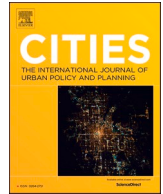




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Examining the causal relationship between bike-share and public transit in response to the COVID-19 pandemic

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ABSTRACT

As urban transportation systems often face disruptive events, including natural and man-made disasters, the importance of resilience in the transportation sector has recently been on the rise. In particular, the worldwide spread of the COVID-19 pandemic resulted in a significant decrease in citizens' public transit use to avoid unnecessary physical contact with others. Accordingly, bike-share has been highlighted as one of the sustainable modes that can replace public transit and, thus, improve the overall resilience of the urban transportation systems in response to COVID-19. This study aims to examine the changes in causal relationships between bike-share and public transit throughout the COVID-19 pandemic in Seoul, Korea. We analyzed bike-share and public transit ridership from Jan 2018 to Dec 2020. We developed a weekly panel vector autoregressive (PVAR) model to identify the bike-transit relationships before and after the pandemic. Our results showed that COVID-19 weakens the competitive relationships between bike-share and bus transit and modal integration between bike-share and subway transit. This study also found that bus and subway transit were more competitive with each other after the outbreak of COVID-19. The study's findings suggest that bike-share can increase the overall resilience of the urban transportation system during the pandemic situation, particularly for those who rely on public transit for their mobility.

1. Introduction

As cities have become more complex over the decades, urban transportation systems often face various disruptive events, including natural and artificial disasters (Wan et al., 2018). Accordingly, the importance of resilience in transportation has also been highlighted recently (Woodruff et al., 2021). However, the transportation systems' resilience generally refers to the capability of a system to recover to normal functioning after being affected by disruptive events (Henry & Ramirez-Marquez, 2012). In other words, the level of transportation systems' resilience depends mainly on whether alternative transportation modes exist when the use of certain modes (e.g., public transit) is restricted by internal or external events (Mattson & Jenelius, 2015).

Bicycling, including private and public bike-share, has recently emerged as an effective means to improve the resilience of urban transportation systems with mobility and economic feasibility (Clemente, 2020). For example, when catastrophic earthquakes occurred in

Japan, Mexico physically restricted private vehicles and public transit. For example, bicycles were used as the safest and fastest option for citizens within the affected area (Sonuparlak, 2011; Jong, 2017). Public transit strikes in Philadelphia and London have also resulted in a significant increase in the city's bike-share ridership (Fuller et al., 2019; Saberi et al., 2018), suggesting that bike-share can fill the gap in the public transit system to some extent when its normal function is being interrupted.

More recently, the worldwide spread of the COVID-19 pandemic has also significantly changed citizens' travel mode choices, particularly between public transit and bike-share (Wang et al., 2021). Before the outbreak of COVID-19, bike-share tends to have competitive and complementary relationships with public transit, depending on the city's physical and social environment (Martin & Shaheen, 2014). During the pandemic, however, most large cities experienced a significant decrease in public transit use, while the city's bike-share ridership has remained or even increased (Shaer et al., 2021; Tirachini & Cats, 2020). In

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addition, the spreading of COVID-19 and the resulting social atmosphere of avoiding unnecessary physical contact with others have strengthened a modal shift from public transit to bike-share (Teixeira & Lopes, 2020; Teixeira et al., 2021).

Though there have been many studies that explored the impact of COVID-19 on public transit and bike-share use, they focused mainly on analyzing the change in bike-share demand or pairwise comparison between bike-share and public transit ridership during the pandemic (Bergantino et al., 2021; Wang & Noland, 2021; Chen et al., 2022; Xin et al., 2022). To further identify the potential role of bike-share in improving the resilience of urban transportation systems during COVID-19, it is necessary to analyze how the integration and substitution between public transit and bike-share changes throughout the pandemic.

This study examines the causal relationships between bike-share and public transit changes throughout the current COVID-19 pandemic in Seoul, South Korea. To this end, we collected bike-transit ridership from Jan 2018 to Dec 2020, which includes a year before and during the COVID-19 periods. Then, the study adopted a panel vector autoregressive (PVAR) model and followed the impulse-response function to identify the changes in bike-transit relationships before and during the pandemic. We hypothesized that during the COVID-19 period, bike-share would have been more competitive and less cooperative with public transit.

Section 2 reviews previous studies regarding the impact of COVID-19 on the existing transportation system and model specifications. The study sites, data preparation, and statistical methods are described in Section 3. Section 4 presents the results of the descriptive analysis and the PVAR model. The final section further discusses the study's findings and identifies potential implications for future research.

2. Literature review

After the COVID-19 outbreaks worldwide, many researchers have examined the modal shift within the urban transportation system during the pandemic. This study focuses on reviewing the literature on the impact of COVID-19 on public transit, bike-share, and their relationships. In addition, we summarize the application of the VAR approach in transportation research that has increased in recent years. Then, in the last part of this section, current research gaps from existing works and our study's strategies to fill these gaps are described.

2.1. The impact of COVID-19 on public transit

One of the most noticeable changes in the urban transportation system in response to the COVID-19 pandemic was a significant decrease in public transportation ridership, including bus and subway transit (Jobe & Griffin, 2021; Monahan & Lamb, 2022). To minimize the risk of virus infection, people tended to avoid using public transit systems for their trips (Hu et al., 2021; Kraus & Koch, 2021). This behavioral change led to an unprecedented decrease in public transit demand, where bus and subway ridership in megacities declined by up to 90 % during the COVID-19 period (Liu et al., 2020; Parker et al., 2021).

Substantial restrictions on authorities also accelerated the sharp decline in public transit ridership. Due to its dense environment and low ventilation, public transit has been considered one of the most infectious modes of transportation in response to COVID-19 in many countries (Paul et al., 2022; Subbarao & Kadali, 2022). Accordingly, governments and local municipalities have restrained public transit use through several countermeasures, such as reducing operating hours and the seating capacity of transit facilities (Huang & Li, 2022; Chen et al., 2022). While the restrictions loosened as infection cases decreased, public transit ridership still has not returned to its pre-pandemic levels (Hsieh & Hsia, 2022).

2.2. The impact of COVID-19 on bike-share

Meanwhile, bike-share demand has also experienced significant changes throughout COVID-19. At the beginning of the pandemic, bike-share ridership drastically decreased, but the drop was much less than in public transit (Hu et al., 2021). For example, the number of bike-share uses in New York City fell by 71 % in the early COVID-19 periods, and subway ridership decreased by nearly 90 % simultaneously (Teixeira & Lopes, 2020). These declines were mainly due to the decrease in citizens' overall outdoor activities in the early stages of the pandemic (Park et al., 2020).

As the COVID-19 spread continued, however, bike-share ridership has gradually rebounded to pre-pandemic conditions in most countries. The level of bike-share ridership recovery has been found to vary across land use and socio-demographics within the city (Padmanabhan et al., 2021). In New York City, for example, researchers revealed that bike-share in 2020 recovered to its 2019 level, particularly for bike trips between 30 and 60 min, while subway trips remained much lower than the normal level (Wang & Noland, 2021). In addition, the city of A Coruña in Spain experienced a relatively higher and faster recovery of bike-share ridership to the previous level compared to bus ridership (Orro et al., 2020). In the case, Seoul's ridership has increased during the COVID-19 period, particularly for commuters and recreational users (Jiao et al., 2022; Kim, 2021; Park et al., 2020). These findings suggest that people tend to change their mode of choice from public transit to bike-share during a new-normal period of the pandemic to carry out essential outdoor activities, such as commuting while keeping social distance from others (Shamshiripour et al., 2020).

2.3. The impact of COVID-19 on bike-transit relationships

The bike-transit relationship may be divided into two types: modal integration and substitution (Martin & Shaheen, 2014). Before COVID-19, geographical and trip characteristics were understood to determine the bike-transit relationship (Kong et al., 2020; Radzimski & Dzięcielski, 2021). Researchers have also shown that bike-share tends to replace short-term bus trips and connect to long-term subway trips (Campbell & Brakewood, 2017; Griffin & Sener, 2016; Kim & Cho, 2021).

