Going the Extra Mile: Investigating the relationship between bikeshare and public transit

by Polly Ren

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Faculty Advisor: Crystal Bae
Environment, Geography and Urbanization Preceptor: Nina Olney

Division of the Social Sciences
Committee on Environment, Geography and Urbanization
The University of Chicago
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Abstract

Bikesharing has emerged as a popular response to the ever-growing need for sustainable, flexible transportation options in urban areas. With the ability to bridge the gaps in traditional transit networks, bikesharing offers a potential solution to the first-mile / last-mile problem, making it easier for commuters to connect to and from public transit. Despite its rapid adoption, little is known about how bikesharing trips interact with public transit usage on the aggregate. This research studies the complex interplay between bikesharing and public transit in three major U.S. cities: Chicago, New York City and Los Angeles. We use bikesharing trip data along with historical general transit feed specification data to investigate the extent to which bikesharing trips integrate with or substitute against public transit in these geographically and demographically distinct cities, as well as how various spatial, temporal and socioeconomic factors may influence these dynamics. Our findings reveal that modal integration is associated with higher service frequency of public transit, while modal substitution tends to be more common in dense urban cores. The interaction between bikesharing and public transit is also shaped by individual and neighbourhood-level social factors. Younger commuters, particularly in college neighbourhoods, and individuals from socioeconomically disadvantaged neighbourhoods are more likely to integrate bikesharing with public transit. Built environment differences between the three cities also influence how bikesharing is used in relation to public transit. These findings support the need to consider built environment and socioeconomic factors when planning for effective integration between bikesharing and public transit systems and, ultimately, sustainable and equitable urban transportation systems.

Keywords: bikeshare, public transit, modal integration, modal substitution, multimodal transportation, shared mobility, micromobility, first-mile / last-mile problem

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1 Introduction

How can we get from point A to point B? It's a question as old as time, yet it remains ever-relevant, especially in today's complex urban landscapes. In recent years, bikesharing has rapidly gained popularity in response to the growing demand for flexible, eco-friendly transportation options. The concept first took shape in 1965 with the launch of the Witte Fietsen ("White Bikes") program in Amsterdam, marking the beginning of a global movement towards shared micromobility. Shared micromobility refers to transportation options that provide users with short-term access to lightweight vehicles on an as-needed basis, including programs such as bikeshare, shared electric scooters and shared mopeds (Gkavra et al., 2025; Heumann et al., 2025; Kong et al., 2025). Since the inception of the White Bikes program, bikeshare programs have evolved through many iterations, with the introduction of program operators, customer tracking, coin-deposit systems, electronic docks and fobs, and telecommunication systems (DeMaio, 2009). Modern bikeshare systems often rely on smartphone apps, GPS tracking, real-time bike availability data and demand-responsive rebalancing, and include pedal-assisted electric bikes and dockless technology to improve convenience, user experience and operational efficiency (DeMaio, 2009; Lazarus et al., 2020). Today, there are more than nine million bikes in operation within bikeshare systems around the world, spanning over 2,000 cities (DeMaio & O'Brien, 2024). In the United States alone, 53 operators manage 8,838 docking stations, providing coverage across many urban areas, including Chicago, New York City, Los Angeles, Boston and Minneapolis ("Bikeshare and e-scooters in the U.S.", 2024).

The attractiveness of bikeshare systems is widely attributed to the range of health, environmental and social benefits they bring about. Cycling and bikeshare systems have been found to significantly improve public health outcomes by increasing physical activity and reducing urban air pollution and greenhouse gases (Chen et al., 2023; Clockston & Rojas-Rueda, 2021; DeMaio, 2009). For example, in Ningbo, China, public bikesharing lowers carbon emissions by an average of 1.97 kilograms per person (Lu et al., 2022). In the United States, bikeshare systems are estimated to prevent the loss of 737 disability-adjusted life years (DALYs) annually, contributing an estimated $36 million in health economic impact each year (Clockston & Rojas-Rueda, 2021). Bikesharing can also help normalise the image of cycling, promote a culture of cycling and encourage more active commuting, further supporting improved public health outcomes (Goodman et al., 2014; Shaheen et al., 2017). Bikeshare and bike rental schemes have been found to enhance bike-transit integration in general (Kager & Harms, 2017). This ultimately enhances the sustainability of the urban transport system by reducing reliance on private cars in favour of active commuting. Moreover, beyond these health and environmental advantages, bikeshare programs can also promote social equity, particularly benefiting low-income users, people of colour, and individuals without cars who rely on bikesharing for a variety of trip purposes (Mohiuddin et al., 2023). These systems can help improve the connectivity, liveability and health of disadvantaged communities (Oates et al., 2017).

1.1 The first-mile / last-mile problem

In addition to the plethora of health, environmental and social benefits, bikeshare systems offer a viable solution to the first-mile and last-mile (FMLM) problem, which refers to the challenge of connecting riders between transit stops and their origin or destination (Romm et al., 2022). The roots of this problem stem from the infeasibility of public transit systems to completely cover areas within a city, leaving riders to find alternative means of travel to connect from their points of origin or destination to transit hubs. This gap can limit the effectiveness of public transportation, reduce accessibility and discourage the use of public transit altogether, particularly for those without private vehicles or in areas with limited transit coverage (Park et al., 2021). The use of multiple transportation modes by way of shared micromobility systems such as bikeshare can help extend the range of public transportation and provide a sustainable, convenient, flexible and cost-effective mode of transportation (Chiou & Wu, 2024; Kager & Harms, 2017; Pucher & Buehler, 2017). In addition, cycling enables individuals to access more distant transit options than otherwise accessible via walking, and bikeshare in particular can increase accessibility of employment opportunities when compared to rail (Welch et al., 2020).

However, do bikeshare systems truly serve as the connector for areas with limited transit availability, enhancing the accessibility of the transportation network as intended? Or do they inadvertently introduce competition and substitution between the two modes, potentially complicating efforts to build an integrated, multimodal system? Understanding the dynamic relationship between bikeshare and transit can inform the design of transportation systems that facilitate the seamless integration between these modes and optimise the benefits of each. Through effective integration, bikeshare can bridge critical gaps in transit coverage, making it easier for individuals to access public transit and reducing the dependence on private vehicles. At the same time, patterns of substitution can reveal shortcomings in the existing transit network, such as limited coverage or poor service quality. For urban planners and policymakers, facilitating multimodal transportation options like bikeshare is not only a step towards increasing public transit usage but also an avenue for fostering a more connected and environmentally friendly urban mobility network. By encouraging the integration of transit systems and shared mobility solutions, cities can create transportation systems that are both accessible and environmentally friendly, ultimately supporting more resilient and inclusive urban environments.

1.2 Research and conceptual framework

Bikeshare systems, when effectively integrated with public transit, can significantly enhance urban mobility by improving transit accessibility, promoting active transportation and supporting equitable access to mobility options. However, these benefits may not be distributed uniformly across time and space. Motivated by these disparities, this research seeks to answer the following questions:

1. To what extent is bikesharing used to integrate with public transit, and to what extent is bikesharing used to substitute against public transit?
2. How do underlying built environment, demographic and socioeconomic, and mobility factors shape these interactions?

To address these questions, this thesis performs statistical and spatial analyses using bikeshare trip records and public transit schedules across three cities: Chicago, New York City and Los Angeles. These cities are intentionally selected for their distinct transportation infrastructures, urban forms and socioeconomic landscapes. Chicago, characterised by its radial street grid, extensive rail and bus networks and centralised business district, provides a model of a highly transit-oriented city with a growing bikeshare presence. New York City, with its dense, multi-modal transportation system and large-scale adoption of bikesharing, offers a complex setting to examine how bikesharing functions in a transit-saturated environment. Los Angeles, by contrast, represents a sprawling, car-dependent city where recent investments in both public transit and bikesharing present an opportunity to explore the role of active transportation in less traditionally transit-reliant contexts.

For each city, bikeshare trips are classified as either modal integration or modal substitution trips based on their spatial and temporal connections to public transit systems. These classifications are then contextualised by analysing built environment characteristics, demographic makeup, and socioeconomic profiles of the nearby communities. This approach enables a multi-layered understanding of the factors that influence bikeshare usage patterns in relation to public transit. Through this integrated analysis, the research empirically substantiates the following thesis statement: **Built environment, demographic, socioeconomic and transit accessibility factors at the community and census tract level influence the extent to which bikeshare systems are used to integrate with or substitute against public transit.**

1.3 Roadmap

This thesis starts by discussing the existing literature on multimodal transportation, bikeshare and public transit in Section 2. Section 3 outlines the data sources and details the classification methodology developed to integrate and analyse these various sources. The results of these analyses are presented and interpreted in Section 4, followed by a discussion of their implications and limitations in Section 5.

2 Background and related work

This section discusses the background for this thesis and prior work relating to bikeshare and public transit, exploring the spatial, temporal and socioeconomic dimensions of multimodal transportation. Key areas of discussion include the influence of urban design and the built environment, the role of socioeconomic and demographic factors and the impact of mobility and accessibility in informing bikeshare usage and public transit interactions.

2.1 Dimensions of multimodal transportation

Multimodal transportation encompasses the complex interactions between various modes of travel. Within multimodal transportation, research tends to align with three broad themes: *urban design and the built environment*, which examines the influence of infrastructure on transit accessibility and integration; *socioeconomic and demographic influences*, which explores how social and economic factors shape who uses these systems and the benefits they derive; and *mobility and accessibility*, which investigates how user preferences and decisions influence transportation mode selection. This subsection discusses how the existing literature addresses these themes, particularly in the context of bikeshare and public transit.

2.1.1 Urban design and the built environment

The built environment and the physical infrastructure of an urban area play a pivotal role in shaping the modes of transportation that its inhabitants use. Cao et al., 2007 highlight how increases in accessibility, safety and social opportunities can reduce car reliance and promote active transportation modes like biking and walking. Walkability and bikeability have also been found to be key determinants of biking frequency; individuals are more inclined to bike more frequently in areas with higher bikeability indices, and individuals who live in highly walkable neighbourhoods also tend to walk and bike more, on average (Codina et al., 2022; Wali et al., 2024).

The connectivity within the built environment also plays a critical role in facilitating multimodal travel. Li et al., 2020 emphasise the importance of well-connected transit systems in supporting bikeshare as a feeder mode to the metro, while Koh and Wong, 2013 highlight how safety, comfort, aesthetics and accessibility of bike routes drive multimodal usage to a greater extent than the distance to-be-travelled and hence, the time required for the trip. Similarly, Sun et al., 2017 reveal that bus transit often complements bikeshare better than rail, due to the flexibility of bus routes and their accessibility to diverse locations. For bikeshare and metro systems in particular, Rogers et al., 2023 also identify connectivity and the density of bikeshare stations near transit as critical for integration. In addition to connectivity and bikeability, the built environment also informs the types of bikeshare infrastructure present. Station-based systems (with docked bikes) tend to be favoured in areas with a high concentration of travel demand and close proximity to metro stations and commercial properties; on the other hand, free-floating systems (with dockless bikes) are commonplace in areas with a higher density of major roads and housing (Cheng et al., 2020). The bikeshare options in the three cities of interest involve a hybrid of docked and dockless bikes.

However, these built environment effects are not always linear; factors such as population density and land use support integration up to a point but may diminish utility in overly dense environments (Cheng et al., 2022). In dense cities like Washington, D.C., bikeshare has been found to serve as a substitute for public transit but as a complement in more sprawling cities like Minneapolis (Shaheen et al., 2017). Moreover, the built environment factors are likely to vary between the trip origin and destination, with several built environment factors such as intersection, link and cul-de-sac density having a greater influence at the destination compared to the origin (Hurvitz & Moudon, 2012; Welch et al., 2020). Together, these studies illustrate how the built environment and physical infrastructure mediate the interactions of different modes of transportation across different urban contexts.

2.1.2 Socioeconomic and demographic influences

Socioeconomic and demographic factors also significantly shape how individuals interact with transportation systems, reflecting broader patterns of income, education, age and cultural attitudes towards mobility. Appleyard and Ferrell, 2017 highlight how crime significantly affects modal choices, distinguishing between *exposed* modes—those that pose a risk of personal harm, such as walking and public transit—and *property* modes, which involve the risk of property loss or theft, such as biking. They find that exposed modes are more sensitive to violent crime, whereas property modes are more affected by property crime at destinations. These findings suggest that in high-crime areas, individuals might prefer bikeshare over personal bikes to avoid theft risks or might avoid public transit entirely, using bikeshare as a substitute (Appleyard & Ferrell, 2017). Lusk et al., 2019 extend this by exploring perceptions of safety in lower-income, higher-crime neighbourhoods, finding that improved infrastructure can help mitigate safety concerns.

Bikeshare has been found to be an effective transportation option for individuals living in disadvantaged urban areas to improve the connectedness, livability and health of these communities (Oates et al., 2017). Low income households that earn less than 30% of median income generally have a higher demand for public transit to connect to job and other opportunities, as they tend to have more limited access to personal vehicles (Haughey & Sherriff, 2010; Oh & Chen, 2022). However, in reality, Qian and Jaller, 2020 observe that bikeshare usage is comparatively lower in those same communities as a result of the absence of employment opportunities nearby, whereas Oates et al., 2017 find that neighbourhoods with higher levels of socioeconomic disadvantage tend to have greater bikeshare usage. The results of these studies reveal that socioeconomic indicators shape bikeshare usage in complex and potentially contradictory ways.

Age also plays an important role: younger commuters may be drawn to the cost-effectiveness of integrating bikeshare with transit, whereas older people are more sensitive to the distance to transit and availability of transit facilities (Liu et al., 2020; Yang et al., 2022). Household size and the per-capita access to personal vehicles also influence modal choice, with larger families and higher per-person car ownership favouring driving for commutes rather than walking or biking (Tilahun et al., 2016). Education level has also been found to shape transportation preferences; cyclists with higher educational attainment are often more open to cycling for transportation (Ji et al., 2024; Xing et al., 2010). These tensions highlight the complex interplay between the various socioeconomic factors; it is critical to consider these complexities to ensure equitable and effective transportation systems across communities.

2.1.3 Mobility and accessibility

People travel for many reasons—commuting to work, running errands or recreational outings—and their transportation choices often reflect these varied purposes. In addition to the built environment and socioeconomic factors previously discussed, research on mobility and choice highlights the nuanced factors influencing individual travel decisions, such as user preferences, perceptions of safety and convenience, and the overall availability of transportation options. L. Ma et al., 2014 emphasise that it is not only the objective environment but also perceptions of safety and accessibility that inform these preferences and, ultimately, decisions. Similarly, Stinson and Bhat, 2004 conclude that perceptions of safety, travel time and bike lane and bike facility availability influence route choice and frequency of bicycle community, while Xing et al., 2010 show that community attitudes and supportive infrastructure encourage biking over other modes. Anable and Gatersleben, 2005 add that convenience, flexibility, predictability and reliability are key for work trips, while freedom, relaxation and the absence of stress are more important for leisure trips. Understanding these subjective and contextual factors is essential for interpreting how individuals navigate multimodal travel environments.

