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Unraveling the network effects in station ridership growth patterns under metro network expansion

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ABSTRACT

To address the mobility challenges associated with rapid urbanization, many cities have expanded their metro networks. This requires massive investment, but it does not uniformly translate to ridership growth across stations. The factors influencing station-level ridership dynamics and the underlying network effects are complex and poorly understood. This study thoroughly investigates the station-level ridership growth dynamics under network expansion, utilizing spatiotemporal lag fixed effects models to capture both the supply-side and demand-side network effects as well as temporal dynamics. Utilizing the evolution of Shanghai Metro from 2014 to 2019, we demonstrate that the network effects has a significant and intricate influence on station ridership and its relative growth patterns. On the supply side, neighboring stations show competitive relationships leading to reduced ridership growth, while stations on the same metro line can complement each other. For the whole network, the station betweenness and closeness centralities exhibit divergent impacts on ridership growth rate. On the demand side, we confirm the existence of spatial spillover effects of station ridership, especially at the line level. Additionally, the time-lagged and heterogeneous effects of network expansion are revealed. Our findings provide valuable insights for informed and targeted decisions regarding metro network planning and infrastructure investment.

1. Introduction

Recent decades have witnessed accelerating urbanization, marked by a significant shift of populations from rural to urban areas, especially in developing countries. While urbanization has driven substantial economic, social, and environmental advancements globally, it has also introduced a series of transportation challenges, including traffic congestion, air pollution, and a high incidence of road accidents (Zhao et al., 2022). Metro systems have emerged as a key solution to these issues, offering a reliable, efficient, and environmentally friendly mode of urban transportation to support burgeoning populations and economic activities (Wu et al., 2022). China, in particular, has undergone rapid metro expansion in the last few decades, with cities such as Shanghai, Beijing, and Guangzhou developing some of the world's largest and most heavily utilized metro systems. By the end of 2023, 59 cities in mainland China had established metro systems, comprising 338 operational lines and extending over 11,224 km (China Association of Metros, 2024). Furthermore, 46 cities were in the midst of metro construction projects, with the total length of lines under construction reaching 6118 km.

Despite these rapid developments and the massive investment required, actual ridership in some cities has not met the expectations set during the planning phase (Xin and Feng, 2024). According to the 2022 annual reports and audits released by metro companies across 32 Chinese cities, only five have achieved profitability. Moreover, the expansion of urban metro infrastructure does not uniformly translate to ridership growth across stations. As we will show later, certain stations may experience a decline in patronage even as the network expands. This observation underscores a research gap in understanding the long-term ridership dynamics at the station level, particularly in relation to

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network expansion and its effects. Understanding such dynamics is crucial for cost-effective metro system expansion and sustainable urban development.

Metro network expansion can redistribute ridership within the network (Du et al., 2023), both from the supply side and demand side. The supply-side effects are driven by changes in the metro network infrastructure. This includes the introduction of new stations, lines, or expansions of existing lines, which modify the network topology, extend service coverage into new areas, and create additional origin-destination (OD) travel opportunities. In this sense, the supply side refers to the physical infrastructure that enables travel options.

The demand-side effects, in contrast, refer to changes in ridership at a station due to shifts in passenger flows at other stations within the network. These effects reflect the spatial interactions between stations and the spillover effects, where growth or decline in ridership at one station can influence ridership at nearby stations. Compared to supply-side effects, demand-side effects capture changes in passenger behavior driven by shifts in demand. For example, when new stations are added or lines are expanded, passengers may alter their travel choices. If new metro lines enhance accessibility to certain areas, passengers who previously relied on buses or other modes may switch to the metro. Additionally, passengers might change their destination preferences, choosing a newly accessible station over nearby alternatives. These shifts can lead to increased ridership at some stations while causing a decline at others that are bypassed or less optimally located. Thus, the demand side captures how the movement of passengers across the network influences ridership at individual stations, reflecting the interconnected nature of travel demand within the system.

Both the supply-side and demand-side network effects can manifest at different scales, including the local level, line level, and global level. The local level refers to the interactions between stations that are spatially close to one another, typically influenced by short-distance travel or physical proximity. The line level focuses on stations located along the same metro line, where network effects are shaped not only by shared characteristics of the line (e.g., service frequency and transfer opportunities) but also by the connection among stations, which may benefit from no-transfer cost advantages. The global level encompasses all stations in the metro network, capturing the broader, system-wide effects. For example, the competitive relationships may be dominant for nearby stations at the local level, while at the global level stations tend to be more complementary. Due to the specific service design of metro systems, the network effects between stations along the same line also require special attention. Overall, it is necessary to develop a comprehensive understanding about the impact of metro system expansion on station ridership dynamics considering such diverse network effects.

Previous research has used station characteristics such as centrality to explore the relationship between metro network topology and ridership (An et al., 2019; Luo et al., 2020; Shao et al., 2020). For instance, Li et al. (2024) developed multi-mode public transportation network models to describe public transportation usage. Li et al. (2023) proposed an improved centrality measure to identify critical nodes in multiplex networks. These studies have significantly advanced the understanding of metro ridership dynamics from complex network perspectives. Nevertheless, limited research has systematically examined changes in station ridership within the context of evolving networks. To our best knowledge, only Liu et al. (2019) and Xin and Shalaby (2024) investigated the impact of metro network expansion on ridership changes over multiple years. While they measured the influence of network expansion using certain supply-side network indices such as accessibility and betweenness centrality, the demand-side network effects and the variation across different scales are not sufficiently considered.

Additionally, for stations at different locations and with different ridership growth patterns, the impact of network expansion may differ in both the magnitude and direction. For instance, fast-growing stations may exhibit different sensitivities to infrastructure changes than declining ones, and a one-size-fits-all approach may overlook these critical differences. Understanding such heterogeneity across stations can inform specific ridership intervention measures, though current studies on metro expansion mostly focus on the average effects (Liu et al., 2019; Xin and Shalaby, 2024). Furthermore, the temporal dynamics of network expansion have not been fully investigated. While Xin and Shalaby (2024) examined the time lag effects of station betweenness centrality on ridership, other network features warrant further investigation.

To bridge these research gaps, this study aims to establish a comprehensive framework for exploring the underlying mechanisms of ridership growth dynamics in the context of metro network expansion, with a specific focus on network effects between stations. We use both supply- and demand-side network features, at the local, line and global levels, to comprehensively assess the impact of network expansion. In addition, given the varying characteristics of stations within the metro system, we will investigate how the network effects vary across stations with different ridership growth patterns and locations. Specifically, Shanghai's metro system, called Shanghai Metro, is chosen as a case study, with multi-year network expansion and station ridership data used for empirical analysis. The study findings will shed light on the complex interplay between network expansion and station-level ridership dynamics, contributing to more informed and cost-effective urban metro development and rail investment strategies. Our specific contributions are the following:

- We delve into an extensive analysis of the mechanisms driving station-level ridership growth by incorporating network effects across multiple scales and from both supply side and demand side. This allows us to understand how network structure changes and spatial interactions affect station patronage over time and to uncover the competition and cooperation relationships between stations.
- We propose a spatiotemporal lag fixed effects model (ST-FEM) that captures both the spatial and temporal ridership dynamics. This model effectively identifies the spatial interactions of ridership within the metro network and examines the time-lagged effects of changes in network structure on ridership growth.
- We investigate the heterogeneity of network effects, demonstrating their variability among stations with different passenger flow patterns and spatial locations. This nuanced analysis not only provides valuable insights into the context-specific impact of network effects, but also informs the development of tailored strategies for network expansion.

2. Literature review

2.1. Urban impacts of metro system expansion

The evolution and development of metro systems play a pivotal role in shaping urban landscapes, fostering connectivity, and driving urban growth. Previous research has provided extensive empirical evidences about the impact of metro expansion on urban economic growth. For instance, metro development is found to have a significant positive effect on urban GDP growth (Zhang, 2020) and the labor market improvements (Cats, 2017; Zhang, 2020; Pang and Shen, 2024). Metro lines can significantly boost local accessibility, which in turn affects land and property values (Gibbons and Machin, 2005; Billings, 2011; Kaneko et al., 2019). Such accessibility enhancements also stimulate local economic activities, thereby offering more consumer amenities and services to urban residents (Zheng et al., 2016).

Beyond economic growth, metro development also significantly influences various regional development indicators, including population growth, air quality, and urban form (Pokharel et al., 2023). It can discourage car ownership among households (Zhang et al., 2017) and reduce road congestion (Winston and Langer, 2006; Yang et al., 2018), leading to significant reductions in air pollution (Gendron-Carrier et al., 2022; Xiao et al., 2020). Additionally, metro expansions can alter urban form and encourage decentralization (King, 2011; Gonzalez-Navarro and Turner, 2018). Metro development often leads to the rejuvenation of underutilized areas, transforming them into vibrant urban centers that attract both businesses and residents (Lin et al., 2022). New metro stations can revitalize the areas surrounding suburban stations more than those in the city center (Tan et al., 2019), and the expansion of metro networks might contribute to depopulation in central cities (Levinson, 2008).

2.2. Transit ridership dynamics and its influencing factors

The day-to-day (Reades et al., 2016; Ceapa et al., 2012) and seasonal (Li et al., 2018) periodic patterns of transit ridership have been extensively investigated. However, research on metro ridership patterns spanning multiple years is relatively scarce (Matas, 2004; Litman, 2004; Paulley et al., 2006; Melo et al., 2019; Canavan et al., 2018). These studies typically observe an increasing trend in metro ridership over the years (Melo et al., 2019; Matas, 2004), driven by network expansion and population growth within cities, barring unforeseen events such as financial crises (Melo et al., 2019) and pandemic outbreaks (Yang et al., 2023a). However, such studies primarily focus on general trends for the entire metro system, neglecting the ridership dynamics within the system, particularly the station-level ridership growth patterns over time.

