Journal of Infrastructure, Policy and Development 2024, 8(14), 8447.
https://doi.org/10.24294/ jipd8447

Article

Can highway development mitigate regional decline in South Korea?—Focus on economic development and population inflow

Kyungjae Lee

Seoul National University, Seoul 08826, Korea; lkj9311@snu.ac.kr

CITATION

Lee K. (2024). Can highway development mitigate regional decline in South Korea?—Focus on economic development and population inflow. 8(14): 8447. https://doi.org/10.24294/jipd8447

ARTICLE INFO

Received: 7 August 2024
Accepted: 9 October 2024
Available online: 5 December 2024

Abstract: South Korea has experienced rapid economic development since the 1960s. However, pronounced regional disparities have concurrently emerged. Amid the escalating regional inequalities and persistent demographic challenges characterized by low fertility rates, regional decline has become a pressing issue. Therefore, the feasibility of expanding transportation networks as a countermeasure to regional decline has been proposed. This study utilizes the synthetic control method and spatial difference-in-differences methodologies to assess the impact of the 2017 opening of Seoul–Yangyang Expressway on economic development and population inflow within Hongcheon-gun, Inje-gun, and Yangyang-gun. The purpose of this study is to evaluate the effectiveness of highway development as a policy instrument to mitigate regional decline. Findings from the synthetic control method analysis suggest a positive impact of the opening of the expressway on Hongcheon-gun's Gross Regional Domestic Product (GRDP) in 2018, as well as Yangyang-gun's net migration rates from 2017 to 2019. Conversely, the spatial difference-in-differences analysis, designed to identify spillover effects, reveals negative impacts of the highway on the GRDP and net migration rates of adjacent regions. Consequently, although targeted transportation infrastructure development in key non Seoul Metropolitan cities may contribute to ameliorating regional imbalances, results indicate that such measures alone are unlikely to suffice in attracting population to small- and medium-sized cities outside the Seoul Metropolitan Area.

Keywords: highway opening; regional decline; synthetic control method; spatial difference-in-differences; spillover effects

1. Introduction

Since the 1960s, South Korea (hereafter Korea) has experienced rapid economic growth driven by industrialization. However, this growth has led to pronounced regional disparities (Ahn and Heo, 2008). As of 2019, Korea exhibited the second-highest level of regional disparities in gross regional domestic product (GRDP) among Organisation for Economic Co-operation and Development member countries (Kim et al., 2021). In addition, there has been a continuous migration from nonSeoul Metropolitan Areas to the Seoul Metropolitan Area (SMA), with a particular notable shift in the young population between 2000 and 2020 (Shin et al., 2023). Therefore, the population of the SMA surpassed that of nonSMA in 2020, and as of 2024, more than half of the total population of Korea resides in the SMA (Statistics Korea, 2024). The intensifying economic and demographic disparities between regions, coupled with the ongoing low fertility rate, have led to the "regional decline" phenomenon[1].

In response to this crisis, it has been proposed that regional decline should be mitigated through the expansion of transportation networks in areas facing such threats (Kang, 2018; Kim, 2022; Park et al., 2020; Shin et al., 2023). Nonetheless, they often lack detailed explanations of the specific mechanisms through which such expansion mitigates regional decline. Regarding the effects of highway development, existing studies present conflicting findings. Some argue that improving transportation accessibility enhanced the economic productivity of socially and economically lagging regions. Conversely, others highlight potential adverse effects, such as the "straw effect," in which resources from relatively underdeveloped areas are siphoned off by nearby metropolitan areas, exacerbating regional disparities. Despite these divergent perspectives, empirical evidence conclusively demonstrating the efficacy of expanded transportation networks in mitigating regional decline remains elusive. Moreover, comprehensive research examining the impact of transportation network expansion on regions at risk of decline is notably absent from the extant literature.

This study aims to evaluate the economic development and population inflow effects of the Seoul–Yangyang Expressway, inaugurated in 2017, on the beneficiary regions (Hongcheon-gun, Inje-gun, Yangyang-gun) and adjacent areas. Utilizing GRDP data from 229 local governments and internal migration statistics obtained from Statistics Korea spanning from 2005 to 2019, this study utilizes the synthetic control method (SCM) to assess the impact of the opening of the expressway on the GRDP and net migration rates of the beneficiary regions. Furthermore, the spatial difference-in-differences (Spatial DiD) method is applied to examine potential spillover effects on surrounding areas. The findings reveal that the opening of the expressway had a positive impact on Hongcheon-gun's GRDP in 2018 and Yangyang-gun's net migration rates from 2017 to 2019, while the highway negatively affected the GRDP and net migration rates of adjacent regions, as indicated by the Spatial DiD analysis. This research seeks to contribute to the rationale of the multifaceted impacts of the highway opening, providing policy-relevant insights to address regional decline.

2. Theoretical background

Reducing transportation costs is essential for enhancing national and regional competitiveness (Percoco, 2016). Expansions of transportation networks can yield multiple benefits, such as decreased logistics and transportation expenses, augmented labor and capital productivity, and stimulated demand for goods and services, collectively contributing to economic growth (Cook and Munnell, 1990; Januário et al., 2023; Munnell, 1990; Qi et al., 2020). Moreover, the productivity gains derived from improved transportation accessibility significantly influence corporate location decisions, ultimately leading to increased employment and income within regions (Aschauer, 1989; Han and Kim, 2016; Percoco, 2016). Notably, Aschauer (1989) identified a significant correlation between public capital investment and national productivity, particularly emphasizing the substantial impact of transportation infrastructure such as highways, airports, and public transit systems on productivity.

Conversely, the effects of transportation infrastructure expansion, particularly the network effects that extend beyond the immediate investment area, have yielded inconsistent findings in scholarly research. Munnell (1992) posited that investments in transportation infrastructure in one region can generate positive spillover effects in other regions, which is supported by studies in various countries (Cai et al., 2022; Cantos et al., 2005; Chen et al., 2019; Kim et al., 2021; Rodrigues et al., 2023; Yu et al., 2013). Expanding on this, Hewings and Kim (2009) contended that synergy effects are particularly pronounced in less developed regions, proposing that highway development can play a significant role in alleviating regional disparities. Moreover, empirical evidence suggests that highway expansions can facilitate the spatial redistribution of industrial facilities and foster industrial agglomeration on a national scale (Liu et al., 2022). The agglomeration economies, arising from the dynamic exchange of labor, capital, and technology, are enhanced by improved regional transportation accessibility, which serves as a key catalyst for this phenomenon. Furthermore, investments in transportation infrastructure have been observed to facilitate the decentralization of urban populations to peripheral areas and attract new residents to regions with such infrastructure development (Baum-Snow et al., 2017; Cervero, 2003; Levkovich et al., 2020).

However, transportation infrastructure investments may also exacerbate regional disparities through the so-called straw effect (Cavallaro et al., 2023; Huang and Lin, 2021; Meijers et al., 2012; Zhang et al., 2019). This occurs when increased economic activity concentrates in specific areas owing to agglomeration economies, allowing beneficiary regions to enjoy relatively higher economic growth rates, thereby widening regional disparities (Chen and Haynes, 2017; Faber, 2014). Moreover, because improvements in transportation infrastructure tend to be concentrated in already well-developed corridor regions (Kim and Sultana, 2015; Kim and Yi, 2019), such investments might further increase accessibility and economic benefits across regions. Boarnet (1998) argued that highway investments positively impact the output of beneficiary regions by absorbing production factors from neighboring regions. Consequently, regions benefiting from transportation infrastructure investments can develop a comparative advantage in production and supply, leading to a spatially imbalanced system. Furthermore, transportation infrastructure investments, such as high-speed rail, have been shown to accelerate the outflow of populations from already depopulating regions, thereby intensifying regional decline (Deng et al., 2019).

Several studies have examined the effects of transportation network investments in Korea (Kim, 2023; Kim and Lee, 2022; Kim and Yi, 2019; Kim et al., 2006; Park et al., 2020). Kim et al. (2006) posited that the completion of road and rail projects improves regional accessibility, promoting the influx of production factors such as population, thereby increasing GRDP. In addition, regions with relatively low transportation accessibility are more likely to experience population decline (Kim and Kim, 2024). On the contrary, Park et al. (2020) found that while improved road accessibility positively influences population influx and GRDP in beneficiary regions, it negatively impacts population influx in adjacent regions, hindering their GRDP growth. Furthermore, while regions with newly constructed commuter highways experience population growth, highways connecting metropolitan municipalities do not exhibit such an effect (Lee and Kim, 2022).