In this context, transit accessibility emerges as a critical determinant of mobility choices. The location of bikeshare docks plays an important role in which communities have access to bikeshare, and numerous studies have examined the optimal placement of these bikeshare docks, considering economic efficiency and equity concerns (Banerjee et al., 2020; Jiang, 2022; Nikiforiadis et al., 2021; Qian et al., 2022; Wilkesmann et al., 2023). Proximity to bikeshare docks benefits disadvantaged communities, in particular, by increasing access to jobs and other essential services (Qian & Niemeier, 2019). Individuals whose workplaces are further from bus stops have also been found to engage less with active commuting, as transit accessibility has a strong influence on whether an individual ultimately chooses to use transit (Sun et al., 2017; Tilahun et al., 2016; Wali et al., 2024). This is consistent with Xylia et al., 2024, who find that physical accessibility is one of the top three determinants of modal choice, with the other two determinants being reliability and punctuality. In the context of bikeshare-metro integration, Liu et al., 2022 highlight how perceptions of train congestion and multiple transfers discourage integration, while the availability of shared bikes facilitates it. Proximity and accessibility influence the ease and convenience with which individuals use bikeshare and commute actively in general. Together, these studies illustrate the complex interplay of individual preferences, infrastructural and socioeconomic factors in shaping multimodal transportation.

2.2 Bikeshare and public transit

Many existing studies underscore the complexity of the relationship between bikeshare and public transit, a relationship that can be both complementary and competitive in nature (Kager & Harms, 2017; Welch et al., 2020). Martin and Shaheen, 2014, for instance, highlight the spatial distinctions within this relationship, noting that bikeshare often serves as a substitute for public transit in densely populated urban cores, while in less dense peripheral areas, it functions more as a complement. This spatial difference is further nuanced by observed shifts in public transit modes: bikeshare is associated with increased bus use but reduced rail usage, suggesting that bus networks may be more amenable to integration with bikeshare than rail in urban cores (Martin & Shaheen, 2014).

Demographic factors also influence this integration. Young adults, particularly those aged 18-30, are the most active in integrating bikeshare and metro systems, especially near the central business district (Liu et al., 2020). This pattern aligns with the notion that bikeshare appeals to commuters seeking flexible, multimodal options, especially among younger users who may not own a car or earn enough income to consider other transportation options. Meanwhile, Kong et al., 2020 complicate this understanding by examining bikeshare-public transit relationships across multiple U.S. cities, including Chicago, New York, Washington, D.C. and Boston. Their findings reveal that, while bikeshare-transit integration is significant during weekdays across all these cities, bikeshare tends to substitute public transit on weekends. This temporal variation suggests that *when* the trip occurs influences the relationship between the two modes more than *where* the trip takes place or who takes the trip (Kong et al., 2020). Moreover, they found that modal integration trips generally involve shorter bikeshare trips and begin in areas with higher public transit service frequency.

2.3 Research motivation and relevance

As discussed in Section 1, the integration of bikeshare and public transportation is desirable because it promotes active transportation, reduces greenhouse gas emissions and enhances the overall efficiency, accessibility and sustainability of urban transportation systems. Understanding the factors that drive this integration is critical to designing systems that can promote multimodal transit in a sustainable and equitable way.

While a number of studies explore how individuals integrate bikeshare and public transportation in specific subsets of the population, there has been limited work on these modal choices on an aggregate level. Even fewer studies have attempted to quantify the spatial, temporal and socioeconomic factors that drive these relationships. This research seeks to address these gaps by examining and statistically quantifying bikesharing and public transportation integration at an aggregate level to uncover overarching trends and patterns that may remain obscured in smaller, isolated studies. Quantifying these factors allows for a clearer understanding of the extent to which each factor influences multimodal travel behaviour, providing insights into their individual and combined impacts. Ultimately, this understanding will offer a more holistic view of how bikesharing systems interact with public transportation networks, highlighting key factors that influence multimodal travel behaviour across diverse urban environments. By examining spatial, temporal and socioeconomic drivers more broadly, this research can inform the development of more equitable and efficient transportation policies, as well as guide decisions on infrastructure improvements and strategies to promote sustainable, integrated mobility solutions that are tailored to the needs and preferences of diverse communities.

3 Data and methodology

This section describes the data sources used throughout this research, as well as the methodology employed to classify bikeshare trips as either modal integration or modal substitution. This section also introduces the spatially weighted ordinary least squares regression and spatial lag of X model used for the analyses.

3.1 Data

This subsection outlines the datasets used to investigate bikeshare-transit interactions. The regression variables chosen to capture socioeconomic, transit accessibility and built environment characteristics are also discussed.

3.1.1 Bikeshare data

Ride history data in Chicago, Los Angeles and New York City are publicly available on the respective bikeshare operator's official website. This data was downloaded and analysed for the 2023 calendar year across the three bikeshare systems in Chicago (Divvy), Los Angeles (Metro Bike Share) and New York City (Citi Bike) ("Citi Bike System Data", 2023; "Divvy Data", 2023; "Metro Bike Share", 2023). The ride history data contains information on each trip's duration, date, starting and ending time, origin and destination stations and the geographic coordinates of these stations, bike type (regular or electric bike), and user type (subscriber or customer). Monthly and hourly usage patterns, along with trip duration trends, are shown in Figures A.1, A.2 and A.3, offering an overview of bikeshare activity across the three cities. This data provides the spatial and temporal context that will facilitate the association between bikeshare and public transit trips. This methodology is discussed in greater detail in Section 3.3.

	Chicago	New York City	Los Angeles
Total bikesharing trips, filtered	3,904,668[a]	30,801,156[b]	327,535[c]
Member / casual counts			
Member	2,597,823	25,225,065	250,142
Casual	1,306,845	5,576,091	77,393
Bike type counts			
Classic (non-electric) bike	2,543,613	15,340,611	155,109
Electric bike	1,361,055	15,460,545	172,426

[a] Total Divvy trips in 2023 before filtering: 5,719,877
[b] Total Citi Bike trips in 2023 before filtering: 35,107,030
[c] Total Metro Bike Share trips in 2023 before filtering: 441,110

Table 3.1: **Bikeshare trip counts.** These counts include the bikeshare trips in each city made in 2023 that start and end at a station. The data was filtered to exclude trips ending at the same station as their starting point, and trips shorter than 1 minute or longer than 90 minutes.

3.1.2 General Transit Feed Specification (GTFS) data

General transit feed specification, or GTFS, data is a standard format for representing public transit routes, stops and schedule data. The 2023 historical GTFS data was sourced from Transitland, an open-data repository containing current and historical transit data feeds for over 2,500 transit operators ("Welcome to Transitland", 2025). This data was then filtered and parsed for buses and trains operated only by the Chicago Transit Authority (CTA), Los Angeles County Metropolitan Transportation Authority (Metro) and the Metropolitan Transportation Authority (MTA). Since Transitland aggregates GTFS feeds over irregular intervals of time between different transit options, the transit schedule from the beginning of each quarter was chosen as the representative schedule for that quarter to ensure consistency across transit options and maintain computational manageability. From that data, the route ID, route type and the scheduled arrival and departure times were extracted for each stop along the planned transit route. This location and scheduling information enables the inference of bikeshare trips as modal integration or modal substitution in relation to public transit. The approach used for integrating these data sources to classify trips is discussed in Section 3.3.

3.1.3 Socioeconomic, accessibility and built environment data

To understand the community-level factors influencing the relationship between bikeshare and public transit interactions, socioeconomic, built environment and transit accessibility data are integrated into the analysis. Socioeconomic and demographic characteristics influence transportation choices, while the surrounding built environment affects bikeshare accessibility and connectivity to transit infrastructure.

Socioeconomic and demographic data was sourced from the United States Census Bureau's American Community Survey (ACS) 5-year estimates from 2023 and the Longitudinal Employer-Household Dynamics (LEHD) Workplace Area Characteristics (WAC) dataset from 2022. These sources provide insight into the sociodemographic context of the areas examined, including median household income, the number of households with children, the number of housing units and the number of jobs at the granularity of the census tract. In addition to socioeconomic and demographic characteristics, ACS data further captures patterns in commuting and mobility at the tract level. This includes information on workers' modes of transportation, in particular, whether they walk to work. To approximate transit accessibility, this data was augmented with data on the number of transit stops per census tract using Transitland stops data, as well as data on the number of bikeshare docks in each tract derived from station information published by each bikeshare provider.

The built environment also provides crucial spatial context that influences bikeshare integration with public transit. Factors such as urban form, number of streets and intersection density shape how easily bikeshare can be incorporated into daily travel patterns. Rather

Variable	Description	Mean (Standard deviation) Chicago	New York City	Los Angeles
Urban design and built environment				
Number of streets[a]	Number of streets in tract	145.9 (91.35)	45.08 (42.75)	100.32 (87.72)
Intersection density[b]	Real nodes divided by tract area	339.25 (165.36)	267.98 (134.06)	202.51 (87.26)
Average traffic[c]	Mean of average daily traffic counts	21,049.7 (35,118.96)	16,154.32 (24,073.98)	22,704.93 (12,025.64)
Socioeconomic and demographic				
Median HH income[d]	Median income of households	93,875.74 (46,646.94)	90,049.12 (48,546.06)	70,434.39 (34,547.2)
HHs with children[d]	Number of households in tract with children	708.2 (480.94)	1039.65 (740.39)	525.21 (373.55)
Number of housing units[d]	Number of houses and other living quarters intended for occupancy	1,907.78 (1,233.6)	2,029.72 (1,292.13)	1,712.88 (801.9)
Number of jobs[e]	Number of jobs in tract	3,398.3 (18,869.9)	3,374.61 (8,372.44)	4,759.06 (11,696.76)
Mobility and accessibility				
Number of transit stops[f]	Number of bus and rail stops	14.0 (10.29)	5.9 (4.2)	9.2 (9.22)
Number of docks[g,h,i]	Number of bikeshare docks	1.86 (1.7)	2.16 (1.45)	1.61 (1.04)
% commute by walk[d]	Proportion of workers aged 16+ who commute to work by walking	0.07 (0.1)	0.11 (0.1)	0.09 (0.1)

[a] Pan et al., 2024
[b] Ailshire et al., 2023
[c] Finlay et al., 2022
[d] United States Census Bureau, American Community Survey, 2023
[e] United States Census Bureau, Longitudinal Employer-Household Dynamics, 2023
[f] "Transitland", 2025
[g] "Divvy Data", 2023
[h] "Citi Bike System Data", 2023
[i] "Metro Bike Share", 2023

Table 3.2: **Regression variables, data sources and descriptive statistics.** This table shows the regression variables and their mean and standard deviations in each city.

than relying on aggregate indices such as a bike or walk score, which attempt to summarise these characteristics into a single metric, I used built environment measures that directly capture the underlying factors that influence bikeshare feasibility. This data was obtained from the National Neighborhood Data Archive (NaNDA), an open data repository run by the University of Michigan Institute for Social Research, which contains various measures of the physical, demographic and social environment at different spatial scales across the United States (Ailshire et al., 2023; Finlay et al., 2022; Pan et al., 2024).

A summary of the demographic, socioeconomic, mobility and built environment data sources and variables used can be found in Table 3.2. This comprehensive approach allows for the examination of how socioeconomic characteristics, urban infrastructure and commuting patterns at the census tract level influence bikeshare-transit integration and, more generally, multimodal travel behaviour.

3.2 Public transit coverage measurement

Survey results and prior research have confirmed that the distance between the bikeshare dock and transit station plays a major role in users' decision to integrate the two transit modes (Médard de Chardon et al., 2017). To effectively quantify the relationship between bikeshare and public transit, I leverage the concept of *coverage*, which measures how transit services are distributed within a walkable radius (Eboli et al., 2014; Kong et al., 2020). This metric reflects the spatial availability and accessibility of bikeshare stations from transit stops. Many existing studies use a 200-500 metre buffer region around bikeshare docks to capture trips that feasibly connect with public transit, a distance that can reasonably be covered in ten minutes of walking (Bachand-Marleau et al., 2012; Kong et al., 2020; T. Ma & Knaap, 2019; Qian & Jaller, 2020; Tarpin-Pitre & Morency, 2020). A 400-metre threshold strikes a practical balance, capturing most realistic bikeshare-transit connections while excluding outliers, so 400 metres was chosen as the threshold distance to measure coverage.

3.3 Classifying trips as modal integration or substitution

Bikeshare systems tend to operate independently from public transportation systems. For example, in Chicago, buses and trains are operated by the Chicago Transit Authority and Metra, whereas the Divvy bikeshare system is owned by the Chicago Department of Transportation and operated by Lyft ("About Divvy", 2025). Due to the independence of these entities, bikeshare and public transit data are rarely integrated, making it difficult to determine which bikeshare trips are used to connect to public transit and which function as independent, alternative modes of transportation. Moreover, transit providers do not provide the station-level boarding information required to accurately map bikeshare trips to specific transit connections. Without direct links from bikeshare trips to transit boarding, the purpose of a bikeshare trip in relation to public transit usage must be inferred from bikeshare and historical public transit GTFS data.

To address these challenges, Kong et al., 2020 developed a method classifying bikesharing trips as modal integration, modal substitution or modal complementation using trip characteristics such as origin, destination and duration while considering GTFS information of nearby transit options. A modified version of this method was applied to classify bikesharing trips as either modal integration, modal substitution or neither; a diagram of this modified approach is illustrated in Figures 3.1 and 3.2. Importantly, this classification using bikeshare trip time and location to infer the purpose of that trip; hence, it imperfectly captures integration and substition dynamics at best. The limitations of this classification methodology are discussed in greater detail in Subsection 5.2.

3.3.1 Modal integration

Modal integration (MI) refers to trips that use bikeshare to connect to or from public transit. This occurs when either the trip origin or the trip destination, or both, is within 400 metres of a transit station. The former represents the potential use of bikeshare as a last-mile solution (MI-LM) to connect from a transit station to the final destination, so the starting time of the bikeshare trip should also be within 10 minutes after a bus or train arrives at a nearby station, given that typical transit users are willing to wait between 5-10 minutes for a bus (Arhin et al., 2019). The latter represents the potential use of bikeshare as a first-mile solution (MI-FM) to connect to a transit station from an initial origin; the ending time of MI-FM trips should be within 10 minutes before a bus or train departs from a nearby station. A bikeshare trip can also be used to connect between transit stations, in which case it is classified as both a first-mile and last-mile solution (MI-FLM).

