bus ridership through substitution.

To investigate this relationship, I constructed a route-month panel dataset between January 2019 and August 2025. I combined monthly Muni ridership data with Bay Wheels trip records and General Transit Feed Specification (GTFS) data. I calculated the distance between bus stops and bikeshare stations and defined treatment as the number of unique Bay Wheels stations within a 400 meter radius of a bus route's stops.

Using a two-way fixed effects (TWFE) model, I estimate the effect of station density on the average weekday ridership (log). I find that adding one more bikeshare station within 400 meters of a bus route is associated with a 1.47% increase in average daily bus ridership on that route. To support this result, I re-estimate the model using different buffer sizes and use an event study to show the parallel trends assumption holds.

The rest of this paper is organized as follows. Section 2 reviews prior work. Section 3 describes the data. Section 4 explains the empirical strategy and threats to identification. Section 5 presents the results. Section 6 concludes the paper.

Literature Review

My study is closely related to the broader literature examining the effects of bikeshare systems on external outcomes. However, within that literature, only a small number of them focus on San Francisco. This paper addresses that gap.

Campbell and Brakewood (2017) provide one of the earliest examples, exploiting the phased rollout of bikeshare stations in New York City. Using a difference-in-differences framework, they show that the installation of bikeshare stations along bus routes led to a reduction in daily ridership in Manhattan and Brooklyn. Graehler et al. (2018) expand the scope of study beyond New York to include multiple large U.S. cities. They use a panel random effects model and show that bikeshare programs decrease bus ridership.

Most recently, Huang et al. (2023) examined the staggered rollout of bikeshare systems across 36 cities in China using a difference-in-differences design. Their analysis focuses on dockless bikeshare systems, where bicycles can be rented and left without a docking station. They find that these systems significantly decrease bus ridership.

Data

I constructed a monthly route level panel dataset spanning January 2019 to August 2025. I combine three different datasets: SFMTA ridership, GTFS spatial data, and trip data from Bay Wheels. From the SFMTA ridership data, I use the average daily ridership by route and month as my outcome variable. I restricted the data to weekdays and removed transportation services including cable cars, streetcars, and Owl routes. To identify the location of each bus route's stops, I merged SFMTA's GTFS data to associate every bus stop with its own coordinate location. I then projected these coordinates to a metric system to allow for distance calculations in meters.

I inferred station opening dates using the Bay Wheels trip data, which contains over 20 million observations. I removed test stations and standardized station names. I defined a bikeshare station's opening date as the first month the station appeared in the dataset. The result is a dataset of unique stations along with their coordinates and timestamps for when they first appeared.

To measure the treatment variable, I used a spatial join between the bus stops and the bikeshare stations. For each bus stop, I created a 400 meter buffer zone and counted the number of unique Bay Wheels stations located within that zone. The result is a variable that serves as my treatment, allowing me to estimate how bus ridership changes as the density of nearby bikeshare stations increases.

Methodology

Two-Way Fixed Effects Model

To estimate the relationship between bikeshare station density and bus ridership, I use a two-way fixed effects model (TWFE). My estimation equation is:

$$\ln(Y_{it}) = \beta S_{it} + \gamma_i + \theta_t + \epsilon_{it}$$

where Y_{it} is the average weekday ridership on route *i* in month *t*. The continuous treatment S_{it} represents the number of unique Bay Wheels stations within 400 meters of route *i* in month *t*. I use the natural log of ridership as the outcome variable, so the coefficient β can be interpreted as a percentage change.

Some routes are simply busier than others regardless of stations. For example, the 49 Van Ness/Mission route passes through dense commercial areas while the 54 Felton mainly passes through residential neighborhoods. So, the 49 will almost always have higher ridership because of where it runs. To account for these differences route fixed effects γ_i are included in the model. The term θ_t denotes month-year fixed effects that capture shocks affecting all bus routes in the same period. Finally, ϵ_{it} is an error term clustered at the route and month-year levels.