During the COVID-19 period, however, the relationships between bike-share and public transit have experienced a dramatic shift. Recent studies have shown that more citizens prefer bike-share over public transit, whether by bus or subway (Esposti et al., 2021; Nikiforiadis et al., 2020). In particular, the proportion of bike-share users who combine public transit for their trips has significantly decreased to lower the risk of virus infection (Schaefer et al., 2021; Teixeira et al., 2022). In addition, the authorities' social distancing measures on public transit, such as capacity restrictions, increased bike-transit substitution (Wang et al., 2022). Those findings suggest that bike-share can improve the resilience of the urban transportation system in response to the epidemic circumstances as an alternative to public transit (Bi et al., 2022).

2.4. The application of VAR models in transportation research

The vector autoregressive (VAR) model is a multivariate time series model that captures the relationship between endogenous variables over time (Hatemi-J, 2004). The VAR model has an advantage, because it does not require any theoretical background among variables in interpreting their relationships. The models have traditionally been used in finance and econometrics (Stock and Mark, 2001), but the models have been recently adopted in various fields, including epidemiology, biology, and even the social sciences (Wen & Zhang, 2019; Khan et al., 2020; Caruso et al., 2020).

Recently, many studies in transportation research have adopted VAR models. For example, several researchers examined the impact of upstream and downstream traffic conditions on traffic flows (Chen et al.,

2016; Deng, 2016) and public transit ridership spillover effects on nearby regions (Li et al., 2020). Also, the causal relationship between perceived service and public transit use has been analyzed using the VAR model with public survey and ridership data over multiple years (Kawabata et al., 2020). Results show that improving public transit service quality leads to higher user frequency with time lags.

More recently, some studies have examined the impact of COVID-19 on the urban transportation system by adopting the VAR model. For example, Seong et al. (2021) analyzed the Granger causality between the level of social distancing and the number of subway uses during the COVID-19 period in Korea. They revealed significant associations between COVID-19 and subway ridership. Another study in Turkey conducted causality tests among eight mobility indicators and the number of COVID-19 cases (Kartal et al., 2021). The results showed that neither driving nor walking significantly correlated with the pandemic.

While many existing studies have examined the change in bike-transit ridership in response to COVID-19, they have mainly focused on pairwise comparison rather than their causal relationships. However, it would be helpful to adopt a time-series approach with long-term usage data to thoroughly understand the behavioral shift between bike-share and public transit during the pandemic. To this end, the study aims to capture the causal relationships between bike-share and public transit by developing the panel VAR model before and during COVID-19.

3. Materials and methods

3.1. Study area

Seoul, the capital of South Korea, is the most populated city in the country, where more than ten million citizens live within the 605 km² total land area (Jiao et al., 2022). Currently, the city has 426 administrative districts ('dong') in 25 counties ('gu') within the boundary.

Seoul has a dock-based public bike-share system called Seoul Bike,

which has been operating since Sep 2015. With the city's densely populated environment, Seoul Bike has experienced rapid growth over the past few years. The average daily ridership of the Seoul Bike increased from 1000 in the first year of introduction to >52,000 in 2019 (<http://data.seoul.go.kr>). As of 2020, Seoul Bike operates approximately 37,500 bikes at 2228 stations (Fig. 1).

Seoul also has a dense public transportation system, with approximately 300 subway stations and 8000 bus stops. Public transit has been the city's most dominant means of transportation.

In 2019, the daily ridership of buses and subways was 7.7 and 13.4 million, which accounts for 24 % and 41.6 % of total travel in Seoul, respectively (<https://news.seoul.go.kr/traffic/archives/289>). In the same year, the proportion of private vehicles and taxis was 24.5 % and 5.7 %.

During the COVID-19 period, however, there has been a clear shift in both the number of bike-share and public transit uses. Fig. 2 illustrates the temporal trend of weekly bike-share, bus, and subway ridership in Seoul, as well as the number of COVID-19 cases and significant policy measures from Jan 2018 to Dec 2020. Since the number of bike-share ridership is much smaller than public transit, we divided the public transit ridership by 100.

The first confirmed COVID-19 case in Seoul occurred on Jan 23, 2020 (<https://www.seoul.go.kr/>). During this period, the weekly public transit ridership in Seoul has decreased by approximately 20 % compared to the previous week. However, it was mainly due to the Lunar New Year period, one of the largest holidays in Korea, rather than the effects of the COVID-19 pandemic (Park, 2020). Indeed, the number of public transit uses during the Lunar New Year in 2019 has decreased by >30 %. Until March 2020, public transit ridership in Seoul has gradually recovered to the pre-pandemic level.

The first explosive spread of COVID-19 in Seoul occurred in Daegu, beginning on 9 Mar 2020. This week, the authority implemented the first social distancing measures that restricted the unnecessary going out

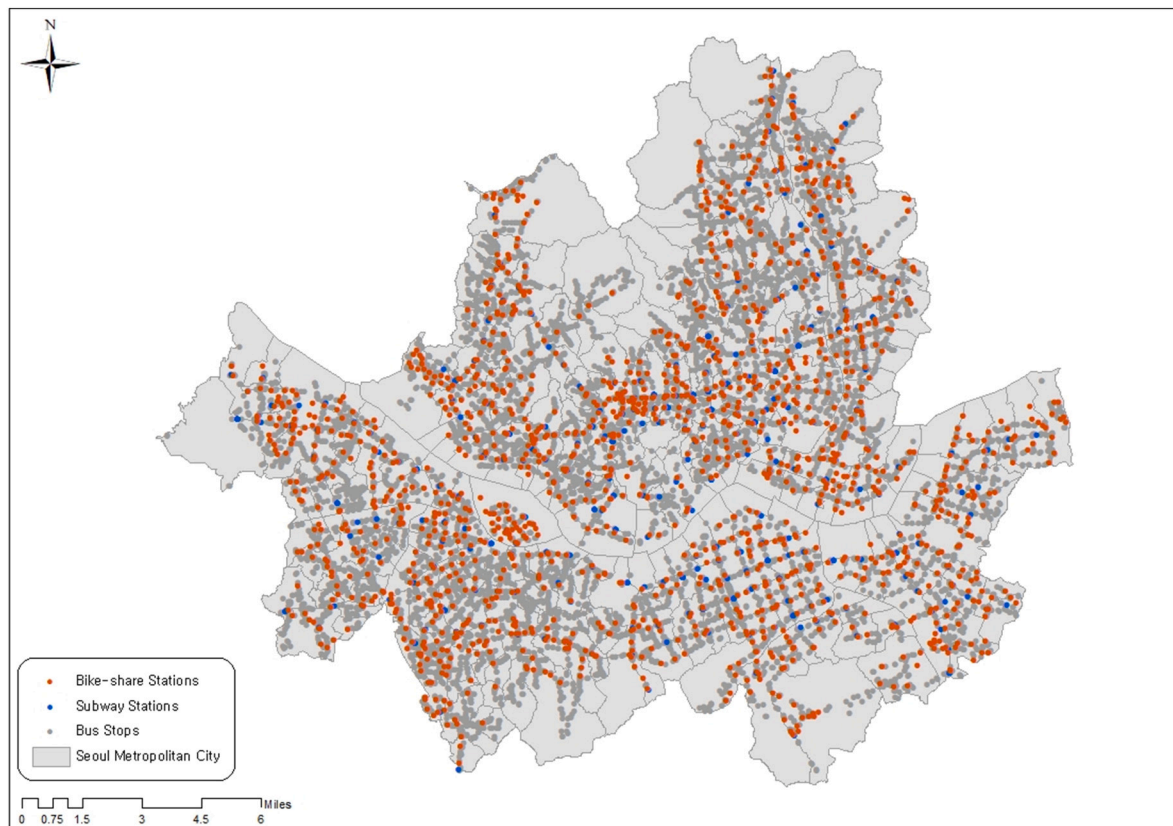


Fig. 1. Spatial distribution of bike-share and public transit facilities in Seoul (as of 2020).

