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Long- and short-run determinants of metro ridership in Seoul: A vector error correction model approach

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ABSTRACT

The metro system is essential infrastructure underpinning urban sustainability and citizen mobility. The Seoul metro system has experienced continuous infrastructure expansion, multiple policy changes, and major external shocks over the past 25 years. This study examined the short- and long-run dynamics of Seoul Metro ridership using 300 monthly time-series observations from January 2000 to December 2024. The analysis considered monthly total metro ridership together with population, bus ridership, precipitation days, gasoline prices, and seasonality and incorporated major policy changes, such as the integrated fare system, metro line extensions, and fare increases, as well as the external shock of the COVID-19 pandemic. Methodologically, a Vector Error Correction Model, in conjunction with Impulse Response Functions and Forecast Error Variance Decomposition, was employed to analyze the short-run dynamics and long-run equilibrium relationships. The Johansen cointegration test identified two cointegrating relationships among Seoul Metro, Seoul bus, and Gyeonggi bus ridership. The empirical results indicate that Seoul Metro demand exhibited a negative short-run association with Seoul bus ridership, suggesting a substitution relationship, and a positive association with Gyeonggi bus ridership, suggesting a complementary relationship at the metropolitan scale. Gyeonggi population showed a significant negative association with metro ridership, while gasoline prices showed a positive association. Seasonal effects were also significant, whereas precipitation days were not statistically significant. By contrast, the short-run effects of the integrated fare system, fare increases, metro line extensions, and COVID-19 were not statistically significant. This study demonstrates how multiple socioeconomic, transport, and policy-related factors are associated with metro demand at the aggregate metropolitan-system level and fills a critical gap in the literature, which has focused on short-term impacts. The findings provide empirical evidence to support sustainable public transport policies in large metropolitan areas.

1. Introduction

Public transport systems serve as pivotal infrastructure to enhance urban mobility and accessibility, and are closely linked to urban sustainability (Cervero & Sullivan, 2011). Their ridership is influenced not only by well-known determinants such as population size and private vehicle ownership but also by the complex interplay of transport policies, spatial factors, seasonal effects, and

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meteorological conditions (Cervero, 1996; Jun et al., 2015; Thompson & Brown, 2006). Therefore, identifying the multifaceted factors that influence public transport demand and quantitatively assessing their evolving impacts are essential for evidence-based policy formulation. Although public transport comprises multiple modes, metro systems play a critical role by providing massive, rapid, convenient, and highly punctual connections between major urban centers (Kim et al., 2024).

Seoul Metro is widely regarded as one of the world's premier urban rail systems, facilitating more than 7 million passenger trips per day on average (Seoul Metropolitan Government, 2026). Since the 1980s, the network has expanded significantly from 4 to 23 lines, driving a steady increase in ridership. However, recent demographic shifts, characterized by a population outflow from Seoul to the surrounding areas, have led to a population decline within the capital, even as they fuel growth in the neighboring Gyeonggi Province and Incheon. Such demographic transitions are closely associated with changes in public transport usage, and can substantially influence ridership variations (Cervero & Kockelman, 1997; Zhao et al., 2013). Furthermore, external shocks, most notably the COVID-19 pandemic, have recently disrupted the metro demand. Although these shocks caused sharp short-run contractions, the long-run patterns suggest a recovery toward pre-pandemic ridership levels (Li et al., 2024). Over this extended period, Seoul Metro has also undergone numerous policy interventions, including network extensions and fare adjustments, all of which have cumulatively shaped ridership dynamics.

Despite these developments, the literature lacks a comprehensive analysis of the diverse long-term determinants of metro demand. Most studies focus on quantifying the isolated and short-term effects of specific policies and external shocks. Consequently, there is a pressing need for empirical analyses that jointly examine the short- and long-term effects of multiple determinants. To address this gap, we constructed a longitudinal monthly time-series dataset spanning 25 years (300 months, 2000–2024). By analyzing the long-run equilibrium relationships alongside short-run dynamics, this study provides a holistic understanding of Seoul's metro ridership. These insights are intended to support sustainable operation of the system and offer policy-relevant guidance for metropolitan transport strategies.

Specifically, this study employs a Vector Error Correction Model (VECM) to systematically examine the long-run equilibria and short-run adjustments among co-integrated time-series variables. The VECM framework is well-established in economics, finance, and transportation research (Andrei & Andrei, 2015; Engle & Granger, 1987; Litterman & Weiss, 1983; Liu et al., 2023; Pradhan & Bagchi, 2013). By applying this model, this study examined the relationships between metro ridership and a comprehensive set of explanatory variables, including population size, bus ridership, seasonal effects, policy interventions, and external shocks. These findings provide robust empirical evidence that supports strategic public transport planning in Seoul and other global megacity regions.

2. Literature review

Understanding and forecasting public transport demand is a pivotal undertaking for urban sustainability and the efficient operation of transport systems. Public transport demand is not determined by a monolithic determinant; rather, it is shaped by the complex interaction of socioeconomic conditions, the built environment, and transport-related policies (Giuliano, 2005; Tang & Thakuriah, 2012). Consequently, an integrated analytical framework that encompasses these multidimensional factors is essential to capture the inherent complexity of public transport demand. Before examining the determinants of Seoul Metro ridership, this section provides a systematic review of the key factors that have been established in the literature as influencing public transport demand.

2.1. Macro-socioeconomic determinants of public transport demand

The aggregate public transport demand is largely dictated by citywide demographic dynamics and broader macroeconomic conditions. Previous studies have consistently demonstrated that macro-level indicators such as population size, income levels, and fuel prices play a pivotal role in explaining temporal variations in transit usage (Efthymiou & Antoniou, 2017).

Population size is widely regarded as the most fundamental determinant of baseline public transport demand (An et al., 2019). Extensive research indicates that growth in a city's resident population translates directly into higher trip generation. For instance, a study in Shenzhen, China, identified local population size and housing prices as the dominant factors explaining fluctuations in metro ridership (Wu et al., 2022). Similarly, empirical evidence from Daegu, South Korea, suggests that subway boarding demand is strongly and positively correlated with the residential population within station catchment areas (Kim, 2013). These findings underscore that, from a macro-structural perspective, demographic shifts define the long-run trajectory of public transport demand.

Fuel price fluctuations also serve as a key macroeconomic catalyst for shifts in transit demand. Rising fuel prices increase the marginal cost of private vehicle use, rendering driving less economical than public transport (substitution effect) and also reduce households' discretionary income for automobile-related expenditures (income effect). This dual pressure incentivizes commuters to shift toward more affordable alternatives (Ahmad et al., 2024). An empirical analysis of ten U.S. urban areas found that a 10% increase in gasoline prices was associated with a public transit ridership increase of up to 1.16% (Iseki & Ali, 2014). Conversely, research in Southern California observed that declining transit ridership was primarily driven by the expansion of vehicle ownership among existing users; specifically, lower vehicle prices stimulated car acquisition, leading to a shift away from public transport (Manville et al., 2023). Collectively, these studies indicate that the modal competition between public transport and private vehicles—mediated by evolving economic conditions—is a critical determinant of demand. Overall, public transport demand exhibits significant sensitivity not only to demographic scales but also to macroeconomic drivers, such as fuel prices and vehicle accessibility, which function as structural pillars of long-run ridership patterns.

2.2. Regional spatial structure and intermodal interaction

Public transport demand is dictated not only by the aggregate population size but also by shifts in urban spatial structure and the resulting dynamic interactions among transport modes (Chen et al., 2022; Shin et al., 2026). Previous studies have demonstrated that metropolitan expansion and the characteristics of transit infrastructure collectively reshape travel patterns, reconfiguring the competitive and complementary relationships between modes (Chai et al., 2025; Yang et al., 2023).

Metropolitan expansion and the functional segregation of urban spaces induce structural transformations in travel behavior (Zhang et al., 2024). Research on Shanghai and Beijing emphasizes that commuting flows between residential suburbs and employment-dense central business districts constitute the backbone of the metro network demand (Li et al., 2023; Sun et al., 2016). Similarly, Kim (2013) found that metro boarding demand is primarily influenced by residential characteristics, whereas alighting demand is largely driven by employment-site attributes in Daegu, South Korea. These findings suggest that in mega-metropolitan areas, such as Seoul, demographic shifts in residential peripheries versus urban cores may exert structurally distinct effects on metro demand. Consequently, an analysis of metropolitan demand must account for the spatial distribution of the population across regions, rather than relying solely on total population figures.

Within this spatial framework, the relationship between bus and metro systems transcends simple competition, often evolving into a complementary synergy, depending on the spatio-temporal context. Recent international studies highlighted this dual nature of intermodal interactions (Hasan et al., 2025). Evidence from Shenzhen, China, indicated that buses and metros maintain dynamic relationships, alternating between competition and cooperation based on time and location (Yue et al., 2018). Furthermore, research in Nanjing demonstrated that buses play a vital feeder role, enhancing accessibility to the metro network (Zhao et al., 2017). Notably, in environments such as Seoul—where an integrated fare system facilitates seamless, cost-free transfers—buses serve as a crucial complement to the metro, thereby bolstering the overall public transport ridership (Abbasi et al., 2021; Kim et al., 2023; Sharaby & Shiftan, 2012). Moreover, infrastructure and policy interventions, such as the inauguration of new metro lines or the restructuring of bus routes, significantly recalibrate ridership levels (Hwang & Chung, 2022).