Moreover, trips that exceed two miles are unlikely to serve as connections to or from

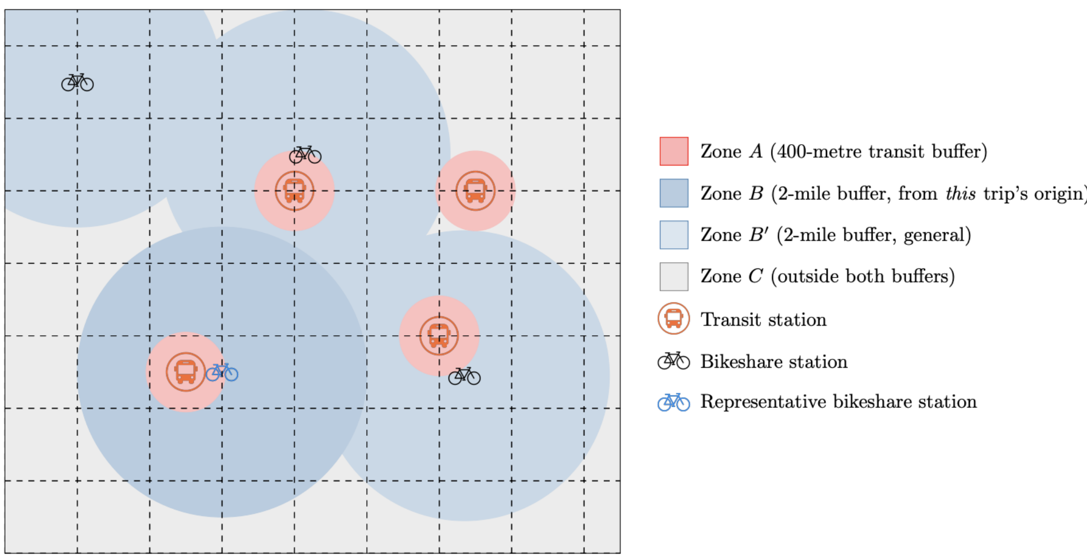

Figure 3.1: **Bikeshare and transit buffer zones.** This illustration shows the relationship between bikeshare and transit buffer zones. Zone A represents the 400-metre buffer around a transit stop; trips starting or ending in this buffer are considered to originate or terminate "near" a transit stop. The blue bike icon represents the representative bikeshare station. Zone B represents the 2-mile buffer around this representative station; this demarcates the region in which the bikeshare trip originating from the representative bikeshare station should end (approximated by time) in order to be considered as a potential modal integration trip. Each non-representative bikeshare station has a 2-mile buffer, denoted Zone B'. Finally, Zone C represents the area outside both the transit and bikeshare station buffers; however, because this research consider only trips that begin and end at a bikeshare station, all trips, for these purposes, occur between Zones A and B or B'. These zones are used for buffer analysis, which is described in Section 3.3 and Figure 3.2.

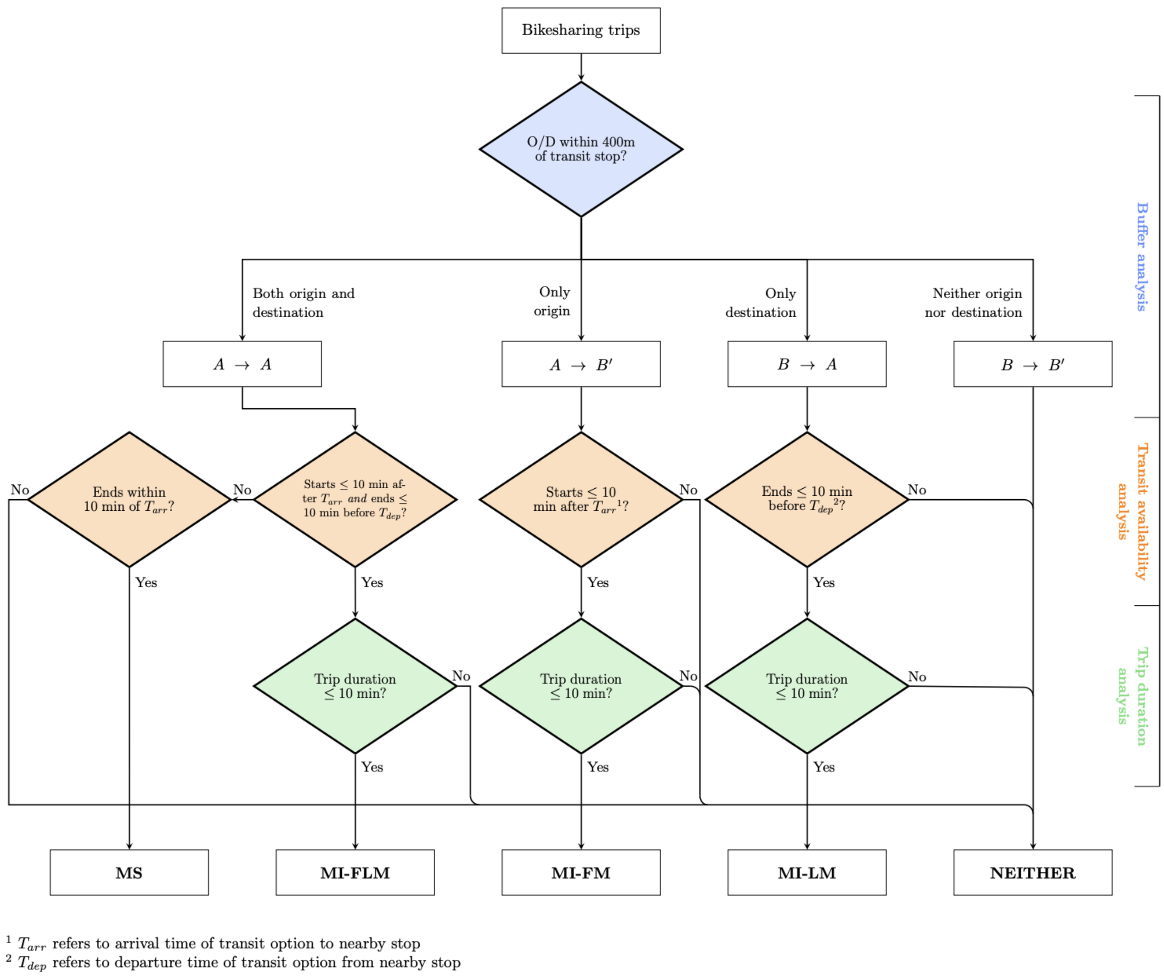

Figure 3.2: **Bikeshare trip classification framework.** The classification involves a three-step approach based on trip origin and destination, public transit availability and trip duration. In relation to public transit, bikeshare trips are ultimately either modal integration trips (MI) or modal substitution trips (MS). Trips that are neither modal integration nor modal substitution are classified as neither. Modal integration trips are further classified as either first-mile (MI-FM), last-mile (MI-LM) or both (MI-FLM). The zones used for buffer analysis are illustrated in Figure 3.1.

transit, so I stipulate that MI trips of all types should not exceed this distance. However, shared bikes are typically not GPS-tracked, meaning bikeshare data records only the Cartesian distance between the origin and destination, which does not accurately reflect the route taken or the true distance travelled by the rider. Therefore, trip duration is instead used as a proxy for the true distance travelled. Assuming an average cycling speed of 12 miles per hour, MI trips of all types are restricted to be no longer than 10 minutes in duration, in addition to the criteria above (Eriksson et al., 2019).

3.3.2 Modal substitution

Modal substitution (MS) refers to trips that use shared bikes to replace public transit altogether. For a particular bikeshare trip, this occurs when both the trip's origin and destination are within 400 metres of a transit station, and the trip's ending time is within 10 minutes of a bus or train arriving at a nearby station. This captures the bikeshare trips that serve as a substitute for a transit segment, where the rider had the option to feasibly take public transit but ultimately chose to use bikeshare instead. Notably, no requirements are imposed on the trip's starting time in relation to transit departure; this choice allows flexibility for riders to adjust their trip schedule, such as departing earlier, to use bikeshare instead of public transit.

3.3.3 Computing the proportion of modal integration and modal substitution trips at the census tract level

After classifying all trips, the trips are aggregated by the census tract of their origin. Census tracts with fewer than 100 trips over the course of the year are removed, as they introduce excessive noise and may not provide reliable estimates of modal integration and substitution patterns. The proportion of modal integration (MI) trips originating in each census tract is used to quantify the extent to which bikeshare trips serve as a complement or substitute for public transit. It is calculated as follows:

$$\text{MI proportion in tract } i = \frac{\text{Number of MI trips starting in tract } i}{\text{Total bikeshare trips in tract } i}$$

The number of MI trips is the sum of the number of MI-FLM, MI-FM and MI-LM trips. An analogous approach is used to compute the proportion of MI trips ending in each census tract. These origin and destination proportion computations were then repeated for modal substitution trips.

3.4 Regression analysis

After all bikesharing trips are classified, regression models are applied to explore how built environment, socioeconomic and mobility factors influence the proportions of modal integration (MI) and modal substitution (MS) trips at the census tract level. The objective of this analysis is to identify key factors that influence bikeshare's role in multimodal transportation and assess how different urban contexts across different cities shape these interactions.

The dependent variable in each regression model is the proportion of trips in a given census tract classified as either MI or MS, described in Subsection 3.3.3. The regressors, described in Subsection 3.1.3, are used to capture features of the built environment, socioeconomic characteristics and mobility opportunities that may shape bikeshare usage patterns in a given census tract. To ensure the reliability of the regression models, independent variables with high variance inflation factor (VIF) values were examined for redundancy, and adjustments were made where necessary to improve model interpretability and avoid issues arising from multicollinearity. The regression analysis was conducted separately for each city to account for regional differences in urban form and transit network characteristics. Furthermore, to ensure comparability across regressors with different units and scales, these regressors were standardised by subtracting the mean and dividing by the standard deviation. Standardising the variables allows for a more direct comparison of effect sizes across different features while also improving numerical stability in the regression models. The regression model is given by:

$$\mathbf{Y} = \mathbf{X}\beta + \epsilon$$

where $\mathbf{Y}$ is the vector of MI or MS proportions across all the census tracts in a city, $\mathbf{X}$ is a matrix of the various explanatory variables for each tract, β is a vector of regression coefficients and ϵ is a vector of error terms.

The regression analysis was conducted separately for each city to account for regional differences in urban form and transit network characteristics; for instance, built environment characteristics that may influence bikeshare usage patterns in Los Angeles could have very different effects on bikeshare usage pattern in Chicago or New York City. In addition to accounting for city-level differences, trip origins and destinations are modelled separately. Specifically, modal integration proportion at the trip origin, modal integration proportion at the trip destination, modal substitution proportion at the trip origin and modal substitution proportion at the trip subsitution are separately modelled. This distinction allows for the determination of whether certain environmental, socioeconomic or mobility factors exert different influences depending on where bikeshare trips begin versus where they end; existing studies have found that the level of influence that each factor has varies between the trip's origin and destination (Tilahun et al., 2016).

3.4.1 Spatial weights matrix

Given the inherently spatial nature of the data, it is necessary to account for spatial dependencies when modelling the relationship between bikeshare usage and environmental, socioeconomic and mobility factors. Tobler's first law of geography says that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). Ignoring this spatial dependence can lead to biased estimates, making spatial econometric techniques important in this analysis (Anselin & Griffith, 1988).

A spatial weights matrix, $\mathbf{W}$, is constructed to encode the spatial relationships between census tracts. The spatial weights matrix is used to introduce spatial structure into the regression models, allowing spillover effects from neighbouring tracts to be effectively captured. The elements of the spatial weights matrix, w_{ij}, define the degree of spatial connectivity between census tract i and census tract j. Because bikeshare data has low contiguity in Los Angeles and the cleaning process described in Subsection 3.3.3 removed some otherwise contiguous census tracts, a traditional contiguity-based spatial weights matrix would result in many tracts having no defined neighbours and thus limit the ability to model spatial dependencies effectively. As such, a distance-based approach is used to construct the weights matrix with a 1-mile threshold. That is, census tracts whose centroids are within one mile of one another are considered neighbours:

$$w_{ij} = \begin{cases} 1 \text{ if tract } i \text{ is within 1 mile of tract } j \\ 0 \text{ otherwise} \end{cases}$$

To ensure comparability across tracts with varying numbers of neighbours, the weights are row-standardised so that the weights in each row sum to 1. Using `libpysal`, spatial weights are applied when conducting the OLS regression. The coefficients retain their values expected under OLS without spatial weights, but the use of spatial weights helps refine standard errors, improving the reliability of statistical inference and reducing the risk of falsely identifying significant relationships due to spatial autocorrelation.

3.4.2 Spatial regression analysis

In addition to using spatial weights, spatial econometric models were used to address potential spatial dependencies. Diagnostic tests, including Moran's I and Lagrange Multiplier (LM) tests, were conducted to determine the most appropriate spatial model. Based on these results, spatial lag terms were introduced to account for spatial spillover effects. The choice between the spatial lag of X (SLX) and spatial autoregressive (SAR) models is predicated on the significance of spatial dependencies detected in the regression residuals. Because spatial diagnostic tests showed that autocorrelation effects were generally limited to the explanatory variables, a Spatial Lag of X (SLX) model was selected for spatial regression. The SLX model is given by:

$$\mathbf{Y} = \mathbf{X}\beta + \mathbf{WX}\gamma + \epsilon$$

where $\mathbf{Y}$, $\mathbf{X}\beta$ and ϵ have the same interpretations as under OLS. The matrix product of the weights matrix $\mathbf{W}$ and the matrix of explanatory variables $\mathbf{X}$ gives $\mathbf{WX}$, which captures the spatial spillovers from neighbouring tracts. γ is the vector of regression coefficients associated with the spatially-lagged explanatory variable.

4 Results and analysis

This section presents and analyses the results, including the classification of bikeshare trips and spatiotemporal dynamics of integration and substitution. Additionally, it discusses the factors that influence these patterns and dynamics through spatially-weighted ordinary least squares regression and a spatial lag of X model.

4.1 Results of classification

Using the three-step approach, all bikeshare trips were classified as either modal integration, modal substitution or neither. Table 4.1 and Figure B.1 provide an overview of the total number of trips in each classification for each city, along with the mean, median and maximum values across the census tracts in each city. The chi-square goodness of fit test shows that the counts differ significantly from the uniform distribution for each city and origin / destination combination.