In summary, the expansion of transportation networks positively impacts the beneficiary regions but has ambiguous effects on surrounding areas. While overall economic development might be achieved through improved transportation networks, there is the potential for accelerated regional disparities owing to population decline in adjacent areas. Therefore, this study empirically investigates the economic and demographic consequences of highway inauguration, focusing on the beneficiary and adjacent regions. By analyzing the impact of the Seoul–Yangyang Expressway, this research evaluates the effectiveness of transportation network expansion as a policy tool for mitigating regional decline.

3. Methodologies and data

3.1. Methodologies

3.1.1. SCM

This study utilizes the SCM to analyze the impacts of highway inauguration. The SCM is particularly effective for analyzing aggregate data at regional and national levels, especially when it is challenging to identify comparable control units for treatment units, such as cities or countries where specific policies have been implemented. By leveraging this method, a precise analysis of the effects of the highway opening in Hongcheon-gun, Inje-gun, and Yangyang-gun is conducted.

The SCM yields significant advantages by constructing robust counterfactual control groups for a limited number of treatment units. This method has been widely adopted in economic and regional analysis research (Abadie, 2021; Athey and Imbens, 2017; Ha et al., 2022; Kim, 2022; Kim and Kim, 2021; Kim and Lee, 2019; Lee and Moon, 2020; Lee et al., 2020; McGraw, 2020). Through a data-driven approach, the SCM calculates weights to synthesize control groups that closely mimic the pretreatment characteristics (outcomes and predictor variables) of the treatment group. Unlike the DiD method, the SCM minimizes subjective researcher intervention by employing a data-driven approach, thereby reducing challenges associated with sample acquisition and allowing for policy effect evaluation using a single treatment unit and a few comparison entities. Furthermore, the SCM offers greater flexibility in estimating policy effects when the parallel trend assumption, a fundamental requirement of DiD, is not met (Kreif et al., 2016).

The detailed explanation of the SCM is as follows (Abadie, 2021). Suppose there are J + 1 regions, where the first region (j = 1) is designated as the treatment group, indicating the area where the highway has opened. The donor pool for control group synthesis consists of J regions (j = 2, ..., J + 1), which are areas where the highway has not been opened. The study period spans T units of time, with the period from 1 to T_0 representing the pretreatment period and the period from T_0+1 to T representing the posttreatment period. The outcome variable of interest at a specific time for each region (j), depending on the treatment status ({0, 1}), encompasses variables such as the GRDP and net migration rate of the region. The highway opening effects after T_0 can be expressed as follows:

$$\tau_{1t} = Y_{1t}^1 - Y_{1t}^0 \quad (1)$$

where Y_{1t}^1 is the outcome variable at time t for a region where a highway has been opened and Y_{1t}^0 is the potential outcome that would have been observed at time t if the highway had not been opened in that region. Therefore, the difference between the actual and potential outcomes is represented as τ_{1t}, indicating the effect of the highway opening at time t for $t > T_0$.

The primary objective of synthetic control is to estimate the potential outcome Y_{1t}^0, which would have been observed after the intervention period if the policy intervention had not taken place. This is achieved by synthesizing a control group using a weighted average of data from multiple regions rather than relying on a single comparison region. This approach has the advantage of creating a control group that closely resembles the treated group. The treatment effect derived through synthetic control is calculated as follows:

$$\hat{\tau}_{1t} = Y_{1t}^{1} - \sum_{j=2}^{J+1} w_j^* Y_{jt}^{0} \tag{2}$$

The SCM has the advantage of objectively setting a control group without relying on the subjectivity of a researcher, as the weights w_j^* of the control group are determined through a data-driven approach. The weights are estimated in such a way as to minimize the error between groups, allowing the synthesis of a control group that exhibits similar characteristics to the treatment group based on observable characteristics from the pretreatment period. The specific process is described as follows:

$$\|X_1 - X_0 W\| = \left(\sum_{h=1}^{k} v_h \left(X_{h1} - w_2 X_{h2} - \cdots - w_{j+1} X_{hJ+1}\right)^2\right)^{\frac{1}{2}} \tag{3}$$

where all weights are constrained to values between 0 and 1, with the sum of the weights equating to 1 ($\sum_{j=2}^{J+1} w_j = 1$). This weight assignment method prevents extrapolation among the data. X_{kt} denotes predictor variables for each unit, encompassing k variables that represent demographic and socioeconomic characteristics of the region. In Equation (3), v_h is a constant variable that indicates the relative importance of the h^{th}predictor variable. This constant variable can be specified by the researcher based on judgment or optimally derived for use. The optimal v_h^* is determined by minimizing the mean squared prediction error, following the approach of Abadie and Gardeazabal (2003):

$$\sum_{t \in \tau_0} \left(Y_{1t} - w_2(V) Y_{2t} - \cdots - w_{J+1}(V) Y_{J+1t}\right)^2 \; for \; \tau_o \subseteq \{1, 2, \cdots, T_0\} \tag{4}$$

The significance of the estimated effect of the highway opening utilizing the SCM can be assessed using a placebo effect test. To validate results obtained from the SCM, a placebo effect is estimated for a randomly selected control group that is not the treatment unit (Abadie et al., 2010). Specifically, a permutation distribution is generated based on placebo policy effects that are arbitrarily created for each region in the pool of control candidates. This distribution is then compared with the actual policy effect of the treatment unit to test for statistical significance. If the policy effect of the treatment unit exceeds the placebo policy effects in the permutation distribution, it is considered significant. In this context, the difference in policy effects between the treatment group and the synthesized control group is evaluated by examining how closely the control group matches the treatment group before the intervention. The test statistic proposed by Abadie et al. (2010) is as follows:

$$R_j(t_1, t_2) = ((\frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2}(y_{jt} - \hat{y}_{jt}^N))^{\frac{1}{2}} \tag{5}$$

where $\hat{y}_{jt}^N$ denotes the outcome variable of the synthetic control group at time t when the j^{th}group is assumed to be the treatment unit. Consequently, Equation (5) presents the root mean squared prediction error for the synthetic control estimator. To reflect how well the synthetic control was constructed before the intervention, the fit is assessed by comparing the root mean squared prediction error before and after the intervention, which was calculated as a ratio:

$$r_j = \frac{R_j(T_{0+1}, T)}{R_j(1, T_0)} \tag{6}$$

The empirical p value for inferring the significance of the policy effect is calculated based on the aforementioned permutation distribution of r_j, as follows:

$$p = \frac{1}{J+1}\sum_{j=1}^{J+1} I_+(r_j - r_1) \tag{7}$$

At this point, $I_+(\cdot)$ is a function that returns 1 if $r_j - r_1 \geq 0$ and 0 otherwise. The empirical p value used in this study was calculated as in Equation (7).

The SCM is typically utilized for a single treatment region affected by a policy. However, when multiple regions are designated as treatment areas, as in this study, various methods can be applied. Acemoglu et al. (2016) applied the SCM to each treatment region individually, whereas Kreif et al. (2016) assigned weights to multiple treatment regions to integrate them into a single treatment area for analysis (Ha et al., 2022). In this study, to determine whether there are differential effects of the highway openings across regions, the SCM was applied to Hongcheon-gun, Inje-gun, and Yangyang-gun, respectively, and the policy effects were compared.

3.1.2. Spatial DiD

While the SCM is effective for analyzing the impact on the treatment region, it has limitations in assessing the effects on the surrounding regions. To address this limitation, this study utilizes the fixed-effect Spatial DiD method to complement the SCM and examine the spillover effects of the highway openings on adjacent areas. The general formula for the fixed-effect DiD method is presented in Equation (8), and the Spatial DiD method is presented in Equation (9):

$$y_{it} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 Treat_i + \alpha_3 Post_t + \alpha_4 (Treat_i \times Post_t) + \gamma_i + \delta_t + \varepsilon_{it} \tag{8}$$

$$\begin{aligned} y_{it} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 Treat_i + \alpha_3 Post_t + \alpha_4 (Treat_i \times Post_t) \\ + \alpha_5 \sum_{j \neq i} W_{ij}\,(Treat_i \times Post_t) + \gamma_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{9}$$

where y_{it} represents the GRDP and net migration rate of region i at time t and X_{it} denotes control variables. $Treat_i$ indicates whether the region is affected by the highway opening, with the regions Hongcheon-gun, Inje-gun, and Yangyang-gun assigned a value of 1 at all times, and all other regions were assigned a value of 0.