Rail extensions and other transit investments may also affect public transport demand through accessibility and land-use pathways that are not fully captured by short-term changes in aggregate ridership. Network expansion can increase station-level accessibility and alter the relative attractiveness of existing stations, while surrounding land-use changes may further shape station-level ridership growth (Liang et al., 2025; Liu et al., 2019). From a land-use perspective, transit-oriented development (TOD) links rail accessibility with higher-density, mixed-use, and pedestrian-oriented development around stations, suggesting that rail investment may gradually reshape travel demand by changing the spatial distribution of activities rather than by producing an immediate system-wide ridership spike (Cervero, 2006; Cervero & Kockelman, 1997; Ratner & Goetz, 2013). Evidence from Seoul Metro Line 9 also indicates that rail transit investment can generate proximity, accessibility, and neighborhood effects that differ by land type, land value, and station location, implying that the benefits of line extensions may be highly localized and unevenly distributed across station areas (Lee, 2022). These findings suggest that the effects of line extensions should be interpreted not only through aggregate ridership changes but also through localized ridership growth, route redistribution, accessibility gains, and longer-term station-area development.

Ultimately, public transport demand emerges as a complex outcome of the interplay between urban spatial structure, intermodal dynamics, and the broader accessibility and land-use effects of transit investment, necessitating analytical approaches that comprehensively incorporate these structural contexts.

2.3. External shocks and demand volatility

Beyond internal structural factors, public transport demand is subject to short-run volatility and structural shifts precipitated by unforeseen external shocks. The COVID-19 pandemic has led to profound structural transformations in public transport demand. Heightened concerns over infection risks and the implementation of social distancing protocols have led to sharp declines in ridership, and these shocks have been reported to influence not only immediate demand but also longer-term travel mode choice behavior (Lee et al., 2026; Medlock et al., 2021; Park et al., 2025). Furthermore, post-pandemic recovery trajectories have varied significantly across regions, suggesting that external shocks can exert persistent or long-run effects on time-series demand patterns (Gim & Park, 2025; Jun & Yun, 2023; Lee et al., 2024; Shi et al., 2025). Weather conditions are also key drivers of short-run demand fluctuations (Jiang & Cai, 2023). Previous studies have indicated that rainfall can significantly reduce off-peak metro demand (Zhou et al., 2017), whereas adverse weather conditions may increase metro-to-bus transfer demand through mode shift effects (Wu et al., 2022). Temperature has also been identified as an important determinant of metro usage. For instance, evidence from Beijing reveals that higher temperatures are positively associated with metro ridership (Wu & Liao, 2020).

This synthesis of prior literature confirms that public transport demand is modulated by a multifaceted array of external environmental factors—including socioeconomic conditions, infrastructure, and policy contexts—which culminate in complex interactions that shape ridership patterns. Building upon these insights, the present study integrated the variables identified in previous research, to analyze how these diverse factors collectively dictate the dynamics of public transport demand.

2.4. Research gap

Existing studies on public transportation demand significantly advanced our understanding of its relationships with policy interventions, socioeconomic characteristics, and environmental factors (Halvorsen et al., 2020; Hwang & Chung, 2022; Lee et al., 2013). Spatial regression models and machine learning techniques have been increasingly employed to capture spatial heterogeneity

and non-linear relationships with greater precision (Li et al., 2023; Ma et al., 2025; Peng et al., 2025). However, several critical limitations remain. First, many studies rely predominantly on cross-sectional analyses at specific points in time, which constrains their ability to elucidate temporal relationships and the long-run dynamic interactions among variables. Second, a heavy emphasis on micro-level station-area characteristics often comes at the expense of macro-level considerations. Consequently, there is insufficient evidence on how broader factors, such as shifting population structures and fuel prices, are associated with changes in public transport demand over time.

To address these gaps, this study utilizes a longitudinal monthly dataset spanning 2000 to 2024, incorporating fuel prices, seasonal variables, bus ridership, and population size, along with key policy-related factors believed to influence Seoul Metro demand. By examining these variables through a long-term lens, this research analyzed both the individual effects and the interrelationships among the determinants. This approach allowed for the examination of long-run relationships within the endogenous system alongside short-run dynamics involving the broader set of variables.

Furthermore, this study employed a VECM to simultaneously scrutinize short-run stochastic adjustments and long-run equilibrium relationships. To supplement the VECM, Impulse Response Functions (IRF) and Forecast Error Variance Decomposition (FEVD) were conducted to quantitatively assess the magnitude and duration of responses to innovations within the endogenous system. Ultimately, this methodological framework provided robust quantitative evidence for policy formulation and offered an integrated interpretation of metro demand dynamics, thereby filling a critical gap in the existing literature.

3. Methodology

3.1. Study area and metro ridership

This study focused on the Seoul Metropolitan Area (SMA), the largest and most densely populated urban region in the Republic of Korea. Centered around Seoul, the national capital, the SMA encompasses Incheon and Gyeonggi Province and serves as the nation's political, economic, and sociocultural nexus (Fig. 1). Spanning approximately 11,872 km^2, the SMA recorded a population of roughly 26 million in 2023, representing approximately 50% of the national total.

The SMA's public transport infrastructure operates as a seamlessly integrated system, comprising municipal buses and metro services for intra-urban mobility, alongside metropolitan railways and express buses that facilitate inter-city connectivity. At the core of this network is the metro system, which spans 1,118 km across 23 lines and 624 stations and supports major commuting flows throughout the region. Specifically, this research analyzed the ridership of Seoul Metro Lines 1–9, which constitute the primary backbone of the SMA transit network and exhibit the highest ridership density.

Within this metropolitan system, Seoul's public transport network is strongly integrated through a fare system that allows transfers across buses, subway lines, and some metropolitan railways (Kim et al., 2026). In 2025, Seoul recorded approximately 8.88 million average daily purpose-based trips, alongside 4.64 million bus trip records, 6.22 million subway trip records, and 0.73 million taxi trips (Seoul Metropolitan Government, 2026). The purpose-based trip measure represents complete trips by travel purpose, whereas the mode-specific figures represent individual mode-use records and may therefore include multiple records within a single trip involving transfers. In terms of main-mode share, bus and rail together accounted for 58.8% of trips in Seoul in 2022, compared with 37.1% for passenger cars (Yang et al., 2025). Previous research also characterizes Seoul as a compact metropolitan city with an advanced transit system, where the subway serves as a major transport mode supporting mobility between Seoul and its surrounding metropolitan areas

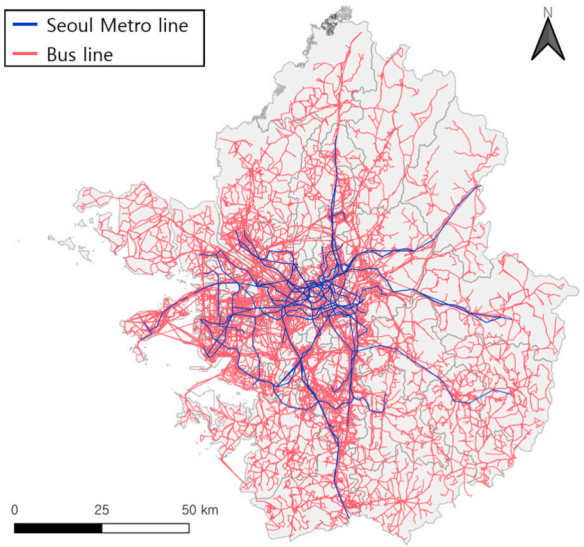


Fig. 1. Study area.

(Lee et al., 2021; Kwon et al., 2023).

Regarding motorization, South Korea recorded 413.6 passenger cars per 1,000 inhabitants in 2023 (CEIC, 2024), which is lower than the 500–800 passenger cars per 1,000 inhabitants often discussed as saturation levels in studies of highly motorized countries (Dalkic-Melek et al., 2025). Although changes in car ownership may form part of the broader background of long-term ridership change, Seoul's modal-share structure indicates that metro demand has evolved in a setting where public transport remains more dominant than passenger cars. Overall, Seoul represents a high-transit-use metropolitan setting in which metro demand is closely linked to bus–metro integration, metropolitan connectivity, and comparatively moderate passenger-car ownership.

Although the SMA includes both Gyeonggi Province and Incheon, the empirical analysis focuses on Gyeonggi-related variables because preliminary diagnostic tests indicated strong multicollinearity between Incheon and Gyeonggi indicators due to highly similar temporal patterns. Moreover, recent large-scale urban development in Gyeonggi Province has strengthened transport linkages with Seoul, making the Seoul–Gyeonggi corridor central to understanding evolving metropolitan commuting dynamics (Im & Ko, 2026).

In this study, monthly Seoul Metro ridership is defined as the aggregate number of passenger trips recorded on Seoul Metro Lines 1–9. This system-level measure is appropriate for examining long-run demand dynamics because it directly reflects the total load placed on the metro network. The demand base of Seoul Metro also extends beyond the administrative boundary of Seoul, as the system serves a substantial number of metropolitan commuters from surrounding areas, particularly Gyeonggi Province. Therefore, population change is treated as a key explanatory factor in the VECM, allowing the model to examine how demographic redistribution is associated with changes in total metro demand.

This study synthesized SMA-level data into an integrated longitudinal dataset, to analyze the determinants of Seoul Metro demand. The variables encompassed metro ridership, population dynamics, bus ridership, meteorological factors, fuel prices, and policy interventions such as network expansions and fare adjustments. The temporal scope spanned from January 2000 to December 2024, a 25-year period (300 monthly observations) following the consolidation of the core urban rail network centered on Lines 1–8. Monthly ridership data were aggregated specifically for Lines 1 to 9 operated by Seoul Metro. Notably, Line 9—which was inaugurated and subsequently expanded during the study period (Phase 1 in August 2009, Phase 2 in April 2015, and Phase 3 in December 2018)—was not treated as part of the initial baseline network. Instead, its phased openings were incorporated as policy-driven interventions to capture their incremental impacts on the overall system. This longitudinal approach allowed for a robust examination of how both continuous socioeconomic trends and discrete policy events collectively shape metro demand.