To understand the determinants of transit ridership, a substantial number of empirical studies have identified a plethora of factors that can be broadly classified into five categories: (1) socio-demographics (Chu et al., 2004; Chow et al., 2006; Chava et al., 2018; Ding et al., 2019; Yang et al., 2023b), including the residential population characteristics, household car ownership, income, and property prices; (2) land use (Gutiérrez et al., 2011; Jun et al., 2015; Sohn and Shim, 2010; Shao et al., 2020; Yang et al., 2023b), such as the residential density, job density, and land use diversity; (3) external connectivity (Estupiñán and Rodriguez, 2008; Zhao et al., 2013; An et al., 2019), including the road/intersection density and distance to the city center; (4) intermodal connections (Kuby et al., 2004; Sohn and Shim, 2010; An et al., 2019; Li et al., 2020), such as the number of feeder bus lines and bicycle park-and-ride spaces; and (5) station types (Sohn and Shim, 2010; Cardozo et al., 2012; Zhao et al., 2014; Gan et al., 2020b), such as regular, terminal, or transfer stations.

2.3. Influence of metro network effects on station ridership

Station areas not only function as key nodes for travel on metro networks but also provide a wealth of activity opportunities, and thus metro ridership is influenced by both the station's geographical and network locations (Bertolini, 1996; Gan et al., 2020a). In this study, the network location is regarded as the supply-side network effects that reflect the network topology dynamics. Cao et al. (2020) highlighted the significance of a station's node value, represented by its network centrality and accessibility, as having a fivefold greater impact on station ridership compared to its place value, represented by socioeconomic and land-use characteristics of the station area. Ding et al. (2024) use station centralities as predictors to forecast metro station ridership in expanding scenarios. Shao et al. (2020) identified station betweenness centrality as the most predictive factor for metro ridership.

Existing studies on the relationship between metro networks and ridership can be divided into four categories based on whether the spatial unit is station-level or system-level, and whether the analysis is longitudinal or cross-sectional. The system-level cross-sectional analysis typically conducts topological evaluations of metro networks across multiple cities, highlighting the significant role of network topology in increasing metro ridership (Derrible and Kennedy, 2009; Saidi et al., 2017). On the other hand, system-level longitudinal analysis examines the impact of network evolution on the entire metro system's ridership (Matas, 2004; Xin and Feng, 2024). These studies often employ multiple years of metro ridership data, generally finding a positive relationship between network expansion and metro ridership. Station-level cross-sectional analysis assesses how a station's importance within the network affects its ridership by calculating network metrics for each station (Luo et al., 2020; An et al., 2019; Su et al., 2022). Compared to the other three categories, station-level longitudinal analysis has been less explored. Our study falls into this category. Most existing research in this area focus on the impacts of specific new lines or stations by analyzing ridership differences before and after expansion (Werner et al., 2016; Fu and Gu, 2018; Du et al., 2023), but they do not distinguish the impact of network topology changes across multiple scales. Additionally, due to the lack of continuous expansion analysis, these studies cannot examine the time lag effects of network expansion.

For metro systems, it has been suggested that the ridership observed at one station can influence neighboring stations (Du et al., 2023). In this study, this spatial interactions among stations is regarded as demand-side network effects. However, most existing research only focuses on spatial dependency among stations at the local or global level (Cardozo et al., 2012; Gan et al., 2019), overlooking the spatial interactions at the line level.

In this study, we aim to explore the effects of metro network expansion on station ridership growth patterns. To the best of our knowledge, very limited research has been conducted on this topic. Liu et al. (2019) investigated the station-level ridership growth in relation to metro network expansion, considering factors including the network scale and station accessibility. They found that an increase in accessibility is positively related to station ridership growth. However, they did not consider the changes in a station's overall network importance (e.g., centrality). Xin and Shalaby (2024) established a correlation between a station's betweenness centrality and ridership across different expansion stages, concluding that stations with higher centrality are more likely to experience increased ridership pressure in subsequent years. However, these two studies only analyzed the effects of network expansion at a specific scale and from the supply side alone. Additionally, the heterogeneity of these effects is not fully explored. This study aims to fill these gaps.

3. Methods

3.1. Research framework

This study aims to uncover the effects of metro network expansion on station ridership growth patterns. To this end, we have developed a detailed research framework, illustrated in Fig. 1. In this study, we will integrate multi-sourced data, including multi-year metro flow data, metro network expansion records, and urban context information. Network features from both the supply side and demand side will be defined to represent the expansion process over time, and ridership growth patterns will be identified for each station in each year. The effects of metro network expansion on station ridership growth patterns will be estimated using a series of bespoke spatiotemporal lag fixed effects models.

Our analytical approach is structured in three parts. First, we introduce a base ridership model (*Model 1*), where the average daily ridership at each station in each year serves as an observational unit to uncover the relationship between network features and station-level passenger volumes. This model sets the foundation for understanding the basic dynamics of metro ridership. Next, we construct a ridership growth model (*Model 2*) to explore the influence of network expansion on station-level annual ridership growth rates. Model 2 extends Model 1 by incorporating the dynamic network effects on ridership fluctuations between consecutive years, offering a more nuanced view of how network expansion affects station ridership over time. Furthermore, we are particularly interested in discerning how the network effects might vary between stations at different locations with different ridership growth patterns. Therefore, built on Model 2, a heterogeneous ridership

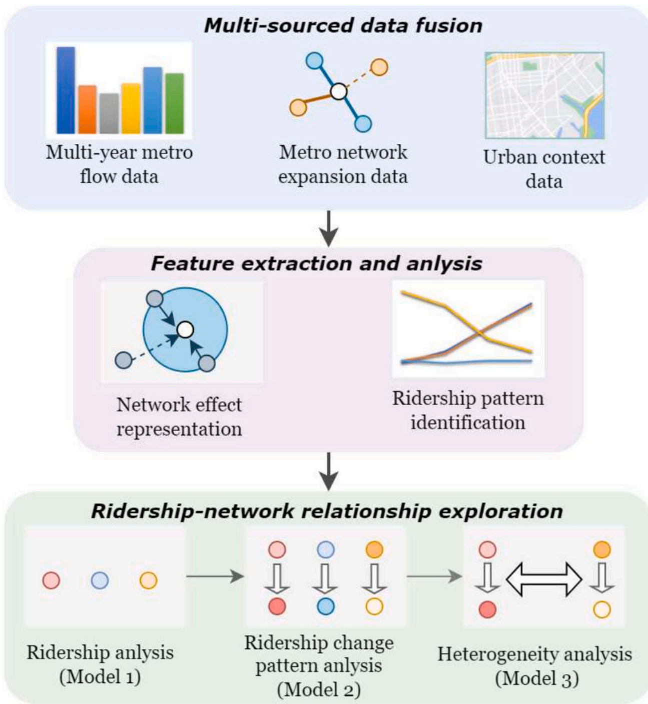


Fig. 1. Research framework.

growth model (*Model 3*) is developed to uncover station-specific influence mechanisms, thereby providing insights for more targeted demand management and planning strategies. This tiered modeling approach allows us to comprehensively understand the complex effects of metro network expansion on station ridership growth patterns.

3.2. Key variable definition

In our study, we define station ridership dynamics using two metrics: annual average daily ridership (AADR) and its growth rate (GR). The former mainly differentiates a station from others, while the latter highlights a station's relative change from year to year. AADR is defined as the daily average ridership of a station in a given year, which is calculated from that year's inflow and outflow daily averages. The AADR of station i in year t is computed as follows:

$$\mathrm{AADR}_{i,t} = \frac{1}{2n}\sum_{d=1}^{n}\left(\mathrm{Inflow}_{i,t,d} + \mathrm{Outflow}_{i,t,d}\right) \tag{1}$$

where t represents the year, n is the number of operational days for station i in year t, $\mathrm{Inflow}_{t,d}$ is the daily inflow ridership for day d of year t, and $\mathrm{Outflow}_{t,d}$ is the daily outflow ridership for the same day. The growth rate (GR) is defined as the percentage change in daily average ridership between the the next year and the current year. The GR of station i in year t is computed as follows:

$$\mathrm{GR}_{i,t} = \frac{\mathrm{AADR}_{i,t+1} - \mathrm{AADR}_{i,t}}{\mathrm{AADR}_{i,t}} \times 100 \tag{2}$$

where $\mathrm{AADR}_{i,t}$ is the AADR for the current year (year t), and $\mathrm{AADR}_{i,t+1}$ is the AADR for the next year $t+1$. This rate represents the percentage change in ridership from year t to year $t+1$.

To analyze how changes in network structure affect ridership, we define network topology features as supply-side network effects. To capture the spatial interactions among stations, we define the spatial lag terms of ridership dynamics as demand-side network effects. Additionally, to account for complex network effects at multiple scales, we consider local, line-level, and global network features for each station.

3.2.1. Supply-side network effects

For local features, we consider the number of nearby stations and node degree, denoted as *NS* and *DG*, respectively. *NS* is defined for each station based on a given distance radius *r*. The node degree is calculated by counting the number of links that are directly connected to a given station (Cats, 2017).

For line-level features, we consider the number of stations on the lines where a station is located, denoted as *SL*. This index represents the number of stations that can be reached directly from this station without transfer. Additionally, to reflect network changes, we assess whether there are new stations on the same metro lines during the next year, denoted as *NSL*. This metric provides insights onto how network expansion might affect existing stations at the line level. Furthermore, we also consider the changes in these indicators over time, namely the number of new nearby stations and increase in the node degree, denoted as ΔNS and ΔDG, respectively. These measures help assess the local effects of network expansion.

Global network topology features include betweenness centrality *BC*, and closeness centrality *CC*. Betweenness centrality identifies a station's role as a critical junction for traffic flow across the network, while closeness centrality reflects how easily a station can reach all other stations in the network. A higher closeness centrality suggests shorter paths on average to all other stations. In addition, the changes in betweenness and closeness are also considered, denoted as ΔBC, and ΔCC.

Specifically, the betweenness centrality $BC(v)$ of a station v is calculated as:

$$BC(v) = \sum_{s \neq v \neq t}\frac{\sigma_{st}(v)}{\sigma_{st}} \tag{3}$$

where σ_{st} is the total number of shortest paths from station s to station t, $\sigma_{st}(v)$ is the number of those paths that pass through v. This standardized betweenness centrality represents the proportion of all shortest paths within the network that pass through a specific station.