$Post_t$ is a variable representing the period after the highway opening, where all regions are assigned a value of 1 for data from 2017 onward and a value of 0 for data before 2016. In this study, applying the Spatial DiD method resulted in the exclusion of $Treat_i$ and $Post_t$ variables from the model owing to perfect collinearity (Lee and Sohn, 2018). The interaction term $Treat_i \times Post_t$ represents the DiD estimator, which is the key variable in this methodology, used to measure the effect of the highway opening before and after the event in the affected regions. This term takes a value of 1 only for the regions with the highway openings in the postopening period and 0 otherwise.

The Spatial DiD method extends the traditional DiD approach by adding the term $\alpha_5 \sum_{j \neq i} W_{ij} \, (Treat_i \times Post_t)$[2]. This term combines the effect of the highway opening with a spatial weight matrix W, capturing the spillover effects on neighboring regions (Delgado and Florax, 2015). Here, γ_i denotes the fixed effects for region i, δ_t represents the fixed effects for the year, and ε_{it} is the error term. In this study, an inverse distance matrix was utilized as the spatial weight matrix, which assigns higher values to regions that are closer in proximity.

3.2. Data

This study selected Hongcheon-gun, Inje-gun, and Yangyang-gun as the treatment areas owing to their improved accessibility to the SMA following the opening of the Seoul–Yangyang Expressway in 2017. It is noteworthy that Hongcheon-gun and Yangyang-gun were the regions experiencing population decline in 2021. By examining the effects of the expressway opening in these regions, this study aims to evaluate the efficacy of expanding transportation networks as a policy instrument to mitigate regional decline.

To assess the impact of the highway opening, this study utilizes real GRDP, measured in trillions of Korean won, as the primary outcome variable. GRDP is a widely used indicator in empirical research, serving as a proxy for the regional economic level. The GRDP data utilized in this study are obtained from Statistics Korea at the municipality level and cover the 2005–2019 period. In addition, this study examines the net migration rate, defined as the net number of people migrating into the region per 1000 population. Given that migration to the SMA exacerbates regional disparities and raises concerns about the population decline of small cities (Kim and Kim, 2023), the net migration rate is a pertinent indicator to evaluate the effectiveness of the expressway opening as a policy measure to regional decline. This variable is calculated using domestic migration statistics and population data provided by Statistics Korea from 2005 to 2019.

Meanwhile, this study relied solely on the outcome variables, GRDP and net migration rate, without incorporating additional predictor variables to estimate the effects of highway inauguration. The impact of the highway opening was exclusively assessed using outcome variables across all pretreatment time points. Owing to the subjectivity inherent in controlling specific time points of the outcome variables and the limited explanatory power of predictor variables when used concurrently with outcome variables for certain years (Ferman et al., 2020), the inclusion of predictor variables was deemed unnecessary[3].

To ensure the robustness of the SCM analysis, a donor pool comprising regions with characteristics similar to the treatment units was carefully constructed (Abadie, 2021). Given the rural nature of the regions benefiting from the Seoul–Yangyang Expressway and the heightened risk of regional decline in rural areas, the donor pool comprises rural regions nationwide that shared similar characteristics with the treatment units. Furthermore, to mitigate potential confounding effects, regions in which expressway openings coincided with the treatment period were excluded from the donor pool, resulting in a final donor pool of 73 regions.

Table 1 provides the explanation of the variables controlled for in the Spatial DiD analysis. The dependent variables were identical to those in SCM analysis (GRDP and net migration rate), with the control units also consisting of rural areas. In addition to the DiD estimator, the model included control variables such as the number of firms, average firm size, specialization in manufacturing and agriculture, industrial diversity, population density, and the proportion of the elderly population.

The number of firms is a significant indicator of the economic activity levels within a region; a high number of businesses suggests a more vibrant local economy, thus necessitating its control. In addition, along with the number of firms, the average firm size, reflecting the scale of enterprises within the region, was selected as a control variable. Specialization in manufacturing was controlled for using the location quotient index of regional manufacturing as expressed in Equation (10). Given that manufacturing is a key industry in the economy of Korea, essential for understanding the structure and growth of regional economies, this variable was included as a control. Industrial diversity, derived through Equation (11), was controlled in the model, considering that a great industrial diversity positively impacts regional economic growth and resilience (He et al., 2022). Population density, reflecting population distribution and competition levels within the region, was controlled in the model, recognizing that high population density can directly influence economic activities. Moreover, the proportion of the elderly population, the percentage of individuals aged 65 and older, was controlled owing to its potential to cause economic issues such as labor shortages. In Model 2, where the net migration rate was the dependent variable, population density and the proportion of the elderly population were excluded from the model because these variables are likely to be endogenous to population movement:

$$LQ = \frac{E_i^j / E^j}{E_i^n / E^n} \tag{10}$$

$$N_c \left[1 - \frac{\sum \left| E_i^j - \overline{E^j} \right| / 2}{E^j} \right] \tag{11}$$

In Equation (10), E_i^j is the number of employees in the manufacturing industry in the region, E^j is the total number of employees in the region, E_i^n is the number of employees in the manufacturing industry nationwide, and E^n is the total number of employees nationwide. In Equation (11), N_c is the number of industry classifications and $\overline{E^j}$ is the average number of employees per industry in the region. All control variables, except for the proportion of the elderly population, were log transformed.

Table 1. Description of variables for spatial DiD analysis.

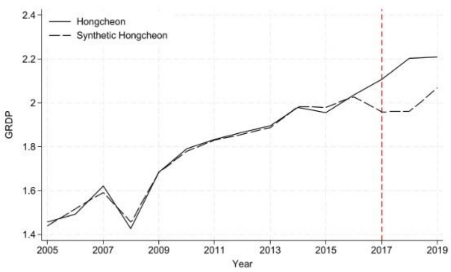
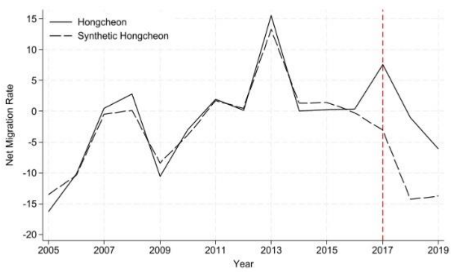
	Variables	Definition	Model 1	Model 2
Dependent Variables	GRDP	Gross Regional Domestic Product (trillion won)	○	
	Net Migration Rate	(In-migrants–Out-migrants)/(Population/1000)		○
Independent Variables	$Treat_i \times Post_t$	DiD Estimator	○	○
	$W\_(Treat_i \times Post_t)$	Spatial DiD Estimator	○	○
Control Variables	Number of Firms	(log) Number of firms per 1000 people	○	○
	Firm Size	(log) Number of employees per firm	○	○
	LQ	(log) Manufacturing LQ index	○	○
	Diversity	(log) Regional industrial diversity	○	○
	Density	(log) Population per total area (persons/km²)	○	
	Elder	Proportion of population aged 65 and older (%)	○	

Refer to Appendix for the descriptive statistics of the treatment units and control group.

4. Results

4.1. SCM results

Figure 1 visually presents the changes in GRDP and net migration rates for Hongcheon-gun, Inje-gun, and Yangyang-gun following the opening of the Seoul–Yangyang Expressway. The solid lines within the graph delineate the actual outcome variables (GRDP and net migration rates) for the three regions, whereas the dashed lines represent the synthetic control group, illustrating the potential outcome variables of Hongcheon-gun, Inje-gun, and Yangyang-gun under a counterfactual scenario wherein the highway opening did not occur. The vertical dashed line marks the opening of the expressway in 2017. The trends exhibited by the outcome variables of the synthetic control group closely parallel those of the treated regions before the intervention, suggesting the appropriateness of the comparison between the treated regions and the synthetic control group[4]. Consequently, the disparities observed between the treated regions and the synthetic control group are the impacts of the highway opening on GRDP and net migration rates.