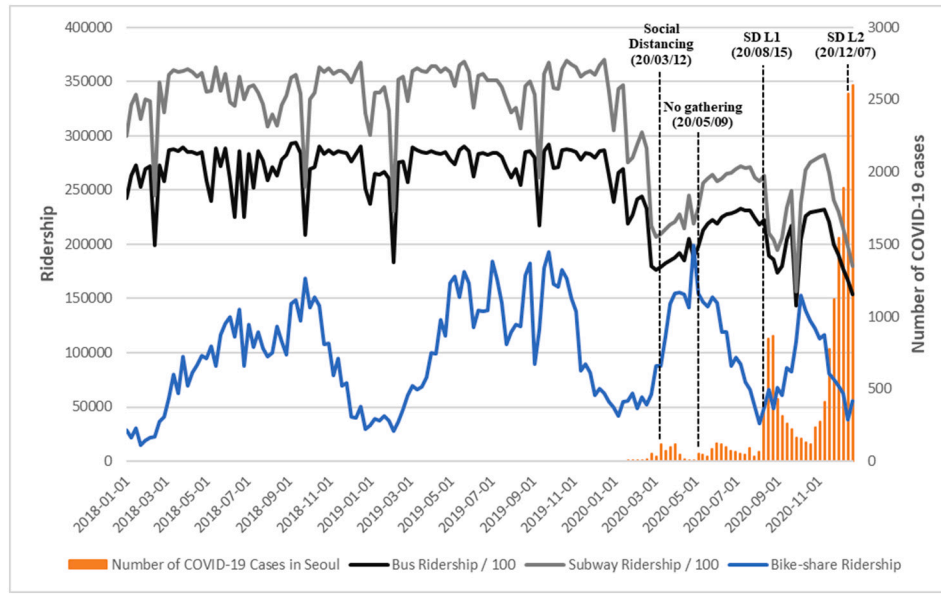


Fig. 2. Temporal trend of bike-share, bus, subway ridership & COVID-19 cases and major policy measures in Seoul (2018–2020).

of citizens (Park, 2020). As a result, the number of bus and subway users in Seoul decreased by 35 % and 40 %, respectively, compared to the previous year. However, the bike-share ridership rebounded by about 10 % during the same period.

The “Second Wave” of COVID-19 occurred on 9 May 2020, with sporadic chain infections derived from Itaewon. This mass infection lasted until June, and the government of Seoul announced the ‘no gathering’ policy—that all entertainment facilities in the city were prohibited from gathering (Shim et al., 2021). During this period, the authorities banned passengers without masks from public transit and local boarding when occupation density exceeded a certain level (Ku et al., 2021). It directs to a significant decrease in bike-share ridership, but transit ridership has slightly increased.

During the “Third Wave” and “Fourth Wave,” which recorded the most explosive confirmed cases of COVID-19 from Aug to Dec 2020, both bus and subway ridership decreased to around 30 %, while bike-share ridership slightly increased to 10 %. To slow down the spread of infection, the government has strengthened the level of social distancing

measures (Choi et al., 2021).

3.2. Data

For this study, we used bike-share, bus, and subway ridership, and living population data in Seoul from Jan 2018 to Dec 2020. These were all collected from the Seoul Open Data Platform (www.data.seoul.go.kr), which provides daily recorded ridership with different spatial units. For the analysis, we aggregated each data into a ‘dong’ (the administrative district in Korea) and a weekly panel dataset (Fig. 3).

3.2.1. Bike-share ridership

The Seoul Open Data Platform provides the following bike-share ridership data: the name, ID, and XY coordinates of origin and destination pairs of bike-share stations and a borrow-return timestamp. Referred to previous studies’ findings that the trip distance (or duration) of bike-share is one of the significant factors in determining bike-transit relationships (Durand et al., 2016; Kim & Cho, 2021; Saberi et al., 2018),

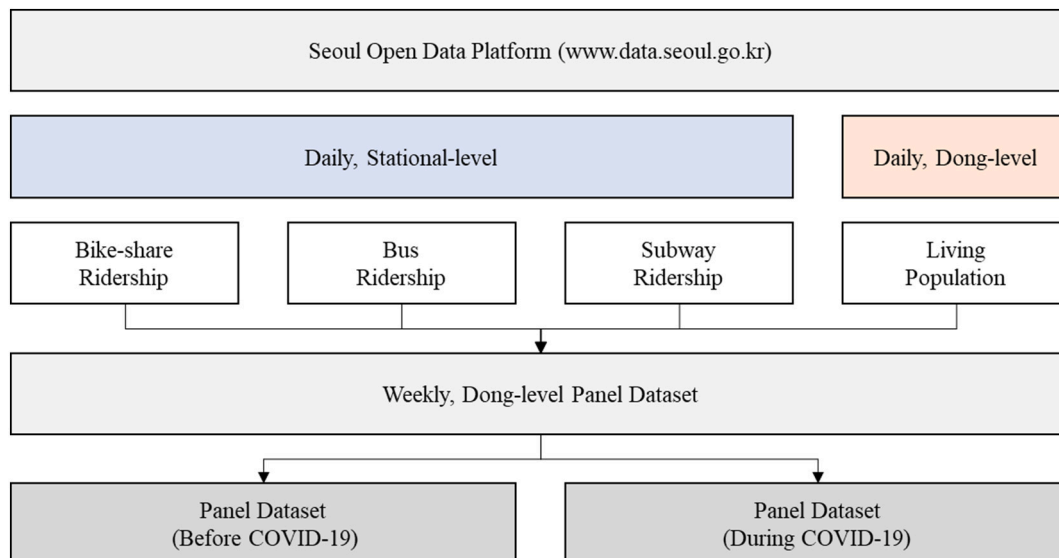


Fig. 3. Data processing of the study.

this study divided bike-share trips into three distance groups: (1) <2 km, (2) 2–5 km and (3) Over 5 km, bike-share trips. We used online maps API and Python to estimate the trip distance between OD bike-share stations, as introduced by Kim and Cho (2021). Trip distance is the shortest path recommended by Naver Maps (<https://map.naver.com/>), which is one of the most popular online map services in Korea.

In this study, ‘<2 km’ trips refer to short-distance bike-share trips requiring <10 min. They seem more likely to substitute short-term but inefficient public transit trips or integrate long-term public transit to solve the first/last mile problem. For ‘2–5 km’ trips, which require about 10 to 30 min, refer to medium-distance bike-share trips that seem more likely to substitute public transit rather than integrate. Also, ‘Over 5 km’ trips indicate long-distance and long-term (>30 min) bike-share trips generally made for recreational purposes, and thus less likely to interact with public transit.

3.2.2. Public transit ridership & living population

Bus and subway ridership data contain the name, ID, XY coordinates of the bus stop and subway station, and the daily ridership in Seoul. However, the data did not include OD trip information for each public transit use, and thus we constructed station-level ridership data. Finally, we aggregated those into ‘dong’ and weekly panel datasets using ArcGIS 10.4.1.

Living population, which refers to the number of people who stayed in a particular region at a certain time, is currently collected from a mobile company. The number of the living population is estimated by utilizing the mobile signal data collected from a personal smartphone, public transit, the registered population, and building datasets. In this study, we used this variable to control the number of people within the city.

3.2.3. Criteria for dividing before and during COVID-19 periods

To capture the changes in bike-transit relationships in response to infectious diseases, choosing a reasonable criterion for dividing before and during the pandemic is crucial. However, researchers have argued that the concrete separation of the pre- and post- COVID-19 periods is difficult due to the vagueness of specifying when the virus affects people’s behavior (Xin et al., 2021). Therefore, recent studies have considered social distancing policies and people’s behavioral shifts in response to COVID-19 (Ha et al., 2022; Kamga et al., 2021).

In this regard, we assumed that the actual effect of COVID-19 in Seoul occurred in week 115 (2020/03/09–2020/03/15) when the first social distancing policy was announced in Korea (Jo et al., 2020). As part of the measures, the government urged citizens to refrain from unnecessarily going out and closed multi-use facilities, such as fitness centers (Kang et al., 2022). That week, bus and subway ridership in the city decreased by 39 % and 41 %, respectively, compared to the previous week.

3.3. Panel vector auto-regressive (PVAR) model

This study adopted the panel vector auto-regressive (PVAR) model to analyze the temporal change in the relationships between bike-share, bus, and subway ridership in response to COVID-19. The vector auto-regressive (VAR) model is a time-series statistical model to capture the causal relationships among multiple quantities over time (Hatemi-J, 2004). The PVAR model refers to the vector auto-regression model in panel-data settings, quantifying the relationships among endogenous variables and the potential interaction across panels over time (Canova & Ciccarelli, 2009; Holtz-Eakin et al., 1988).