The closeness centrality $CC(v)$ of a station v is defined as the reciprocal of the sum of the length of the shortest paths between station v and all other stations in the network. The equation can be represented as:

$$CC(v) = \frac{1}{\sum_{u \neq v} d(v,u)} \tag{4}$$

where $d(v,u)$ is the distance between stations v and u, typically the shortest path length. This definition implies that station closeness centrality increases for higher accessibility to all other stations in the network, indicating the efficiency in network connectivity.

3.2.2. Demand-side network effects

The demand-side network effects for station i can be computed as $\sum_j \omega_{ij} y_j$, where y_j represents AADR/growth rate of station j, which is spatially related to station i, and ω_{ij} denotes the spatial weight between stations i and j. There are primarily two strategies for creating weights to quantify the relationships among stations: binary adjacency or distance decaying (Getis, 2009). However, for a metro system, the spatial correlation between two stations on the same line may be stronger because people dislike transfers between lines, which has been overlooked in existing studies. In this study, we define three levels of spatial dependency among stations targeted for the metro system: local level, line level, and global level. Therefore, the demand-side network effects include *AADR_local*, *AADR_line*, *AADR_global*, *GR_local*, *GR_line*, and *GR_global*. The first three metrics represent the spatial interaction of AADR at the local, line, and global levels, respectively. The last three metrics represent the spatial interaction of the AADR growth rate at these same three levels. The three levels of spatial dependency are shown in Fig. 2.

In Fig. 2, the top three subfigures illustrate the dependency graph for

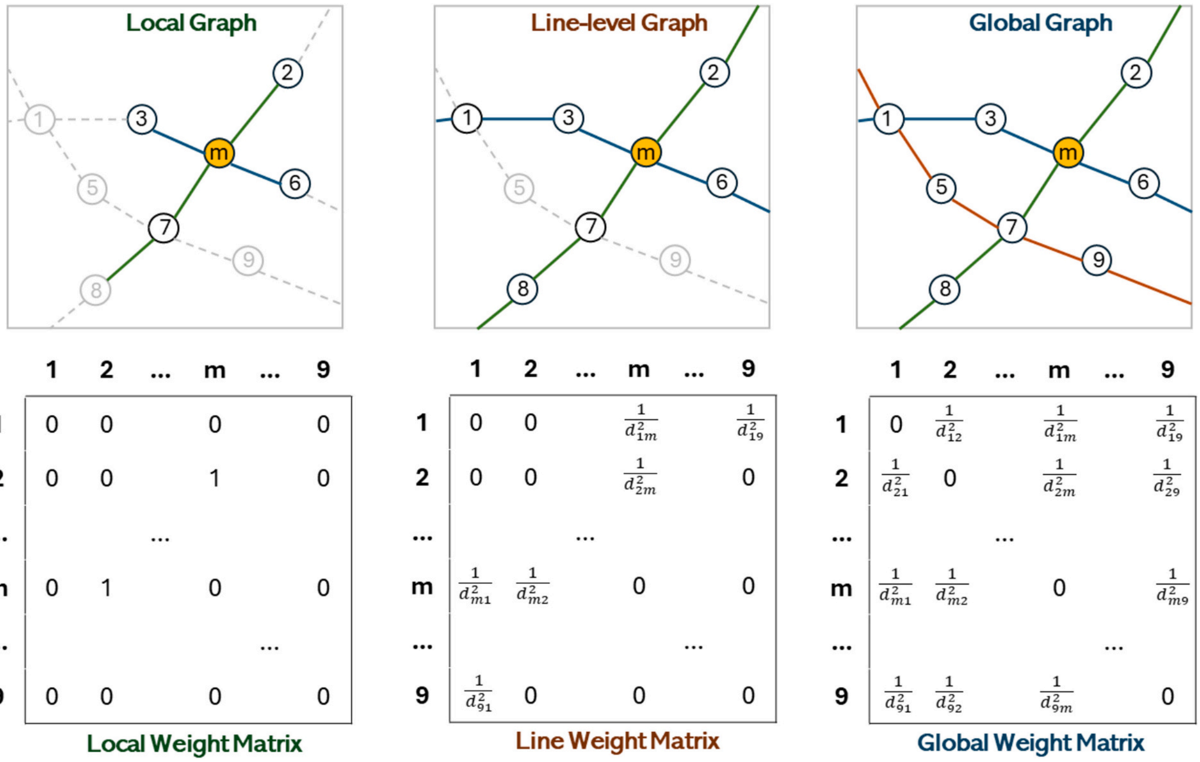


Fig. 2. Three definitions of spatial weights between metro stations.

station m at the three levels, while the bottom part shows the weight matrices among all the stations. The local weight matrix reflects the adjacency between stations, and is represented as:

$$\omega_{ij} = \begin{cases} 1 & \text{if } i \neq j \text{ and } d_{ij} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where d_{ij} represents the shortest distance between stations i and j, defined as the minimum number of line segments between the two.

The line weight matrix captures the dependency between two stations along the same metro line. $t(i,j)$ represents the number of transfers required between two stations, and the line weight is defined as follows:

$$\omega_{ij} = \begin{cases} \dfrac{1}{d_{ij}^2} & \text{if } i \neq j \text{ and } t(i,j) = 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

The global weight matrix quantifies the weight between any two stations using the inverse distance function (Getis, 2009), represented as follows:

$$\omega_{ij} = \begin{cases} \dfrac{1}{d_{ij}^2} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \tag{7}$$

To ensure consistency and facilitate comparisons, all the weight matrices are row-normalized, in which the elements of each row in the weight matrix sum to unity.

3.3. Spatiotemporal lag fixed effects model

3.3.1. Fixed effects model

The fixed effects model (FEM) is a widely used statistical method for analyzing panel data. It effectively controls for unobservable, individual-specific heterogeneity that might affect the dependent variable (Yu et al., 2024). In this study, to examine the impact of network expansion on station ridership patterns, each observation corresponds to a station in a particular year. The basic formulation of the FEM is as follows:

$$y_{i,t} = \alpha + \beta x_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{8}$$

where $y_{i,t}$ represents the dependent variable (ridership or its growth rate) for the ith metro station in year t. It is modeled using a set of explanatory variables, with $x_{i,t}$ representing the explanatory variables, including the supply-side network attributes and other control variables. β is the coefficient corresponding to the explanatory variables, α is the intercept, μ_i signifies the station-specific fixed effects, λ_t indicates the time-specific fixed effects, and $\varepsilon_{i,t}$ is the error term.

3.3.2. Spatial lag fixed effects model

In this study, we introduce a Spatial Lag Fixed Effects Model (S-FEM), which incorporates the demand-side network effects—ridership patterns of neighboring stations into the FEM to account for spatial autocorrelation. This is typically represented by a spatial weighting matrix. The formulation of S-FEM is as follows:

$$y_{i,t} = \alpha + \rho \sum\nolimits_{j=1}^{N} \omega_{ij} y_{j,t} + \beta x_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{9}$$

where ρ is a spatial parameter and $\sum_j \omega_{ij} y_j$ denotes the demand-side network effects mentioned in Section 3.2.2. The spatial autocorrelation is negative when $\rho < 0$, and positive when $\rho > 0$.

3.3.3. Spatiotemporal lag fixed effects model

The impact of network expansion on ridership patterns may exhibit a time lag effect (Xin and Shalaby, 2024). In other words, changes in network topology may not immediately influence a station's ridership after the metro is expanded. People need time to become aware of the network changes, relocate their residences and workplaces, adjust their travel behavior, and ultimately adapt to the new system. Therefore, we further extend the S-FEM by incorporating time-lagged terms of the network topology change indices to explore dynamic relationships. The Spatiotemporal Lag Fixed Effects Model (ST-FEM) can be expressed as:

$$y_{i,t} = \alpha + \rho \sum_{j=1}^{N} \omega_{ij} y_{j,t} + \beta_0 x_{i,t}^{(1)} + \sum_{k=1}^{K} \beta_k x_{i,t-k}^{(2)} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{10}$$

where $x_{i,t}^{(1)}$ and $x_{i,t-k}^{(2)}$ represent the non-lagged variables and the k-th lag of the network topology change variables (i.e., ΔNS, ΔDG, NSL, ΔBC, and ΔCC), respectively. β_0 and β_k are the coefficients for the current and the k-th lagged explanatory variables, respectively. In this study, we test the lagged time effects at 1 year, 2 years, and 3 years; hence, k takes the values of 1, 2, and 3.

3.4. Quantile regression

In this study, as part of Model 3, we will apply quantile regression to explore the network effect heterogeneity on the ridership dynamics. As an extension of linear regression, quantile regression allows us to examine the variation of regression coefficients in different parts of the dependent variable's conditional distribution such as the tails of the distribution (Koenker and Bassett Jr, 1978). Therefore, it can reveal heterogeneous relationships between network features and station ridership. In addition, it is more robust in handling outliers and applicable to asymmetrical distributions (Koenker, 2005).

In this study, to ensure the convergence of the model, we remove the station fixed effects by demeaning all explanatory variables before quantile regression. This involves accounting for unobserved station effects by subtracting the mean of each variable within each station over time. The form of the quantile regression can be written as follows:

$$Q_\tau\left(\widetilde{y}_{i,t}\right) = \alpha(\tau) + \rho(\tau) \sum_{j=1}^{N} \omega_{ij} \widetilde{y}_{j,t} + \beta_0(\tau) \widetilde{x}_{i,t}^{(1)} + \sum_{k=1}^{K} \beta_k(\tau) \widetilde{x}_{i,t-k}^{(2)} + \lambda_t(\tau) + \widetilde{\varepsilon}_{i,t}(\tau) \tag{11}$$

where τ is the conditional quantile of interest, the $\widetilde{(\cdot)}$ notation denotes the demeaned variables. The quantile functions are estimated by minimizing an asymmetrically weighted sum of absolute errors, as specified in the following equation:

$$min \sum_{i=1}^{n} \gamma_\tau \left(\widetilde{y}_{i,t} - \alpha(\tau) - \rho(\tau) \sum_{j=1}^{N} \omega_{ij} \widetilde{y}_{j,t} - \beta_0(\tau) \widetilde{x}_{i,t}^{(1)} - \sum_{k=1}^{K} \beta_k(\tau) \widetilde{x}_{i,t-k}^{(2)} - \lambda_t(\tau) - \widetilde{\varepsilon}_{i,t}(\tau) \right) \tag{12}$$

$$\gamma_\tau(v) = \tau max(v, 0) + (1 - \tau) max(-v, 0) \tag{13}$$

where $\gamma_\tau(v)$ is the quantile loss function.