During the study period, the average monthly metro ridership was approximately 137 million passengers (SD = 14 million), ranging from a minimum of 92.9 million to a maximum of 160.6 million. Fig. 2 illustrates the long-run trajectories of Seoul Metro ridership alongside fluctuations tied to major external shocks. In the early 2000s, ridership expanded rapidly as the urban rail network matured, reflecting both infrastructure expansion and the consolidation of transit-oriented mobility. Until the early 2010s, demand exhibited a pattern of gradual growth, punctuated by periods of stagnation at high-level plateaus. After reaching a peak in 2011, the ridership entered a gradual contraction between 2015 and 2018. However, the decline during this period was moderate rather than abrupt. By contrast, the 2020 COVID-19 outbreak triggered an unprecedented and precipitous contraction within a short interval, followed by a phased recovery process. Similar non-monotonic patterns were observed internationally, where successive pandemic waves and changes in government restrictions were associated with repeated declines and partial recoveries in public transport ridership (Buehler et al., 2025). In Seoul, ridership declined sharply following the initial outbreak in early 2020 and subsequently showed a partial recovery. However, the renewed outbreak in the Seoul metropolitan area in mid-August, together with the strengthening of social distancing measures, coincided with another decline in ridership (Kwon et al., 2023). Ridership declined again toward the end of 2020 as distancing measures were tightened from November to December (Ha et al., 2022). As shown in the inset of

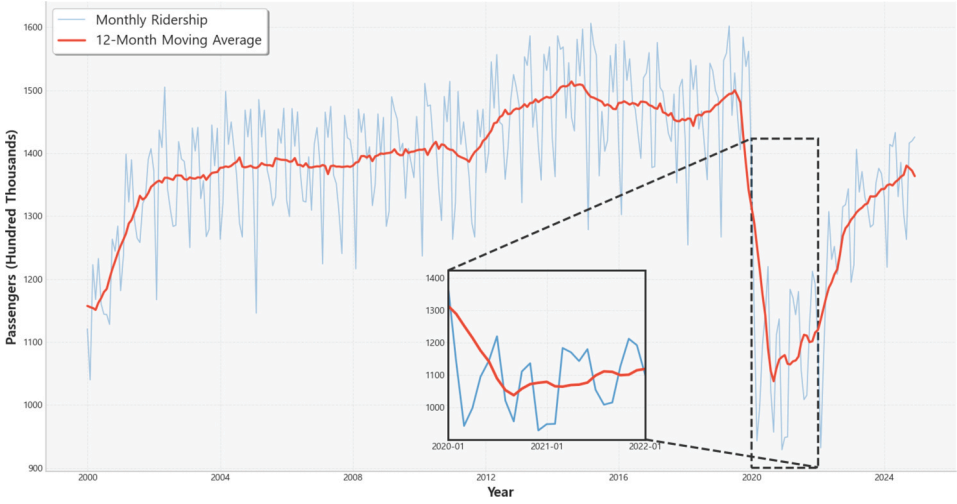


Fig. 2. Seoul Metro monthly ridership and 12-month moving average (2000–2024) Note: The y-axis does not start at zero; the scale is adjusted to highlight temporal variation in the series.

Fig. 2, the pandemic period therefore involved repeated sharp declines and partial recoveries rather than a single monotonic drop. Notably, by the end of the analysis period, ridership had yet to fully return to the pre-pandemic peak levels.

3.2. Explanatory variables

As an explanatory variable, population data were obtained from the resident registration statistics at the administrative district level, whereas bus ridership data were compiled from route-level monthly passenger counts and official statistical yearbooks. To capture the frequency of rainfall, meteorological data were incorporated using the monthly number of "precipitation days," defined as days with daily rainfall of at least 1 mm, in accordance with World Meteorological Organization (WMO) standards. Information on major policy interventions, including metro line expansions and fare adjustments, was synthesized from Seoul Metro's historical archives. Given that certain variables were only available at an annual frequency for specific sub-periods, monthly values were estimated to ensure a consistent temporal resolution across the 300-month dataset. Specifically, the annual population data for Seoul and Gyeonggi Province (January 2000–April 2006) were converted into monthly values using linear interpolation, assuming minimal month-to-month volatility. For bus ridership data available only in annual aggregates—specifically for Seoul (2000–2014) and Gyeonggi Province (2000–2010, 2019–2020)—the annual total passenger volumes were distributed across months to reflect the inherent seasonal patterns.

Specifically, the estimated ridership for month m in year y, denoted as $P_{y,m}$, was calculated by multiplying the observed annual total ridership $P_{y,Total}$ by a monthly seasonality index S_m, as expressed in Eq. (1).

$$P_{y,m} = P_{y,Total} \times S_m \left(where \sum_{m=1}^{12} S_m = 1 \right) \tag{1}$$

in this formulation, S_m (seasonality index) is the average seasonal share for month m derived from periods in which the observed monthly bus ridership data were available. By ensuring that the sum of the seasonal shares across the 12 months equals unity, this approach preserved the observed annual totals while effectively capturing intra-annual fluctuations.

Furthermore, because bus ridership data for Gyeonggi Province were unavailable for the period from January to December 2024, the monthly values for this interval were derived using supplementary official statistics. Specifically, the monthly bus ridership was derived by applying the monthly bus mode share—obtained from official records provided by the Gyeonggi-do Government—to the corresponding monthly total public transport ridership for the province. This approach ensured that the derived ridership figures for 2024 remained consistent with the broader public transport usage trends observed in the region.

Fig. 3 illustrates a comparison of the population and bus ridership datasets before and after the application of interpolation and adjustment procedures. As shown in the figure, the refined datasets maintain the underlying long-term trends of the original annual aggregates while successfully providing the continuous monthly resolution required for the time-series analysis. The reconstructed series broadly preserve the long-term patterns of the original data. However, because temporal reconstruction may affect the time-series properties of the variables, additional robustness checks were conducted using alternative reconstruction methods and samples that reduce or exclude reconstructed observations. Detailed results are reported in Appendix B and discussed in Section 4.4.

Following these preprocessing steps, the final set of variables was established, comprising continuous longitudinal data such as

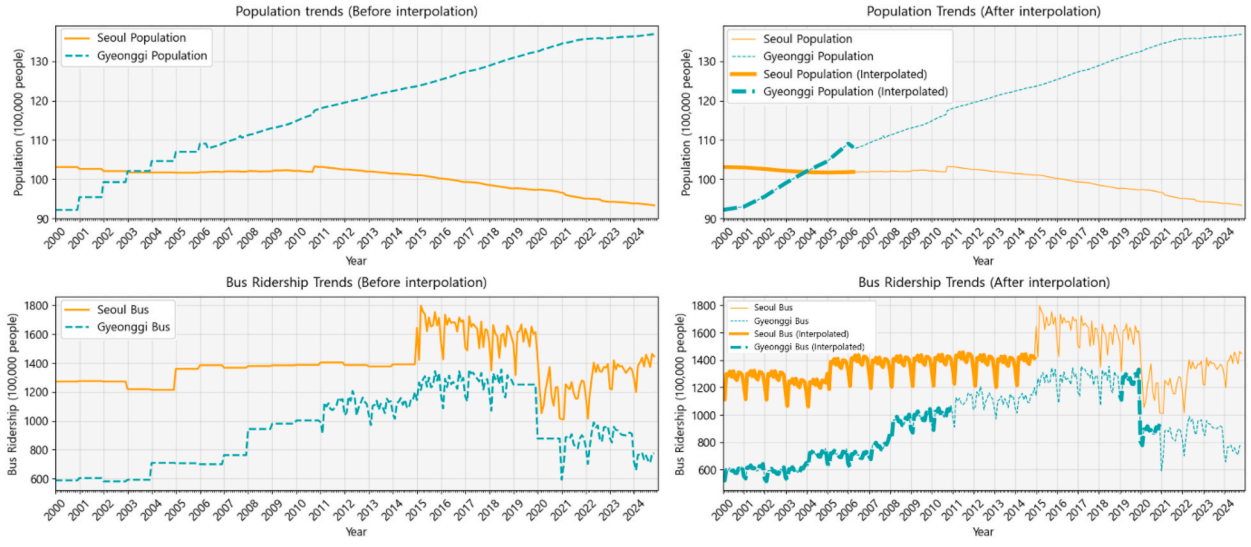


Fig. 3. Comparison of population and bus ridership data before and after interpolation. Note: The y-axis does not start at zero; the scale is adjusted to highlight temporal variation in the series.

Seoul Metro ridership, population, and bus ridership for both Seoul and Gyeonggi Province, the number of precipitation days, and monthly nominal gasoline prices. We also considered vehicle-related variables, including total vehicle registrations and vehicle registrations per 1,000 persons in Seoul and Gyeonggi Province. However, both measures were highly correlated with the population variables, particularly with Gyeonggi population, indicating substantial overlap in the long-term information captured by these variables. Therefore, vehicle-related variables were not included in the final VECM. Moreover, dichotomous event variables were constructed to capture the timing of major policy shifts and external shocks, most notably the COVID-19 pandemic, implementation of the Seoul integrated public transport fare system, and fare adjustments. The fare adjustment variables indicate the timing of major nominal fare revisions in Seoul's public transport system. Nominal fare revisions were used because the analysis aimed to examine whether officially implemented fare increases were associated with changes in metro ridership, rather than to estimate inflation-adjusted real fare effects. The physical expansion of the metro network during the study period, as illustrated in Fig. 4, was explicitly incorporated to account for the effects of incremental infrastructure growth on demand. Seasonal dummy variables were included to control for recurrent periodic fluctuations in ridership. Detailed operational definitions and data sources for all variables are synthesized in Table 1.