This study considered a k-variate VAR of lag order p with panel fixed effects, followed by:

$$Y_{it} = Y_{it-1}A_1 + Y_{it-2}A_2 + \dots + Y_{it-p}A_p + u_i + e_{it} \quad (1)$$

where Y_{it} refers to a $(1 \times k)$ vector of endogenous variables and u_i and e_{it}

are $(1 \times k)$ panel-specific fixed effects and residual vectors, respectively. A_i is a matrix coefficient of variable Y_{it-1} .

To compare the temporal bike-transit relationships before and during the COVID-19 periods, this study specified two panel VAR models as below:

$$\begin{aligned} Bike_{it} = & \sum_{a=1}^{114} Bike_{it-a}\alpha_{ia} + \sum_{b=1}^{114} Bus_{it-b}\beta_{ib} + \sum_{c=1}^{114} Subway_{it-c}\gamma_{ic} \\ & + \sum_{d=1}^{114} LivingPop_{it-d}\delta_{id} + u_i + e_{it}, \text{ if } Week < 115 \end{aligned} \quad (2)$$

$$\begin{aligned} Bike_{it} = & \sum_{a=115}^{156} Bike_{it-a}\alpha_{ia} + \sum_{b=115}^{156} Bus_{it-b}\beta_{ib} + \sum_{c=115}^{156} Subway_{it-c}\gamma_{ic} \\ & + \sum_{d=115}^{156} LivingPop_{it-d}\delta_{id} + u_i + e_{it}, \text{ if } Week > 114 \end{aligned} \quad (3)$$

Eqs. (2) and (3) refer to the panel VAR model before and during COVID-19, respectively. Both models include bike-share, bus, subway ridership, and living populations as endogenous variables.

The PVAR approach also provides several post-estimation statistics that capture the causal relationships between variables: (1) the Granger causality test, (2) impulse-response function (IRF), and (3) forecasting error variance decompositions (FEVD). First, the Granger causality test is based on the null hypothesis that there is no improvement in forecasting y when the lagged values of x are added as predictors (Bose et al., 2017). This null hypothesis can be rejected if coefficients for the lagged values of x on predicting y are statistically significant.

The impulse-response function (IRF) and forecasting error variance decompositions (FEVD) examine the direction and amount of causal relationships between endogenous variables over time (Lütkepohl, 2009; Abrigo & Love, 2016). The IRF simulates the system’s response when a shock is given on endogenous variables.

The simple IRF can be computed by

$$\Phi_i = \begin{cases} I_k & i = 0 \\ \sum_{j=1}^i \Phi_{i-j}A_j & i = 1, 2, \dots \end{cases} \quad (4)$$

K is the number of endogenous variables, and A is the coefficient matrix. If Φ_i is negative, it can be interpreted that a shock acted in the direction of lowering the dependent variable.

The FEVD, which estimates the amount of Φ_i over time, can be expressed as:

$$Y_{it+h} - E(Y_{it+h}) = \sum_{i=0}^{h-1} e_i(t+h-i)\Phi_i \quad (5)$$

where Y_{it+h} refers to the actual vector at time $t+h$, and $E(Y_{it+h})$ is the h -step ahead predicted vector at time t .

4. Results

4.1. Descriptive analysis

Table 1 shows the descriptive statistics of variables used in the analysis. Among the 422 administrative districts in Seoul, 297 dongs were used in the analysis, with at least one bike-share, bus, or subway station within each boundary.

The total number of weekly bike-share trips has not significantly changed before and during the COVID-19 period. However, the weekly bike-share ridership within 2 km of the trip decreased from 130 to 119 on average. In comparison, ridership over 5 km significantly increased after COVID-19 occurred. This increase suggests that people increased their likelihood of using long-term bike-share trips during the COVID-19 period, rather than short-term trips.

Table 1
Descriptive statistics of transit ridership.

Periods		Total weeks (2018.1.1–2020.12.27)		Before COVID-19 (2018.1.1–2020.3.8)		During COVID-19 (2020.3.9–2020.12.27)	
Number of samples		46,332		33,858		12,474	
Number of panels		297		297		297	
Number of weeks		156		114		42	
Variables		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Bike-share ridership	Total	331.26	499.36	324.50	488.10	349.61	528.28
	~2 km	127.44	189.57	130.59	197.40	118.87	166.18
	2–5 km	108.63	159.69	108.43	160.14	109.17	158.45
	Over 5 km	34.07	68.37	32.70	63.86	37.79	79.22
Bus ridership/1000		84.85	65.31	90.68	68.65	69.00	52.00
Subway ridership/1000		105.01	155.95	113.84	167.29	81.05	116.54
Living population/1000		4677.52	2248.28	4721.90	2300.31	4557.09	2095.92

On the contrary, bus and subway ridership both experienced a substantial decrease, as the number of COVID-19 cases in Seoul has explosively increased. The reduced bus and subway ridership rate after week 115 was 24 % and 29 %, respectively. It is noteworthy that the decrease in subway ridership is slightly larger than bus ridership. We speculate that the citizens' perceived risk of infection is higher on the subway compared to buses (Carrington, 2020; Lee et al., 2021; Qi et al., 2021), and long-distance commuting trips by subway have been largely reduced during COVID-19 (Tan & Ma, 2021).

Our study corresponds with findings for other cities (Carrington, 2020; Qi et al., 2021), reflecting that the citizen's perceived risk of infection is much higher in the subway compared to buses (Lee et al., 2021). In addition, the increasing trend of commuting at home seems to have reduced the number of office workers' subway ridership (Tan & Ma, 2021).

4.2. Pre-tests for the PVAR model

The PVAR model requires several pre-tests to evaluate its suitability for analysis (Abrigo & Love, 2016). First, we need to check whether the endogenous variables of the study are stationary and co-integrated. Second, when all endogenous variables are static and not co-integrated, the optimal lag order needs to be determined as a parameter of the PVAR model. To implement pre-tests for the PVAR model, we utilized the 'pvar' package in Stata 13.1. developed by Love and Zichino (2006).

4.2.1. Panel unit root & co-integration test

To check whether the study's constructed endogenous variables are stationary or not, we conducted the Fisher-type test (Choi, 2001) and Levin-Lin-Chu (LLC) test (Levin et al., 2002). Fisher-type tests are unit-root tests for each panel, with the *p*-values combined from these tests to produce an overall result. In addition, the Levin-Lin-Chu tests assume that all panels have the same auto-regressive parameters and require strongly balanced panels. Results show that all endogenous variables constructed in this study satisfy at least one stationarity condition when they are log-transformed and, thus, not required to be differentiated (Table 2).

In addition, we conducted panel co-integration tests developed by Westerlund (2007) to test whether endogenous variables are co-integrated (Table 3). It tests the null hypothesis of no co-integration by inferring whether the error-correction term in a conditional panel error-correction model equals zero. The results showed that we could not reject at least one null hypothesis of no co-integration for all bike-share distance groups before and during the COVID-19 periods. This condition allows us to develop a panel VAR model for this study (Chang, 2004; Westerlund, 2007).

4.2.2. Optimal lag order test

Determining optimal lag order is essential to specifying the VAR

Table 2
Panel unit root test.

Periods		Before COVID-19 (2018.1.1–2020.3.8)		During COVID-19 (2020.3.9–2020.12.27)	
Number of weeks		114		42	
Variable		Fisher (Dickey- Fuller)		Fisher (Dickey- Fuller)	
ln(Bike-share ridership)	Total	–42.947*	–20.562*	–3.523*	–5.341*
	~2 km	–30.061*	–17.361*	–3.906*	–5.691*
	2–5 km	–35.909*	–18.489*	–0.423	–5.095*
	Over 5 km	–22.592*	–8.941*	–0.095	–5.584*
ln(Bus ridership)		–5.411*	13.027	–1.173	–12.716*
ln(Subway ridership)		–3.478*	7.997	–6.323*	–14.533*
ln(Living population)		–19.738*	–16.783*	–7.888*	–17.890*

* Significant at the 99 % level.

models and following several causality tests (Ozcicek and Douglas Mcmillin, 1999). Specifically, selecting a higher-order lag length can result in over-fitting the problems of the models (Lütkepohl, 2009). In this study, we calculated the MBIC (Bayesian information criterion), MAIC (Akaike information criterion), and MQIC (Hannan and Quinn) to derive the optimal lag length of the PVAR model. For all bike-share distance groups, the third-order panel VAR was the most preferred model, as it had the smallest criterion value (Table 4).