4. Data

4.1. Data description

To demonstrate the proposed research framework, the metro system in Shanghai, called Shanghai Metro, is chosen as a case study. Since commencing operations in 1993, the Shanghai Metro system has provided over 30 years of service. By the end of 2019, it comprised 16 lines (excluding the Maglev Line) and an extensive network spanning 676 km. Notably, it led the global rankings in terms of annual ridership, recording 3.88 billion rides in 2019 (Huang et al., 2024). Fig. 3 highlights our study area and the distribution of the metro network, which covers most of Shanghai and connects the central area with its suburban regions.

Note: Shanghai's central area refers to the region within the outer ring roads.

The metro ridership dataset encompasses daily passenger inflow and outflow for each station from 2014 to 2019. The data samples are presented in Table 1. Due to a technical issue, data from April to October 2014 are missing. However, since our analysis operates on an annual basis, the data from the remaining months in 2014 are still sufficient to capture the average ridership trends for that year. Specifically, for 2014, the AADR is calculated using the available days, while for the years 2015–2019, the full year's data (i.e., 365/366 days) are used to compute

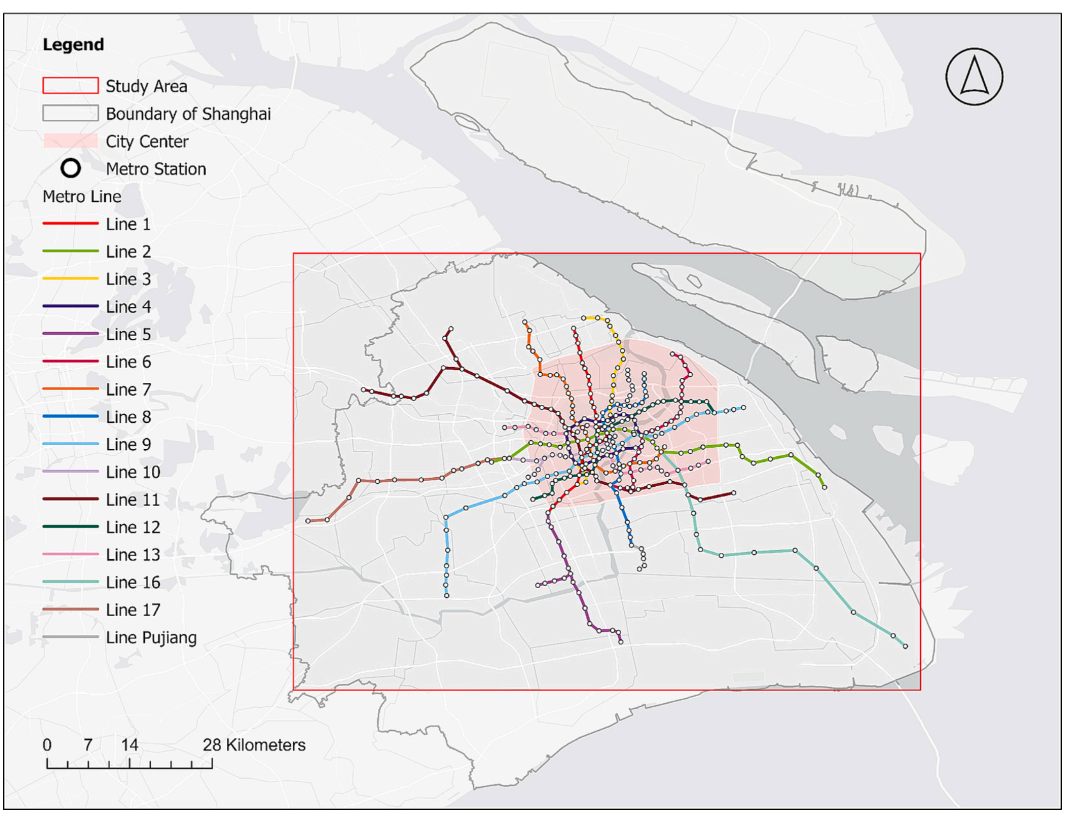


Fig. 3. The study area and the metro network in Shanghai in 2019.

Table 1
Data samples of Shanghai metro ridership dataset.

Date	Station Name	Inflow	Outflow
2014/1/1	Xinzhuang	60,778	63,355
2014/1/1	Waihuanlu	9322	10,308
2014/1/1	Dishui Lake	12,287	12,965
…	…	…	…
2019/12/31	Xinzhuang	62,757	64,870
2019/12/31	Waihuanlu	15,348	14,259
2019/12/31	Xuelin Road	4617	4902
2019/12/31	Zhangjiang Road	13,871	12,455

the AADR. As a result, an AADR value is calculated for each station in each year. The growth rate of the AADR between two consecutive years for a given station can then be determined.

Fig. 4 illustrates the AADR of the whole Shanghai Metro system and the number of stations each year from 2014 to 2019. As shown in the figure, the overall ridership for the system demonstrates a steady increase over this period. Additionally, the figure highlights three significant network expansions in 2015, 2017, and 2018. In Fig. 5, we further demonstrate the evolving metro network layout across years. Nodes colored blue represent existing stations built before the current year,

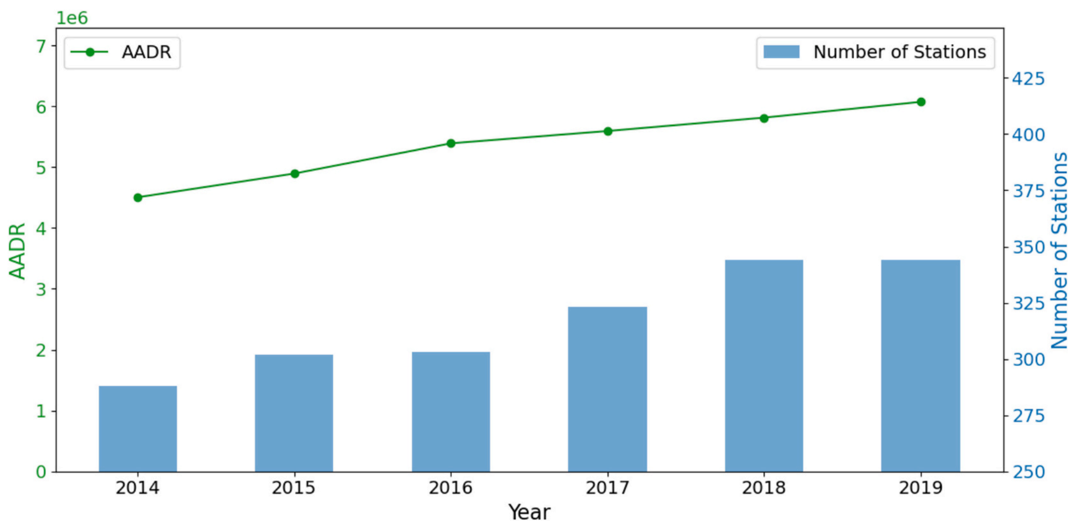


Fig. 4. AADR and number of stations from 2014 to 2019.

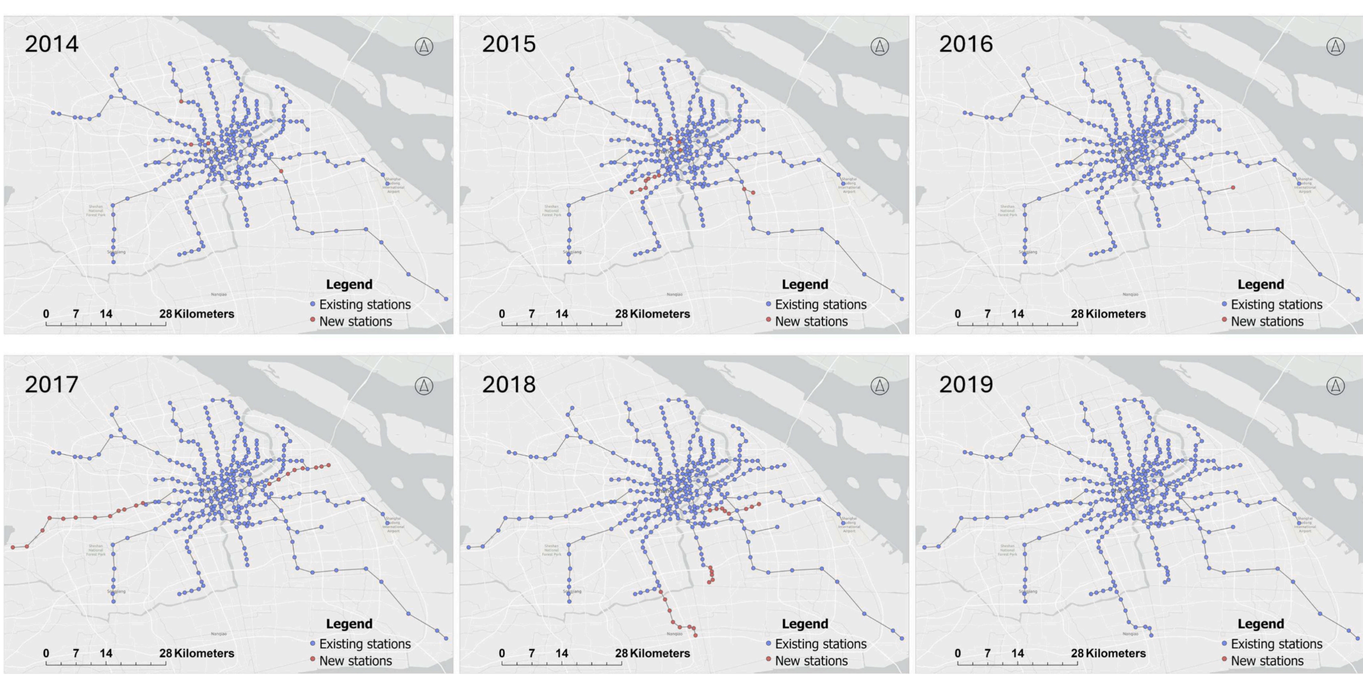
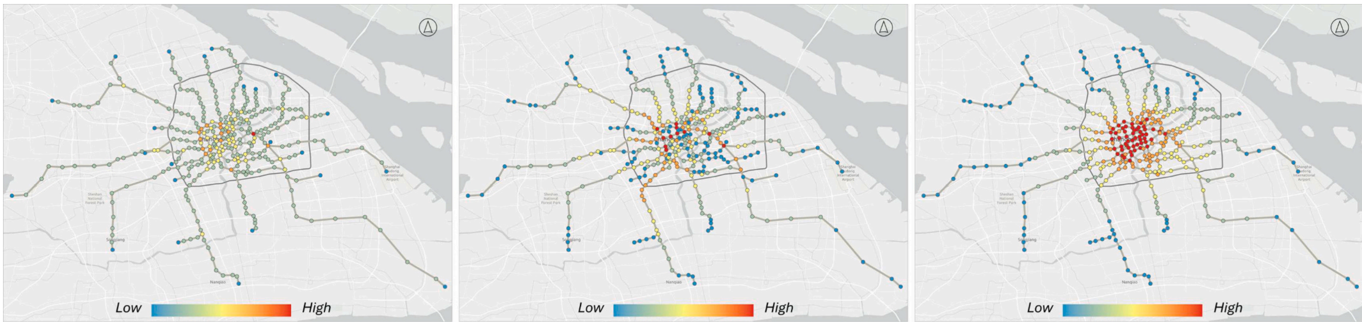