3.3. Analytical procedure

In this study, a VECM was employed to analyze the determinants of subway ridership in Seoul. The VECM framework is suitable for cases in which non-stationary variables exhibit unit roots yet share cointegrating relationships, thereby enabling the estimation of both short- and long-run equilibrium dynamics (Engle & Granger, 1987; Johansen, 1988). Eq. (2) was derived from a p-order Vector Autoregression (VAR) model and expressed in a first-difference form for an endogenous variable X_t, simplified within the structure of the VECM (Johansen, 1988). In the empirical specification, the endogenous system consists of the variables specified for the cointegration analysis, while the remaining variables are incorporated separately as short-run exogenous variables according to their time-series properties and model specification. The model applied in this study is as follows:

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + BZ_{t-1} + \varepsilon_t \tag{2}$$

here k denotes the lag order of the underlying VAR model. The matrix Γ_i represents the short-run coefficient matrices capturing the effects of past changes in the endogenous variables, in which each Γ_i measures the impact of the i-th lag of ΔX on current changes in X. The coefficient matrix Π captures the long-run equilibrium relationships and can be decomposed into the product of two matrices, α and $\beta(\Pi = \alpha\beta')$. The matrix β represents the cointegration vectors (long-run equilibrium relationships), and α serves as the adjustment matrix, measuring how the endogenous variables respond to deviations from the cointegrating relationships. ΔX_t denotes the first difference of X_t, capturing short-run fluctuations. The term $\sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i}$ describes the short-run effects of past changes in X. The vector Z_{t-1} denotes the short-run exogenous variables, which enter the model either as one-period lagged levels or as one-period lagged first

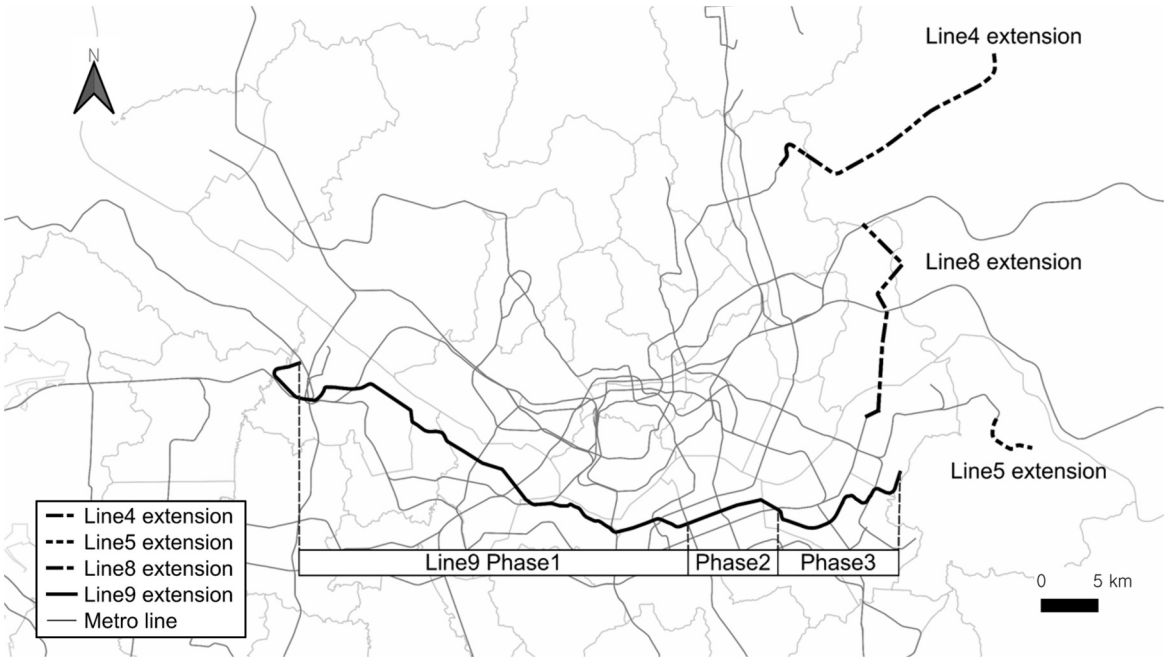


Fig. 4. Expansion of the Seoul Metropolitan Subway network (2000–2024).

Table 1
Definition and sources of variables.

Variables	Description	Source	Notes
Seoul Metro ridership	Monthly number of metro boardings on Lines 1–9 (100,000 riders)	Seoul Metro	
Seoul population	Monthly resident population of Seoul (100,000 persons)	Korean Statistical Information Service	Jan 2000 to Apr 2006 (linear interpolation)
		Gyeonggi-do Government	May 2006 to December 2007
		Ministry of the Interior and Safety	January 2008 to December 2024
Gyeonggi population	Monthly resident population of Gyeonggi Province (100,000 persons)	Korean Statistical Information Service	January 2000 to April 2006 (linear interpolation)
		Gyeonggi-do Government	May 2006 to December 2007
		Ministry of the Interior and Safety	January 2008 to December 2024
Seoul bus ridership	Monthly number of bus passengers in Seoul (100,000 riders)	Gyeonggi-do Bus Transport Business Association	January 2000 to December 2014 (seasonally adjusted)
		Seoul Metropolitan Government	January 2015 to December 2024
Gyeonggi bus ridership	Monthly number of bus passengers in Gyeonggi Province (100,000 riders)	Gyeonggi-do Bus Transport Business Association	January 2000 to December 2023 (2000–2010 and 2019–2020 seasonally adjusted)
		Gyeonggi-do Government	January 2024 to December 2024
Precipitation days	Monthly number of days with ≥ 1 mm precipitation (days)	Korea Meteorological Administration	
Gasoline price	Monthly average nominal retail gasoline price (KRW per liter)	Korea National Oil Corporation	
Spring	Dummy = 1 for March–May, otherwise 0		
Summer	Dummy = 1 for June–August, otherwise 0		
Autumn	Dummy = 1 for September–November, otherwise 0		
Winter	Dummy = 1 for December to February, otherwise 0		
COVID-19	Dummy = 1 during social distancing period (Mar 2020 to Oct 2021), otherwise 0		
Integrated fare system	Introduction of the distance-based integrated public transit fare system, applied regardless of transit mode or number of transfers (Dummy = 1 after July 2004, 0 otherwise)		
Line 9 Phase 1	Opening of Seoul Subway Line 9 by 25.5 km, adding 25 new stations (Dummy = 1 from August 2009 to March 2015, 0 otherwise)		
Line 9 Phase 2	Extension of Seoul Subway Line 9 by 4.5 km, adding 5 new stations (Dummy = 1 from April 2015 to November 2018, 0 otherwise)		
Line 9 Phase 3	Extension of Seoul Subway Line 9 by 9.2 km, adding 8 new stations (Dummy = 1 after December 2018, 0 otherwise)		
Line 5 extension	Extension of Seoul Subway Line 5 by 2.9 km, adding 3 new stations (Dummy = 1 after April 2021, 0 otherwise)		
Line 4 extension	Extension of Seoul Subway Line 4 by 14.9 km, adding 3 new stations (Dummy = 1 after April 2022, 0 otherwise)		
Line 8 extension	Extension of Seoul Subway Line 8 by 12.8 km, adding 6 new stations (Dummy = 1 after September 2024, 0 otherwise)		
Fare increase 1	Dummy = 1 when nominal base fare raised from KRW 1,050 to 1,250 (Jul 2015 to Sep 2023), otherwise 0		
Fare increase 2	Dummy = 1 when nominal base fare raised from KRW 1,250 to 1,400 (Oct 2023 onward), otherwise 0		

differences according to their specification, and the coefficient matrix B captures their effects on the endogenous variables. The error term ε_t captures unexplained innovations. Crucially, the term ΠX_{t-1} is equivalent to $\alpha\beta' X_{t-1}$, in which $\beta' X_{t-1}$ constitutes the error correction term. This term reflects the magnitude of the deviation from the long-run equilibrium, allowing such deviations to affect subsequent short-run adjustments in the endogenous system.

Eq. (2) describes the entire system of n endogenous variables in a matrix form, and the VECM equation for an individual endogenous variable $x_{j,t}$ can be expressed as Eq. (3).

$$\Delta x_{j,t} = \sum_{i=1}^{k-1} \gamma_{j,i} \Delta X_{t-i} + \sum_{r=1}^{R} \alpha_{jr} EC_{r,t-1} + \delta_j Z_{t-1} + \varepsilon_{j,t} \tag{3}$$

here $\gamma_{j,i}$ denotes the element of the short-run coefficient matrix corresponding to the j-th equation, capturing the short-run effect of the i-th lag of ΔX on $\Delta x_{j,t}$. The term $\sum_{r=1}^{R} \alpha_{jr} EC_{r,t-1}$ represents the error-correction component, where R denotes the cointegration rank, $EC_{r,t-1}$ denotes the one-period-lagged disequilibrium associated with the r-th cointegrating relationship, and α_{jr} measures the

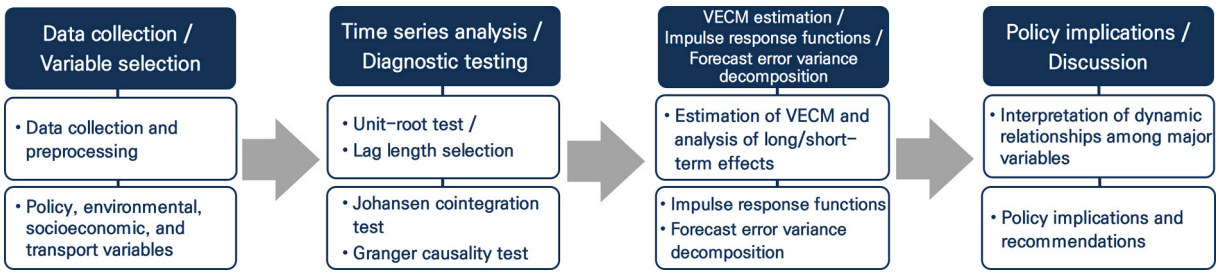


Fig. 5. VECM application process.

adjustment response of the j-th endogenous variable to that disequilibrium. The term $\delta_j Z_{t-1}$ captures the short-run effects of the exogenous controls on the j-th endogenous variable. This equation illustrates the influence of past short-run variations and deviations from the cointegrating relationships on the current change in an individual endogenous variable. This specification allows for the individual examination of the short-run dynamics of each variable $x_{j,t}$. In this context, the adjustment coefficients α_{jr} represent the speed of adjustment, indicating how quickly the specific endogenous variable $x_{j,t}$ responds to disequilibria in the cointegrating system (Engle & Granger, 1987). Thus, the VECM framework facilitates the simultaneous estimation of short-run adjustments through differenced terms, and long-run equilibrium relationships via level variables and the error correction mechanism. The distinction between the long run and the short run is not based on the length of time, but on the nature of equilibrium relationships and adjustment mechanisms among variables. Long-run relationships refer to cointegrating relationships among the level variables, whereas short-run relationships capture the transitory shocks and adjustment processes reflected in the lagged terms of the differenced variables and the short-run exogenous controls.