Region	GRDP	Net Migration Rate
Hongcheon		

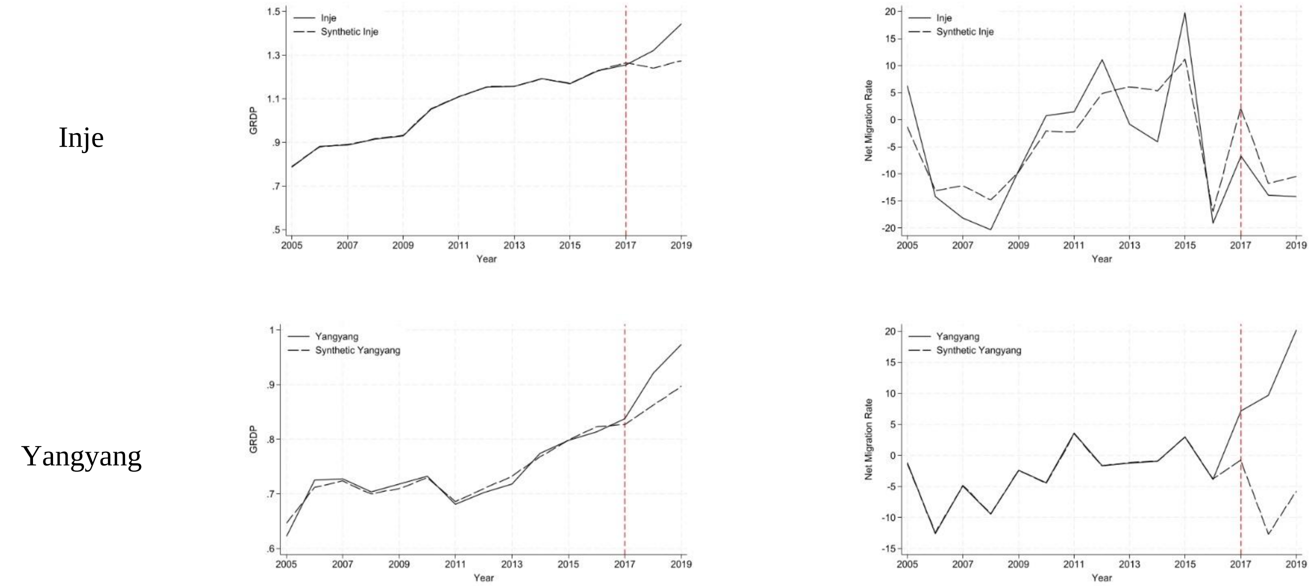


Figure 1. Results of SCM analyses.

Table 2 presents the estimated impact of the highway inauguration on Hongcheon-gun, Inje-gun, and Yangyang-gun. Relative to a counterfactual scenario without the highway opening, the GRDP of Hongcheon-gun is estimated to have been approximately 148 billion KRW higher in 2017, 241 billion KRW higher in 2018, and 141 billion KRW higher in 2019. This translates to an average annual treatment effect of approximately 177 billion KRW over the 3-year period. For Inje-gun, the treatment effect is estimated to be around−10 billion KRW in 2017, 81 billion KRW in 2018, and 170 billion KRW in 2019, leading to an average annual GRDP increase of approximately 80 billion KRW. Finally, for Yangyang-gun, the treatment effects are estimated to be around 11 billion KRW, 59 billion KRW, and 77 billion KRW over the 3 years, respectively, resulting in an average annual GRDP increase of approximately 49 billion KRW attributable to the highway opening.

When multiple regions undergo treatment, the formula presented in Equation (12) by Dube and Zipperer (2015) allows for a comparison of the distinct treatment effects for each region. By dividing the average treatment effect calculated using Equation (2) by the average value of the outcome variable of the synthetic control group posttreatment, the average percentage difference can be computed:

$$\hat{\tau}_1 = \frac{\frac{1}{T}\sum_{t=t_0+1}^{T}(Y_{it} - \sum_{j=2}^{J+1} w_j^* Y_{jt}^0)}{\frac{1}{T}\sum_{t=t_0+1}^{T}\sum_{j=2}^{J+1} w_j^* Y_{jt}^0)} \tag{12}$$

An examination of the average ratio values computed using this method reveals a value of 0.0885 for Hongcheon-gun, 0.0403 for Inje-gun, and 0.0565 for Yangyang-gun. These findings suggest that Hongcheon-gun experienced the most substantial increase in GRDP in absolute and relative terms.

Table 2. Impact of highway construction on GRDP of beneficiary regions.

Region	2017	2018	2019	Average	Average Ratio
Hongcheon	0.1484	0.2410	0.1405	0.1766	0.0885
Inje	−0.0096	0.0813	0.1696	0.0804	0.0403
Yangyang	0.0109	0.0586	0.0767	0.0487	0.0565

Table 3 presents the fluctuations in net migration rates for Hongcheon-gun, Inje-gun, and Yangyang-gun after the Seoul–Yangyang Expressway inauguration. An analysis of regional net migration rate variations reveals that Hongcheon-gun recorded an approximate net migration rate increase of 10.67 individuals in 2017, 13.24 individuals in 2018, and 7.66 individuals in 2019, culminating in an average annual additional net inflow of approximately 10.52 individuals per 1000 population over the 3-year period. Conversely, Inje-gun experienced a treatment effect of approximately −8.93 individuals in 2017, −2.18 individuals in 2018, and −3.71 individuals in 2019, resulting in an average annual additional net outflow of approximately 4.94 individuals per 1000 population. Finally, Yangyang-gun exhibited an estimated increased net migration rate of approximately 7.94 individuals in 2017, 22.39 individuals in 2018, and 25.88 individuals in 2019, translating to an additional net inflow of approximately 18.73 individuals per 1000 population annually over the 3-year period.

An examination of the average ratio values calculated using Equation (12) reveals a value of −1.0157 for Hongcheon-gun, 0.7428 for Inje-gun, and −2.9353 for Yangyang-gun. Nonetheless, given that the net migration rates of the synthetic control groups for Hongcheon-gun and Yangyang-gun were estimated to be negative, the average ratio values exhibited negative signs despite the positive treatment effects. Therefore, it can be inferred that the net migration rate in Yangyang-gun has the most substantial increase in absolute and relative terms as a result of the highway opening.

Table 3. Impact of highway construction on net migration rate of beneficiary regions.

Region	2017	2018	2019	Average	Average Ratio
Hongcheon	10.6734	13.2377	7.6558	10.5223	−1.0157
Inje	−8.9310	−2.1834	−3.7075	−4.9406	0.7428
Yangyang	7.9373	22.3894	25.8756	18.7341	−2.9353

4.2. Robustness check

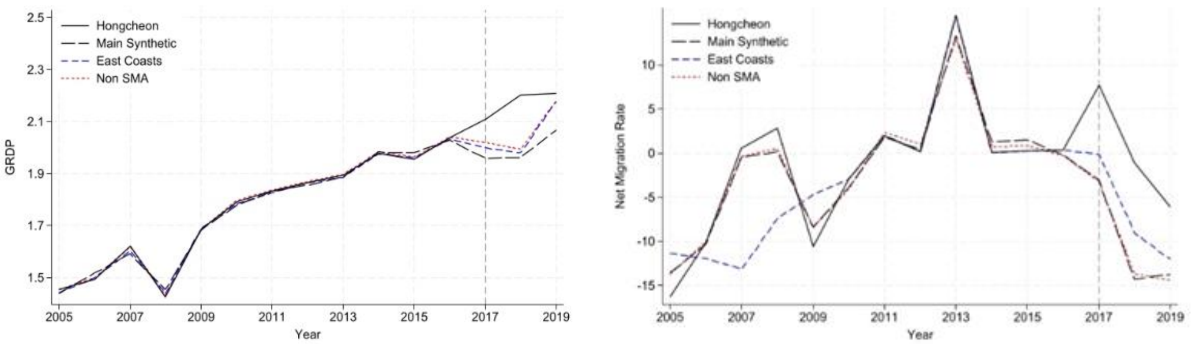
This study adopts the testing methods outlined by Lee and Kim (2019) and Lee et al. (2020) to conduct the supplementary analyses. First, the donor pool regions for the synthetic control group were either restricted to the East Coast border regions (Busan, Gangwon, Gyeongbuk, Gyeongnam, Ulsan) or expanded to nonSMAs to recalculate the effects of the highway opening. **Figure 2** presents the estimation results when the donor pool is modified. The solid black lines are the actual outcome variable values for each region. Results of the original analysis using rural areas as the donor pool are labeled “Main Synthetic”, results when the donor pool is restricted to the East Coast regions are labeled “East Coasts”, and results when the donor pool is expanded to nonmetropolitan areas are labeled “Non SMA”.

Results reveal that changing the donor pools caused differences in the trends of the synthetic control group before the treatment period. First, regarding GRDP, the synthetic control groups for each region were similarly constructed to match the pretreatment trends, despite changes in the donor pools. While there were slight differences in the magnitude of the treatment effects, the highway opening consistently exerted a positive impact on GRDP in all regions.