4.3. Model results

We developed a third-order panel VAR model based on the derived optimal lag order. We followed post-estimation statistics that examined the direction and amounts of causal relationships among endogenous variables over time.

4.3.1. PVAR model results

Table 5 presents the estimation results of the panel VAR model. The results showed that bike-share ridership was negatively associated with bus ridership, while subway ridership was positively associated with before the COVID-19 outbreaks. This is in line with findings in previous studies (Griffin & Sener, 2016; Kim & Cho, 2021; Ma et al., 2019), in which bike-share tends to compete with bus transit while integrating with rail transit.

During the COVID-19 period, however, the associations between bike-share and public transit ridership varied for each lag. For example, in the first and third lag, particularly for short- and mid-term trips, bike-share use increased with bus ridership, and subway ridership decreased. The opposite pattern occurred in the pre-COVID-19 periods, suggesting significant changes in the bike-transit relationship that occurred after COVID-19.

Table 3

Panel co-integration test.

Periods		Before COVID-19 (2018.1.1–2020.3.8)				During COVID-19 (2020.3.9–2020.12.27)			
Number of weeks		114				42			
Westerlund test statistics		Gt	Ga	Pt	Pa	Gt	Ga	Pt	Pa
ln(Bike-share ridership)	Total	−2.13	−11.06	−32.38*	−12.41*	−1.25	−5.17	−16.44	−4.71
	~2 km	−2.35	−11.71	−29.90*	−12.52*	−1.37	−5.57	−15.60	−4.98
	2–5 km	−2.17	−11.53	−28.71*	−11.93*	−1.39	−5.71	−16.49	−5.01
	Over 5 km	−2.03	−11.83	−19.83	−10.95*	−1.65	−7.98	−15.19	−6.81

* Significant at the 95 % level.

Table 4

Optimal lag order test of panel VAR model.

Periods			Before COVID-19 (2018.1.1–2020.3.8)			During COVID-19 (2020.3.9–2020.12.27)		
Number of weeks			114			42		
Dep. var		Lags	1	2	3	1	2	3
ln(Bike-share ridership)	Total	MBIC	1358.23	613.02	356.31*	485.93	137.29	51.18*
		MAIC	1737.64	865.97	482.78*	817.45	358.30	161.68*
		MQIC	1613.52	783.22	441.41*	703.51	282.35	123.70*
	0–2 km	MBIC	1398.37	461.55	172.93*	356.08	42.92	22.96*
		MAIC	1776.38	713.55	298.93*	687.00	263.53	133.27*
		MQIC	1652.54	630.99	257.65*	573.21	187.67	95.33*
	2–5 km	MBIC	1442.94	542.66	300.65*	432.16	34.92	13.64*
		MAIC	1821.84	795.26	426.95*	763.49	255.81	124.09*
		MQIC	1697.82	712.58	385.61*	649.60	179.88	86.12*
	Over 5 km	MBIC	1449.50	722.36	370.08	377.63	5.98	−25.81*
		MAIC	1823.73	971.85	494.83	704.87	224.14	83.57*
		MQIC	1700.65	889.80	453.80	591.90	148.83	45.91*

* Significant at the 95 % level.

Table 5

Panel var model estimates.

Dep. var			ln(Bike-share ridership)			
Period	Variable		Total	0–2 km	2–5 km	Over 5 km
Before COVID-19 (2018.1.1–2020.3.8)	ln (Bike-share ridership)	Lag 1	0.863**	0.675**	0.721**	0.623**
		Lag 2	0.241**	0.253**	0.283**	0.328**
		Lag 3	−0.028	0.086**	0.021	0.082**
	ln (Bus ridership)	Lag 1	−2.672**	−1.936**	−2.511**	−2.701**
		Lag 2	−1.244**	−0.599*	−1.095**	−0.382*
		Lag 3	−0.872**	−0.877**	−0.800**	−0.738*
	ln (Subway ridership)	Lag 1	2.744**	2.080**	2.687**	2.952**
		Lag 2	0.838**	0.370	0.637*	0.122
		Lag 3	1.972**	1.540**	1.827**	2.000**
	ln (Living population)	Lag 1	−4.730**	−3.231**	−4.535**	−4.739**
		Lag 2	−0.431	−0.585*	−0.322	0.088
		Lag 3	−3.954**	−2.508**	−3.578**	−4.065**
During COVID-19 (2020.3.9–2020.12.27)	ln (Bike-share ridership)	Lag 1	0.875**	0.813**	0.770**	0.574**
		Lag 2	0.172**	0.281**	0.259**	0.248**
		Lag 3	0.104**	0.079**	0.057*	0.125**
	ln (Bus ridership)	Lag 1	1.560**	1.097**	1.225**	1.741**
		Lag 2	−0.755**	−0.367	−0.633**	0.668
		Lag 3	0.778**	1.032**	0.943**	−0.102
	ln (Subway ridership)	Lag 1	−1.816**	−1.222**	−1.350**	−1.740**
		Lag 2	0.467*	0.243	0.323	−0.975
		Lag 3	−0.704**	−0.956**	−0.800**	0.166
	ln (Living population)	Lag 1	1.158*	0.461	0.890	0.941
		Lag 2	−0.405	−0.743	−0.287	0.935
		Lag 3	0.548	0.841	0.656	0.382

* Significant at the 95 % level.

** Significant at the 99 % level.

4.3.2. Granger causality test

To check the robustness of the PVAR model results, we conducted Granger causality tests among the endogenous variables of the study (Table 6). Before COVID-19 outbreaks, the chi2 for all endogenous variables was statistically significant, rejecting the null hypothesis that there are no causal relationships among bike-share, bus, subway

ridership, and living populations. In other words, the bike-share ridership of a certain ‘dong’ Granger-causes the bus, subway ridership, and living populations, and vice versa.

During the COVID-19 period, however, the size of living populations did not Granger-cause bike-transit ridership. Therefore, it implies that the size of living populations is no longer the important factor in

Table 6

Panel Granger causality test.

Period	H0 = B does not Granger-cause A		ln(Bike-share ridership)			
			Total	0–2 km	2–5 km	Over 5 km
			chi2	chi2	chi2	chi2
	A	B				
Before COVID-19 (2018. 1. 1–2020. 3. 8)	Bike-share	Bus	73.54**	56.26**	54.45**	54.95**
		Subway	82.44**	66.96**	65.70**	68.33**
		Living population	89.29**	56.45**	69.89**	67.06**
	Bus	Bike-share	96.43**	61.15**	75.88**	98.83**
		Subway	587.72**	655.85**	575.42**	557.97**
		Living population	30.74**	31.15**	30.44**	21.49**
	Subway	Bike-share	126.74**	96.34**	98.12**	142.29**
		Bus	167.56**	183.59**	157.84**	151.34**
		Living population	40.92**	40.38**	38.96**	28.63**
	During COVID-19 (2020. 3. 9–2020. 12. 27)	Bike-share	51.24**	35.43**	36.14**	21.16**
		Subway	67.09**	36.47**	37.08**	26.37**
		Living population	5.61	4.56	3.51	4.10
	Bus	Bike-share	54.46**	33.37**	39.35**	39.28**
		Subway	88.67**	58.37**	71.21**	51.49**
		Living population	7.78	7.94*	7.33	0.51
	Subway	Bike-share	58.23**	32.68**	43.45**	48.02**
		Bus	110.24**	73.04**	88.87**	66.59**
		Living population	10.00*	8.19*	8.05*	2.06

* Significant at the 95 % level.

** Significant at the 99 % level.

predicting bike-transit ridership, as COVID-19 outbreaks have changed ordinary travel patterns.