Fig. 5. Metro network expansion process from 2014 to 2019.



(a) Degree (b) Betweenness centrality (c) Closeness centrality

Fig. 6. Centrality of all stations in 2019.

while nodes colored orange indicate new stations opened within that year. It is clear that during the expansion process, more suburban areas were integrated into the metro system. Spatially, metro stations are more densely clustered in the central city areas.

4.2. Feature extraction

Note that new stations are added at different months of a year. To ensure data robustness, we only consider a station to be operational in a year if the station has ridership data for more than two months within that year. For instance, if a station was opened in December of a given year, we would not consider its AADR for that year since the station was not fully operational then. In later analyses, we refer to the first operational year with valid data for a station as the station's first operational year.

To calculate *NS*, a distance radius of $r = 2$ km is selected to define the area around each station. This is because the distances between stations generally range from 1 to 2 km, and our preliminary tests on different radius values show that a 2 km radius provides the best performance in our models. The detailed analysis of radius selection process is shown in Appendix A. The spatial distribution of station degree is illustrated in Fig. 6 (a), showing that the degree is higher in central areas where station density is greater. In addition, the betweenness and closeness centrality metrics of all stations in 2019 are shown in Fig. 6(b-c). It is apparent that the closeness centrality exhibits a decreasing trend from the city center outward.

In addition to network features, other influencing factors are included as control variables, encompassing socio-demographic factors, the built environment within the station catchment area (such as land use, external connectivity, and intermodal connections), and station attributes.

Table 2
Descriptive analysis of features.

Variables	Summary	Definition
Built Environment		
Landuse diversity	1.943 (0.297)	Landuse entropy of catchment area, computed from POI categories
POI density	1.534 (1.603)	POI density of catchment area $\left(thousand/km^2\right)$
Population density	22.309 (20.018)	Population density of the raster where the station is located $\left(thousand/km^2\right)$
Socio-economics		
House price	48.540 (19.314)	Average house price for neighborhoods in the catchment area (1000 CNY/m^2)
Station Attributes		
Terminal	177 (9.6 %)	Whether the station is a terminal station (0/1)
Age_less_3y	181 (9.8 %)	Whether the station's operation age is less than 3 years (0/1)
Age_3-6y	310 (16.7 %)	Whether the station's operation age is between 3 and 6 years (0/1)
Age_greater_6y	1361 (73.5 %)	Whether the station's operation age is more than 6 years (0/1)
Supply-side Network Effects		
NS	4.354 (3.510)	The number of stations within 2 km of the station
DG	2.371 (1.080)	Node degree
SL	33.829 (15.644)	Number of stations in the same lines
BC	6.983 (1.793)	Betweenness centrality, scaled up by a factor of 100
CC	2.212 (0.602)	Closeness centrality, scaled up by a factor of 10,000
ΔNS	0.060 (0.317)	The number of new stations within 2 km area during the next year
ΔDG	0.029 (0.239)	Difference in node degree between the current year and the next year
NSL	244 (13.2 %)	Whether there are new stations in the same metro lines during the next year (0/1)
ΔBC	−0.036 (1.010)	Difference in betweenness centrality compared between the current year and the next year, scaled up by a factor of 100
ΔCC	−0.074 (0.098)	Difference in closeness centrality between the current year and the next year, scaled up by a factor of 10,000
Demand-side Network Effects		
AADR_global	19.004 (7.669)	The spatial interaction of AADR at global level
AADR_line	19.666 (13.254)	The spatial interaction of AADR at line level
AADR_local	19.575 (16.642)	The spatial interaction of AADR at local level
GR_global	6.932 (9.360)	The spatial interaction of AADR growth rate at global level
GR_line	7.109 (12.603)	The spatial interaction of AADR growth rate at line level
GR_local	7.214 (14.398)	The spatial interaction of AADR growth rate at local level

Note: For binary variables, the "Summary" column represents the count (percentage) of instances where the variable equals 1; for continuous variables, the "Summary" column represents mean (std).

Specifically, for road density, we have road network data for the years 2013, 2015, 2018, and 2020. Land use is represented by categorized point of interest (POI) data obtained from the Gaode API[1] for the years 2015, 2016, and 2017. Population density data are sourced from the Gridded Population of the World by CIESIN at Columbia University (CIESIN, 2018), providing population estimates in a raster format for the years 2010, 2015, and 2020. Housing prices for the years 2014 to 2019, serving as an indicator of the socio-economic status, are extracted from the website of *Lianjia*,[2] one of the largest real estate intermediary companies in China. The catchment area is delineated by a buffer radius of 500 m around each station, consistent with previous research (Sohn and Shim, 2010; Sung and Oh, 2011; Xin and Shalaby, 2024). We have data spanning multiple years for most of the variables, which allows us to interpolate the missing data for the intervening years.

The summary statistics of these variables are presented in Table 2.

5. Results

5.1. Ridership pattern identification

While Fig. 4 indicates an overall increase in ridership concurrent with metro network expansion, this trend does not uniformly apply to all stations within the metro system. Fig. 7 illustrates station ridership dynamics in terms of AADR and its growth rate.

Fig. 7(a-b) present the AADR for each station in 2014 and 2019, respectively. Additionally, the Coefficient of Variation (CV) is computed as a measure of relative variability, which is defined as the ratio of the standard deviation to the mean ridership. Based on the same legend split by quantiles, the ridership dynamics from 2014 to 2019 can be observed. In 2014, stations in the most central locations exhibited particularly high ridership, denoted by the darkest color. By 2019, the ridership distribution becomes more uniform, as indicated by a lower CV value, suggesting a trend of metro demand spreading outward.

Fig. 7 (c-d) display the AADR growth rate for each station from 2014 to 2015 and from 2018 to 2019, respectively. Here, different growth stages are split by quantiles and distinguished by different colors, ranging from declining to fast-growing. These figures reveal that stations within the central city areas tend to experience lower growth in ridership, a trend that became even more pronounced between 2018 and 2019. The higher CV in 2018–2019 compared to 2014–2015 further confirms the increased disparity in growth rates. Conversely, stations located along newly expanded lines witnessed notable ridership growth during the same period.

To reveal heterogeneity in station ridership growth trends, we depict the AADR growth patterns for each station from 2014 to 2019 in Fig. 8 (a) and their spatial distribution in Fig. 8 (b). In Fig. 8 (a), stations are color-coded based on their operational years. Each station starts with a baseline value of 1, and the relative ridership values for each subsequent year, compared to the first year of operation (or 2014, whichever is later), are displayed. The statistical summary of each station's relative ridership in 2019 compared to the first operational year is also listed. The data reveal that most stations exhibit a relatively modest increase in ridership, with their 2019 demand ratios slightly above 1. Certain stations, particularly those that commenced operations within the observation period, have seen their ridership multiply several times by 2019 relative to their inaugural year. However, a significant number of stations have witnessed declines in patronage, with “Wuwei Road” station even falling below a 0.5 ratio compared to its first year.

5.2. Ridership model results

As outlined in Section 5.1, in the backdrop of metro network expansion, some stations experience rapid ridership growth, while others face stagnation or even declining ridership. The ridership model (Model 1) aims to uncover the factors influencing station ridership patterns, with a particular emphasis on network effects. It incorporates a total of 1852 station-year observations from 344 stations in Shanghai Metro, with AADR as the dependent variable. All features have been vetted for multicollinearity, and different regression methods are adopted and compared. The model results are presented in Table 3.

Model 1–1 is a base model that employs OLS regression, while Models 1–2 to 1–5 utilize FEMs that account for both station and year fixed effects (see Section 3.3.1). For these models, singleton observations are removed, reducing the number of observations to 1836. Furthermore, Model 1–2 only considers the supply-side network effects using FEM while Models 1–3 to 1–5 extend Model 1–2 by incorporating global, line-level, and local demand-side network effects, leveraging S-FEMs with different spatial weight matrices (see Section 3.3.2).

When comparing model 1–1 with model 1–2 to 1–5, the results demonstrate that FEMs can achieve better model fit than OLS as indicated by higher adjusted R-squared values. Notably, compared to Models 1–2 to 1–5, the coefficients for land use diversity and closeness centrality show opposite signs in Model 1–1. This is likely due to OLS's inability to control for unobserved variables that correlate with both the independent and dependent variables, which can lead to biased estimations. Therefore, we will rely on the results from FEMs to analyze the impact of network features on station ridership.

Moreover, although the incorporation of demand-side network effects contributes trivially to the model fit, this could be because, after introducing the fixed effects, the model 1–2 has already absorbed most of the variation (with R-squared improving from 0.647 to 0.987). At this point, the additional variation that new variables can explain is quite limited. Nonetheless, the significance of the demand-side network effects demonstrates that they still provide valuable new information.