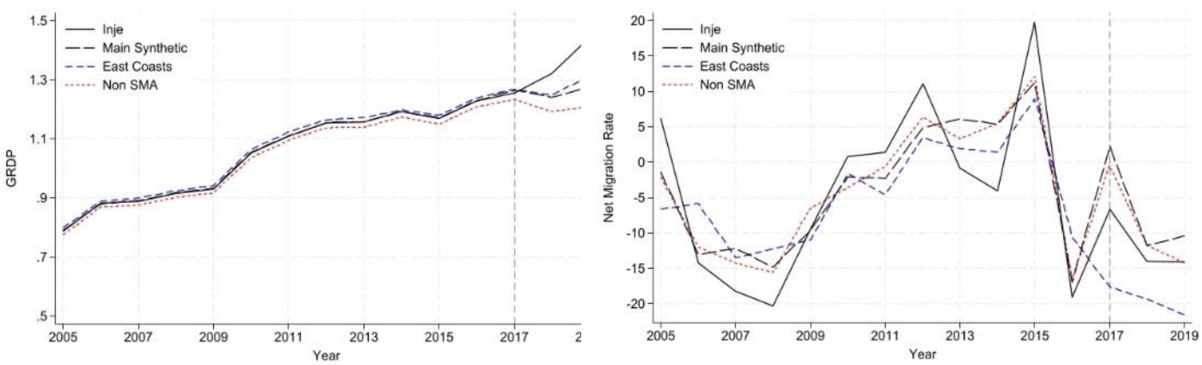
With respect to net migration rates, the synthetic control group of Hongcheon-gun closely mirrored the pretreatment trend regardless of donor pool modifications, and the highway opening positively influenced net migration rates. Conversely, the synthetic control group for Inje-gun exhibited less reliability, particularly when employing the East Coast region donor pool, leading to inconsistent findings regarding the impact of the highway on net migration rates. Finally, for Yangyang-gun, the synthetic control group proved inappropriate when utilizing the East Coast region donor pool, although the treatment effect remained positive. Expanding the donor pool to nonmetropolitan areas improved the synthetic control group and confirmed the positive impact of the highway opening. In conclusion, while donor pool alterations resulted in some variations, the overall findings pertaining to the positive influence of the highway opening on GRDP across all regions and net migration rates in Hongcheon-gun and Yangyang-gun demonstrated relative robustness.

Region **GRDP** **Net Migration Rate**

Hongcheon



Inje



Yangyang

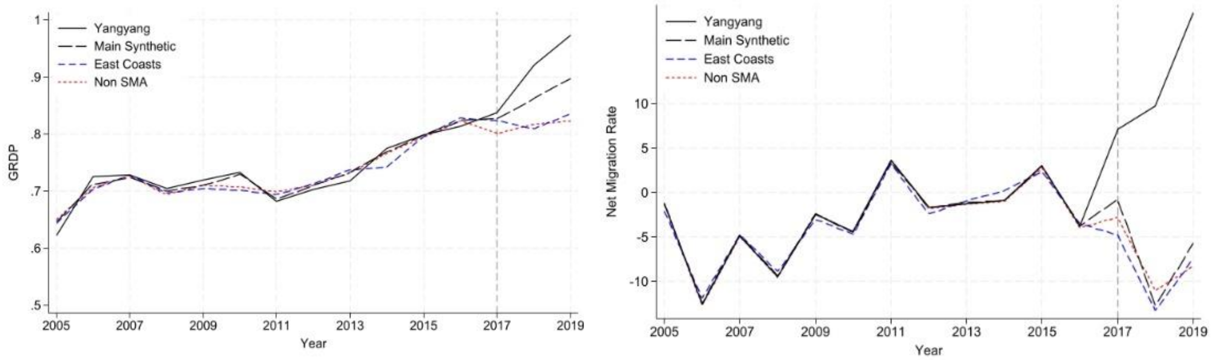


Figure 2. Comparison of different results for robustness check.

Subsequently, a placebo effect test was conducted by designating each region within the donor pool as a treatment region and comparing the resulting treatment effects with those of Hongcheon-gun, Inje-gun, and Yangyang-gun. During this process, some regions exhibited substantial deviations in pretreatment outcome variable trends owing to inappropriate control group synthesis. The treatment effects associated with these regions were interpreted as differences resulting from the inadequately synthesized control groups (Abadie et al., 2010). Consequently, regions with mean squared prediction error values more than five times greater than those of the treatment units, indicating inadequate control group synthesis, were excluded from the comparison of treatment effects across regions (Lee and Kim, 2019; Lee et al., 2020).

Afterward, the significance of the treatment effects was tested using the empirical *p* value, representing the proportion of placebo regions that exhibited treatment effects equal to or greater than those of the actual treatment regions (Abadie et al., 2015). A smaller empirical p value indicates a lower likelihood of observing the treatment effects by chance.

Figure 3 presents the results of the placebo effect test. The black line represents the treatment effect observed in each treatment region, whereas the gray lines represent the estimated treatment effects for regions outside the treatment areas. If the treatment effects for Hongcheon-gun, Inje-gun, and Yangyang-gun are relatively larger than those in the nontreatment regions, the treatment effects can be considered significant. An examination of the GRDP revealed that all three regions exhibit relatively high treatment effects. With respect to net migration rates, Hongcheon-gun demonstrates a relatively larger effect, and Yangyang-gun shows the highest treatment effect than other regions. However, Inje-gun shows a lower treatment effect in comparison.

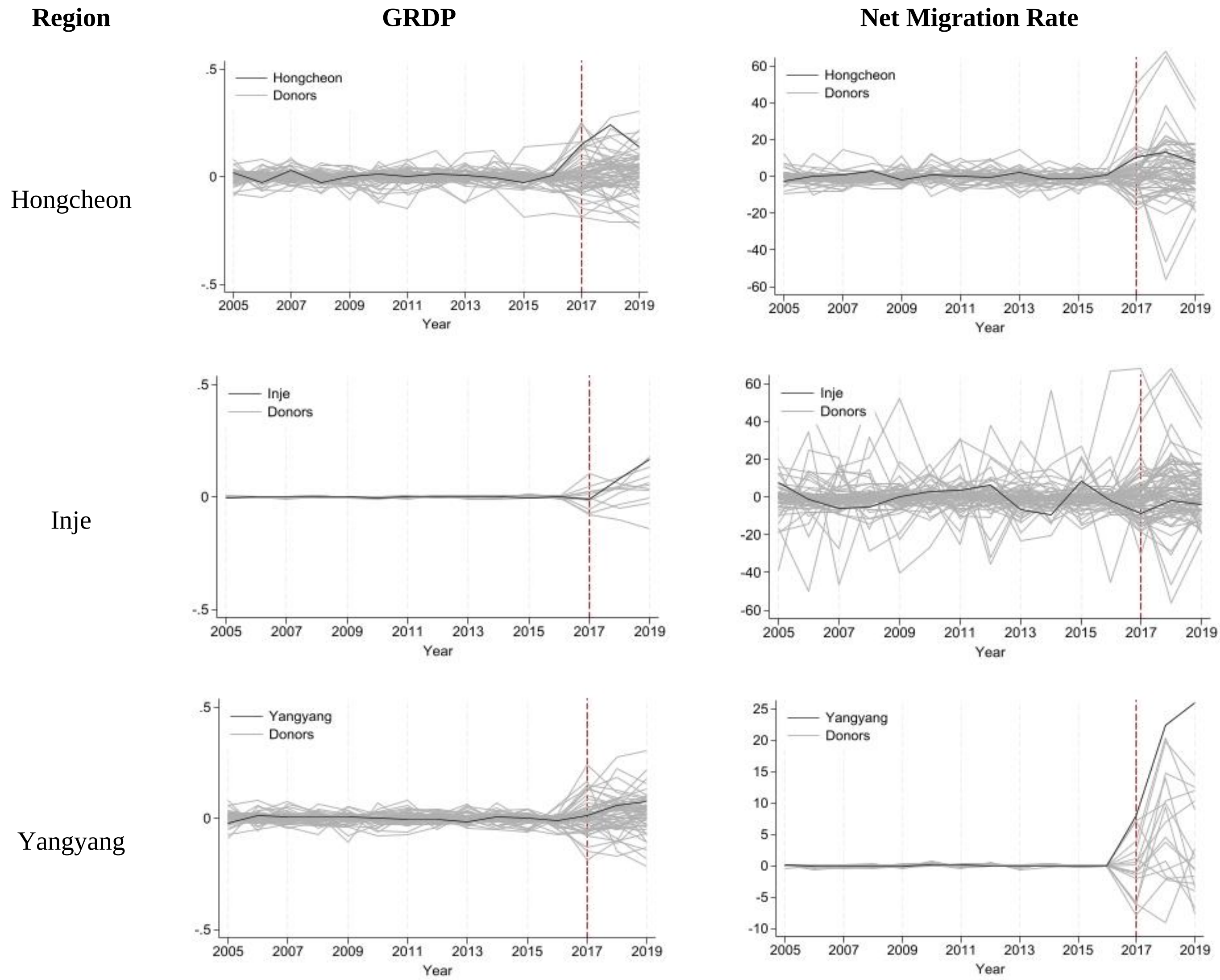


Figure 3. Placebo effects test results.