The proportion of modal integration (MI) and modal substitution (MS) trips is substantial for both Chicago and New York City, with approximately 40% of all bikeshare trips in these cities serving either to integrate with or substitute against public transportation. In New York City, MI trips account for a greater proportion of trips (25.0%) compared to MS trips (16.8%). Chicago exhibits a different trend, with modal substitution trips making up over a quarter (25.5%) of all bikeshare trips—higher than the proportion of all modal integration trips. Los Angeles, in contrast, sees far less multimodal interaction, with 81.0% of bikeshare trips not classified as MI or MS. Nonetheless, in all three cities, modal integra-

Classification	Metric	Chicago		New York City		Los Angeles	
		Origin	Dest.	Origin	Dest.	Origin	Dest.
MI-FLM	Count*	251,066	251,082	2,724,637	2,724,744	5,958	5,958
	Median	2	2	15	0	0	0
	Mean	734.11	760.85	2,754.94	2,984.39	42.86	42.86
	SD	3,209.21	3,237.03	7,577.63	8,133.88	115.62	120.07
	Max	41,061	36,100	79,317	87,809	774	873
MI-FM	Count*	93,952	93,978	2,205,434	2,205,597	16,451	16,451
	Median	23	8	310	41	0	0
	Mean	274.71	284.78	2,229.96	2,415.77	118.35	118.35
	SD	1,054.15	1,028.83	6,217.2	5,873.12	284.47	312.01
	Max	15,960	9,706	68,258	64,503	2,732	1,959
MI-LM	Count*	271,071	271,170	2,764,704	2,764,876	17,223	17,223
	Median	19	75	28	596	0	40
	Mean	792.61	821.73	2,795.45	3,028.34	123.91	123.91
	SD	2,666.33	2,840.65	6,937.67	7,456.4	302.16	245.21
	Max	22,017	40,168	71,203	80,124	1,840	1,998
MS	Count*	992,673	992,886	5,183,021	5,183,262	22,657	22,657
	Median	376	72	84	6	0	0
	Mean	2,902.55	3,008.75	5,240.67	5,677.18	163	163
	SD	7,261.2	9,775.96	13,642.15	15,017.73	459.08	408.61
	Max	69,645	80,800	145,875	156,128	3,922	2,559
None	Count*	2,290,744	2,291,249	17,917,871	17,919,699	265,246	265,246
	Median	2,863	2,865	8,988	9,735	994	1,015
	Mean	6,698.08	6,943.18	18,117.16	19,627.27	1,908.24	1,908.24
	SD	10,902.14	11,364.23	27,644.04	29,179.28	2,663.91	2,684.24
	Max	101,654	110,885	390,532	382,411	16,108	16,593
Goodness of fit test	χ^2	4,278,771	4,279,705	28,927,829	28,931,856	763,517	763,517
	p-value	0.0	0.0	0.0	0.0	0.0	0.0

* Counts differ for origin and destination in Chicago and New York City as a result of post-classification cleaning. In particular, census tracts with fewer than 100 total trips in 2023 were removed.

Table 4.1: **Summary of bikeshare trip classifications.** This table shows the breakdown of the classification of all 2023 bikeshare trips based on the trip origin and destination. The summary statistics are calculated at the census tract level for both trip origins and destinations across each of the three cities. The chi-square goodness of fit test compares the distribution of modal counts against the uniform distribution; the highly significant result indicates that the observed frequencies differ substantially from the uniform distribution.

tion trips are more commonly used as a last-mile solution rather than a first-mile solution or a transit connector; that is, modal integration trips primarily help public transit users travel from a station to their final destination, rather than facilitating access to transit at the beginning of a trip or serving as an intermediate link between public transit options.

Overall, these findings highlight key differences in how bikeshare is used across these cities. New York City has the highest proportion of bikeshare trips used to integrate with public transit, indicating a strong multimodal relationship between bikeshare and transit. Chicago shows the greatest use of bikeshare as a substitute for public transit trips, suggesting that bikeshare frequently serves to replace rather than complement transit. Meanwhile, Los Angeles exhibits minimal multimodal usage, showing that bikeshare is primarily a standalone mode of transportation for leisure or localised commuting rather than a component of the broader multimodal transportation network.

4.2 Temporal dynamics of integration and substitution

By acting as a first- and last-mile solution, bikeshare extends the reach of transit stations, filling accessibility gaps. The timing of modal integration and modal substitution trips provides insights into bikeshare's function in urban transportation networks, particularly in relation to commuting patterns, seasonal variations and overall transit dependency.

As shown in Figure B.3, there are strong seasonality trends in bikeshare usage overall, particularly in Chicago and New York City, with ridership surging in the warmer spring and summer months and declining in the colder winter months. The proportion of modal integration and modal substitution trips also aligns with these overall trends, with the proportion of MI and MS trips steadily increasing in the spring and peaking around August. The seasonality appears to have a greater influence on ridership patterns in Chicago, where the total trip count and the proportion of MS trips more than double from the winter to the summer months. The warm-weather peak suggests that MS trips in Chicago may be more sensitive to seasonal changes in biking conditions. Los Angeles, on the other hand, shows relatively stable MI and MS trip rates throughout the year, likely due to its milder climate allowing for more consistent year-round bikeshare use. Unlike Chicago and New York City, bikeshare usage and MI and MS trip proportions do not peak in the summer months, likely owing to the difference in weather between the cities. Rather, there is a relative decline in MI and MS proportions in the summer months, with the proportions returning to pre-summer levels in the cooler months of September and October.

In addition to monthly usage patterns, MI and MS trips also exhibit distinctive hourly usage patterns, illustrated in Figures B.2, B.4 and B.5. In both Chicago and New York City, there is a pronounced bimodal distribution of MI trip counts, with a small peak in the morning (7 to 9 AM) and a larger peak in the evening (5 to 7 PM). This aligns neatly with the start and end of a typical workday, highlighting the role of bikeshare as a crucial connector to or from public transit for daily work commutes, or as a means to replace commuting via public transit altogether. Interestingly, while there are more MI trips by count during the evening rush hour, a greater *proportion* of bikeshare trips are MI during the morning commute hours. This suggests that while more users tend to use bikeshare at the end of the workday, a larger share of those riding in the morning rely on it specifically for transit integration, reinforcing bikeshare's role as a structured component of commute routines. The evening peak may, in contrast, reflect a mix of commute-related trips as well as more discretionary travel, leading to a lower proportion of trips being used to connect to or from public transit. As with the seasonal trends, Los Angeles does not share similar work-commute-related hourly trends, with MI trips being more evenly distributed across the day. This suggests that bikeshare in LA does not serve as a dominant first- or last-mile commuting solution but may be used for more sporadic, short-distance transit connections throughout the day. Across all three cities, the proportion of MS trips remains fairly steady throughout the day, indicating that bikeshare as a substitute for public transit is not as closely tied to traditional work-related commuting patterns as MI trips. This distinction underscores the flexibility of bikeshare as a transit alternative, with MS trips being less constrained by the structure of work schedules. Also, in all three cities, there is minimal integration and substitution during the late night and early morning hours (between midnight and 4 AM) as a result of reduced public transit availability during this time.

4.3 Spatial dynamics of integration and substitution

While temporal trends reveal *when* bikeshare is used for transit integration and substitution, spatial patterns highlight *where* these trips occur, emphasising the geographic factors that influence whether bikeshare is used to integrate with or substitute against public transit. To assess the spatial distribution of modal integration and modal substitution trips, I computed and mapped the proportion of MI trips and the proportion of MS trips for each census tract within the city, shown in Figures B.6 and B.7.

In Chicago and New York City, the origin of MI trips tends to be concentrated around the central business districts and major transit hubs, which can be seen in Figure B.6. In Chicago, census tracts in the Loop, which features many bus and train connections, have relatively high proportions of modal integration, and there are decreasing proportions of modal integration moving away from the Loop. A similar trend holds for New York City, where the origins of MI trips are concentrated around major subway hubs, such as Grand Central Terminal and Penn Station, and high-density transit corridors in Manhattan and Brooklyn. However, this spatial clustering around the central business district and major transit corridors is even more prominent for MI trip destinations. This is also in line with a previous observation that there is a higher proportion of modal integration trips that are used as last-mile connections as opposed to first-mile connections. The spatial alignment of MI trips with the locations of major employment centres and high-density transit infrastructure suggests that bikeshare is well-integrated into daily work commutes in Chicago and NYC.

Los Angeles has particularly unique spatial patterns in bikeshare-transit integration proportions. Since the distribution of bikeshare stations in Los Angeles is relatively sparse compared to Chicago or New York City, there is a more diffuse and decentralised pattern of

MI trips. Though there is increased integration around Union Station and some Metro Rail stations, this spatial effect is much less intense than the same effect in the two other cities. Along with the absence of salient temporal patterns, the lack of strong spatial concentration of MI and MS trips suggests that bikeshare is used more flexibly in LA, serving a wider range of trip purposes beyond commuting for work.

Across all three cities, there also appears to be a higher MI proportion in college neighbourhoods, which typically have increased public transit access. In Chicago, there are MI hotspots near the University of Illinois Chicago and DePaul University in the Loop and the University of Chicago in the southeastern portion of the city. Similarly, in New York City, MI trip concentrations are noticeable around university campuses such as Columbia University in Upper Manhattan and New York University in Lower Manhattan. In Los Angeles, there is greater modal integration near the University of Southern California in downtown LA and UCLA in the western part of the city.

As with modal integration, modal substitution trip origins tend to cluster around high-density transit areas and central business districts, shown in Figure B.7. Chicago exhibits a similar spatial distribution of MS trips as MI trips, with trips clustered prominently in the Loop. This spatial overlap suggests that even in areas with strong public transit infrastructure, bikeshare may serve as a more flexible or time-efficient alternative for certain trips, such as those with longer headways or requiring several transfers. In Los Angeles, MS trip origins are even more concentrated in the central business district, with fewer MS trips starting or ending in periphery neighbourhoods; several census tracts that exhibit moderate levels of modal integration have virtually no MS trips, and substitution activity is more tightly concentrated around LA's downtown core. This suggests a more limited role for bikeshare as a transit alternative outside this downtown area. Unlike the comparatively concentrated MS trip patterns in Chicago and Los Angeles, New York City exhibits a more spatially dispersed distribution of substitution trips. MS trips originate outside Manhattan's core transit corridors in peripheral neighbourhoods such as Brooklyn and Queens. This contrast with

MI trip origins, which are highly concentrated around major transit hubs, suggests that in NYC, bikeshare often serves as a substitute for public transit in areas where subway and bus coverage may be less dense or less frequent.

Notably, in all three cities, the prevalence of MS trips is reduced in college neighbourhoods, in contrast to the MI hotspots previously observed near university campuses. This suggests that while students may use bikeshare to connect to public transit, they are less likely to rely on bikeshare as a substitute for transit entirely. The lower proportion of MS trips in these areas may also reflect better transit service frequency, walkability or the availability of subsidised transit options for students, reducing the need to replace transit with bikeshare altogether.

The divergence between MI patterns and MS patterns across the three cities further illustrates the spatial nuance of the bikeshare-transit relationship. Whereas MI trips are largely used to integrate with transit in high-density, transit-rich hubs and employment centres, MS trips appear to reflect a need for more flexible mobility options, especially in areas with less accessible or less frequent public transit. The differing spatial patterns of MI and MS trips between cities further confirm that bikeshare's role in the broader transportation networks is city-dependent. While bikeshare in Chicago and New York City appears closely integrated with dense transit infrastructure and employment centres, its more decentralised and flexible use in Los Angeles points to a distinct mobility function shaped by LA's urban form and transit availability. The infrastructural and socioeconomic factors that give rise to these distinct spatial trends will be further explored in the next subsection.

4.4 Factors that influence integration and substitution

The spatial and temporal patterns of modal integration (MI) and modal substitution (MS) trips suggest that bikeshare usage is shaped by a combination of transit accessibility and local commuting behaviours. Regression analysis is used in order to quantify these specific relationships and identify the factors that drive bikeshare's relationship with public transit.

	Chicago	New York City	Los Angeles
(Intercept)	0.000 (0.057)	0.000 (0.048)	0.000 (0.126)
Urban design and built environment			
Number of streets	-0.152* (0.091)	-0.047 (0.065)	-0.152 (0.227)
Intersection density	-0.142** (0.070)	0.045 (0.059)	-0.152 (0.160)
Average traffic	0.200*** (0.061)	-0.041 (0.050)	0.045 (0.134)
Socioeconomic and demographic			
Median household income	-0.068 (0.066)	-0.187*** (0.057)	0.001 (0.170)
Households with children	-0.080 (0.072)	0.001 (0.070)	-0.097 (0.163)
Number of housing units	0.299*** (0.070)	0.047 (0.062)	0.239* (0.138)
Number of jobs	0.045 (0.084)	0.098* (0.053)	-0.182 (0.186)
Mobility and accessibility			
Number of transit stops	0.057 (0.098)	0.320*** (0.051)	0.150 (0.217)
Number of bikeshare docks	0.029 (0.092)	-0.049 (0.055)	0.240 (0.156)
Percentage walking commute	0.139** (0.067)	0.072 (0.056)	-0.066 (0.172)
Statistical summary			
Number of observations	250	376	65
Coefficient of determination (R^2)	0.2188	0.1558	0.1483

[a] Significance codes: *=0.1, **=0.05, ***=0.01
[b] Standard errors are shown in parentheses.

Table 4.2: **Summary of OLS model results for modal integration trip origins.** This table shows the factors influencing modal integration trip proportions based on trip origin. Coefficients and standard errors are computed using a spatially-weighted ordinary least squares regression.

	Chicago	New York City	Los Angeles
(Intercept)	0.000 (0.054)	0.000 (0.050)	0.000 (0.120)
Urban design and built environment			
Number of streets	-0.159* (0.086)	0.039 (0.067)	-0.390* (0.217)
Intersection density	-0.042 (0.066)	-0.065 (0.061)	0.152 (0.153)
Average traffic	-0.030 (0.057)	-0.026 (0.051)	-0.008 (0.129)
Socioeconomic and demographic			
Median household income	-0.007 (0.062)	-0.231*** (0.058)	-0.136 (0.163)
Households with children	-0.269*** (0.068)	-0.010 (0.072)	-0.132 (0.156)
Number of housing units	0.404*** (0.066)	-0.004 (0.064)	0.220 (0.133)
Number of jobs	-0.045 (0.079)	0.050 (0.055)	0.414** (0.178)
Mobility and accessibility			
Number of transit stops	0.150 (0.092)	0.232*** (0.054)	0.074 (0.208)
Number of bikeshare docks	0.022 (0.086)	-0.064 (0.057)	0.205 (0.150)
Percentage walking commute	0.128** (0.063)	-0.016 (0.058)	-0.261 (0.165)
Statistical summary			
Number of observations	250	376	65
Coefficient of determination (R^2)	0.3068	0.0997	0.2180

[a] Significance codes: *=0.1, **=0.05, ***=0.01
[b] Standard errors are shown in parentheses.

Table 4.3: **Summary of OLS model results for modal integration trip destinations.** This table shows the factors influencing modal integration trip proportions based on trip destination. Coefficients and standard errors are computed using a spatially-weighted ordinary least squares regression.

This section presents the results of the regression analysis, identifying how transit availability, built environment characteristics and demographic factors influence bikeshare's role in multimodal transportation networks in Chicago, New York City and Los Angeles.

Tables 4.2 and 4.3 present the numerical results of performing ordinary least squares regression on modal integration trip proportions. As evidenced by the spatial results, contributors to the proportion of MI trips originating in a census tract include the built environment, transit accessibility and socioeconomic factors. One notable finding is the negative relationship between the number of streets in a census tract and the proportion of MI trips. Since neighbourhoods with more streets are typically considered more walkable, this result suggests that walking may be a feasible alternative in more pedestrian-friendly neighbourhoods, and bikeshare may be less necessary as a transit connection. Instead, areas with more limited street connectivity tend to have higher MI proportions, as bikeshare serves as a more critical link to public transit in these areas.