The results underscore the significant influence of network features on station ridership. For the supply-side topology features, at the local level, stations with a higher number of neighboring stations and degree tend to exhibit lower ridership, suggesting that nearby stations may compete for ridership. At the line level, station ridership increases with the number of stations on the same line, indicating that stations that can reach more destinations without transfers tend to attract more passengers. At the global level, betweenness centrality is positively correlated with station ridership. Stations with high betweenness centrality play a crucial role in the network's connectivity, facilitating efficient travel across the entire network, and thus tend to experience higher ridership. Conversely, closeness centrality negatively correlates with ridership. This could be due to how closeness centrality is defined in this study, where its values generally decrease with network expansion.

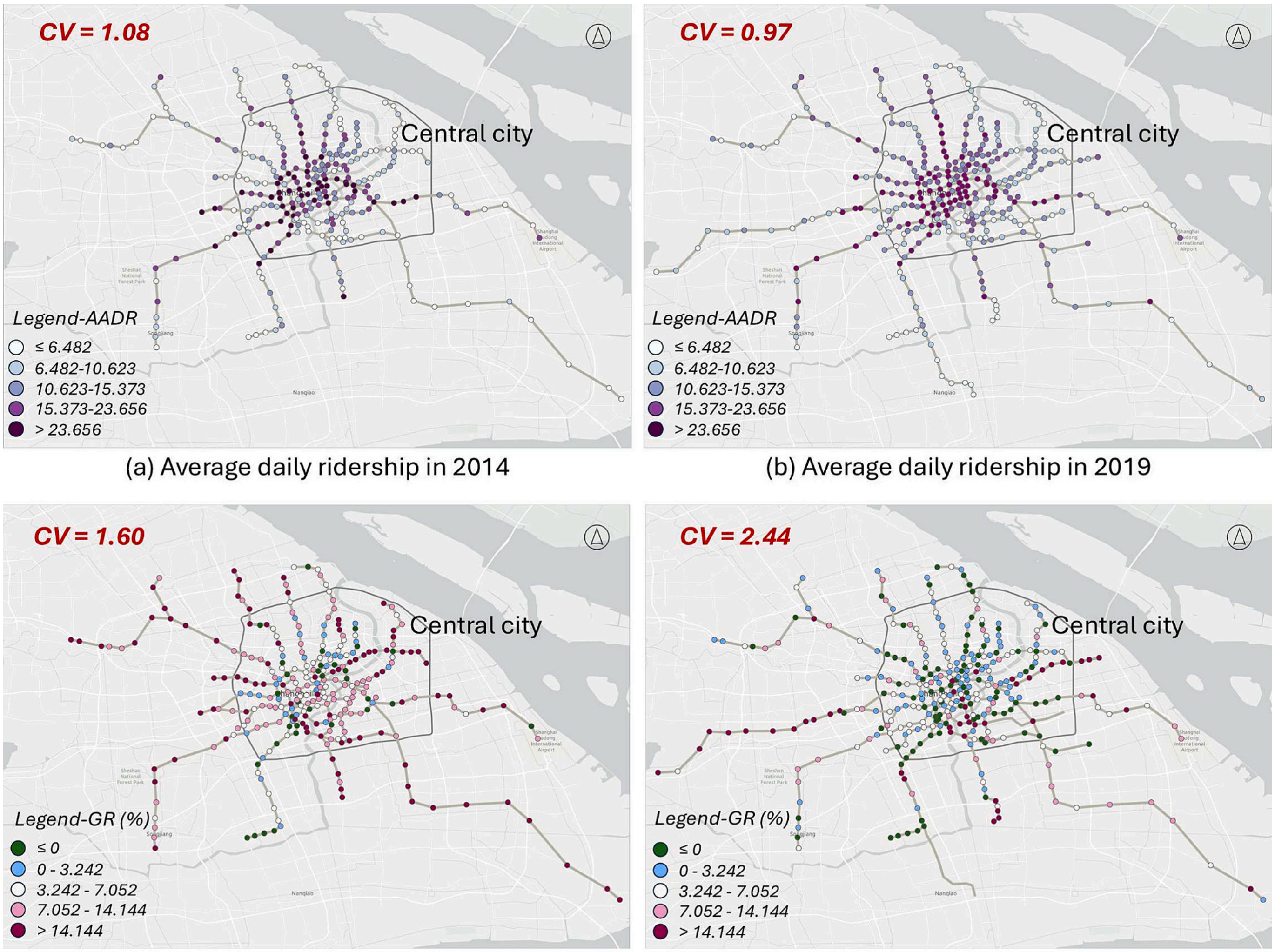
For the demand-side network features, the spatial autocorrelation shows positive effects at the global level and negative effects at the line and local levels. This indicates that higher ridership in one station might lead to lower ridership in directly adjacent stations and stations on the same metro line. While from a global network perspective, the positive spatial autocorrelation suggests a regional synergistic effect.

Model 1 also confirms the strong influence of the built environment and station attributes on station ridership. Specifically, station ridership is found to increase with higher road/POI density and more diverse land use, generally aligning with findings from previous studies (Sohn and Shim, 2010; Jun et al., 2015; An et al., 2019; Li et al., 2020). Population density has a negative impact on ridership, which seems contrary to conventional perceptions. This result may be attributed to the measurement of population density, which is based on residential density data from national censuses and population registers. Stations in areas with high activity densities but low residential densities, such as those in commercial centers and industrial parks, can still experience high ridership. Similar findings have been reported in Du et al. (2023) and Andersson et al. (2021).

Terminal stations are more likely to have lower ridership.

[1] https://lbs.amap.com/

[2] https://m.lianjia.com/



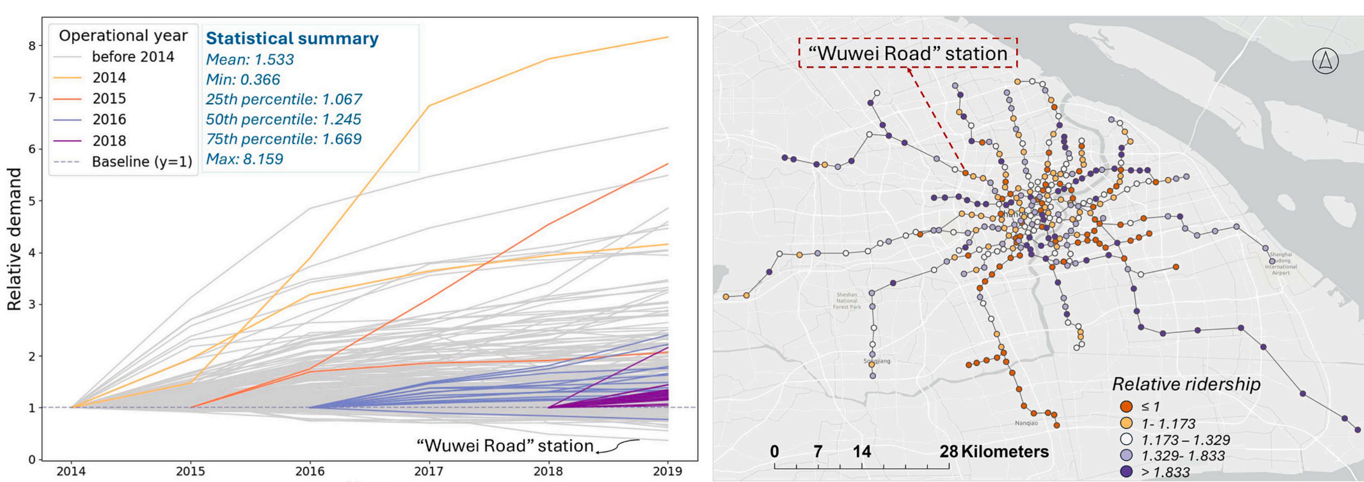
(a) Average daily ridership in 2014

(b) Average daily ridership in 2019

(c) Ridership change percentage from 2014 to 2015

(d) Ridership change percentage from 2018 to 2019

Fig. 7. Spatial and temporal ridership patterns across all stations.



(a) Relative ridership dynamics from 2014 to 2019.

(b) Spatial distribution of relative ridership in 2019 compared to inaugural year.

Fig. 8. Relative ridership dynamics from 2014 to 2019.

Table 3
The regression results of Model 1 (Ridership Model).

VARIABLES	(1–1)	(1–2)	(1–3)	(1–4)	(1–5)
Built Environment					
Road density	0.435***	0.433***	0.426***	0.443***	0.445***
Landuse diversity	−2.971***	2.978***	2.956***	2.920***	2.909***
POI density	6.658***	0.922***	0.956***	0.971***	0.970***
Population density	−0.095***	−0.203***	−0.183***	−0.211***	−0.215***
Socio-economics					
House price	0.018	0.010	0.014	0.007	0.008
Station Attributes					
Terminal	6.530***	−2.839***	−3.002***	−2.775***	−2.755***
Age_3-6y	0.668	1.511***	1.304***	1.785***	1.680***
Age_greater_6y	3.554***	2.458***	2.142***	2.896***	2.738***
Network Effects					
NS	−1.792***	−1.060***	−1.019***	−1.046***	−1.038***
DG	0.546	−0.410	−0.276	−0.887**	−0.778*
SL	0.205***	0.166***	0.162***	0.173***	0.170***
BC	0.901***	0.338***	0.355***	0.331***	0.346***
CC	2.512***	−8.929***	−8.664***	−8.982***	−8.970***
AADR_global	–	–	0.202***	–	–
AADR_line	–	–	–	−0.146***	
AADR_local	–	–	–	–	−0.097***
Fixed Effects	×	✓	✓	✓	✓
Constant	−7.126***	22.989***	17.871***	26.650***	25.550***
Observations	1852	1836	1836	1836	1836
R-squared	0.647	0.987	0.987	0.987	0.987
Adjusted R-squared	0.645	0.984	0.984	0.984	0.984

Note: ***, ** and * represent the significance at the confidence level of 99 %, 95 % and 90 %, respectively.