This study adopted a time-series analytical approach centered on a VECM model, as illustrated in Fig. 5, to examine the temporal evolution of Seoul Metro demand and its dynamic relationships with socioeconomic, transport, and policy variables. The analysis begins with unit-root tests to assess the stationarity of the continuous time-series variables because non-stationary time series can yield spurious results in standard regression or VAR models. Accordingly, unit-root tests are conducted on both the level and first-differenced series to determine each variable's order of integration, I(d) (Ryan et al., 2025). Based on the identified integration properties, the variables used in the cointegration analysis and the short-run specification were determined accordingly. For the VECM's dynamic structure, an optimal lag length of two was selected, corresponding to a VAR(2) specification. This choice balances stability and interpretability, consistent with the evidence that excessive lag lengths in multivariate time-series models erode degrees of freedom and destabilize estimation (Ivanov & Kilian, 2005; Kilian, 2001). The selected lag length was consistently applied throughout the Johansen cointegration test and VECM estimation, with the corresponding lag structure also maintained in the subsequent dynamic analyses where applicable.

In the empirical specification, the endogenous system for the cointegration analysis consists of Seoul Metro ridership, Seoul bus ridership, and Gyeonggi bus ridership, thereby focusing the long-run system on interdependence among the three public transport ridership series. Although Seoul population and gasoline price are also I(1), previous transit-demand studies have treated demographic and fuel-price conditions as external demand-related factors affecting transit ridership (Taylor et al., 2009; Sung, 2017; Iseki & Ali, 2015). Accordingly, these two variables were excluded from the cointegration space and entered the VECM as lagged first differences. The roles and functional forms of the remaining short-run exogenous variables were specified according to their time-series properties and the nature of the effects they were intended to capture. Gyeonggi population and precipitation days, which are I(0), were included as lagged level exogenous variables. Seasonal indicators were also entered in lagged levels, while the integrated fare system variable was specified in level form to represent the post-implementation regime. By contrast, COVID-19, line-extension, and fare-increase variables were entered as lagged first differences to capture discrete transition effects associated with their occurrence or implementation.

Next, the Johansen cointegration test was employed to identify the existence of long-run equilibrium relationships among these three endogenous variables. For the deterministic specification, the Johansen test included a constant term and no deterministic trend, while the VECM was estimated with the constant restricted to the cointegration relation. Cointegration implies that, although individual variables may exhibit non-stationary trends, they may form stationary linear combinations representing long-run relationships, thereby providing the theoretical foundation for applying the VECM (Johansen, 1988). In transport demand research, cointegration-based approaches have been used to understand long-run relationships within multivariate demand systems (Milioti & Karlaftis, 2014). Once cointegration is confirmed, the VECM becomes an appropriate modeling framework because it allows for the joint estimation of short-run adjustments and long-run equilibrium relationships. The error correction coefficient indicates how an endogenous variable responds to deviations from the cointegrating relationships (Alogoskoufis & Smith, 1991).

Granger causality tests are used to assess temporal effects and directionality by evaluating whether past values of one variable improve the predictions of another, rather than implying true causation (Granger, 1969). For non-stationary variables, stationary transformations based on the unit-root results were used in the causality analysis, together with the selected lag structure. Accordingly, Granger causality analysis is well suited to identifying predictive temporal relationships and intermodal interactions, and it has been widely applied in transport research to examine dynamic relationships among variables (Thompson & Brown, 2006).

Subsequently, the IRFs were derived to observe the dynamic effects of innovations to the endogenous variables in the VECM system on metro demand. IRF analysis allows us to examine the magnitude and persistence of responses to endogenous system shocks, making it a valuable tool for interpreting dynamic propagation effects (Pradhan & Bagchi, 2013). FEVD was also conducted to compare the relative contributions of innovations in the endogenous variables to fluctuations in metro demand, thereby identifying the key sources of forecast-error variability within the endogenous system (Andrei & Andrei, 2015). Specifically, the FEVD was calculated using a generalized formulation that avoids dependence on variable ordering, and the resulting variance shares were normalized to sum to 100% at each forecast horizon. Through these analyses, we provide an integrated interpretation of how long-run cointegrating relationships and short-run dynamics jointly characterize changes in Seoul Metro demand.

4. Results

4.1. Unit-root test

The unit-root tests reported in Table 2 indicate that the Gyeonggi population and precipitation days are stationary in levels, consistent with an I(0) process, whereas the other five continuous variables contain unit roots but become stationary after first differencing, consistent with an I(1) process. Accordingly, Seoul Metro ridership, Seoul population, Seoul bus ridership, Gyeonggi bus ridership, and gasoline price were classified as I(1), whereas Gyeonggi population and precipitation days were classified as I(0). Seasonal and policy/intervention variables were treated as short-run exogenous variables and were therefore not subject to the unit-root test. The lag lengths were automatically selected using information criteria to control for serial correlation, and may differ between level and first-differenced specifications owing to differences in variance and autocorrelation.

4.2. Johansen cointegration test

To identify the long-run equilibrium relationships among Seoul Metro ridership, Seoul bus ridership, and Gyeonggi bus ridership, which constitute the endogenous system for the cointegration analysis, the number of cointegrating vectors (r) was sequentially tested using both the trace statistic and maximum eigenvalue statistic. The test results indicate that the null hypotheses of no cointegration ($r \leq 0$) and at most one cointegrating vector ($r \leq 1$) are both rejected at the 5% significance level. This implies the presence of at least two cointegrating relationships among the endogenous variables. By contrast, the null hypothesis of at most two cointegrating vectors ($r \leq 2$) cannot be rejected, as neither statistic exceeds its corresponding critical value (Table 3). Applying the Johansen procedure, which identifies the number of cointegrating vectors at the first stage at which the null hypothesis is not rejected, the results indicate the presence of two cointegrating vectors ($r = 2$) among the endogenous variables (Johansen, 1988). This implies that, although the individual series are non-stationary, they share two cointegrating relationships, represented as stationary linear combinations of the variables. These results provide the theoretical justification for employing the VECM to analyze long-run equilibrium relationships and short-run adjustment processes simultaneously. To examine whether the full-sample cointegration result was sensitive to structural instability, an additional cointegration-rank test allowing for an unknown level shift was conducted (Lütkepohl et al., 2004). The estimated level-shift location was January 2020, and two cointegrating relationships were identified after allowing for this shift (Appendix A).

4.3. Granger causality test

Granger causality tests were used to examine the temporal precedence and predictive relationships among the variables. The results indicate whether the past values of one variable significantly improve the predictions of another (Granger, 1969). Given the cointegrating relationships among the endogenous variables, short-run Granger causality was examined within the VECM framework based on the lagged first-difference terms. Seoul Metro ridership in the first difference (d_Seoul Metro ridership) was specified as the dependent variable, and the predictive relationships from Seoul bus and Gyeonggi bus ridership to Seoul Metro ridership were examined (Table 4).

The results show that lagged changes in Seoul bus ridership significantly predict changes in Seoul Metro ridership at the 10% significance level ($p = 0.0686$), while lagged changes in Gyeonggi bus ridership show a statistically significant predictive relationship with Seoul Metro ridership ($p = 0.0007$). These results indicate short-run predictive relationships between bus and metro ridership.

4.4. VECM estimation results

Based on the cointegration relationships identified earlier, a VECM corresponding to a VAR(2) specification was estimated to examine the dynamic interactions between Seoul Metro ridership and the key explanatory variables. Table 5 reports the estimated adjustment coefficients associated with the two cointegrating relationships in the Seoul Metro ridership equation. Both adjustment coefficients are statistically significant at the 5% level ($ec1 = -0.320$, $p < 0.001$; $ec2 = -0.142$, $p = 0.030$). In addition, a joint Wald

Table 2
Unit-root test results.

Variables	Level		First difference	
	t-stat	lags	t-stat	lags
Seoul Metro ridership	−2.819	13	−4.888***	15
Seoul population	3.478	0	−15.425***	0
Gyeonggi population	−3.433**	2	−5.653***	2
Seoul bus ridership	−2.498	13	−4.291***	12
Gyeonggi bus ridership	−1.556	16	−3.548**	16
Precipitation days	−4.030**	16	−6.355***	15
Gasoline price	−2.568	13	−5.620***	12

Note: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table 3
Johansen cointegration test results.

Null	Alternative	Trace test		Maximum eigenvalue test	
		Statistics	CV (5%)	Statistics	CV (5%)
$r \leq 0$	$r > 0$	52.90*	29.80	33.06*	21.13
$r \leq 1$	$r > 1$	19.85*	15.49	16.48*	14.26
$r \leq 2$	$r > 2$	3.36	3.84	3.36	3.84

Notes: 1. *r* denotes the number of cointegrating vectors.
2. * denotes rejection of the hypothesis at the 0.05 level.
3. The Johansen test was conducted using Seoul Metro ridership, Seoul bus ridership, and Gyeonggi bus ridership as the endogenous variables in the cointegration system.