Socioeconomic factors also play an important role. In both Chicago and New York City, census tracts with lower median household income tend to have a higher proportion of MI trips, indicating that bikeshare is frequently used as an affordable first- or last-mile connection by transit-dependent populations in these cities. Additionally, a higher number of housing units and a greater number of jobs are associated with greater MI trip proportions across all three cities. This is in line with the principle of transit-oriented development—the idea that the design of high-density residential and employment centres can better facilitate multimodal transportation by ensuring that both housing and workplaces are well-connected to transit infrastructure (Choi & Guhathakurta, 2024; Ibraeva et al., 2020; Zhao et al., 2024). In all three cities, the number of transit stops is also positively associated with MI trip proportions, meaning that increased transit accessibility makes bikeshare a more attractive option for completing multimodal trips.

The contributors to the proportion of MI trips ending in a census tract follow similar trends as trip origins but with some key differences. Across all three cities, traffic congestion has a negative relationship with MI trip proportions, suggesting that bikeshare is used less frequently in highly congested areas; this could potentially be a result of safety concerns or poor road and cycling infrastructure. As with trip origins, lower median household income is associated with a higher proportion of MI trips in all three cities, reinforcing existing research that bikeshare serves as an important component of multimodal transportation for lower-income communities. Transit accessibility remains a major factor determining MI trip proportions; destination tracts with a greater number of transit stops tend to have higher MI trip proportions. Interestingly, the number of bikeshare docks at a trip's destination is positively associated with MI trip proportions in Chicago and Los Angeles but not in New York City; this may be because Citi Bike has a more uniform distribution of docks across NYC, so the effects of dock availability are less pronounced compared to Chicago and LA, where bikeshare infrastructure is more unevenly distributed and dock placement plays a larger role in shaping usage patterns.

The factors influencing the proportion of modal substitution trips originating in a census tract closely mirror those influencing modal integration trips. The numerical results are shown in Tables 4.4 and 4.5. Firstly, there is negative relationship between the number of streets in a census tract and the proportion of MS trips across all three cities, suggesting that bikeshare is more frequently used as a transit substitute in areas with fewer direct pedestrian connections. Additionally, census tracts with lower median household incomes tend to also have higher MS trip proportions, supporting the idea that bikeshare is a mobility option for lower-income populations who may have limited access to cars and must rely on a combination of bikeshare and public transit for commuting. Household composition also plays a role, as census tracts with fewer households that have children tend to have a higher proportion of MS trips, likely reflecting differences in travel behaviour for individuals without childcare responsibilities. As with MI trips, the number of housing units is positively associated with MS trip proportions, further supporting the role of high-density residential environments in fostering bikeshare adoption. Interestingly, the presence of more transit stops in a census

	Chicago	New York City	Los Angeles
(Intercept)	0.000 (0.057)	0.000 (0.049)	0.000 (0.123)
Urban design and built environment			
Number of streets	-0.016 (0.089)	-0.062 (0.066)	-0.179 (0.223)
Intersection density	-0.098 (0.069)	0.064 (0.060)	-0.172 (0.157)
Average traffic	0.140** (0.060)	-0.041 (0.051)	0.025 (0.132)
Socioeconomic and demographic			
Median household income	-0.065 (0.066)	-0.197*** (0.058)	-0.101 (0.166)
Households with children	-0.087 (0.071)	0.000 (0.071)	-0.194 (0.160)
Number of housing units	0.344*** (0.070)	0.069 (0.063)	0.248** (0.136)
Number of jobs	0.025 (0.084)	0.109** (0.053)	-0.158 (0.182)
Mobility and accessibility			
Number of transit stops	0.032 (0.097)	0.309*** (0.053)	0.173 (0.213)
Number of bikeshare docks	0.024 (0.092)	-0.042 (0.057)	0.262** (0.153)
Percentage walking commute	0.196*** (0.066)	0.108** (0.057)	-0.114 (0.168)
Statistical summary			
Number of observations	247	356	65
Coefficient of determination (R^2)	0.2345	0.1697	0.1826

[a] Significance codes: *=0.1, **=0.05, ***=0.01
[b] Standard errors are shown in parentheses.

Table 4.4: **Summary of OLS model results for modal substitution trip origins.** This table shows the factors influencing modal substitution trip proportions based on trip origin. Coefficients and standard errors are computed using a spatially-weighted ordinary least squares regression.

	Chicago	New York City	Los Angeles
(Intercept)	0.000 (0.057)	0.000 (0.051)	0.000 (0.121)
Urban design and built environment			
Number of streets	-0.249*** (0.090)	0.052 (0.068)	-0.371* (0.220)
Intersection density	-0.154** (0.070)	0.004 (0.062)	0.113 (0.155)
Average traffic	0.156** (0.061)	-0.067 (0.052)	-0.013 (0.130)
Socioeconomic and demographic			
Median household income	0.012 (0.066)	-0.196*** (0.059)	-0.059 (0.164)
Households with children	-0.113 (0.072)	-0.001 (0.073)	-0.095 (0.158)
Number of housing units	0.319*** (0.070)	-0.037 (0.065)	0.229* (0.134)
Number of jobs	0.037 (0.085)	0.050 (0.055)	0.176 (0.180)
Mobility and accessibility			
Number of transit stops	0.088 (0.097)	0.280*** (0.054)	0.237 (0.210)
Number of bikeshare docks	0.006 (0.093)	-0.106* (0.059)	0.296* (0.151)
Percentage walking commute	0.068 (0.067)	0.015 (0.059)	-0.175 (0.166)
Statistical summary			
Number of observations	247	356	65
Coefficient of determination (R^2)	0.2255	0.1182	0.2032

[a] Significance codes: *=0.1, **=0.05, ***=0.01
[b] Standard errors are shown in parentheses.

Table 4.5: **Summary of OLS model results for modal substitution trip destinations.** This table shows the factors influencing modal substitution trip proportions based on trip destination. Coefficients and standard errors are computed using a spatially-weighted ordinary least squares regression.

tract is related to a higher proportion of MS trips; this suggests that even in areas with strong transit availability, some individuals actively choose to substitute public transit with bikeshare instead. This may indicate that bikeshare services can serve as an alternative to transit when transit options may be less direct or slower. The number of bikeshare docks also plays a role in shaping the proportion of MS trips originating in a tract: in Chicago and Los Angeles, the number of bikeshare docks in a census tract is positively associated with MS trip proportions, suggesting that greater access to bikeshare infrastructure encourages more individuals to opt for bikeshare instead of transit; an analogous trend does not occur in NYC, possibly as a result of widespread availability of docks. In Chicago and New York City, census tracts with a higher proportion of workers who commute to work by walking also have higher proportions of MS trips; the opposite trend is observed in Los Angeles, where a lower proportion of walking commuters is associated with higher MS trip proportions, possibly reflecting differences in how bikeshare is used in a more car-dependent urban landscape.

The factors influencing the proportion of MS trips ending in a census tract are generally similar to those influencing MS trip origins, further emphasising the connection between bikeshare and employment hubs. Census tracts with a greater number of jobs tend to attract more MS trips, indicating that bikeshare substitution may be used for work commutes. Moreover, census tracts with more streets tend to have a lower proportion of MS trips, reinforcing the idea that areas with more intricate pedestrian networks may see less transit substitution via bikeshare.

4.4.1 Accounting for spatial autocorrelation

The results of the ordinary least squares (OLS) regression with spatial weights indicate that spatial autocorrelation is present among the explanatory variables but not in the residuals. In particular, the Moran's I statistic is generally not significant at the 0.10 significance level for both MI and MS trip origins and destinations (with the exception of MS trip origin in NYC), suggesting that there is limited spatial dependence in the errors terms of the

OLS model. Additionally, the Lagrange Multiplier (LM) tests for spatial lag and spatial error are not statistically significant, further confirming that a spatially lagged dependent variable is unnecessary. However, the LM test for WX and Robust LM WX test suggest that some independent variables exhibit spatial spillover effects, particularly for MI and MS trip origins. That is, factors such as the number of transit stops, number of bikeshare docks and employment opportunities in one census tract may influence bikeshare usage patterns in nearby tracts. Given these findings, a Spatial Lag of X (SLX) model is the more appropriate choice as it accounts for the spillover effects of explanatory variables. The SLX model improves upon the OLS results by incorporating spatially lagged independent variables, which help capture the broader effects of physical infrastructure and socioeconomic opportunities beyond an individual tract.

As demonstrated by the results in Table 4.6, modal integration trips are influenced by factors in neighbouring tracts, reinforcing the importance of the broader transportation network. Across all three cities, the spatial lag of the average traffic has a negative, though statistically insignificant, impact on MI proportion, meaning that increased congestion in nearby tracts reduces the number of trips that are used to connect to public transit. This is interesting because in Chicago and Los Angeles, the average traffic tends to be positively associated with MI proportions; that is, there are more trips used to connect to public transit if there is high congestion in the tract. The contrast between the direct and spatially lagged effects suggests that while congestion within a tract may encourage the use of bikeshare to connect to transit, congestion in nearby areas appears to have the opposite effect, discouraging the use of bikeshare to connect to transit.

All three cities also exhibit a negative spatial lag of the percentage of workers who walk to work. That is, census tracts surrounded by areas with higher proportions of walking commuters tend to have lower proportions of MI trips. This inverse relationship suggests that if walking is a dominant mode of commuting in nearby neighbourhoods, individuals may be less likely to use bikeshare to connect to transit, possibly due to greater walkability

	Chicago	New York City	Los Angeles
(Intercept)	-0.009	-0.020	-0.015
Urban design and built environment			
Number of streets	-0.130	-0.043	-0.234
Intersection density	-0.157**	0.059	-0.059
Average traffic	0.177***	-0.047	0.076
Socioeconomic and demographic			
Median household income	-0.058	-0.178***	0.006
Households with children	-0.080	0.010	-0.105
Number of housing units	0.310***	0.017	0.277
Number of jobs	0.034	0.092*	-0.038
Mobility and accessibility			
Number of transit stops	0.046	0.338***	0.138
Number of bikeshare docks	0.043	-0.044	0.349*
Percentage walking commute	0.112*	0.076	-0.057
Spatially-lagged variables			
Lag: Number of streets	-0.041	-0.024	0.470
Lag: Intersection density	0.124	0.519**	-0.073
Lag: Average traffic	-0.143	-0.288	-0.182
Lag: Median household income	-0.323*	0.166	-0.425
Lag: Households with children	0.025	-0.047	-0.470
Lag: Number of housing units	0.117	-0.662*	0.071
Lag: Number of jobs	0.061	-0.033	-0.408
Lag: Number of transit stops	0.315	0.303	-0.367
Lag: Number of bikeshare docks	-0.426**	-0.240	0.136
Lag: Percentage walking commute	-0.187	-0.074	-0.754
Statistical summary			
Number of observations	250	376	65
Coefficient of determination (R^2)	0.2714	0.1875	0.3034

[a] Significance codes: *=0.1, **=0.05, ***=0.01
[b] Standard errors are omitted for brevity.

Table 4.6: **Summary of SLX model results for modal integration trip origins.** This table shows the factors influencing modal integration trip proportions based on trip origin. Coefficients and spatial lags are computed using a spatial lag of X model.

or proximity to destinations. Interestingly, in Chicago and New York City, the direct effect of the percentage of walking commuters is positive, indicating that within a given tract, higher rates of walking to work are associated with higher levels of modal integration. While walkable neighbourhoods can encourage greater MI, widespread walkability in adjacent areas may reduce bikeshare–transit integration by encouraging more direct travel modes that do not involve public transportation.

In both Chicago and New York City, the number of transit stops and intersection density in neighbouring tracts is positively associated with MI proportions, while the number of bikeshare docks in neighbouring tracts is negatively associated with MI proportions. The opposite is true in Los Angeles. This contrast suggests that in Chicago and NYC, a well-connected surrounding transit and road network encourages users to integrate bikeshare with transit, likely because these cities have more robust transportation systems that make transfers between modes convenient. Conversely, when nearby bikeshare docks are abundant, users may opt to complete their entire trip by bike without needing transit, thus lowering the proportion of MI trips. However, in Los Angeles, the pattern is reversed: greater bikeshare presence in neighbouring tracts appears to support integration, while more nearby transit stops and greater nearby intersection density are associated with lower MI proportions. This may reflect differences in the connectivity of transit in LA, where limited rail coverage and lower bus frequency make bikeshare a more flexible option for bridging gaps in the system. This could also indicate that in LA, bikeshare serves to complement less accessible transit options rather than to truly integrate with public transit.

Moreover, in New York City, the number of housing units exhibits unintuitive spillover effects: while the direct effect of housing units on MI trip proportions is positive but small, the spatial lag is negative and statistically significant. This suggests that though census tracts with a high density of housing units tend to have higher levels of bikeshare integration, if neighbouring tracts also have a large number of housing units, the proportion of MI trips within the focal tract decreases. This may be related to the widespread availability of bikeshare docks throughout NYC, which causes bikeshare trips to be dispersed across multiple nearby tracts based on other factors, such as transit availability rather than concentrated in any single tract. In contrast, in Chicago and LA, the spatial lag of the number of housing units is consistent with the positive relationship between housing units and MI trip proportions; tracts whose neighbouring tracts have a large number of housing units tend also to have higher MI trip proportions.

Modal substitution trips are also influenced by factors in nearby tracts, as shown in Table 4.7. As with modal integration trips, the spatial lag of the average traffic has a negative, still statistically insignificant, impact on MS proportions across all three cities, suggesting that increased congestion in nearby tracts reduces the number of trips that are used to replace public transit. This aligns with the direct effects of average traffic in Chicago and New York City, where increased average traffic is associated with lower proportions of MS trips; this indicates that the presence of traffic and congestion at or near the trip origin potentially dissuades users from replacing transit with bikeshare.

Across all three cities, the spatial lag of the number of transit stops is positively associated with modal substitution proportions, meaning that when neighbouring areas have large numbers of transit stops, individuals tend to use bikeshare to replace public transit more as well. Counterintuitive though it may be, this indicates that MS trips are more common in areas with greater access to transit; rather than lacking transit options or infrastructure, this may be because bikeshare offers a faster or more direct alternative for shorter-distance travel within an already well-connected region. Additionally, the number of transit stops has a positive direct effect on MS proportions in Chicago and New York City, suggesting that even in areas that have greater transit availability in these cities, individuals may still opt for bikeshare over transit, possibly for flexibility or personal preference. Taken together, in census tracts that have more transit stops or are near other tracts that have increased stops, bikeshare trips are generally used to substitute against public transit at higher rates.