Tables 4 and **5** present the significance levels of these treatment effects. With respect to GRDP, no region exhibited significant treatment effects in 2017[5]. In 2018, Hongcheon-gun recorded an empirical *p* value of 0.0167, indicating a significant treatment effect, whereas the other two regions did not demonstrate significant effects. In 2019, none of the regions displayed significant treatment effects. Consequently, except for Hongcheon-gun, in 2018, the highway opening did not lead to a significant increase in GRDP within the beneficiary regions.

Table 4. Treatment effect and empirical *P*-values (GRDP).

Region	**2017**		**2018**		**2019**	
	Treatment Effect	***P*-value**	**Treatment Effect**	***P*-value**	**Treatment Effect**	***P*-value**
Hongcheon	0.1484	0.1167	0.2410	0.0167	0.1405	0.1667
Inje	−0.0096	0.9000	0.0813	0.2000	0.1696	0.1000
Yangyang	0.0109	0.8519	0.0586	0.4444	0.0767	0.3704

Next, by examining net migration rates, Yangyang-gun demonstrated a p value of 0 in all years, indicating the most substantial treatment effect than other rural regions. By contrast, Hongcheon-gun and Inje-gun exhibited empirical p values exceeding 0.1 in all years, suggesting that the highway opening did not significantly impact net migration rates in these two regions. Therefore, although the highway opening led to a significant net inflow of population in Yangyang-gun, no significant net inflow was observed in the other two regions.

Table 5. Treatment effect and empirical p-value (net migration rate).

Region	2017		2018		2019	
	Treatment Effect	***P*-value**	**Treatment Effect**	***P*-value**	**Treatment Effect**	*P*-value
Hongcheon	10.6734	0.2727	13.2377	0.3273	7.6558	0.4545
Inje	−8.9310	0.3699	−2.1834	0.9041	−3.7075	0.7123
Yangyang	7.9373	0.0000	22.3894	0.0000	25.8756	0.0000

4.3. Spillover effects of highway construction

To analyze the spillover effects of the highway opening on adjacent regions, this study utilized the Spatial DiD method, addressing the limitations of the SCM, which cannot capture these effects. **Table 6** presents the results of the Spatial DiD analysis.

First, by examining Model 1, which sets GRDP as the dependent variable, the DiD estimator ($Treat_i \times Post_t$) was found to be negative, indicating that the opening of the Seoul–Yangyang Expressway had a negative impact on the GRDP of Yangyang-gun, Inje-gun, and Hongcheon-gun, though this result was not statistically significant. In addition, the Spatial DiD estimator ($(W\_(Treat_i \times Post_t)$), which measures the impact on GRDP of the surrounding regions, indicated a negative effect, and this was statistically significant at the $p < 0.1$ level. This suggests that the highway opening negatively affected the GRDP of regions surrounding the beneficiary areas.

Probing further into the analysis of the control variables, the number of firms and average firm size were found to have a positive and statistically significant impact on the GRDP ($p < 0.01$). Specialization in manufacturing showed a negative effect; however, this was not statistically significant. Industrial diversity had a positive impact on GRDP and was significant at the $p < 0.1$ level. Moreover, population density positively influenced GRDP ($p < 0.01$), whereas the proportion of the elderly population had a positive, but not statistically significant, effect.

Subsequently, by examining Model 2, which uses net migration rates as the dependent variable, the highway opening was found to have a statistically significant ($p < 0.05$) positive effect on population inflow in the three regions. Conversely, the Spatial DiD estimator indicated that the highway opening caused a population outflow in the adjacent regions ($p < 0.01$). Among the control variables, the number of firms had a negative impact on net migration rates ($p < 0.01$), contrary to results in Model 1. Firm size had a positive effect on net migration rates, which is significant at the $p < 0.05$ level. Manufacturing specialization positively influenced population inflow; however, this result was not statistically significant. Finally, industrial diversity positively impacted net migration rates, similar to Model 1, and was significant at the $p < 0.05$ level.

In summary, the Spatial DiD analyses revealed that the inauguration of the Seoul–Yangyang Expressway did not have a significant impact on the GRDP of the beneficiary regions but negatively affected the GRDP of adjacent regions. The highway opening positively influenced the net migration rates of the beneficiary regions while negatively impacting the net migration rates of the surrounding regions. This suggests the possibility of a "straw effect", where the highway opening attracts the population from neighboring areas. Moreover, among the controlled variables, the average firm size and industrial diversity positively influenced GRDP and net migration rates.

Table 6. Spatial DiD results.

Variables	Model 1 (GRDP)	Model 2 (Net Migration Rate)
$Treat_i \times Post_t$	−0.1334	13.3754**
$W\_(Treat_i \times Post_t)$	−1.6458*	−141.8355***
Number of Firms	1.9978***	−94.1407***
Firm Size	0.8543***	24.2641**
LQ	−0.0978	0.5705
Diversity	0.9783*	46.9571**
Density	5.6546***	
Elder	0.0278	
R^2	0.2640	0.0475
# of Regions	76	76
Time Periods	15	15
N	1140	1140

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5. Conclusion

The widening regional disparities are inextricably linked to income and opportunity inequality (Jeong, 2021) and can exacerbate urban challenges and regional declines. To address these complex issues, various strategies have been proposed, such as the development of extensive transportation networks in nonmetropolitan areas. This study aims to evaluate the efficacy of highway expansion as a policy instrument for mitigating regional decline by examining its impact on economic welfare and population inflow in nonmetropolitan regions using the SCM and Spatial DiD methodologies.

The primary findings of this study are as follows: First, by utilizing the SCM with a donor pool of rural areas, the inauguration of the Seoul–Yangyang Expressway demonstrated positive impacts on GRDP and net migration rates, except for the GRDP of Inje-gun in 2017 and net migration rates in all 3 years. Second, robustness tests confirmed significant increases in the GRDP of Hongcheon-gun to 241 billion KRW in 2018 and the net migration rates of Yangyang-gun, which rose to 7.94, 22.39, and 25.88 from 2017 to 2019, respectively. This indicates that the highway opening did not significantly affect the economic or demographic indicators of Inje-gun. Third, the Spatial DiD analysis to understand the spillover effects of the highway opening revealed that it did not significantly affect the GRDP of beneficiary regions but negatively impacted the GRDP of adjacent regions. Moreover, while the opening positively influenced the net migration rates of the beneficiary regions, it negatively affected the net migration rates of the surrounding areas, suggesting a potential "straw effect" where the highway attracts population from neighboring regions.

In conclusion, the findings from the SCM and Spatial DiD analyses suggest that while the highway inauguration increased GRDP and net migration rates in certain beneficiary regions, it concurrently exerted negative impacts on adjacent areas. These results imply that the development of extensive transportation networks, such as highway construction, may not effectively address regional decline. In fact, such infrastructure investments could potentially exacerbate regional disparities by accelerating the depopulation of small- and medium-sized cities.

Although the analyses of this study focused on the Seoul–Yangyang Expressway, which does not perfectly align with extensive transportation networks centered on regional metropolitan areas, the expansion of transportation networks could potentially promote population inflow from neighboring regions rather than the metropolitan area, thereby accelerating the decline of small- and medium-sized cities. Thus, while developing extensive transportation networks centered around key nonmetropolitan cities may help alleviate the imbalance between SMA and nonSMA by expanding the influence of the beneficiary regions, it may not be effective in addressing the depopulation of nearby small- and medium-sized cities.