Table 4
Granger causality test results.

Cause	Effect	p-value
d_Seoul bus ridership	d_Seoul Metro ridership	0.069
d_Gyeonggi bus ridership	d_Seoul Metro ridership	0.001

Notes: 1. The prefix "d_" denotes the first difference of a variable.
2. Results are based on short-run Granger causality tests within the VECM framework.

Table 5
Error correction terms estimation results in VECM model.

Variables	Coef.	Std. Err	z-value	p-value
Seoul Metro ridership (ec1)	−0.320***	0.067	−4.810	0.000
Seoul Metro ridership (ec2)	−0.142*	0.066	−2.166	0.030

Note: The joint Wald test for the two adjustment coefficients yields $\chi^2(2) = 50.618$, $p < 0.001$. ***p < 0.001; *p < 0.05.

Table 6
VECM short-run relationship estimates.

Variables	Coef.	Std. Err.	z-value	p-value
Endogenous variables				
L1.Δ Seoul Metro ridership (100,000 riders)	−0.262**	0.097	−2.692	0.007
L1.Δ Seoul bus ridership (100,000 riders)	−0.186†	0.111	−1.674	0.094
L1.Δ Gyeonggi bus ridership (100,000 riders)	0.267**	0.098	2.728	0.006
Exogenous controls				
L1.Δ Seoul population (100,000 persons)	25.114	50.532	0.497	0.619
L1.Δ Gasoline price (KRW per liter)	0.134†	0.077	1.732	0.083
L1. Gyeonggi population (100,000 persons)	−2.170***	0.368	−5.892	0.000
L1. Precipitation days (days)	−1.039	1.626	−0.639	0.523
L1. Summer	−42.943*	17.872	−2.403	0.016
L1. Autumn	42.817**	15.208	2.815	0.005
L1. Winter	−41.709*	17.849	−2.337	0.019
L1. Integrated fare system	20.948	16.650	1.258	0.208
L1.Δ COVID-19	−68.072	62.136	−1.096	0.273
L1.Δ Line 9 Phase 1	51.293	85.444	0.600	0.548
L1.Δ Line 9 Phase 2	54.343	122.031	0.445	0.656
L1.Δ Line 9 Phase 3	102.050	150.264	0.679	0.497
L1.Δ Line 5 extension	−93.368	85.946	−1.086	0.277
L1.Δ Line 4 extension	93.515	86.067	1.087	0.277
L1.Δ Line 8 extension	126.218	85.753	1.472	0.141
L1.Δ Fare increase 1	23.864	86.459	0.276	0.783
L1.Δ Fare increase 2	36.884	121.405	0.304	0.761

Notes: 1. "L1" denotes the one-period lag of a level variable, whereas "L1.Δ" denotes the one-period lag of a first-differenced variable.
2. ***p < 0.001; **p < 0.01; *p < 0.05; †p < 0.1.

test rejects the null hypothesis that both adjustment coefficients are jointly zero ($\chi^2(2) = 50.618$, $p < 0.001$). This result indicates that Seoul Metro ridership responds jointly to disequilibria represented by the cointegration space. Together with the Johansen test identifying two cointegrating relationships, these findings support the use of the VECM framework to capture long-run adjustment and short-run dynamics. The two error-correction terms are therefore interpreted jointly as representing deviations from the long-run relationships among the endogenous variables, rather than as separate structural mechanisms.

Table 6 presents the VECM's estimated short-run coefficients, capturing the short-run dynamics among the variables. The results indicate that Seoul Metro ridership exhibits short-run associations with its own past changes, demand for other transport modes, population and gasoline prices, and seasonal factors. Specifically, the coefficient of the one-month lag of Seoul Metro ridership changes (L1.Δ Seoul Metro ridership) is − 0.262 and statistically significant. This negative coefficient indicates that larger ridership changes in the previous month are followed by opposite adjustments in the subsequent period, which is consistent with a corrective mechanism through which temporary shocks dissipate over time (Box et al., 2015; Wooldridge, 2016). This suggests that short-run changes in metro demand tend to be partially reversed following temporary surges or declines.

Regarding intermodal relationships, Seoul bus ridership has a statistically significant negative association with metro demand at the 10% level, consistent with a short-run substitution relationship between buses and the metro within intra-urban travel in Seoul. By contrast, Gyeonggi bus ridership has a statistically significant positive association with Seoul Metro demand, suggesting a complementary relationship between Gyeonggi bus and Seoul Metro demand at the metropolitan scale.

Gyeonggi population has a statistically significant negative coefficient, suggesting that a higher population in Gyeonggi Province may be associated with a greater dispersion of travel demand away from Seoul Metro. Gasoline price has a positive coefficient and is statistically significant at the 10% level. Increases in gasoline prices raise the monetary cost of automobile use and may therefore increase the relative attractiveness of public transport. A similar relationship has also been reported in major metropolitan areas in South Korea, where subway demand was found to be generally more responsive to gasoline prices than bus demand (Lee et al., 2014).

Precipitation days have a negative but statistically insignificant coefficient. Seasonal fluctuations are also evident, with summer and winter showing significant negative coefficients and autumn showing a significant positive coefficient relative to spring. The positive autumn effect may partly reflect the resumption of regular commuting and education-related travel after the summer holiday period, as education travel can account for a meaningful share of public transport demand when schools are in session (Buehler et al., 2025). By contrast, the negative winter effect may be related to winter vacation periods and reduced discretionary travel during colder months, as adverse weather conditions can reduce non-commuting and recreational travel demand (Wu & Liao, 2020). The negative summer coefficient may similarly reflect reduced regular commuting and education-related travel during the summer holiday period.

By contrast, policy-driven and event dummy variables, such as COVID-19, fare increases, line extensions, and the integrated fare system, are not statistically significant in the short-run model. For example, COVID-19 has a negative coefficient of − 68.072, but it is not statistically significant ($p = 0.273$). This result indicates that the pandemic effect is not clearly identified as a discrete short-run transition effect in the VECM equation. COVID-19 involved an abrupt initial decline in ridership, subsequent behavioral adjustments, and a gradual recovery process, which are difficult to capture fully through changes in a single regime indicator. Such opposing movements within the same estimation window may have weakened the statistical precision of the short-run COVID-19 coefficient. This interpretation is consistent with recent comparative evidence showing that COVID-19 produced uneven recovery trajectories and persistent changes in public transport demand across countries, modes, and travel contexts (Buehler et al., 2025).

Similarly, none of the line-extension variables show statistically significant short-run effects in the aggregate monthly ridership model. This result may partly reflect the scale and timing of the analysis. However, the Line 8 extension showed the lowest p-value among the line-extension variables ($p = 0.141$) and the largest positive coefficient (126.218), although it did not reach the conventional 10% significance level. One possible explanation is that the Line 8 extension strengthened metropolitan connectivity between residential areas in Gyeonggi Province and Seoul (Lee & Jung, 2025). Because the extension opened near the end of the study period, however, the available post-opening observations are limited, preventing a firm interpretation of this result. These findings should not be interpreted as evidence that the extensions were ineffective, but rather suggest that their immediate system-wide effects are difficult to identify using aggregate monthly ridership. Overall, line-extension effects may be more clearly observed through station-level, corridor-level, or longer-term accessibility and land-use changes (Lee et al., 2022; Liu et al., 2019).

To examine whether the VECM results were sensitive to the reconstruction of historical population and bus ridership variables, additional robustness checks were conducted using alternative reconstruction methods and fully observed monthly subsamples. Specifically, the population interpolation method was replaced with shape-preserving piecewise cubic Hermite interpolation (PCHIP), the bus ridership reconstruction method was replaced with Chow–Lin temporal disaggregation, and both alternative methods were also applied jointly. In addition, fully observed monthly subsamples for 2015–2018 and 2021–2024 were examined. For the three alternative reconstruction specifications, the Johansen cointegration test was repeated and the VECM was re-estimated. Both the Trace and Maximum Eigenvalue tests identify a cointegration rank of two across all three specifications. The VECM estimates remain highly stable when the alternative population interpolation method is applied. The positive coefficient of Gyeonggi bus ridership also remains statistically significant across all three specifications. The Seoul bus coefficient remains negative under the alternative bus reconstruction, although it is no longer statistically significant when the Chow–Lin method is applied.

The fully observed subsamples were examined separately to assess whether the cointegration results persisted when reconstructed observations were excluded. Both the Trace and Maximum Eigenvalue tests identify a cointegration rank of two for the 2015–2018 subsample, whereas both tests indicate rank one for the 2021–2024 subsample. The latter period contains only 48 monthly observations and covers the later phase of the COVID-19 disruption and the subsequent recovery period, during which public transport demand in Seoul underwent substantial changes. The lower cointegration rank may therefore partly reflect the limited sample length and the distinct mobility dynamics of this period (Jun & Yun, 2023; Lee et al., 2024). Because both fully observed subsamples contain

only 48 monthly observations and include several policy variables with no variation over the respective periods, they were used to assess the sensitivity of the cointegration rank. The robustness check results are reported in Appendix B (Tables B1 and B2).

4.5. Impulse response function (IRF)

Fig. 6 illustrates how Seoul Metro ridership responds temporally to shocks in the endogenous variables based on the estimated VECM. The solid lines represent the mean response paths, and the shaded areas indicate 90% confidence intervals. The dependent variable, metro ridership, is measured in units of 100,000 passengers. Accordingly, for example, a response value of 0.5 corresponds to a change of approximately 50,000 passengers.