The spatial lag of the number of households with children is negative across all three

	Chicago	New York City	Los Angeles
(Intercept)	0.002	-0.009	-0.003
Urban design and built environment			
Number of streets	-0.180**	0.051	-0.412*
Intersection density	-0.043	-0.060	0.163
Average traffic	-0.043	-0.041	0.119
Socioeconomic and demographic			
Median household income	0.010	-0.240***	-0.094
Households with children	-0.266***	0.004	-0.178
Number of housing units	0.400***	-0.034	0.333**
Number of jobs	-0.064	0.055	0.274
Mobility and accessibility			
Number of transit stops	0.152	0.244***	-0.070
Number of bikeshare docks	0.057	-0.052	0.240
Percentage walking commute	0.120*	-0.027	-0.022
Spatially-lagged variables			
Lag: Number of streets	0.203	-0.240	0.811
Lag: Intersection density	0.157	0.356	-0.428
Lag: Average traffic	-0.100	-0.087	-0.172
Lag: Median household income	0.108	0.160	-0.427
Lag: Households with children	-0.041	-0.239	-0.692
Lag: Number of housing units	-0.223	-0.234	0.597
Lag: Number of jobs	0.061	-0.339	-0.355
Lag: Number of transit stops	0.301	0.487*	0.190
Lag: Number of bikeshare docks	-0.439**	0.168	-0.472
Lag: Percentage walking commute	0.205	-0.307	-0.250
Statistical summary			
Number of observations	250	376	65
Coefficient of determination (R^2)	0.3594	0.1295	0.4054

[a] Significance codes: *=0.1, **=0.05, ***=0.01
[b] Standard errors are omitted for brevity.

Table 4.7: **Summary of SLX model results for modal substitution trip origins.** This table shows the factors influencing modal substitution trip proportions based on trip origin. Coefficients and spatial lags are computed using a spatial lag of X model.

cities, suggesting bikeshare trips are less frequently used to substitute for public transit in areas near neighbourhoods with more families and children. The number of households with children is also negatively related to MS proportion in Chicago (statistically significant) and Los Angeles (not statistically significant). This points at broader patterns involving demographics and mobility choices: areas with more families and children may have lower overall bikeshare adoption, likely due to practical constraints such as the need to travel with children or limited child-friendly cycling infrastructure. This, in turn, also dampens substitution behaviour in the nearby tracts in a way that is not as prominent for modal integration. This owes to the longer nature of MS trips, which may be less appealing to families and their children. Modal integration trips, by contrast, which are shorter and more localised by construction, may still occur within these areas with bikeshare being used to connect to transit, rather than replace it entirely.

In both Chicago and New York City, the spatial lag of the median household income has a positive association with the MS proportion, suggesting that individuals more often use bikeshare to substitute for public transit when they are located near higher-income neighbourhoods. This captures an interesting dynamic that the regressors do not fully capture: higher-income neighbourhoods may have better cycling infrastructure that encourages bikeshare use. To add further nuance, in NYC, the median household income has a statistically significant negative influence on MS proportion. This indicates that bikeshare is used to substitute against public transit in lower-income communities, likely for reasons involving flexibility and transit accessibility previously discussed. Along with the effect of the spatial lag, this suggests that while wealthier areas may have infrastructure conducive to modal substitution, the individuals in those same areas may not personally rely on bikeshare as a transit alternative. Instead, it may be neighbouring, lower-income residents who take advantage of the bikeshare-friendly environments created in these wealthier regions. This trend is less striking in Chicago; nevertheless, the positive association of the spatial lag of median household income is stronger than the much weaker immediate effects of income at the tract level, supporting the influence of wealthier nearby tracts on MS proportions.

In Chicago, the number of bikeshare docks exhibits curious spillover effects, with the direct effect being small and positive, and the spatial lag is negative and statistically significant. This demonstrates that while the presence of docks within a given tract may marginally encourage replacing public transit with bikeshare, the presence of more docks in nearby areas is associated with lower levels of modal substitution locally. This may reflect a form of spatial competition; individuals may be more inclined to begin or end their bikeshare trips in adjacent tracts with more docks and, hence, more bike availability. This may further suggest a competitive relationship of bikeshare usage between nearby areas; improving bike and bikeshare infrastructure in one area can potentially shift usage away from nearby neighbourhoods, as people may find it more desirable and accessible to begin their modal substitution trips in those areas. A similar trend is observed in Los Angeles, though much less pronounced. Interestingly, New York City exhibits the opposite phenomenon, with a positive direct effect and a negative spatial lag for the number of bikeshare docks. This may be the result of NYC's more extensive and expansive bikeshare network. As such, infrastructure in one area complements, rather than competes with, usage in surrounding areas.

5 Conclusion

Bikeshare has rapidly grown in recent years, becoming an important part of urban mobility systems. The findings of this research highlight the spatial and temporal dynamics of bikeshare as both a complement and substitute for public transit. The strong relationship between modal integration trip proportions and the number of transit stops reinforces the concept that bikeshare serves as a valuable first- and last-mile solution, particularly in dense urban environments like New York City and Chicago. Similarly, the clustering of modal substitution trips near employment hubs and areas with lower household incomes suggests that bikeshare is often used as an alternative to transit for work commutes, particularly in areas where transit reliability, accessibility or affordability may be concerns. Together, these findings demonstrate that bikeshare is not just a standalone mode of transport but an important component of modern urban mobility systems. As bikeshare programs continue to grow, it is increasingly important to ensure their integration into broader transportation networks, which can foster more effective, equitable and sustainable mobility solutions.

5.1 Policy implications

The model results show that while there are certain factors that increase bikeshare-transit integration across all three cities, the extent to which each factor influences these interactions is highly city dependent. There is no single factor that has the greatest influence on bikeshare-transit integration across all three cities, nor is there a single factor that dominates as the primary driver of modal substitution in all contexts. Nevertheless, transit accessibility and the availability of housing units in a census tract are consistently positively associated with the integration of bikeshare and transit. As such, prioritising the installation of bikeshare docks in transit-heavy and housing-dense areas may see the greatest returns in promoting multimodal connectivity. Ensuring that docks near transit hubs are adequately stocked through timely rebalancing can promote greater use of bikeshare as a last-mile connector. In keeping with transit-oriented design, mixed-use zoning can ensure that residential, commercial and employment centres are located near bikeshare docks and transit lines, where they can be utilised most effectively.

Consistent with existing literature, lower-income neighbourhoods tend to have higher proportions of modal integration and modal substitution, suggesting that bikeshare is a crucial component of mobility in these underserved areas. To this end, ensuring a strong presence of bikeshare infrastructure can support regular use for daily commuting needs. Reduced fare programs can further encourage these communities to adopt bikeshare as a reliable and affordable transportation option, especially for first- and last-mile travel where public transit options may be less robust. Other physical infrastructural improvements, such as bike lanes, street lighting and other safety enhancements, in these areas can help create a more comfortable environment for bikeshare usage and integration with transit.

Ultimately, bikeshare planning and urban planning more broadly must account for the complex and context-dependent nature of urban mobility, balancing competing priorities across cities and communities. Policies that successfully promote multimodal transportation in one region can have completely detrimental impacts on the transit network in a different region. As demonstrated by the regression results, temporal and spatial bikeshare usage patterns vary significantly across the cities and even within a city, influenced significantly by local urban form, infrastructure, and socioeconomic and demographic characteristics. Recognising that bikeshare and public transit usage is deeply intertwined with the spatial context of the surrounding neighbourhoods is crucial for the equitable, effective and sustainable design of transit systems.

5.2 Limitation of findings

It is important to recognise that the analysis and policy implications are inherently constrained by methodological and data limitations. A major limitation of this work is its highly inferential nature: the classification of trips into MI and MS categories relies deeply on assumptions regarding public transit schedules and travel behaviour. Though reasonable, these inferences can never fully capture individual trip purposes or motivations and may be prone to misclassification. For instance, a bikeshare trip may start within the 400-metre buffer of a bus stop just after the bus was scheduled to arrive, yet the rider did not use the bus at all. It is also possible for a rider to use bikeshare to connect to a delayed train, which does not get properly classified as modal integration because the classification methodology does not account for, or even have information on, the actual arrival and departure times of these transit options.

This also relates to the broader inverse problem in statistical analyses. While spatial regression techniques help mitigate some of these concerns, the directionality of relationships cannot always be definitively established. Additionally, this research focused primarily on the services that the major transit operator in each city provides; leaving out municipal and smaller, privately operated services may have led to an incomplete representation of bikeshare's full role in multimodal mobility networks.

Beyond the inferential limitations, procedural constraints and missing data introduce additional challenges. To expedite the classification process, trips that originated or terminated outside of a bikeshare dock were removed; the exclusion of such trips means that certain patterns of usage, particularly involving dockless electric bikes, may not be fully captured in the analysis. As discussed in the literature review, these free-floating bikeshare systems play an important role in the multimodal transportation landscape, so their omission may obscure additional integration patterns with public transit. Census tracts with fewer than a threshold number of bikeshare trips in total were also excluded to minimise noise, yet this filtering process may have inadvertently removed tracts where low bikeshare usage may be meaningful in itself. Tracts with missing data were also dropped in the final analysis, which may have disproportionately affected certain neighbourhoods with incomplete transit or socioeconomic data. It is important to consider these methodological limitations when interpreting the results of the model and drawing policy-related conclusions.

5.3 Future work

This study offers an initial step towards understanding the factors that shape the relationship between bikeshare and public transit. To build a more complete picture of bikeshare's role within multimodal transportation systems, future work can benefit from considering additional perspectives and scales of analysis.

While this research largely examined factors that influence the *presence* of modal integration and modal substitution, it may also be worthwhile to examine the factors, if any, that give rise to low integration and substitution (i.e., examining the proportion of none classifications). Investigating why certain areas exhibit low MI and MS proportions could provide insight into the barriers to bikeshare adoption and multimodal connectivity. Performing more granular regression analysis using member type or by trip time can help identify, more concretely, *who* uses or does not use these systems.

Additionally, future studies could extend the scale of this research. This research models only the major transit operators in each city, but incorporating local transit services, such as smaller municipal buses or university shuttles, can promote a more nuanced view of the bikeshare and transit interactions at the local level. This research also uses data from a single year, which provides a snapshot of the bikeshare-transit dynamics in 2023. While the findings may be generalised to similar contexts, a longitudinal analysis would be valuable in tracking how these trends may have evolved over time, particularly in light of post-pandemic shifts like increased teleworking and reduced transit ridership.

Finally, to complement the quantitative modelling used in this research, qualitative approaches could provide further valuable insight. While spatial and statistical analyses help reveal overarching trends, they cannot fully capture the subjective factors that shape individual mobility choices. Engaging with individuals who actively use bikeshare in tandem with public transit could contextualise factors that are difficult to capture through data alone, such as perceptions of safety, convenience or accessibility. Methods such as semi-structured interviews, participatory mapping and ethnographic observation can shed light on how users navigate multimodal trips, how they respond to disruptions or infrastructural disparities, and the social and psychological factors that influence their route and mode selection. These insights could, in turn, inform the design of more user-centred infrastructure and policies.

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A Additional plots: bikeshare overview

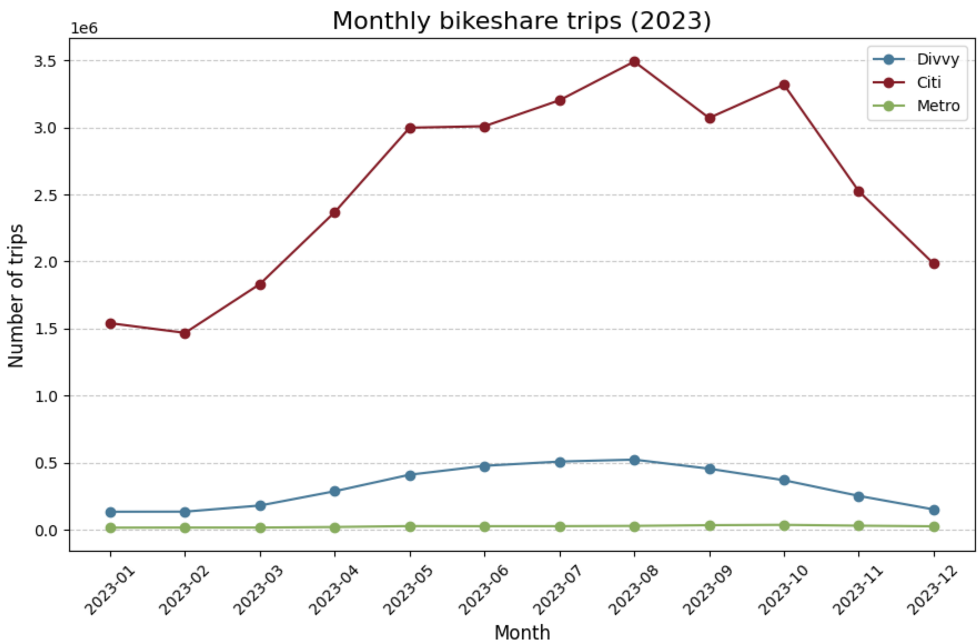

Figure A.1: **Monthly distribution of bikeshare trips.** Between Chicago, NYC and LA, New York City's Citi Bike program had the highest ridership in 2023, followed by Chicago's Divvy program and Los Angeles's Metro Bikeshare program. There are seasonal fluctuations in bikeshare usage; ridership tends to increase during the spring and summer months and decline during the winter months. These fluctuations are particularly prominent in the Citi Bike usage, with the peak number of trips in August being more than double the number of trips in January and February. A similar trend can be observed for Chicago's Divvy bikes.