Event Study

To justify interpreting the results as causal, I test the parallel trends assumption with an event study framework that replaces the treatment indicator with a set of event time indicators. I estimate a modified version of the TWFE model and follow the event study formulation in Matheus Facure Alves's *Causal Inference for the Brave and True* (2022):

$$\ln(Y_{it}) = \tau_{-5}^{lead} D_{it}^{-5} + \tau_{-4}^{lead} D_{it}^{-4} + \tau_{-3}^{lead} D_{it}^{-3} + \tau_{-2}^{lead} D_{it}^{-2} + \sum_{k=0}^{4} \gamma_k^{lag} D_{it}^{k} + \gamma_i + \theta_t + \epsilon_{it}$$

where D^k_{it} is an event time dummy. I define *k* as the number of months away from the first station installation. I bin the endpoints so that *k* = -5 includes all the months more than 5 months prior to the treatment, and *k* = 4 includes all months 4 or more months after the treatment. The reference month is the month before the first station opens or *k* = -1. The model also includes route fixed effects γ_i, month-year fixed effects θ_t, and the standard errors are clustered at the route and month-year levels.

Threats to Identification

The route-panel dataset is not balanced. The dataset contains 3,134 observations across 44 routes from January 2019 to August 2025. A balanced panel would include 80 months per route or 3,520 observations. These missing observations present a potential source of selection bias if the missing data is not random, making the estimates less reliable.

The model is subject to omitted variable bias. While the route and month-year fixed effects absorb time-invariant characteristics and global shocks, it does not control for localized events that change over time and affect specific routes. For example, the 49 Van Ness/Mission route saw significant reconstruction between 2016 and 2021. If ridership decreased due to this reconstruction rather than the introduction of bikeshare stations, the model will incorrectly attribute the ridership loss to the treatment.

There could be measurement errors in treatment timing and mapping. Because there is no official public record of Bay Wheels station installation dates, I used the first appearance of a station in the trip data as a proxy for the treatment start date. Changes in data schemas within the Bay Wheels trip data required filtering that may result in inaccurate first appearance dates. Moreover, some route identifiers were manually changed to standardize the data, possibly introducing classification error.

Results

Table 1 presents the estimates from the TWFE model. The results show that adding a Bay Wheels station within a 400 meter radius of a bus stop is associated with a 1.47% increase in average weekday ridership. To test the sensitivity of this result, the TWFE model was re-estimated using different buffer sizes. From Table 1, the estimates remain consistent and statistically significant across all sizes.

From Figure 3, the coefficients for the 400 meter buffer are statistically insignificant, suggesting that treated and control routes follow similar trends before the first station was installed. As shown in Figures 2 and 4, the parallel trends assumption also holds for the 300 meter and 500 meter buffer sizes. From Figure 3, the assumption does not hold for the 200 meter buffer as the coefficient at $k = -5$ is statistically significant.

Conclusion

This study investigates the impact of Bay Wheels bikeshare expansion on Muni bus ridership. I find that the addition of a station within a 400 meter radius is associated with a 1.47% increase in average weekday ridership. Contrary to my initial hypothesis of substitution, the results suggest a complementary relationship where bikeshare stations help riders travel to and from bus stops. The result remains consistent across different buffer sizes, and the event study analysis supports the parallel trends assumption for buffers at 300 meters and above. Future research should aim to use official station installation records and control for localized events that affect individual bus routes.

References

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Table 1: Regression Results Using Different Buffers

	200 Meters	300 Meters	400 Meters	500 Meters
Number of Stations	0.0289*** (0.0062)	0.0185*** (0.0038)	0.0146*** (0.0031)	0.0124*** (0.0027)
Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.0370	0.0441	0.0437	0.0443
N	3134	3134	3134	3134