Despite the key findings and implications, this study has several limitations. First, the analysis was constrained by data availability, limiting the assessment to a relatively short timeframe and preventing an evaluation of the long-term impacts of the highway opening. The exclusion of data post 2019, owing to the onset of the COVID-19 pandemic, further restricts the scope of the analysis. Second, this study could not reveal the precise mechanism by which the highway opening resulted in population inflow into Yangyang-gun. One possible explanation is that the improved accessibility to the SMA led to the development of the tourism industry in Yangyang-gun, attracting tourists and spurring the growth of tourism-related businesses. This, in turn, may have led to population inflow as individuals moved to the area for employment and business opportunities within the expanding tourism sector. Another explanation is that the highway expanded the commuting range to nearby regional hubs, allowing people to live in Yangyang-gun, where housing costs are relatively lower, while still being able to commute to these neighboring cities for work. The combination of affordable housing and improved commuting options may have made Yangyang-gun a more attractive place to live. However, without detailed data on the exact migration patterns and commuting behaviors, the precise reasons for the population inflow remain uncertain. Future research on the effects of the highway openings and transportation network expansions should address these limitations to provide more rigorous and comprehensive analyses.

Conflict of interest: The author declares no conflict of interest.

Notes

[1] Regional decline, although varying slightly in definition across studies, generally refers to the decline of small- and medium-sized cities in nonSMA owing to low fertility rates, aging populations, and the outmigration of populations to the SMA (Kim and Kim, 2023).

[2] $\alpha_5 = \rho\alpha_4$, where ρ is a coefficient representing the spatial autocorrelation of the dependent variable.

[3] Indeed, when simultaneously controlling for outcome variables across all years and predictor variables, the importance of the predictor variables (v_h) becomes zero.

[4] While a definitive objective criterion for evaluating the suitability of synthetic control groups remains absent (Bouttell et al., 2018), the synthetic control results, except for the net migration rate of Inje-gun, were deemed to align closely with the trends of the actual outcome variables.

[5] Although a definitive significance criterion for empirical p values remains unestablished, this study considers treatment effects significant when the p value is less than 0.1.

References

Abadie, A. (2021). Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects. Journal of Economic Literature, 59(2), 391–425.

Abadie, A., Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. American Economic Review, 93(1), 113–132.

Abadie, A., Diamond, A., Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California’s Tobacco Control Program. Journal of the American Statistical Association, 105(490), 493–505.

Abadie, A., Diamond, A., Hainmueller, J. (2015). Comparative Politics and the Synthetic Control Method. American Journal of Political Science, 59(2), 495–510.

Acemoglu, D., Johnson, S., Kermani, A., et al. (2016). The value of connections in turbulent times: Evidence from the United States. Journal of Financial Economics, 121(2), 368–391.

Aschauer, D. A. (1989). Is public expenditure productive? Journal of Monetary Economics, 23(2), 177–200.

Athey, S., Imbens, G. W. (2017). The State of Applied Econometrics: Causality and Policy Evaluation. Journal of Economic Perspectives, 31(2), 3–32.

Baum-Snow, N., Brandt, L., Henderson, J. V, et al. (2017). Roads, Railroads, and Decentralization of Chinese Cities. The Review of Economics and Statistics, 99(3), 435–448.

Boarnet, M. G. (1998). Spillovers and the Locational Effects of Public Infrastructure. Journal of Regional Science, 38(3), 381–400.

Bouttell, J., Craig, P., Lewsey, J., et al. (2018). Synthetic control methodology as a tool for evaluating population-level health interventions. Journal of Epidemiology and Community Health, 72(8), 673–678.

Cai, W., Wu, Z., Lu, Y. (2022). The Impact of High-Speed Rails on Urban Consumption—From the Perspective of “Local-Adjacent” Effect. Frontiers in Environmental Science, 10.

Cantos, P., Gumbau-Albert, M., Maudos, J. (2005). Transport infrastructures and regional growth: Evidence of the Spanish case. Transport Reviews, 25(1), Article 15261.

Cavallaro, F., Bruzzone, F., Nocera, S. (2023). Effects of high-speed rail on regional accessibility. Transportation, 50(5), 1685–1721.

Cervero, R. (2003). Road Expansion, Urban Growth, and Induced Travel: A Path Analysis. Journal of the American Planning Association, 69(2), 145–163.

Chen, C.-L., Loukaitou-Sideris, A., de Ureña, J. M., et al. (2019). Spatial short and long-term implications and planning challenges of high-speed rail: A literature review framework for the special issue. European Planning Studies, 27(3), 415–433.

Chen, Z., Haynes, K. E. (2017). Impact of high-speed rail on regional economic disparity in China. Journal of Transport Geography, 65, 80–91.

Cook, L. M., Munnell, A. H. (1990). How does public infrastructure affect regional economic performance? New England Economic Review, Sep, 11–33.

Delgado, M. S., Florax, R. J. G. M. (2015). Difference-in-differences techniques for spatial data: Local autocorrelation and spatial interaction. Economics Letters, 137, 123–126.

Deng, T., Wang, D., Yang, Y., et al. (2019). Shrinking cities in growing China: Did high speed rail further aggravate urban shrinkage? Cities, 86, 210–219.

Dube, A., Zipperer, B. (2015). Pooling Multiple Case Studies Using Synthetic Controls: An Application to Minimum Wage Policies. SSRN Electronic Journal.

Faber, B. (2014). Trade Integration, Market Size, and Industrialization: Evidence from China's National Trunk Highway System. The Review of Economic Studies, 81(3), 1046–1070.

Ferman, B., Pinto, C., Possebom, V. (2020). Cherry Picking with Synthetic Controls. Journal of Policy Analysis and Management, 39(2), 510–532.

Ha, J., Ha, J., Lee, S. (2022). The Effect of Car-Free Pedestrian Street Policy on Urban Vibrancy Using Synthetic Control Method (Korean). Journal of the Korean Regional Science Association, 38(2), 59–72.

He, D., Miao, P., Qureshi, N. A. (2022). Can industrial diversification help strengthen regional economic resilience? Frontiers in Environmental Science, 10.

Heo, M., Ahn, G. (2008). A Causality Analysis of Economic Growth and Regional Income Disparity in Korea (Korean). Journal of The Korean Regional Development Association, 20(2), 233–256.

Januário, J. F., Costa, Á., Cruz, C. O., et al. (2023). Effects of regional accessibility on productivity: An analysis based on composite indicators. Journal of Infrastructure, Policy and Development, 7(3). https://doi.org/10.24294/jipd.v7i3.2092

Jeong, J. (2021). Global Value Chain and Regional Disparity Since the 2010s in Korea (Korean). Economy and Society, 131, 88–125.

Kang, I. (2018). The Strategy of Compact City in Japan Local Governments (Korean). The Korea Association for Policy Studies, 27(2), 221–244.

Kim, E., Hewings, G. J. D. (2009). An Application of an Integrated Transport Network: Multiregional CGE Model to the Calibration of Synergy Effects of Highway Investments. Economic Systems Research, 21(4), 377–397.

Kim, E., Yi, Y. (2019). Impact Analysis of High-speed Rail Investment on Regional Economic Inequality: A Hybrid Approach Using a Transportation Network-CGE Model. Journal of Transport Economics and Policy, 53(3), 238–257.

Kim, E., Moon, S., Yi, Y. (2021). Analyzing spillover effects of development of Asian highway on regional growth of Northeast Asian countries. Review of Development Economics, 25(3), 1243–1266.

Kim, E., Park, C., Kim, H., et al. (2006). Dynamic Regional Economic Effects of Highway and Railway Projects: An Application of Multiregional CGE Model (Korean). Journal of the Korean Regional Science Association, 22(3), 3–28.

Kim, H., Lee, D. (2022). Impact of Highway Construction on Internal Migration: A Korea Perspective. Sustainability, 14(21), Article 21.

Kim, H., Lee, J. (2019). Can employment subsidies save jobs? Evidence from a shipbuilding city in South Korea. Labour Economics, 61, 101763.

Kim, H., Sultana, S. (2015). The impacts of high-speed rail extensions on accessibility and spatial equity changes in South Korea from 2004 to 2018. Journal of Transport Geography, 45, 48–61.

Kim, J. (2022). The Paradigm Shift of Regional Development Policy (Korean). Journal of Regional Studies, 30(3), 23–60.

Kim, J., Han, J. (2016). Straw effects of new highway construction on local population and employment growth. Habitat International, 53, 123–132.