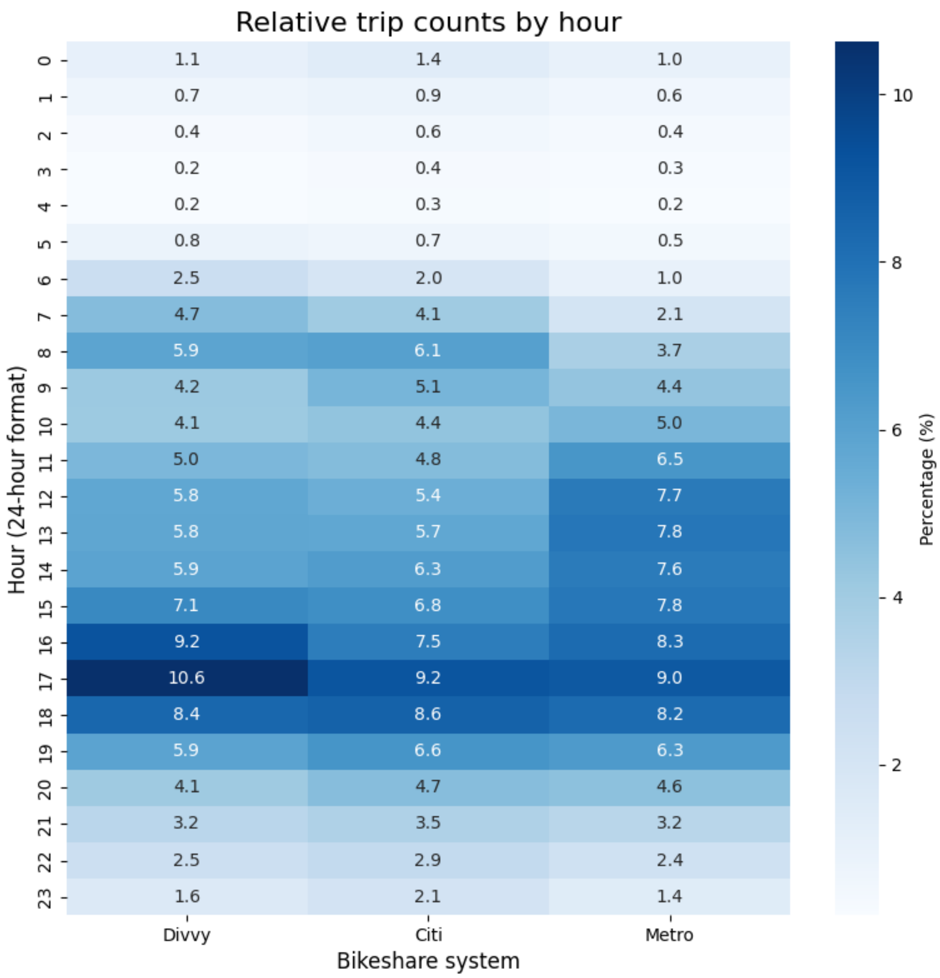

Figure A.2: **Trip counts by time of day.** This heatmap illustrates the hourly variations in bikeshare activity across bikeshare systems, indicating commuting trends and overall temporal usage patterns. Peak usage occurs during evening hours (5 to 6 PM), corresponding to the typical end-of-workday commute. Divvy and Citi Bike show slightly higher relative usage during the evening compared to Metro Bikeshare, which demonstrates a more consistent usage pattern throughout the day. Morning peaks (7 to 9 AM) align with commute times, while early morning (12 to 6 AM) and late-night hours (9 PM to 12 AM) see the lowest usage across all three systems.

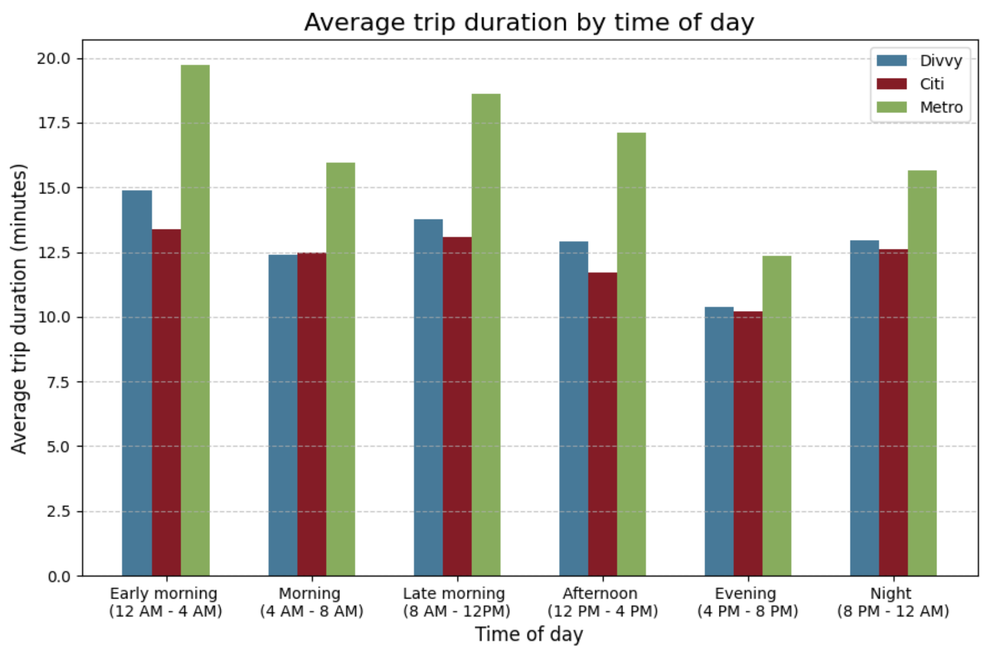

Figure A.3: **Average trip duration by time of day.** This bar chart highlights differences in trip usage patterns across bikeshare systems and times of day. Metro Bikeshare consistently has the highest average trip duration across all time periods, potentially reflecting the urban sprawl of Los Angeles, which may require longer trips to connect users to their destinations. Divvy and Citi Bike exhibit relatively consistent trip durations throughout the day. Across all three systems, trip durations during the morning and evening are slightly shorter, which potentially corresponds to commute-related trips that typically cover shorter distances.

B Additional plots: classification results

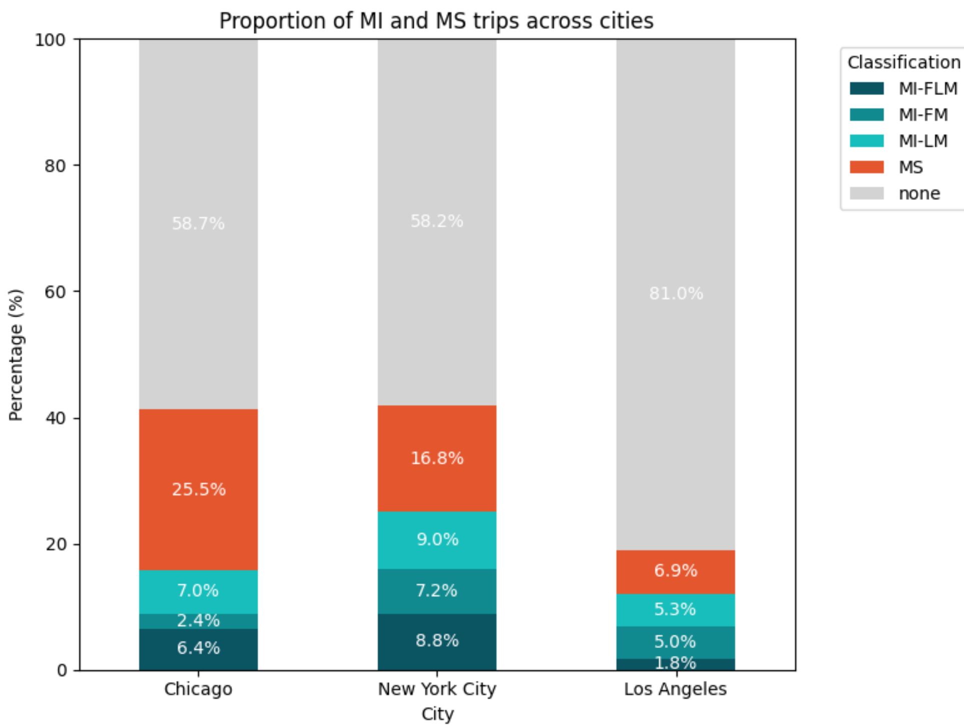

Figure B.1: **Classification percentages.** This chart shows the distribution of bikeshare trip classifications across Chicago, New York City and Los Angeles. The shades of teal represent modal integration trips (either MI-FLM, MI-FM or MI-LM). The orange represents modal substitution trips and the grey represents trips that are not classified as either modal integration or modal substitution. Modal integration trips are most common in New York City, with the combination of modal integration trips of all types making up a quarter of all Citi Bike trips. Modal substitution trips are most common in Chicago, also representing a quarter of all Divvy trips. A large proportion of trips in all three cities are neither modal integration nor modal substitution, especially in Los Angeles, where they constitute a large majority of all trips.

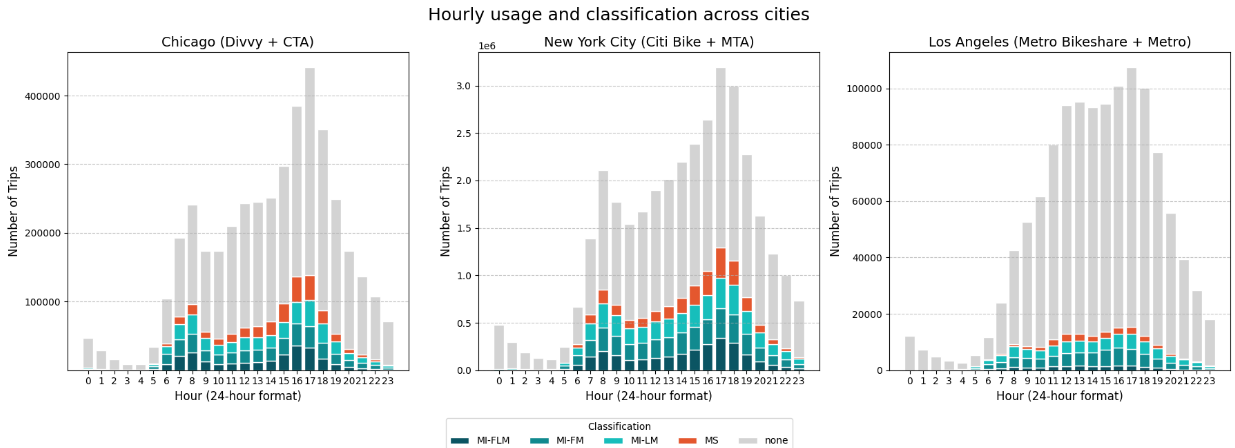

Figure B.2: **Hourly usage and classification across cities.** These charts show the hourly bikeshare and public transit usage patterns across the three cities. For Chicago and NYC, we see that the trends in modal integration and modal substitution largely follow the overall usage trends. For Los Angeles, however, there are fewer trips that integrate with and substitute against public transit, which suggests the use of bikeshare for standalone trips.

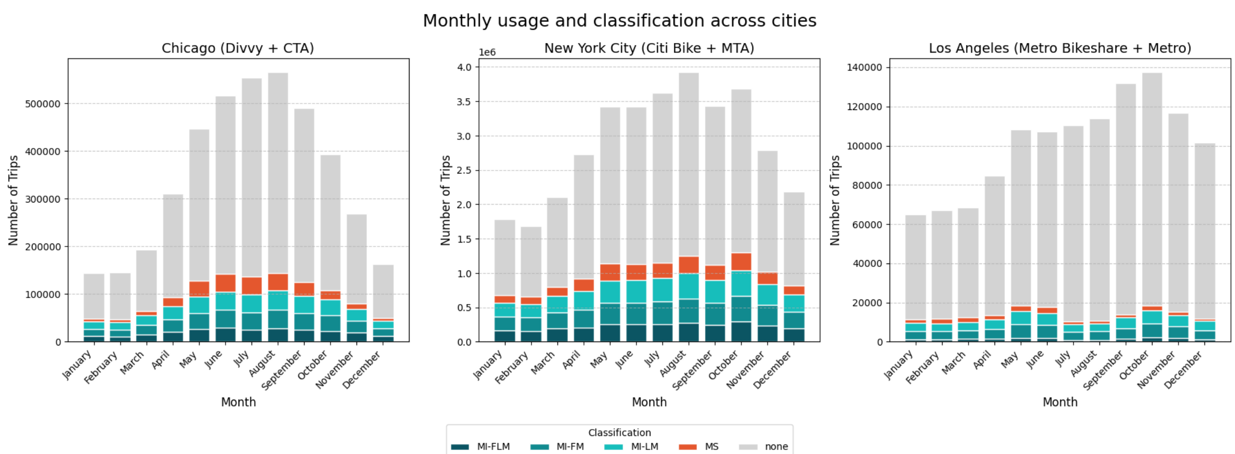

Figure B.3: **Monthly usage and classification across cities.** These charts show the monthly bikeshare and public transit usage patterns across the three cities. Modal integration and modal substitution show strong seasonality trends in Chicago and NYC; bikeshare is used more frequently to integrate with and substitute against public transit in the warmer spring and summer months. An opposite trend is seen in Los Angeles, where the hot summer months see less bikeshare-transit integration and nearly no bikeshare-transit substitution.

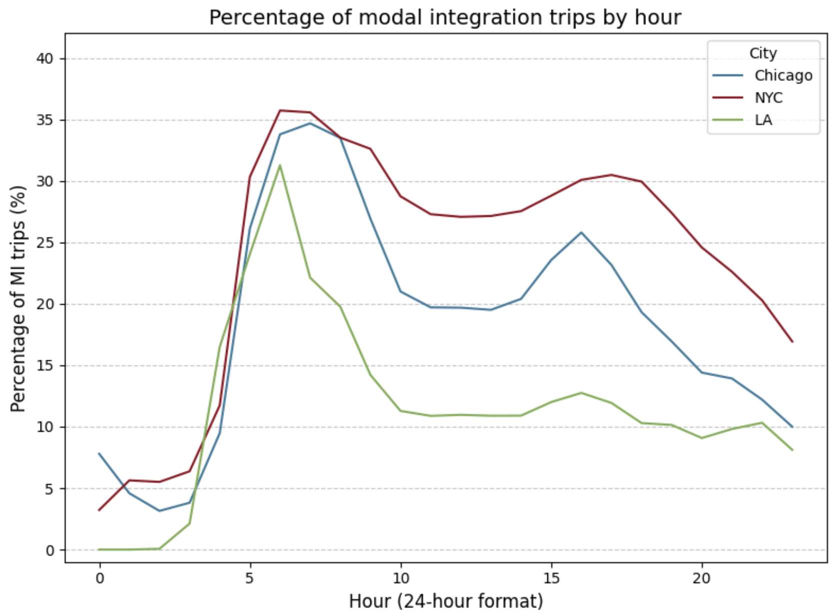

Figure B.4: **Percentage of modal integration trips by hour.** The graph shows the average hourly percentage of modal integration trips throughout the day. In all three cities, and especially in Chicago and NYC, there are peaks during the morning (7 to 9 AM) and evening (5 to 7 PM) commute hours. This reflects the observation that there are not only more bikesharing trips being taken during commute peak times but also more of these trips are being used to connect to or from public transit.

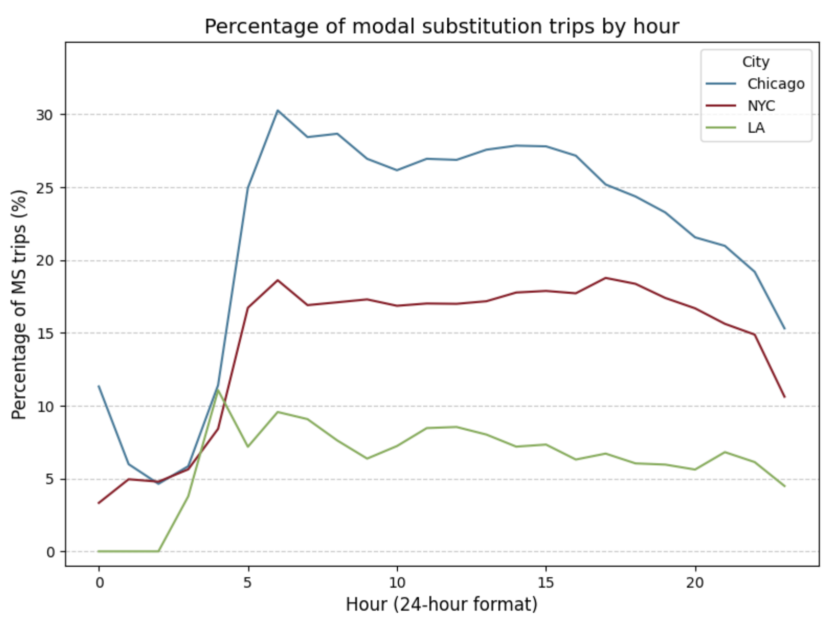

Figure B.5: **Percentage of modal substitution trips by hour.** The graph shows the average hourly percentage of modal substitution trips throughout the day. Unlike the peaks in modal integration trips during peak commute hours, the percentage of modal substitution trips is relatively constant throughout the day.