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 1: 200 Meter Buffer

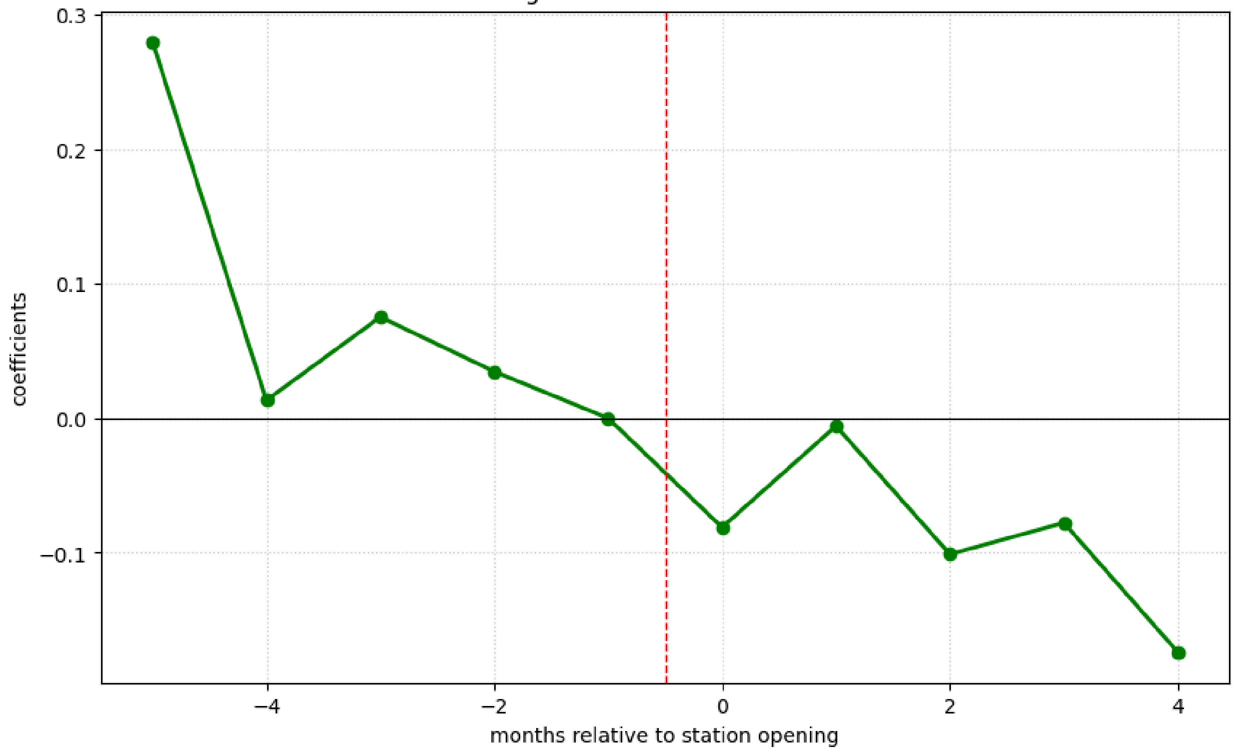

Figure 2: 300 Meter Buffer