A shock to Seoul Metro ridership produces a positive response of approximately 0.42 after one month, which gradually declines to 0.30 after three months and 0.11 after six months. The response approaches zero thereafter, reaching approximately − 0.001 after 12 months and − 0.04 after 24 months. The 90% confidence interval includes zero from approximately the six-month horizon onward, indicating that the initial response dissipates over time.

A shock to Seoul bus ridership produces a negative response in Seoul Metro ridership of approximately − 0.33 after one month. The response remains negative at approximately − 0.26 after three months, −0.20 after six months, −0.18 after 12 months, and − 0.15 after 24 months. Although the confidence interval briefly approaches or includes zero during the early response period, it remains below zero over the subsequent horizons, indicating that the negative response persists over the medium to longer term. This pattern is consistent with the short-run substitution relationship identified in the VECM estimation.

By contrast, a shock to Gyeonggi bus ridership produces a positive response in Seoul Metro ridership of approximately 0.45 after one month. The response remains positive at approximately 0.35 after three months, 0.32 after six months, 0.34 after 12 months, and 0.34 after 24 months. The 90% confidence intervals remain above zero throughout the analysis horizon. This persistent positive response is consistent with a complementary relationship between Gyeonggi bus ridership and Seoul Metro demand at the metropolitan scale.

4.6. Forecast error variance decomposition (FEVD)

Fig. 7 presents the results of the FEVD for Seoul Metro ridership. Shocks to metro ridership itself explain approximately 39.8% of the total forecast error variance after 24 months, representing the largest individual contribution within the three-variable endogenous system. The remaining variance is largely driven by bus ridership shocks. Gyeonggi bus ridership explains 33.9% of the variance, while Seoul bus ridership accounts for 26.3%. Together, the two bus variables account for approximately 60.2% of the forecast error variance. When considered alongside the short-run estimates and IRF results, these findings indicate that substitution and complementary relationships among public transport modes are important in explaining variations in metro demand.

5. Discussion

The empirical results show that Seoul Metro ridership is embedded in a metropolitan public transport system characterized by both long-run interdependence and short-run interactions. The two cointegrating relationships identified among Seoul Metro, Seoul bus, and Gyeonggi bus ridership indicate that the three ridership series share common long-run movements. Rather than being determined by a single dominant driver, metro ridership appears to evolve as part of a broader urban mobility system in which public transport demands are interconnected over time (Engle & Granger, 1987; Johansen, 1988).

The estimation results for the error-correction terms provide further insight into the adjustment of metro demand to deviations from these long-run relationships. Both adjustment coefficients in the Seoul Metro ridership equation are statistically significant, and the joint Wald test also rejects the null hypothesis that the two coefficients are jointly zero. These results indicate that Seoul Metro

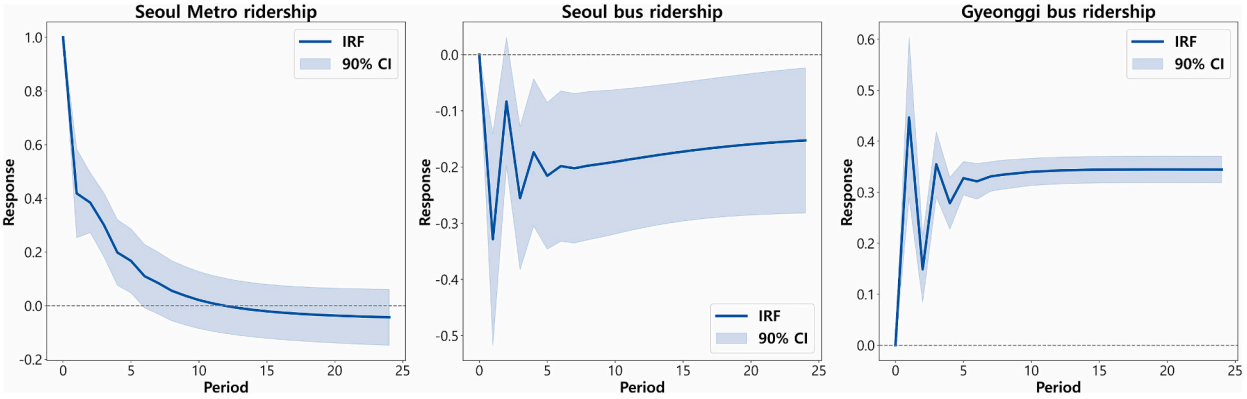


Fig. 6. Impulse responses of Seoul Metro ridership to endogenous ridership shocks.

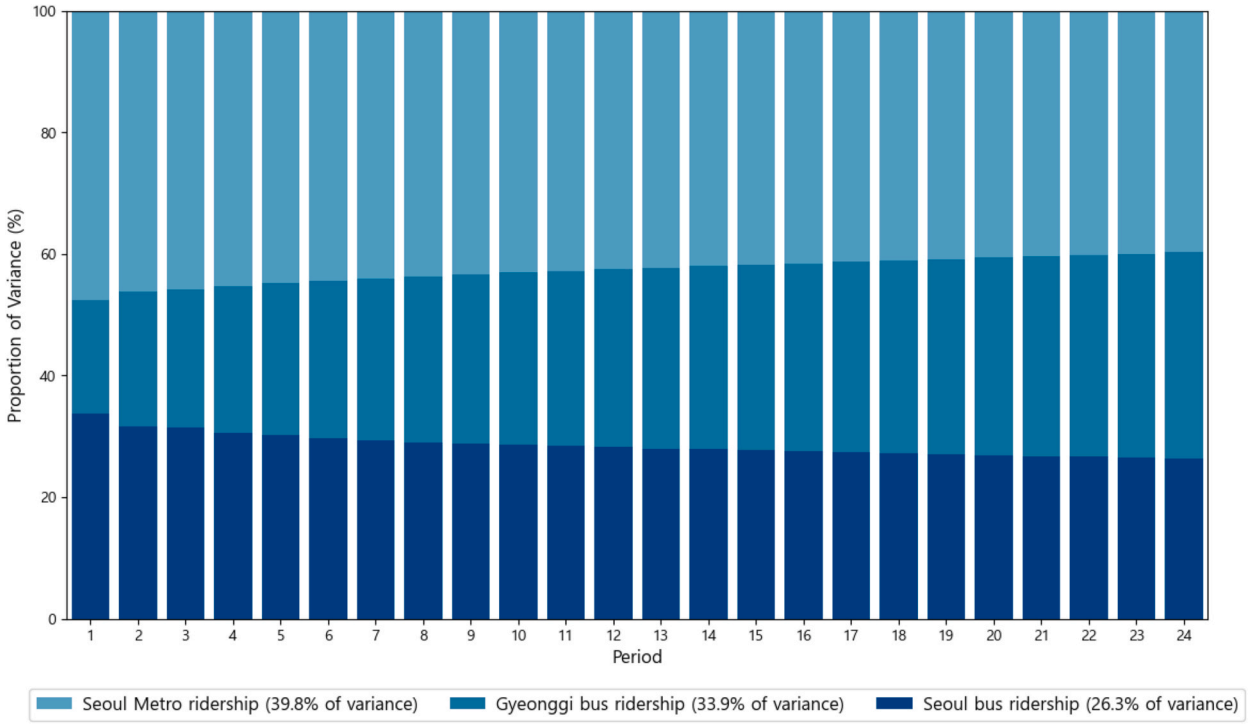


Fig. 7. Forecast error variance decomposition of metro ridership.

ridership responds to disequilibria represented by the cointegration space. This finding highlights a long-run characteristic of metro demand that is difficult to capture through short-run analysis alone, and emphasizes the importance of understanding public transport demand from a long-run system perspective.

The short-run analysis provides further evidence of distinct intermodal relationships within the SMA transport system. Seoul bus ridership is negatively associated with metro ridership, suggesting a substitution relationship between the two modes within Seoul, whereas Gyeonggi bus ridership is positively associated with metro ridership, suggesting complementarity at the metropolitan scale. The IRF results show that these contrasting patterns extend beyond the immediate period, while the FEVD results indicate that bus ridership shocks account for a substantial share of fluctuations in metro demand. These findings suggest that relationships among public transport modes can differ according to spatial scale and travel context (Wang & Ross, 2019; Yue et al., 2018). In particular, the positive relationship with Gyeonggi bus ridership highlights the importance of considering metropolitan bus and metro demand jointly in transport planning and network coordination.

The results also show that short-run metro demand is associated with broader metropolitan and economic conditions. The negative relationship with Gyeonggi population may reflect the dispersion of travel demand as population becomes more distributed across the metropolitan area. The positive association with gasoline prices is consistent with the possibility that higher automobile operating costs increase the relative attractiveness of public transport, which is also consistent with findings from previous studies in major metropolitan areas in South Korea (Lee et al., 2014). Seasonal differences further suggest that recurring travel patterns associated with work, education, and other activities contribute to monthly variations in metro demand.

The results for metro line extensions illustrate the importance of spatial scale when evaluating infrastructure effects. Although none of the line-extension variables is statistically significant in the aggregate monthly model, Line 8 shows a comparatively stronger positive pattern than the other extensions. One possible explanation is that the extension strengthened metropolitan connectivity between residential areas in Gyeonggi Province and Seoul (Lee & Jung, 2025). However, this interpretation remains tentative because the aggregate time-series model cannot directly identify the spatial or behavioral mechanism underlying the observed relationship. Previous research has identified significant ridership effects around specific extension segments and station areas, including the Seoul Metro Line 9 extensions (Lee et al., 2022). The difference is consistent with the broader spatial scope of the present analysis; localized ridership changes may not translate proportionally into changes in aggregate system-wide demand. This suggests that system-level time-series analysis and station- or corridor-level evaluations capture different dimensions of infrastructure impacts and can provide complementary evidence.