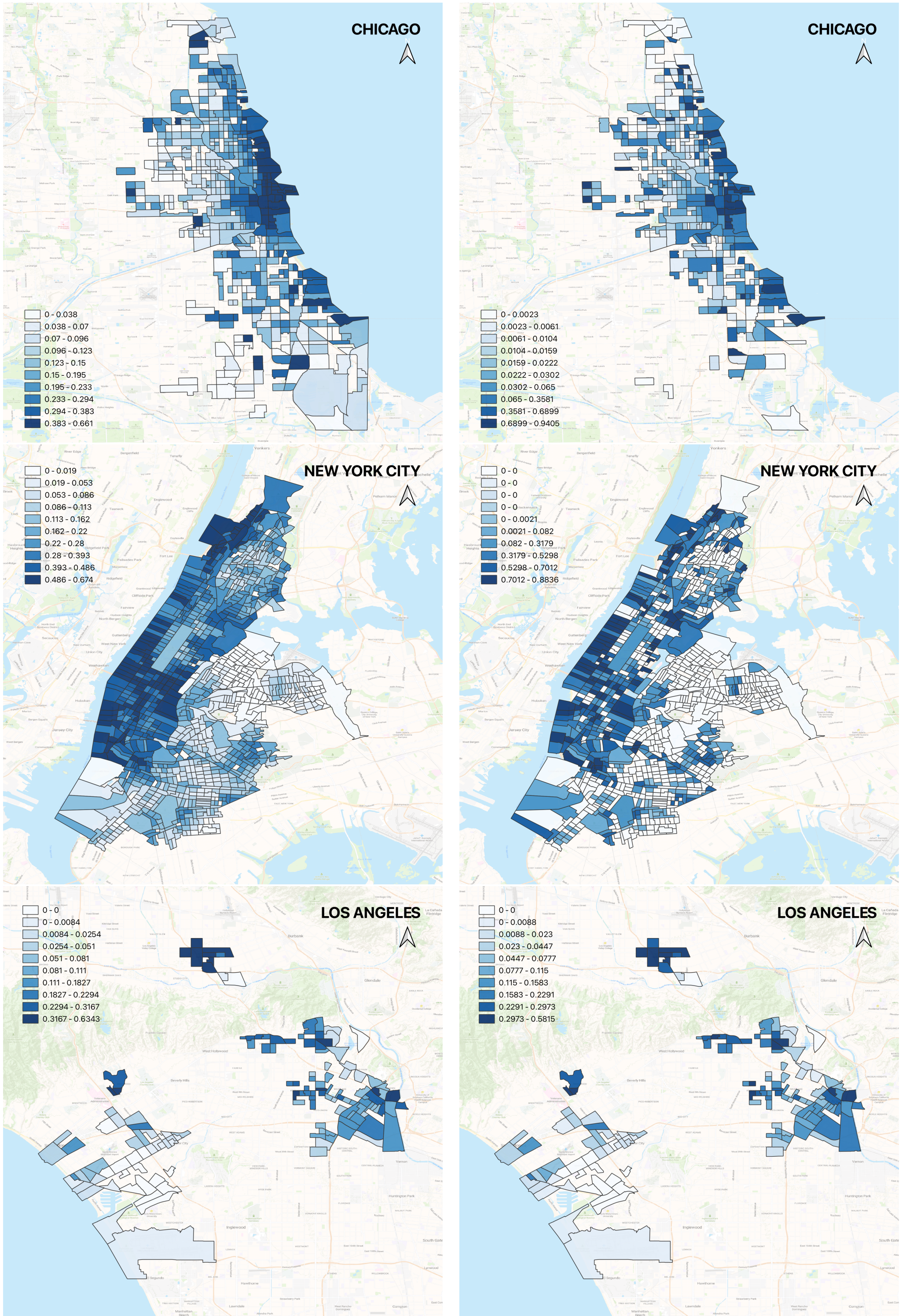

Figure B.6: **Modal integration proportions across cities.** These maps show how modal integration trips are distributed in space across the three cities. The left panel shows the modal integration proportions based on the origin census tract and the right panel shows the proportions based on the destination census tracts. For Chicago and New York City, many census tracts that have a relatively large modal integration origin proportion also have a relatively large modal integration termination proportion.

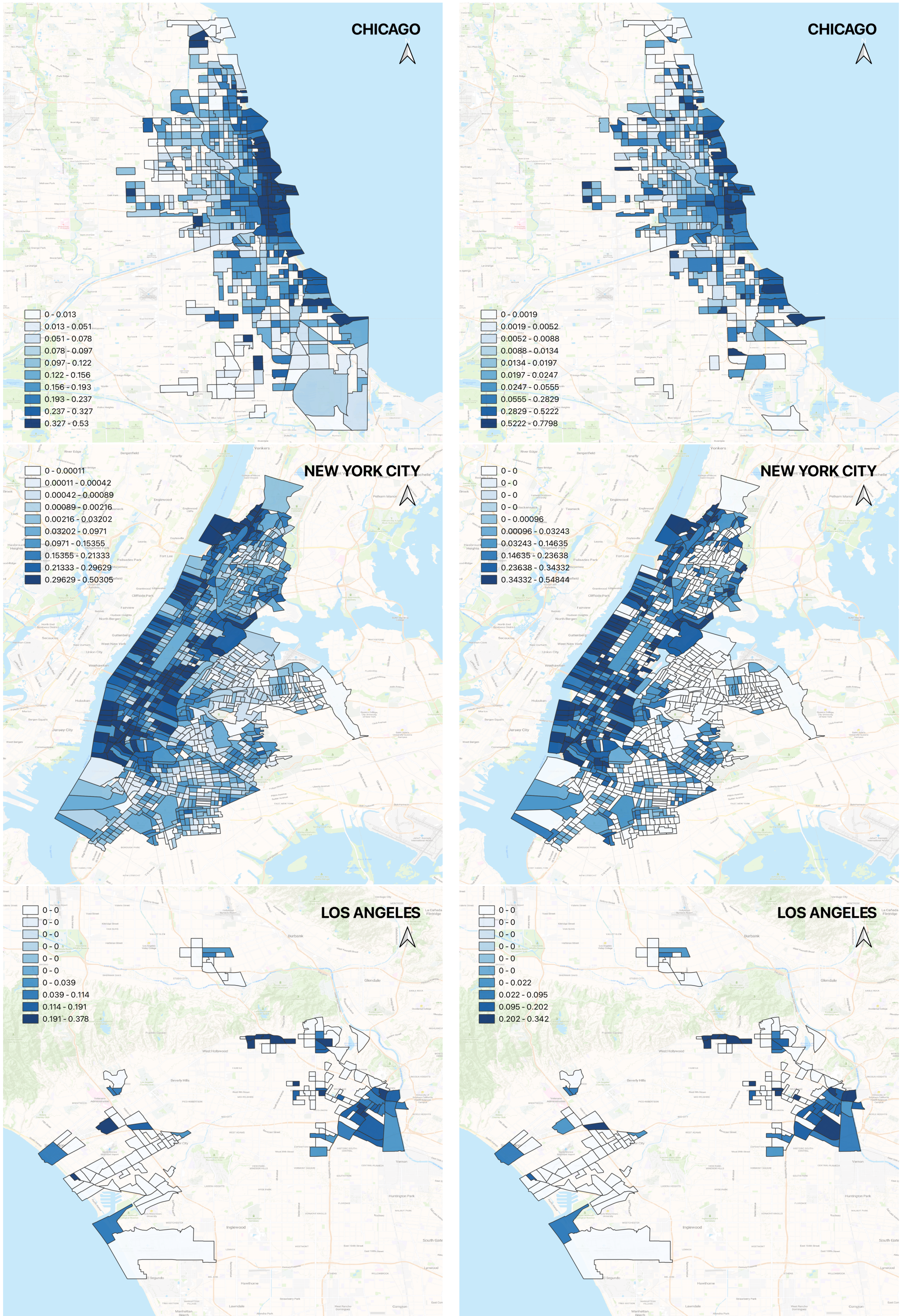

Figure B.7: **Modal substitution proportions across cities.** These maps show how modal substitution trips are distributed in space across the three cities. The left panel shows the modal substitution proportions based on the origin census tract and the right panel shows the proportions based on the destination census tracts. As with modal integration, for Chicago and New York City, several census tracts that have a relatively large modal substitution origin proportion also have a relatively large modal substitution termination proportion.

C Technical implementation details

This appendix describes some of the technical implementation details associated with performing the classification and regression analyses.

C.1 Code

The code is available on GitHub at `https://github.com/pollyren/bikeshare_transit_dynamics`. It is licensed under the MIT License.

C.2 Technical framework

This project uses several open-source technologies and geospatial tools to handle large-scale bikeshare and GTFS data efficiently. At the core of the implementation is a PostgreSQL database extended with PostGIS, which enables spatial querying and manipulation directly within the database. This allows for optimised spatial joins and distance calculations through indexing in a way that would be much more computationally intensive in a purely Python-based workflow. By leaving computationally intensive spatial logic in the database layer, the system minimises the need to frequently transfer large datasets.

Python was used for reading in the data, performing preliminary cleaning and visualising the results. The key libraries include `pandas` for general-purpose data manipulation, `geopandas` for handling shapefiles and geospatial data, `matplotlib` and `seaborn` for plotting and data visualisation, `libpysal` for conducting spatial autocorrelation analyses, and `psycopg2` for interfacing with the database. Additionally, shell scripts were used to download data, set up table schemas and automate various cleaning and processing portions of the analysis pipeline.

C.3 Modal classification, indexing and spatial queries

A central component of this research involves classifying bikeshare trips based on their origin and destination, arrival and departure time and the availability of nearby transit options. This rules-based approach, illustrated in Figures 3.1 and 3.2, categorises trips as various types of modal integration (MI-FLM, MI-FM, MI-LM), modal substitution (MS), or none.

The classification was the most computationally intensive aspect of this project. This is because, for each of the millions of bikeshare trips completed in 2023, the methodology attempts to establish a correspondence to a viable public transit option available in that city, at the relevant time and location. This involves searching through all the transit stops within that city, computing the 400-metre buffer using PostGIS's `ST_Distance` and `ST_DWithin` functions, scanning through the list of stop times for all the transit options within this distance buffer to determine whether bikeshare could have feasibly served as a connector to or from this transit option (modal integration), or whether bikeshare could have feasibly been a substitute for public transit in general (modal substitution). For context, Table C.1 shows the approximate sizes of the datasets used in this project.

Data[1]	**Chicago**	**New York City**	**Los Angeles**
Bikeshare system data	1,151	6,888	60
GTFS data	1,159	1,880	1,222
Post-classification bikeshare data[2]	994	8,041	76

[1] File sizes are in megabytes.
[2] This refers to the bikeshare data after the original system data is cleaned and processed, all trips are classified and the GIS geometries for the starting and ending locations are added.

Table C.1: **Size of datasets used.**

This multi-step evaluation, repeated at scale for all three cities, required efficient indexing in order to manage the computational performance of the classification. To accelerate the classification operations, B-tree indices were created for frequently queried columns in the bikeshare tables, including origin and destination stations, starting and ending times, and trip ID. These indices significantly reduced query runtimes during both the classification and aggregation phases. Additionally, spatial indices were implemented on geometry columns on bikeshare and census tract tables by using generic index structure (`GIST`). This enabled more optimised spatial queries, including distance-based calculations and spatial joins.

After classification, spatial joins were used to aggregate the bikeshare trips by their census tract of origin and destination. These joins were implemented using PostGIS's `ST_Intersects` function, which mapped the point geometry of each trip's origin and destination station to the corresponding census tract polygon based on spatial containment. This step allowed the modal classifications assigned at the trip level to be aggregated to a coarser scale in order to facilitate further regression analysis.

C.4 Query execution times

To better understand the computational demands of this pipeline, I timed the execution of the trip classification queries. These measurements, shown in Table C.2, were conducted for various queries on a MacBook Pro with an Apple M2 Chip and 32 GB of RAM.

Query[1]	**Chicago**	**New York City**	**Los Angeles**
Total classification time	711.39	14,606.66	771.47
Q1 classification	76.05	2,764.88	144.70
Q2 classification	232.08	5,046.51	215.80
Q3 classification	298.31	3,728.92	207.30
Q4 classification	104.94	3,066.35	203.68

[1] Query execution times are in seconds.

Table C.2: **Execution times for classification queries.**

When initially running the classification query without creating B-tree indices, the classification of Citi Bike trips in New York City far exceeded 24 hours and eventually had to be terminated before completion. After adding indices on frequently accessed columns, the total classification runtime dropped dramatically to under six hours, which demonstrates the substantial impact that indexing can have on query performance.

Interestingly, although Chicago's Divvy system had substantially more bikeshare trips than LA's Metro system, the classification queries for Chicago ran faster than the analogous queries for LA. This is, in part, due to LA's marginally larger GTFS dataset, which requires additional time to iterate over. But more interestingly, this could be a noteworthy artefact of the bikeshare and transit systems themselves; as observed through the modal integration and substitution trends in these two cities, Chicago has a much larger proportion of trips classified as modal integration and substitution than LA. As such, the classification process for most Metro Bike Share trips requires first checking that each trip is not a modal integration trip (which requires three passes through the GTFS data for each of MI-FLM, MI-FM and MI-LM), then that each trip is not a modal substitution trip (which requires an additional pass through the GTFS data), before the trip is categorised as neither modal integration nor modal substitution. These additional passes over the GTFS data for each trip incur significant overhead. The classification of Divvy trips avoids this overhead, since the trip can be classified as soon as it satisfies the criteria for one classification type and short circuits the remaining logic that introduces additional passes over the GTFS dataset. Though New York City also has a large proportion of trips classified as MI or MS, the Citi Bike dataset is several times larger than those of Divvy or Metro Bike Share. As such, the overall classification process remains considerably more computationally intensive.

For further exploration, it would also be interesting to experiment with how these execution times change when using an in-process database such as DuckDB, as opposed to a client-server relational database like PostgreSQL. I also did not take advantage of PostgreSQL's parallel querying abilities when running the classification and aggregation operations; it may be worthwhile to explore and benchmark these alternatives for faster execution times.