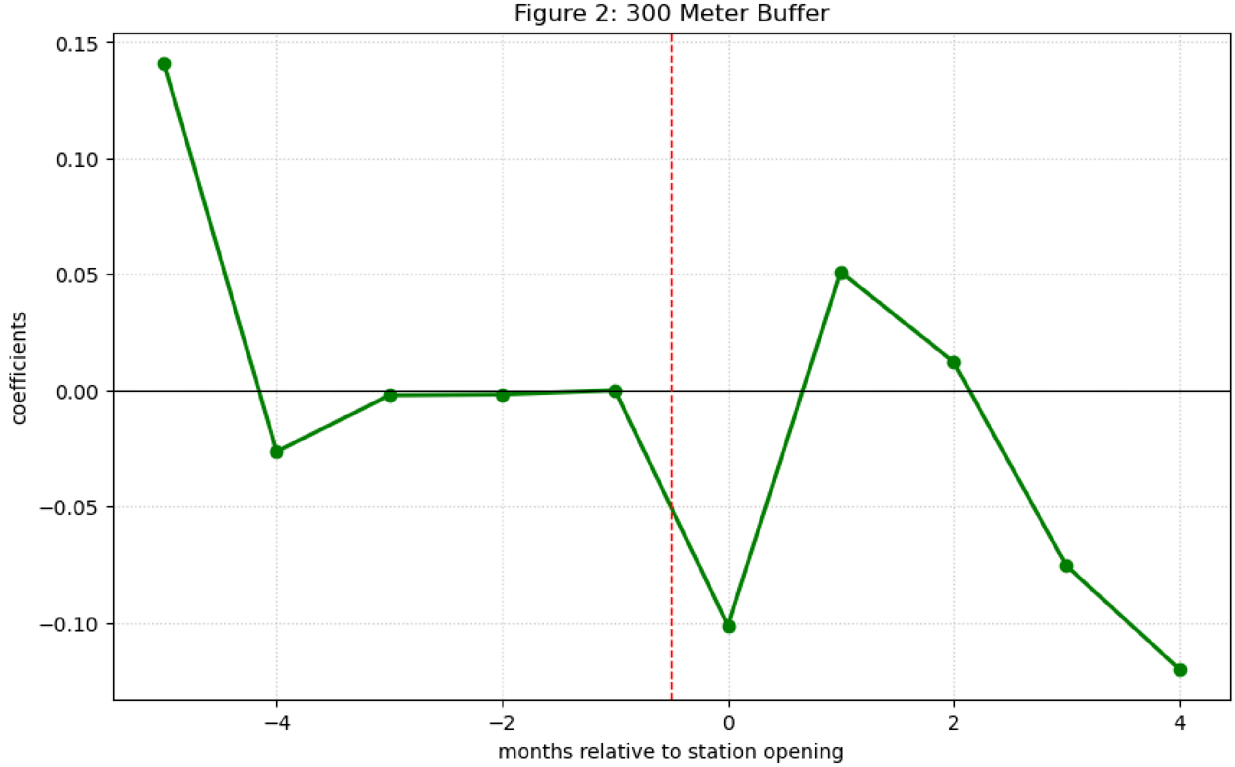

Figure 3: 400 Meter Buffer

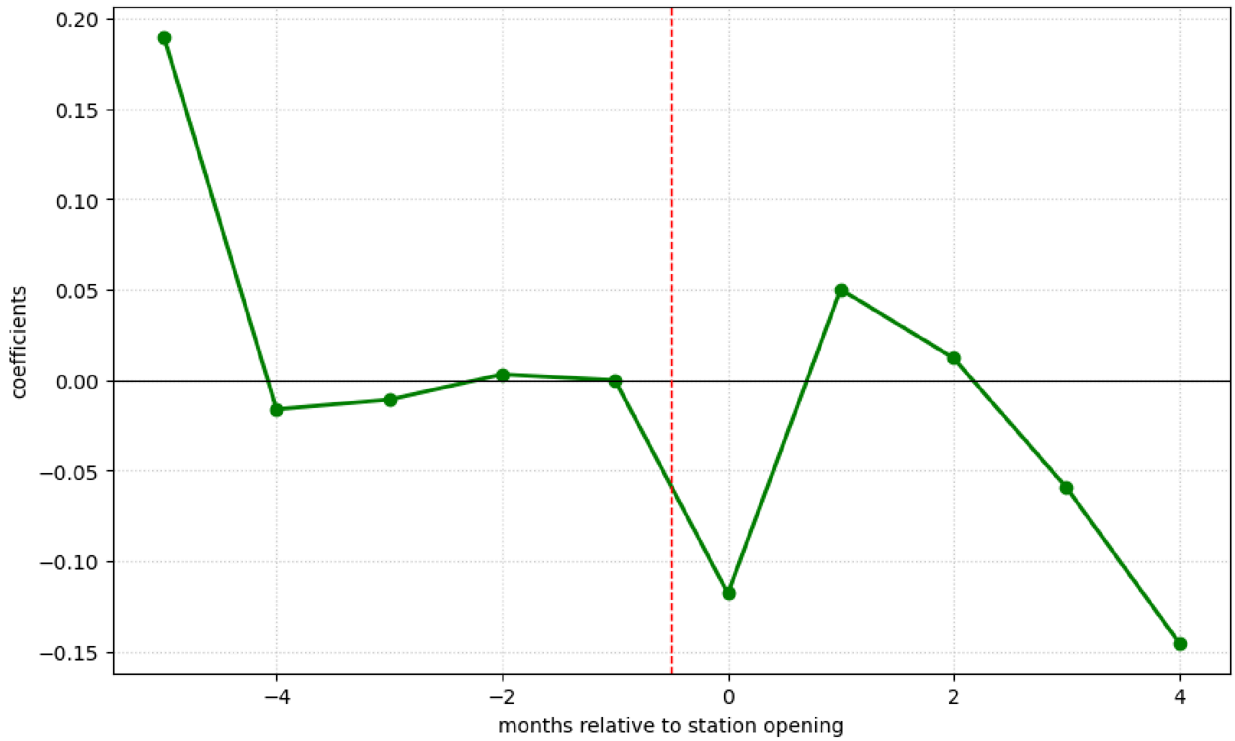

Figure 4: 500 Meter Buffer