4.3.3. Impulse-response function

To improve the assessment of the dynamics of bike-transit ridership, we developed the Impulse-Response Function (IRF) before and during the COVID-19 periods. Tables 7 and 8 illustrate the orthogonalized IRFs that describe the change in bike-share ridership as one standard deviation shock of bus and subway transit, respectively. Table 9 shows the impact of subway ridership change on bus ridership. The x-axis indicates the weeks elapsed after the shock. Based on a Monte Carlo simulation, the dotted lines represent a 95 % confidence interval (Peralta & Kim, 2019).

Results show that a single standard deviation shock of increased bus ridership decreased bike-share ridership, while subway ridership positively affected bike-share ridership before COVID-19 outbreaks for all distance groups. The amount of its impact increases as the week elapses. It reflects the competitive relationships between bike-bus transit and integrative relationships between bike-subway transit. Bus and subway ridership were also positively associated with pre-pandemic periods.

During the COVID-19 period, however, bike-share ridership increased as bus ridership increased, particularly for the over 5 km group. In contrast, bike-share ridership shows constant negative associations with subway ridership for all distance groups. Those results suggest that the outbreak of COVID-19 strengthened competitive relationships between bike-share and subway transit, but weakened competitive relationships between bike-share and bus transit, particularly for long-distance trips. At the same time, bus ridership was adversely affected by the shock of subway ridership, which indicates increasing competitiveness between the bus and the subway.

4.3.4. Forecasting error variance decompositions

To further examine the temporal variation of the impact of bus and subway ridership on bike-share ridership, we estimated forecasting error variance decompositions (FEVD) of endogenous variables (Table 10). This indicates the cumulative contribution of each variable to the whole system (Grossmann et al., 2014).

Results showed that bike-share ridership is most affected by bike-share ridership of previous weeks, both before and during the COVID-19 periods and all distance groups, but its impact decreased as the

week elapsed. Bus ridership generally takes 1 % to 5 % of the system before the COVID-19 period, but it increases during the COVID-19 period, particularly for short-term trips. Subway ridership, however, has a relatively higher impact on bike-share ridership than bus ridership, and its difference became larger during the COVID-19 period. Those findings indicate that bus transit affects short-term bike-share ridership, while subway transit affects long-term bike-share ridership endogenous variables.

5. Discussion and conclusion

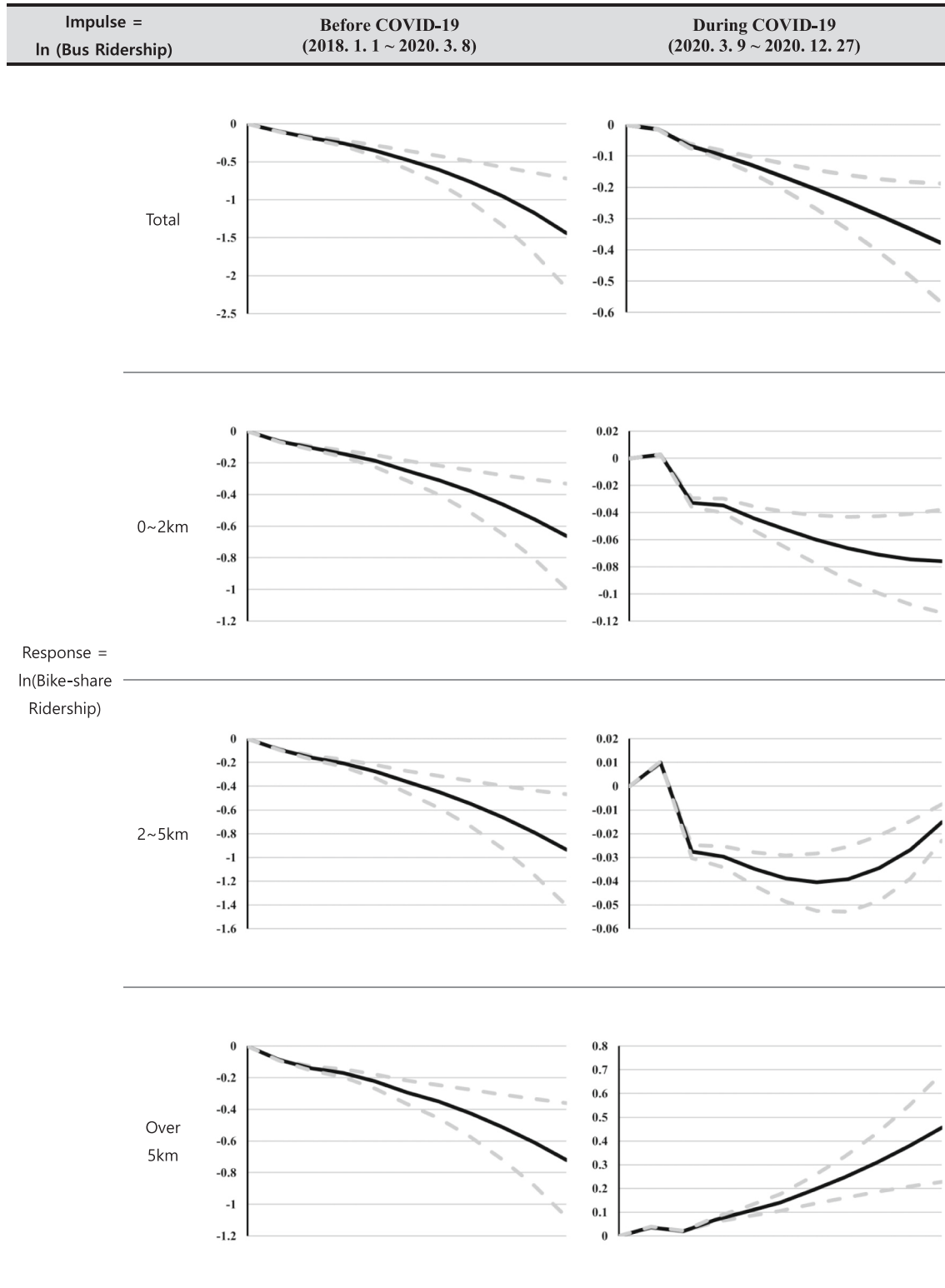
By utilizing three years of weekly bike-share and public transit trips in Seoul, this study examined the changes in bike-transit relationships in response to the COVID-19 pandemic. The findings of the study show that the COVID-19 pandemic significantly reduced public transit use while promoting bike-share use, particularly for long-term trips. Also, this study found that the COVID-19 pandemic weakens the competitive relationships between bike-share and bus transit, and modal integration between bike-share and subway transit. Bus and subway ridership was also more competitive during COVID-19.

Fig. 4 summarizes the findings of the study. First, bike-share substitutes the bus for short-term trips (<5 km of bike distance) but integrates with subway trips before the COVID-19 outbreaks. During the COVID-19 period, however, bike-share has become competitive in bus and subway transit, suggesting that people prefer bike-share instead of public transit to make short-term trips to avoid unnecessary contact with others.

Second, long-term bike-share trips show quite different results in terms of bike-bus relationships after COVID-19 occurs, where bike-share ridership increases as bus ridership increases. However, it does not indicate the increased modal integration between bike-share and bus, since bus and subway ridership has also become more competitive. It is more reasonable to understand this result that people who previously made long-term trips by subway transit tend to choose either bike-share or bus transit for their trips during the COVID-19 period. Thus, bike-share and bus ridership both increased as subway ridership decreased. A higher risk perception of virus infection toward subway transit would increase the possibility of choosing bus transit during the COVID-19 period (Lee et al., 2021).

Compared to previous studies that have addressed the impact of the

Table 7
Impulse-response function results (bus \rightarrow bike-share).