Table 4
The regression results of Model 2 (Ridership Growth Rate Model).

VARIABLES	(2–1)	(2–2)	(2–3)	(2–4)	(2–5)
Current year's ridership	−0.144***	−1.772***	−1.516***	−1.408***	−1.480***
Built Environment					
Road density	−0.408***	−0.294	−0.032	−0.017	0.071
Landuse diversity	−7.766***	−22.580***	−14.924***	−14.402***	−14.085***
POI density	0.267	−0.169	−0.614	−0.427	−0.266
Population density	−0.056**	0.980**	0.418	0.438	0.532
Socio-economics					
House price	−0.004	0.205***	0.083	0.075	0.112*
Station Attributes					
Terminal	0.276	0.675	1.364	1.457	0.729
Age_3-6y	−28.852***	−35.628***	−19.751***	−17.940***	−21.507***
Age_greater_6y	−35.143***	−36.966***	−20.665***	−18.353***	−22.383***
Network Effects					
NS	−0.889***	−7.356***	−7.619***	−7.546***	−7.185***
DG	1.795**	−2.466	0.343	−0.788	−0.834
SL	−0.065	0.426***	0.205	0.258**	0.291**
BC	−0.141	2.007***	1.214***	1.061**	1.240***
CC	10.469***	−18.145**	−8.077	−8.206	−9.821
ΔNS	−0.209	−1.146	−1.973	−2.288	−1.931
ΔDG	−2.104	−3.636	−3.000	−2.863	−2.816
NSL	2.124	0.850	0.033	0.097	0.273
ΔBC	−0.422	0.797	0.295	0.224	0.328
ΔCC	23.509***	−6.415	5.871	4.901	2.589
GR_global	–	–	0.895***	–	–
GR_line	–	–	–	0.662***	–
GR_local	–	–	–	–	0.498***
Fixed Effects	×	✓	✓	✓	✓
Constant	47.995***	146.620***	103.345***	101.004***	100.826***
Observations	1508	1483	1483	1483	1483
R-squared	0.377	0.698	0.757	0.768	0.759
Adjusted R-squared	0.369	0.613	0.689	0.703	0.691

Note: ***, ** and * represent the significance at the confidence level of 99 %, 95 % and 90 %, respectively.

Additionally, stations that have been operational for longer periods tend to have higher ridership (Li et al., 2020). "Older" Stations usually enjoy certain first-mover advantages, as they are typically located in areas with the most pressing travel demand, and can attract more local development over time. The same phenomenon has been observed in bike sharing systems as well (Liang et al., 2023).

5.3. Ridership growth model results

In Model 2, we delve into the impact of network expansion on station AADR growth rate, which is a percentage value and can be negative if a station experience a ridership decline. In addition to the features in Model 1, this model also considers the current year's ridership and changes in network topology features between the current and next year

Table 5
The regression results of extended Model 2 for time lag effects.

	(2–6)	(2–7)	(2–8)
VARIABLES	k=1	k=2	k=3
Current year's ridership	−1.247***	−1.767***	−1.557***
Built Environment			
Road density	−0.559	−0.112	−0.635
Landuse diversity	−13.498***	−5.756	5.185
POI density	0.105	1.081	0.302
Population density	0.359	0.400	−0.179
Socio-economics			
House price	0.080	−0.003	0.008
Station Attributes			
Terminal	3.793	−1.420	4.333
Age_3-6y	−17.742***	0.149	−0.434
Age_greater_6y	−17.936***		
Network Effects			
NS	−4.637***	−10.744***	−10.625***
DG	1.404	−0.713	1.440
SL	0.168	0.127	0.130
BC	0.876**	1.166***	0.646**
CC	−19.924***	−14.258**	−13.965**
$\Delta NS(t-k)$	−2.675**	1.347	−0.076
$\Delta DG(t-k)$	1.694	−2.158	1.895
$NSL(t-k)$	1.226	1.124	−0.717
$\Delta BC(t-k)$	5.943	−34.871	−3.028
$\Delta CC(t-k)$	19.014**	−0.129	−0.682
GR_line	0.614***	0.384***	0.331***
Fixed Effects	✓	✓	✓
Constant	120.536***	109.383***	103.091***
Observations	1480	1176	860
R-squared	0.771	0.720	0.733
Adjusted R-squared	0.707	0.614	0.584

Note: ***, ** and * represent the significance at the confidence level of 99 %, 95 % and 90 %, respectively.

resulting from network expansion. The results are displayed in the Table 4 and Table 5.

Similarly, Model 2–1 based on OLS, Model 2–2 is a base FEM with spatial and temporal fixed effects, and Models 2–3 to 2–5 are S-FEMs that incorporate different spatial weight matrices. The progressively higher adjusted R-squared values prove the effectiveness of considering demand-side network effects. We further extend the S-FEM with line-level spatial weights (Model 2–4) to consider time lag effects of network expansion using a ST-FEM, as shown in Table 5. Models 2–6 to 2–8 test the lagged time effects at 1 year, 2 years, and 3 years, respectively.

Our results demonstrate the demand-side spatial spillover effects of station ridership growth at the local, line, and global network levels. This means that ridership growth in one station can drive the growth not only in stations that are nearby or on the same line, but also all stations on the network. Furthermore, these effects are most significant at the line level, indicated by the highest adjusted R-squared among Models 2–3 to 2–5. Additionally, our results reveal the time lag effects of network expansion, with the 1-year time lag model (Model 2–6) showing the most significant impact. New changes in network features may have insignificant effects on the first year, but they can play a vital role in forecasting the subsequent year's ridership growth rate. We focus on the results of Model 2–6 to identify the influencing factors of station ridership growth.

Again, supply-side network topology features are found to significantly influence station ridership growth. At the local level, competitive relationships are observed among neighboring stations——both the number of nearby stations and its change with a one-year lag are found to negatively influence ridership growth. This suggests that the increase in surrounding stations due to network expansion can dampen the ridership growth. At the line level, the number of stations on the same line positively impacts ridership growth. At the global level, a station's ridership growth rate increases with its betweenness centrality but decreases with its closeness centrality. This phenomenon is similar to that observed from Model 1. Moreover, the change in closeness centrality between the previous year and current year positively influences the ridership growth rate. This underscores that a station's overall accessibility improvement within the network can attract passengers and lead to a substantial increase in travel demand.

The negative coefficient for land use diversity suggests that while stations surrounded by more developed land tend to have higher initial patronage, they may also experience lower ridership growth rates. In other words, stations with relatively singular land functions currently have greater potential for patronage growth. Furthermore, stations with higher ridership in the current year, and those with a longer operational history tend to experience reduced ridership growth. Previous studies, such as Liu et al. (2019), have observed similar trends regarding station operational time, but they reported positive impacts of last-year ridership. This discrepancy could be due to their focus on absolute ridership differences, whereas our analysis concentrates on the percentage growth rate in ridership.

5.4. Heterogeneous ridership growth model results

While Model 2 examines the influencing factors for station-level ridership growth rates, it only reveals the average effects for all stations. Beyond the average effects, it is crucial to understand the differences in influencing mechanisms across stations. Therefore, this section aims to investigate the heterogeneous effects among stations with varying ridership growth patterns and in different locations.

5.4.1. Heterogeneity analysis based on station ridership growth rate

Fig. 9 displays the density distribution of the annual growth rate in station ridership. The values at the 5th, 25th, 75th, and 95th percentiles are marked, corresponding to approximately −5.8 %, 0.5 %, 11.1 %, and 38.0 % growth rates, respectively. These values are representative of four distinct types of stations with diverse ridership growth rates, namely declining, stagnant, growing, and fast-growing. To explore whether and how the effects of network expansion differ between these four types of stations, we employ quantile regression for Model 3–1. In this model, the dependent variable is the annual growth rate in station ridership, and we examine the different effects at the 5th, 25th, 75th, and 95th percentiles of this distribution. The results are presented in the left panel of Table 6.

The results of Model 3–1 reveal that the effects of network expansion on ridership growth are not uniform across stations. Specifically, betweenness centrality is a significant contributor to ridership growth for declining and stagnant stations but has little influence on growing stations. Closeness centrality has a significant negative impact on ridership for growing and fast-growing stations but no significant impact on declining and stagnant stations. Additionally, the time lag effects of ΔNS only show significance in stagnant stations, while the time lag effects of ΔCC mainly contribute to fast-growing stations. Furthermore, the demand-side spatial spillover effects of ridership growth show an increasing trend across quantiles.

Stations of the four categories also exhibit different sensitivities to other attributes. For declining stations, land use diversity plays a vital role in reducing ridership, and population density plays an inverse role. Stagnant stations are highly sensitive to road density, population density, house prices around the stations, and their terminal status.

5.4.2. Heterogeneity analysis based on station location

To explore the heterogeneous network effects based on station location, we further develop Model 3–2 based on ST-FEM to examine whether stations located in central and non-central city areas respond differently to the effects of network expansion.

The right panel of Table 6 presents the results of this model. The first two columns represent the coefficients for non-central and central stations, respectively. Fisher's Permutation test is then applied to examine

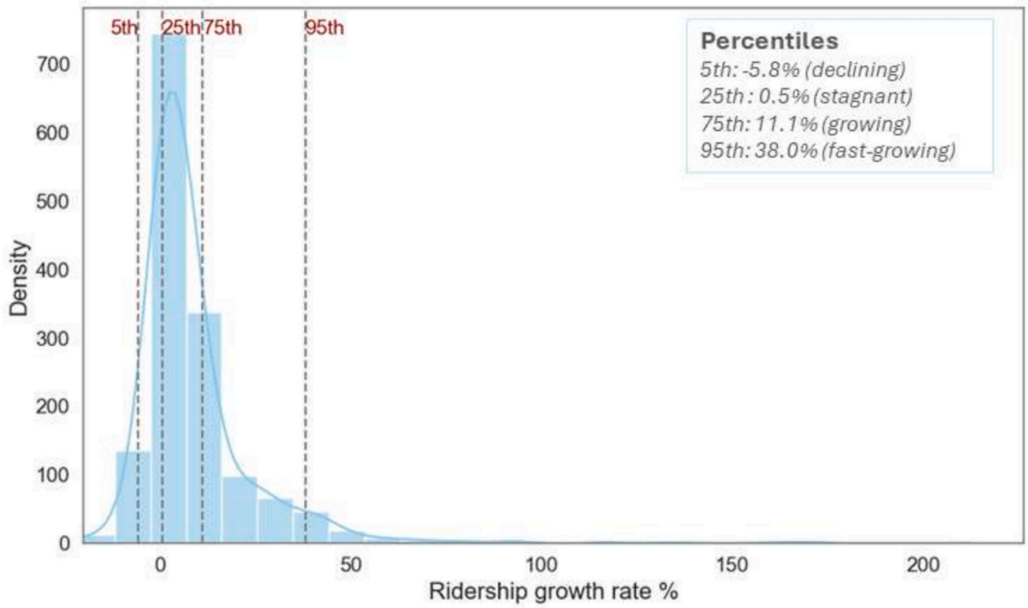


Fig. 9. Heterogeneity of station ridership change patterns.