Kim, K. (2022). The Effect of Capital Flow Management Measures in Korea using Synthetic Control Method (Korean). Journal of Market Economy, 51(1), 29–47.

Kim, S. (2023). The Effect of New Expressways on Local Economy (Korean). Korean Society of Transportation, 41(1), 68–80.

Kim, S., Kim, E. (2023). Analysis of Spatial Economic Patterns in Regions with Declining Populations by Applying Spatial Probit Models (Korean). Journal of Korea Planning Association, 58(6), 128–143.

Kim, S., Kim, E. (2024). Population decline in small and medium-sized cities and spatial economic patterns: Spatial probit model of South Korea. Applied Economics Letters, 1–6.

Kim, T., Kim, E., Shin, H., et al. (2021). Comparison of Income and Employment Gaps between Regions in Korea and OECD Countries (Korean). Korea Research Institute for Human Settlements.

Kim, W., Kim, M. (2021). The Effects of Public Sector Relocation on Population and Employment: The Case of Jinju City (Korean). Journal of The Korean Association of Regional Geographers, 27(2), 144–163.

Kreif, N., Grieve, R., Hangartner, D., et al. (2016). Examination of the Synthetic Control Method for Evaluating Health Policies with Multiple Treated Units. Health Economics, 25(12), 1514–1528.
Lee, H., Choe, C., Kang, D. (2020). Impacts of the Shipping Industry Crisis in 2015 on Local Business Employment: Evidence from Geoje-si and Tongyeong-si (Korean). The Korean Journal of Economic Studies, 68(2), 119–154.
Lee, J., Moon, J. (2020). The Economic Effect of Social Progress Credit on Social Enterprises: Using Synthetic Control Method (Korean). Journal of Strategic Management, 23(1), 81–100.
Levkovich, O., Rouwendal, J., van Ommeren, J. (2020). The impact of highways on population redistribution: The role of land development restrictions. Journal of Economic Geography, 20(3), 783–808.
Lin, Y., Huang, J. (2021). Can Highway Networks Promote Productivity? Evidence from China. Journal of Advanced Transportation, 2021(02), 1–20.
Liu, Z., Zeng, S., Jin, Z., et al. (2022). Transport infrastructure and industrial agglomeration: Evidence from manufacturing industries in China. Transport Policy, 121, 100–112.
McGraw, M. J. (2020). The role of airports in city employment growth, 1950–2010. Journal of Urban Economics, 116.
Meijers, E., Hoekstra, J., Leijten, M., et al. (2012). Connecting the periphery: Distributive effects of new infrastructure. Journal of Transport Geography, 22, 187–198.
Munnell, A. H. (1990). Why has productivity growth declined? Productivity and public investment. New England Economic Review, Jan, 3–22.
Munnell, A. H. (1992). Policy Watch: Infrastructure Investment and Economic Growth. Journal of Economic Perspectives, 6(4), 189–198.
Park, J., Kim, C., Lee, S. (2020). The Effects of Transportation Accessibility on Influx of Population and Gross Regional Domestic Product (Korean). The Korea Spatial Planning Review, 107, 25–40.
Park, K., Lee, Y., Huh, D., et al. (2020). Suggestions of Network-Based Mega Region Development for Balanced National Development (Korean). Korea Research Institute for Human Settlements.
Percoco, M. (2016). Highways, local economic structure and urban development. Journal of Economic Geography, 16(5), 1035–1054.
Qi, G., Shi, W., Lin, K.-C., et al. (2020). Spatial spillover effects of logistics infrastructure on regional development: Evidence from China. Transportation Research Part A: Policy and Practice, 135(C), 96–114.
Rodrigues, P. G., Pereira, A. M., Pereira, R. M. (2023). Railroad infrastructure investment and economic performance in Portugal: An industry-specific analysis. Journal of Infrastructure, Policy and Development, 8(2). https://doi.org/10.24294/jipd.v8i2.2942
Shin, H., Jung, K., Oh, C. (2023). An Exploratory Study of the National and Local Causes of Local Extinction: Focusing on the Econometric Models (Korean). Journal of Local Government Studis, 35(4), 133–160.
Shin, H., Lee, S., Park, D. (2023). A study on the drivers of inter-regional migration of young people to respond to the crisis of local extinction (Korean). Korea Research Institute for Human Settlements.
Sohn, H., Lee, J. (2018). The Application of and Issues in Difference in Difference Estimator in Public Administration and Policy Research (Korean). Modern Society and Public Administration, 28(3), 1–31.
Statistics Korea. (2024). Population by administrative district (city/county/district) and gender. Statistics Korea.
Yu, N., de Jong, M., Storm, S., Mi, J. (2013). Spatial spillover effects of transport infrastructure: Evidence from Chinese regions. Journal of Transport Geography, 28, 56–66.
Zhang, A., Wan, Y., Yang, H. (2019). Impacts of high-speed rail on airlines, airports and regional economies: A survey of recent research. Transport Policy, 81, A1–A19.

Appendix

Table A1. Descriptive statistics of treatment units.

Year	GRDP	Net Migration Rate	Number of Firms	Firm Size	LQ	Diversity	Density	Elder
2005	0.9548	−3.7434	87.8666	2.6066	0.3471	10.7823	35.0541	15.2000
2006	1.0332	−12.3008	92.5848	2.7212	0.3248	11.3268	34.5983	16.0333
2007	1.0797	−7.5294	93.0882	2.7263	0.3257	11.4837	34.4336	16.9000
2008	1.0150	−8.9575	93.6101	2.8191	0.3922	11.1650	34.1914	17.6333
2009	1.1114	−7.4656	93.7786	3.0009	0.3717	10.6770	33.9355	18.2667
2010	1.1926	−2.1959	92.8427	3.0632	0.3730	10.5667	34.0523	18.7333
2011	1.2080	2.3426	94.2249	2.9266	0.3759	10.8869	34.0862	19.2000
2012	1.2410	3.1816	96.9570	2.9211	0.3364	10.9616	34.0606	19.8333
2013	1.2562	4.4678	99.4090	3.0465	0.3303	10.8131	34.1658	20.2000
2014	1.3149	−1.6332	104.7180	2.9984	0.3371	10.8388	34.0493	20.7000
2015	1.3075	7.6507	105.9294	3.0281	0.3644	10.6238	34.1585	21.0000
2016	1.3598	−7.5314	108.9917	3.1037	0.3563	10.3971	33.8618	21.3333
2017	1.4007	2.7036	111.1390	3.1710	0.3647	10.2910	33.8756	22.5000
2018	1.4818	−1.7695	114.8939	3.1869	0.3868	10.3554	33.7874	23.2667
2019	1.5421	−0.0119	117.3787	3.3339	0.3669	10.2898	33.7486	24.3667

Table A2. Descriptive statistics of control group.

Year	GRDP	Net Migration Rate	Number of Firms	Firm Size	LQ	Diversity	Density	Elder
2005	1.1537	−13.2617	66.1240	3.0292	0.8182	9.6850	100.5261	20.3712
2006	1.1928	−10.1851	66.9019	2.9421	0.8413	10.3528	99.6362	21.3000
2007	1.2497	−2.5056	67.4142	2.9827	0.8775	10.3486	99.5124	22.3589
2008	1.2384	−7.1400	67.6297	3.0397	0.8912	10.2294	99.3635	23.0712
2009	1.2585	−0.9223	68.0553	3.1665	0.9098	9.9752	99.4746	23.5849
2010	1.4034	−3.2796	68.3172	3.2622	0.9134	9.8532	99.9763	23.9329
2011	1.4668	1.3491	70.1898	3.2734	0.9099	9.9216	100.0822	24.2836
2012	1.5033	0.4088	72.9070	3.3092	0.9171	9.8864	100.0034	24.9521
2013	1.5481	4.2955	75.6322	3.3360	0.9382	9.8969	100.2309	25.4808
2014	1.6240	3.8383	79.7590	3.3322	0.9573	9.9621	100.4191	26.0616
2015	1.7629	4.6166	81.1411	3.4236	0.9731	9.7185	101.2283	26.5534
2016	1.8025	2.3837	82.0057	3.4396	0.9894	9.6894	101.8834	27.0123
2017	1.8101	2.2792	83.8160	3.4382	1.0078	9.6971	103.1006	27.8137
2018	1.8177	−4.7360	87.2377	3.4677	1.0375	9.6636	103.0679	28.5260
2019	1.8702	−6.2041	91.0625	3.5817	1.0498	9.5895	102.7187	29.5603