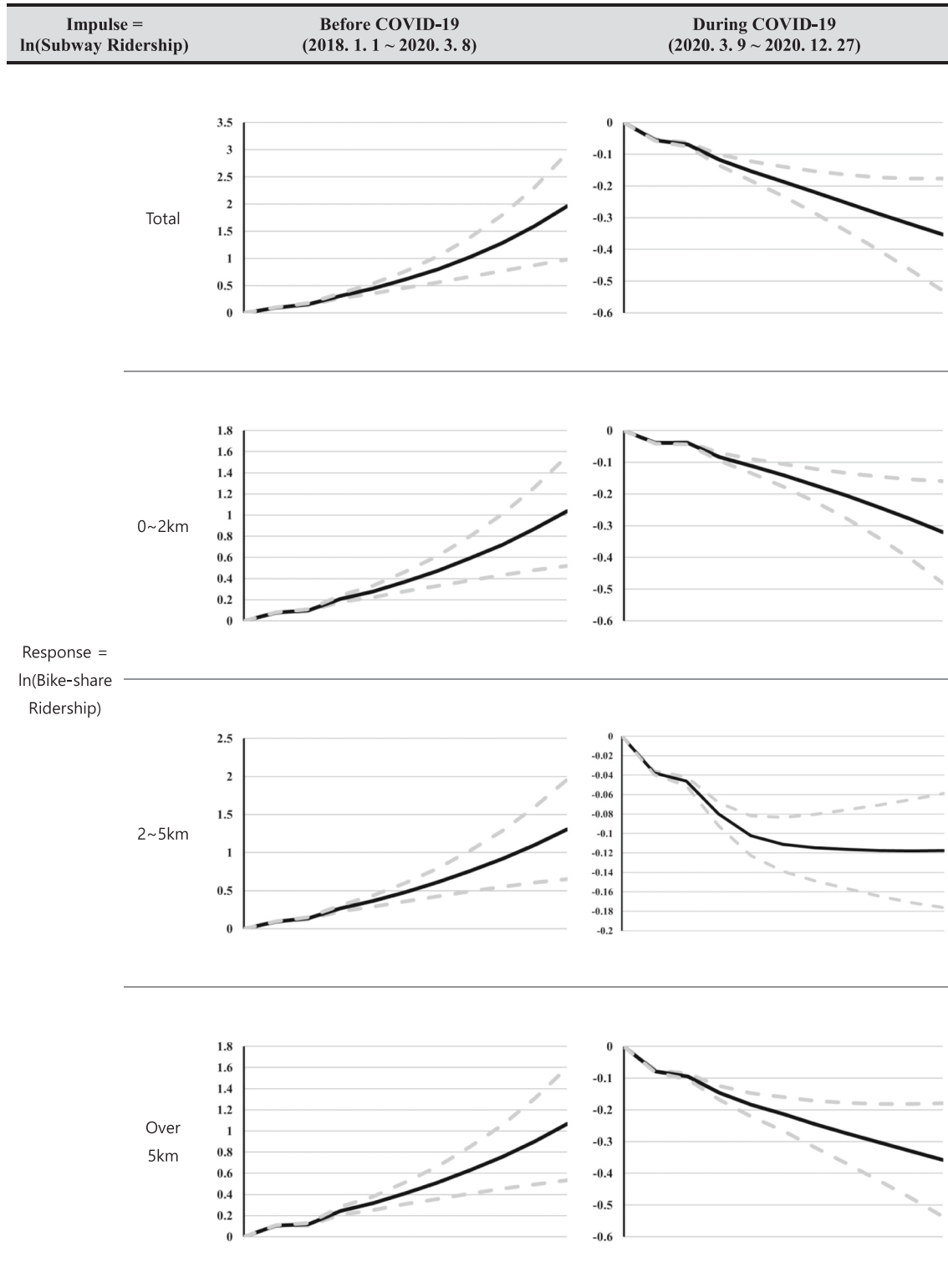


*The dotted line refers to the upper and lower bound at a 95% confidence level.

COVID-19 pandemic on the existing transportation system, this study is novel from both theoretical and methodological perspectives. More specifically, the study can be differentiated from existing literature, in that we divided the pre- and post-COVID-19 periods based on the date of social distancing measures, and analyzed how the causal relationships

among bike-share, bus, and subway changes over time. Overall findings suggest that bike-share has become one of the most preferred travel modes during the pandemic, increasing the resilience of the transportation system, particularly for people who previously relied on public transit (Bucsky, 2020; Wang & Noland, 2021).

Table 8
Impulse-response function results (subway → bike-share).

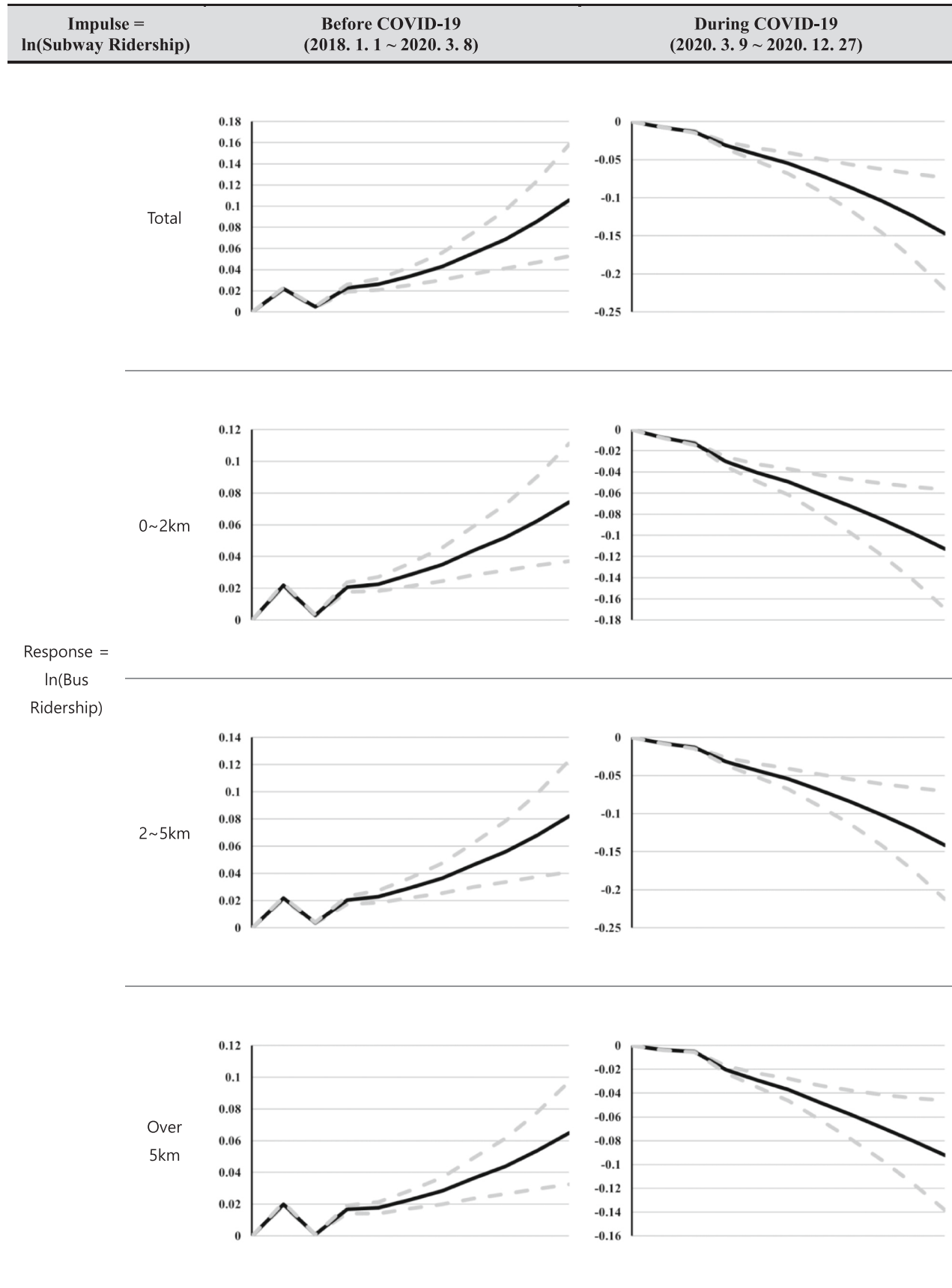


*The dotted line refers to the upper and lower bound at a 95% confidence level.