The absence of statistically significant short-run fare effects may also reflect characteristics of Seoul's public transport system. Seoul has a high-density urban structure and an extensive public transport network, contributing to substantial reliance on public transport (Ha et al., 2023), while fares have remained relatively low by international standards (Ko et al., 2019). Moreover, the fare variables represent nominal fare revisions rather than changes in inflation-adjusted real travel costs. Accordingly, the observed fare adjustments may have produced relatively limited changes in generalized travel costs and, consequently, in aggregate short-run metro demand.

The COVID-19 coefficient is negative but not statistically significant in the short-run VECM. The pandemic, however, involved a sharp initial decline in ridership followed by substantial behavioral changes and a prolonged recovery, making its temporal influence difficult to summarize through a single transition variable. Previous studies likewise show that post-pandemic transit demand has been shaped by changes in commuting patterns, remote work, service conditions, and mode choice (Light et al., 2025; Ashour et al., 2024). The Seoul experience therefore illustrates that major external shocks can generate complex changes in travel behavior that may extend beyond the immediate effects captured by aggregate monthly intervention variables.

6. Conclusion

This study empirically examined the short-run and long-run determinants of Seoul Metro ridership using a VECM based on 25 years of monthly time series data from 2000 to 2024. The results indicate that metro demand in Seoul is shaped by multiple interacting factors, including population dynamics and bus ridership, while seasonality contributes to short-run fluctuations and most policy-related variables and precipitation days show limited short-run effects.

This study contributes to the field by explicitly distinguishing between long-run equilibrium relationships and short-run dynamics among multiple determinants of metro demand. It uses a macro-level empirical approach to extend the existing literature, which largely focused on localized or short-term effects. The results show that metro ridership evolves within an interdependent urban transport system influenced by multiple internal and external factors rather than by a single dominant driver. Applying the VECM allows for a more comprehensive understanding of the long-run relationships within the public transport system and the short-run dynamics associated with multiple internal and external factors.

Our findings provide important insights from a policy perspective. First, the empirical confirmation that Seoul Metro demand is closely linked to bus ridership in Gyeonggi Province highlights the need for integrated metropolitan transport policies that consider the SMA as a whole. Second, when evaluating the effects of public transport policies, such as line extensions and fare increases, policymakers should move beyond assessments based solely on short-term ridership changes. Instead, policy evaluation should adopt a long-run and spatially macroscopic perspective that accounts for broader factors, including intermodal competition and complementarity, seasonality, and weather-related influences.

Despite these academic and policy contributions, this study has some limitations. First, because this study relied on macro-level data such as aggregate Seoul Metro ridership, it was difficult to analyze micro-level changes occurring in specific regions or resulting from particular line extensions. Second, as some data were only available on an annual basis, monthly values for certain periods were reconstructed rather than directly observed. Furthermore, by treating policy variables simply as dummy variables, we were unable to apply sophisticated methodologies to capture the intensity of policy actions or their heterogeneous spillover effects. Future research could address these limitations by conducting station- or route-specific spatial analyses for metro and bus systems, thereby providing more detailed empirical evidence on localized policy effects and further elucidating the complex mechanisms underlying metro demand. Nevertheless, by systematically integrating external and policy-related factors into a macro-level time-series framework, this study offers a comprehensive analysis of the long- and short-run dynamics of Seoul Metro ridership and provides a valuable empirical foundation for the development of sustainable urban transport policies.

CRediT authorship contribution statement

Saehim Kim: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Inseong Lee:** Writing – original draft, Visualization, Investigation, Data curation. **Seunghwa Jang:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Joonho Ko:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Structural-shift cointegration rank test.

H0	Trace statistic	5% CV	Decision
$r = 0$	66.70	24.28	Reject
$r \leq 1$	18.16	12.28	Reject
$r \leq 2$	3.29	4.12	Fail to reject

Note: The structural-shift cointegration rank test allows for an unknown level shift in the three-variable endogenous system comprising Seoul Metro ridership, Seoul bus ridership, and Gyeonggi bus ridership (Lütkepohl et al., 2004). The test was estimated using a VAR(2) specification without a deterministic linear trend. The estimated level-shift location was January 2020, and the test identified two cointegrating relationships at the 5% significance level.

Appendix B

Table B1
Robustness check results for cointegration rank.

Specification	Description	N	Trace rank	Maximum Eigenvalue rank
R1 (Robustness 1)	Population reconstructed using PCHIP	300	2	2
R2 (Robustness 2)	Bus ridership reconstructed using Chow–Lin	300	2	2
R3 (Robustness 3)	Population and bus ridership reconstructed using PCHIP and Chow–Lin	300	2	2
R4 (Robustness 4)	Fully observed sample, 2015–2018	48	2	2
R5 (Robustness 5)	Fully observed sample, 2021–2024	48	1	1

Note: 1. R1 replaces only the population interpolation with shape-preserving piecewise cubic Hermite interpolation (PCHIP) using annual population anchors, while retaining the original bus ridership allocation. R2 retains the original population interpolation but replaces bus ridership reconstruction with a Chow-Lin temporal disaggregation approach. R3 replaces both population interpolation and bus ridership reconstruction using PCHIP and Chow-Lin approaches, respectively. The Chow-Lin reconstruction uses month-of-year indicators and preserves the original annual bus ridership totals. Observed monthly values outside the reconstructed periods are left unchanged.

2. R4 and R5 use fully observed monthly periods for 2015–2018 and 2021–2024, respectively. For these fully observed subsamples, lag orders were re-selected separately using the Akaike information criterion (AIC) to account for differences in dynamic structure across sample periods. R5 is based on a short 48-month sample that begins during the later phase of the COVID-19 disruption and extends through the subsequent recovery period, when public transport demand in Seoul underwent substantial changes (Jun & Yun, 2023; Lee et al., 2024). Accordingly, the lower cointegration rank identified for R5 may reflect both the limited sample length and the distinct mobility dynamics of this period. The reported ranks are based on the 5% critical values

Table B2
Robustness check results.

Variables	R1 (Robustness 1)		R2 (Robustness 2)		R3 (Robustness 3)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Error correction terms						
Seoul Metro ridership (ec1)	−0.320***	0.067	−0.312***	0.067	−0.312***	0.068
Seoul Metro ridership (ec2)	−0.142*	0.066	−0.178**	0.068	−0.179**	0.068
Joint ECT test, $\chi^2(2)$	50.633***	—	54.349***	—	54.375***	—
Short-run relationship estimates						
Endogenous variables						
L1.Δ Seoul Metro ridership (100,000 riders)	−0.261**	0.097	−0.355***	0.102	−0.355***	0.102
L1.Δ Seoul bus ridership (100,000 riders)	−0.186†	0.111	−0.010	0.113	−0.010	0.113
L1.Δ Gyeonggi bus ridership (100,000 riders)	0.267**	0.098	0.233*	0.104	0.232*	0.104
Exogenous controls						
L1.Δ Seoul population (100,000 persons)	23.747	50.586	27.254	50.621	25.805	50.671

(continued on next page)

Table B2 (*continued*)

Variables	R1 (Robustness 1)		R2 (Robustness 2)		R3 (Robustness 3)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
L1. Gyeonggi population (100,000 persons)	−2.180***	0.370	−2.243***	0.369	−2.255***	0.371
L1. Precipitation days (days)	−1.044	1.626	−0.904	1.627	−0.909	1.627
L1.Δ Gasoline price (KRW per liter)	0.134†	0.077	0.149†	0.078	0.149†	0.078
L1. Summer	−42.980*	17.878	−41.137*	17.897	−41.178*	17.903
L1. Autumn	42.758**	15.212	49.468**	15.364	49.404**	15.367
L1. Winter	−41.738*	17.852	−33.294†	17.954	−33.329†	17.956
L1. Integrated fare system	21.165	16.654	18.084	16.354	18.320	16.360
L1.Δ COVID-19	−68.047	62.138	−59.297	62.322	−59.509	62.324
L1.Δ Line 9 Phase 1	51.279	85.444	53.271	85.723	53.252	85.723
L1.Δ Line 9 Phase 2	54.368	122.036	71.523	122.338	71.551	122.341
L1.Δ Line 9 Phase 3	102.084	150.269	123.335	150.557	123.375	150.560
L1.Δ Line 5 extension	−93.419	85.945	−88.090	86.227	−88.142	86.225
L1.Δ Line 4 extension	93.481	86.066	93.262	86.335	93.229	86.333
L1.Δ Line 8 extension	126.343	85.752	134.671	86.013	134.821	86.013
L1.Δ Fare increase 1	23.848	86.462	24.864	86.734	24.848	86.736
L1.Δ Fare increase 2	36.929	121.405	40.124	121.761	40.181	121.760

Notes: 1. R1 replaces only the population interpolation with shape-preserving piecewise cubic Hermite interpolation (PCHIP) using annual population anchors, while retaining the original bus ridership allocation. R2 retains the original population interpolation but replaces bus ridership reconstruction with a Chow-Lin temporal disaggregation approach. R3 replaces both population interpolation and bus ridership reconstruction using PCHIP and Chow-Lin approaches, respectively. The Chow-Lin reconstruction uses month-of-year indicators and preserves the original annual bus ridership totals. Observed monthly values outside the reconstructed periods are left unchanged.

2. R4 and R5 are not included in the short-run coefficient comparison because the fully observed subsamples contain only 48 monthly observations and require subsample-specific lag structures. In addition, several policy variables exhibit no variation within these short periods. Accordingly, these specifications are used primarily to assess the sensitivity of the cointegration rank rather than for direct comparison of short-run VECM coefficients.

3. “L1” denotes the one-period lag of a level variable, whereas “L1.Δ” denotes the one-period lag of a first-differenced variable.

4. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; †$p < 0.1$.

Data availability

Data will be made available on request.

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