Table 6
The regression results of Model 3 (Heterogeneity Model).

	(3–1)				(3–2)		
VARIABLES	q05	q25	q75	q95	Non-central	Central	Diff
Current year's ridership	−0.811***	−0.931***	−1.285***	−1.572***	−0.894***	−1.656***	0.761
Built Environment							
Road density	−0.777	−0.791**	−0.160	0.398	−1.318*	−0.964**	−0.353
Landuse diversity	−19.236*	−4.311	−2.184	−11.204	−15.435*	4.336	−19.772
POI density	4.700	0.937	−0.259	−1.761	5.509	2.065	3.444
Population density	1.738***	0.773***	−0.050	−0.689	2.015	0.484	1.531
Socio-economics							
House price	−0.081	0.089***	0.052	0.000	−0.224	0.116*	−0.34*
Station Attributes							
Terminal	3.981	6.292**	−0.350	5.622	1.928	19.491***	−17.563
Age_3-6y	−28.372***	−20.965***	−13.436***	−8.901*	−19.056***	−17.495***	−1.562
Age_greater_6y	−27.443***	−23.779***	−14.185***	−5.862	−20.232***	−18.319***	−1.913
Network Effects							
NS	−5.260*	−2.468***	−5.079***	−8.130***	−8.11	−3.126***	−4.984
DG	2.781	2.476	3.553	4.045	19.287	1.579	17.708
SL	−0.114	0.089	0.123	0.370	−0.822**	0.159	−0.981**
BC	1.118**	0.643***	0.423	1.087	1.975	0.934**	1.04
CC	−1.379	−0.420	−18.169***	−48.982***	−67.706**	−10.06	−57.646**
$\Delta NS(t-1)$	−5.800	−4.970***	−1.288	1.655	−16.154**	−3.427***	−12.727**
$\Delta DG(t-1)$	2.793	3.202	3.788*	−1.310	−1.357	3.248**	−4.605
$NSL(t-1)$	2.157	1.462*	1.310*	3.078	4.228**	1.4	2.827
$\Delta BC(t-1)$	11.393	15.871	7.869	−4.089	−151.12	17.528	−168.648
$\Delta CC(t-1)$	−8.762	1.860	9.416	46.206***	156.932***	−17.507**	174.439***
GR_line	0.269**	0.319***	0.642***	0.766***	0.335***	0.368***	−0.033
Constant	−10.738***	−1.588	4.976***	17.273***	186.411***	64.466**	121.945
Observations	1500	1500	1500	1500	406	1074	–
R-squared	0.387	0.342	0.356	0.464	0.868	0.728	–
Adjusted R-squared	–	–	–	–	0.821	0.648	–

Note: ***, ** and * represent the significance at the confidence level of 99 %, 95 % and 90 %, respectively. For Moedel 3–1, R-squared refers to Pseudo R-squared.

the significance of the differences in coefficients between the two groups, as shown in the "Diff" column. If the coefficient difference is significant, it indicates that the ridership growth rates of non-central and central stations respond significantly differently to that variable.

The model results show that house price, the number of stations on the same lines, closeness centrality, and the time lags of ΔNS and ΔCC exhibit significant differences for these two groups. Notably, for stations located in non-central city areas, an improvement in closeness centrality significantly contributes to station ridership growth. However, for those in central areas, this may lead to decreased ridership growth. This implies that non-central stations have relatively higher attractiveness for passengers, perhaps due to lower living costs. Our findings echo the previous decentralization observation. Additionally, the demand-side line-level effects exhibit insignificant difference between central and non-central stations.

6. Conclusion

This study delves into the network effect on station-level ridership dynamics under the metro expansion scenarios. Using Shanghai Metro as a case study, both metro ridership and network expansion data from 2014 to 2019 are analyzed. A spatiotemporal lag fixed effects model (ST-FEM) is proposed to estimate station-level annual average daily ridership (AADR) and its growth rate over years, considering evolving supply- and demand-sides network features at the local, line-level and global scales. Additionally, a quantile regression model and a location-based ST-FEM are adopted to unravel the heterogeneous impacts of network expansion on stations with different ridership trends and locations respectively. Overall, this study offers a comprehensive understanding on the connections between evolving metro networks and ridership growth patterns. The main findings can be summarized as follows.

First, it can be concluded that network effects play an important role in station ridership patterns. For supply-side network effects, at the local level, competitive relationships are observed among neighboring stations. At the line level, stations on the same metro line can have cooperative effects, stimulating passenger flow between stations. At the network level, betweenness centrality is positively correlated with both station ridership and growth rate, while closeness centrality has a negative correlation. For demand-side network effects, the spatial autocorrelation between stations is revealed. Ridership growth at one station can drive growth at other stations that are adjacent, on the same line, and in the surrounding area, with the most significant effects observed at the line level. Second, station ridership growth patterns are found to exhibit time lag effects for network expansion, particularly with a one-year lag. Specifically, the one-year lagged change in closeness centrality positively influences the ridership growth rate. Third, network expansion has heterogeneous impacts on ridership growth patterns for stations with varying ridership trends and at different locations. Declining and stagnant stations are particularly sensitive to betweenness centrality, while growing and fast-growing stations respond more to changes in closeness centrality. Improvements in closeness centrality contribute to ridership growth in non-central stations but lead to decreased growth in central stations.

The research outcomes may inform policymakers of the critical relationship between metro network evolution and ridership dynamics, guiding decision-making regarding the planning of metro systems. First, network expansion involves not only physical facility planning but also significant demand interactions among stations. Identifying the network effects from both the supply side and the demand side on ridership patterns can enhance the prediction of ridership changes under different planning scenarios. This, in turn, can inform decisions regarding station planning and network layout. Determining the location of new stations or lines should consider their potential impacts on existing stations. Our analysis can ultimately support benefit-cost analysis for metro development and infrastructure investment, promoting sustainable urban growth. Second, our heterogeneity analysis is crucial for crafting targeted interventions for specific stations based on their ridership dynamics and locations. Our findings enable the development of tailored strategies to enhance ridership at underperforming stations or manage growth more effectively at fast-growing stations. Finally, the proposed ST-FEM model is general and can be adapted to other cities and networks to evaluate the ridership impacts of metro network expansion.

While we uncover the significant effects of network expansion on station ridership growth patterns, further analysis is necessary to broaden the scope of this study and address its limitations. Shanghai Metro is selected as the case study, where new metro stations built in recent years have primarily been in the suburbs, owing to the largely established metro network in the central city. Therefore, some of our findings may not fully apply to cities whose metro development is still in the early stage. The varying impacts across cities need to be investigated in future studies. Nevertheless, our conclusions can serve as effective reference for metro development in other cities. Additionally, due to data availability constraints, certain variables that could impact station ridership were not included in our models, such as job density and household car ownership. In future research, more variables can be integrated to explore their effects.

CRediT authorship contribution statement

Fangyi Ding: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Yan Tang:** Visualization. **Yamin Wang:** Data curation. **Zhan Zhao:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

None.

Data availability

The data that has been used is confidential.

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Appendix A. Radius selection analysis

To calculate the variable *NS* (the number of stations within a specified radius around a given station), we conducted tests using radii of 1 km, 2 km, and 3 km to define the surrounding area for each station. Specifically, in the ridership model, we incorporated NS_1km, NS_2km, and NS_3km individually. For the ridership growth rate model, we included paired variables: NS_1km with ΔNS_1km, NS_2km with ΔNS_2km, and NS_3km with ΔNS_3km. Both OLS and FEM without demand-side network effects were employed for comparative analysis.

The evaluation metrics utilized include R-squared, adjusted R-squared, and Root Mean Squared Error (RMSE). The first two metrics assess model fit, while the latter indicates prediction error magnitude.

Model results are presented in Table A.1. Since variations in radius did not influence parameter significance or sign, we exclusively report metric outcomes. Analysis reveals that a 2 km radius consistently outperforms other distances across both ridership and growth rate models, irrespective of whether OLS or FEM is applied. Consequently, we selected a 2 km radius as the optimal choice for subsequent analyses.

Table A.1
Evaluation of radius selection for variables *NS* and Δ*NS*.

Models	R^2	Adjusted R^2	RMSE
Ridership Model (*NS*)			
OLS			
1 km	0.6336	0.6310	10.4120
2 km	<u>*0.6471*</u>	<u>*0.6446*</u>	<u>*10.2180*</u>
3 km	0.6378	0.6353	10.3520
FEM			
1 km	0.9866	0.9834	2.2101
2 km	<u>*0.9867*</u>	<u>*0.9836*</u>	<u>*2.1971*</u>
3 km	<u>*0.9867*</u>	<u>*0.9836*</u>	<u>2.2023</u>
Ridership Growth Rate Model (*NS* & Δ*NS*)			
OLS			
1 km	0.3722	0.3642	14.4740
2 km	<u>*0.3774*</u>	<u>*0.3694*</u>	<u>*14.4140*</u>
3 km	0.3742	0.3662	14.4510
FEM			
1 km	0.6937	0.6076	11.2441
2 km	<u>*0.6975*</u>	<u>*0.6126*</u>	<u>*11.1728*</u>
3 km	0.6960	0.6107	11.2004

Note: Values with underlines indicate the optimal results for their respective evaluation metrics across all radius categories.

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