This paper also contributes to the field by showing the variability of bike-transit relationships according to bike trip distance. Most previous works analyzed total bike-share ridership in a different temporal unit (daily to monthly) due to the lack of route information between OD bike-share stations (El-Assi et al., 2017; Scott & Ciuro, 2019). For this study,

however, we used the online maps API to derive bike distance between OD bike-share stations in Seoul and divided bike-share ridership into several distance groups. As a result, it improves our understanding of the temporal variations of short-, mid-, and long-term bike-share trips between and during the COVID-19 pandemic and helps further examine

Table 9
Impulse-response function results (subway → bus).



*The dotted line refers to the upper and lower bound at a 95% confidence level.

Table 10
Forecasting error variance decompositions.

Period		Before COVID-19 (2018.1.1–2020.3.8)				During COVID-19 (2020. 3.9–2020.12.27)			
Dep. var = ln(bike)	Lags	ln (Bike)	ln (Bus)	ln (Sub)	ln (Liv Pop)	ln (Bike)	ln (Bus)	ln (Sub)	ln (Liv Pop)
Total	2	0.950	0.010	0.009	0.031	0.969	0.003	0.019	0.008
	4	0.776	0.031	0.038	0.154	0.920	0.018	0.047	0.014
	6	0.604	0.042	0.066	0.288	0.875	0.035	0.068	0.021
	8	0.492	0.048	0.081	0.379	0.847	0.055	0.070	0.026
	10	0.424	0.050	0.089	0.436	0.824	0.079	0.063	0.032
0–2 km	2	0.948	0.008	0.012	0.032	0.991	0.001	0.008	0.001
	4	0.763	0.026	0.045	0.166	0.955	0.003	0.036	0.001
	6	0.569	0.038	0.079	0.315	0.911	0.006	0.079	0.000
	8	0.437	0.044	0.100	0.419	0.879	0.008	0.109	0.000
	10	0.354	0.048	0.113	0.486	0.855	0.011	0.132	0.000
2–5 km	2	0.943	0.010	0.011	0.036	0.988	0.000	0.008	0.004
	4	0.757	0.031	0.041	0.170	0.954	0.003	0.030	0.009
	6	0.569	0.043	0.071	0.317	0.914	0.005	0.061	0.016
	8	0.444	0.049	0.089	0.418	0.885	0.008	0.081	0.023
	10	0.365	0.052	0.098	0.485	0.862	0.010	0.094	0.030
Over 5 km	2	0.944	0.009	0.012	0.035	0.991	0.000	0.007	0.002
	4	0.782	0.025	0.037	0.156	0.943	0.001	0.037	0.017
	6	0.599	0.034	0.063	0.304	0.880	0.002	0.077	0.033
	8	0.473	0.039	0.079	0.410	0.806	0.004	0.127	0.042
	10	0.394	0.041	0.086	0.480	0.725	0.006	0.187	0.044

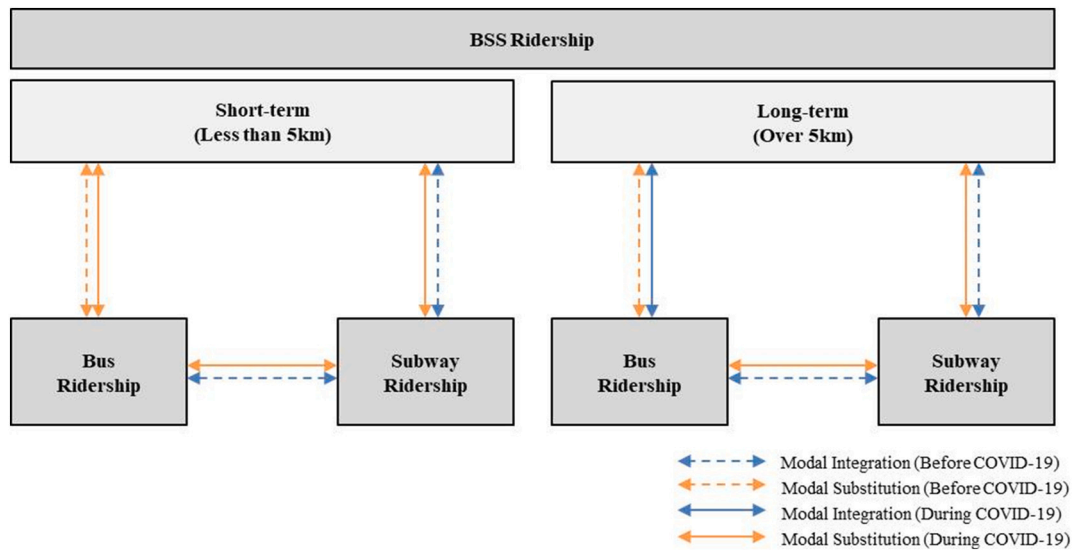


Fig. 4. Bike-transit relationships before and during COVID-19.

their relationships with the public transit system. Furthermore, the results show that the outbreak of COVID-19 significantly decreased short-term bike-share ridership while increasing long-term trips, which implies that bike-share tends to be more competitive, but less integrative to the public transit system.

For this study, we constructed and utilized a panel dataset of bike-transit ridership to examine their relationship changes in response to COVID-19. Furthermore, we adopted the VAR approach for analyzing transportation demand before and during the pandemic, recently highlighted in urban studies (Kuang et al., 2020; Zhang et al., 2022). By developing panel VAR models and corresponding post-estimation statistics, including the impulse-response function, we found that the outbreak of COVID-19 strengthened the modal substitution and weakened the modal integration between bike-share and public transit.

The study's findings suggest several implications for policy and decision-makers in the public transport sector. First, bike-share can increase the resilience of the public transit system during the pandemic, particularly for those who previously relied on public transit for their mobility. One of the most apparent changes in the urban transportation system in response to COVID-19 was the modal shift from public to

private transportation modes (Das et al., 2021). However, researchers have pointed out that the increased modal share of private vehicles in response to COVID-19 can reduce the city's sustainability (Esposti et al., 2021; Zhang et al., 2015). In this respect, bike-share may ameliorate a potential modal shift from public transit to private vehicles during the pandemic. To reduce the pressure on public transit in the post-COVID-19 era, authorities need to install more bike-share facilities in major trip generators where there is less private car ownership.

Second, bike-share substitutes bus and subway transit for short-term trips, while bike-share and bus transit can partially substitute subway transit for long-term trips. In other words, people tend to replace their short-term bus trips with bike-share, and their long-term subway trips with bus and bike-share trips during the COVID-19 period. This finding implies that increasing the usability and accessibility of bike-share and bus systems, including bike-friendly infrastructure, can improve the resilience of public transit systems during a disastrous pandemic.

While the study contributes to the literature on urban transportation changes in response to the COVID-19 pandemic, there are some limitations and suggestions for further studies. First, although we divided bike-share trips into several distance groups to examine their differences

in the associations with public transit, bus and subway ridership were only utilized as total ridership due to the lack of trip distance information. Public transit ridership data provided by the Seoul Open Data Platform does not contain OD trip attributes. Public transit ridership can also be classified into distance groups for further analysis using smart card data or travel diaries obtained from a survey. It would be better to examine the bike-transit relationships for short-, mid-, and long-term trips.

Second, this study divided the weekly bike-share ridership data into two periods, before and after week 114, when the first explosive increase of infected cases of COVID-19 occurred. Previous researchers have also tried to define pre- and post-COVID-19 pandemic criteria. For example, some marked the first occurrence of COVID-19 (Milani, 2021; Mzoughi et al., 2020) or the first social distancing measures (Ha et al., 2022; Kamga et al., 2021), but they did not have theoretical evidence of diving them. If future research develops a more scientific methodology to define the phases of the COVID-19 pandemic, it would be more helpful to understand the temporal dynamics of bike-transit relationships in the disastrous pandemic situation.

Lastly, future research should examine the effects of bike-share on public transit, private vehicles, and other transportation modes to further understand the dynamics of the urban transportation system before and during the COVID-19 period. In particular, analyzing the effects of shared transportation modes, including bike-share and e-scooter, on increasing the resilience and sustainability of urban transportation systems is required in response to future disasters.

CRedit authorship contribution statement

Minjun Kim: Conceptualization, Methodology, Writing – original draft, Formal analysis, Investigation, Software, Visualization. **Gi-Hyoung Cho:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition, Resources.

Declaration of competing interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data availability

Data will be made available on request.

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