ADBI Working Paper Series

MODELING THE SPATIOTEMPORAL URBAN SPILLOVER EFFECT OF HIGH-SPEED RAIL INFRASTRUCTURE DEVELOPMENT

Satoshi Miyazawa, Jetpan Wetwitoo,
and KE Seetha Ram

No. 960
May 2019

Asian Development Bank Institute

Satoshi Miyazawa is a project researcher at the Center for Spatial Information Science of the University of Tokyo and a project consultant at the Asian Development Bank Institute (ADBI). Jetpan Wetwitoo is a consultant from Creative Research and Planning Co. in Tokyo. KE Seetha Ram is senior consulting specialist for capacity building and training projects at ADBI.

Suggested citation:

Miyazawa, S., J. Wetwitoo, and KE Seetha Ram. 2019. Modeling the Spatiotemporal Urban Spillover Effect of High-Speed Rail Infrastructure Development. ADBI Working Paper 960. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/modeling-spatiotemporal-urban-spillover-effect-hsr-infrastructure-development

Please contact the authors for information about this paper.

Email: smiyazawa@adbi.org

Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

The study introduces and applies the concept of spillover effects to high-speed rail development to formulate the economic impact on increasing the regional tax revenue. The previous study covered JR-Kyushu's development of the Kyushu Shinkansen (Kagoshima Route) in Kyushu region, Japan. The construction started in 1991, and it commenced operation in 2004 and became fully operational in 2011. This study aims to extend the idea to spatiotemporal modeling and analysis by developing a spillover effect extent estimation model. We use spatiotemporal land cover, land price panel, and municipality tax revenue data to conduct a preliminary analysis to understand the regional trend. The preliminary analysis suggests that the land price and the property tax revenue increased in the municipalities around high-speed rail stations during the construction period of the Kyushu Shinkansen. However, the trend around each station varied during the operation period. Our model takes those input data and estimates the spillover extent in a 1 km grid of land cover to highlight the characteristics of the spillover effect around each station. It optimizes the extent based on the compound annual growth rate in each target phase of high-speed rail (HSR) development. The result suggests that some of the features around stations promote the spillover effect while other features may obstruct it.

Keywords: high-speed rail, urban development, spillover effect extent estimation model

JEL Classification: O18, R4, R42

Contents

1. INTRODUCTION

1.1 Background

High-speed rail (HSR) development stimulates the local and regional economy mainly due to the large-scale development project itself and the connectivity to other markets (Albalate and Bel 2012); this is especially notable in the People's Republic of China (PRC) with the rapid growth of the national economy (Yin, Bertolini, and Duan 2015). Still, one of the major challenges of high-speed rail projects is the high cost of the infrastructure development. Typically, regional governments cover the construction cost, as they will benefit from residential or corporate income tax and the increase in the tourist inflow. An infrastructure development such as a high-speed rail project creates a spillover effect on incremental tax revenues, improving the performance of private investors (ADBI 2018).

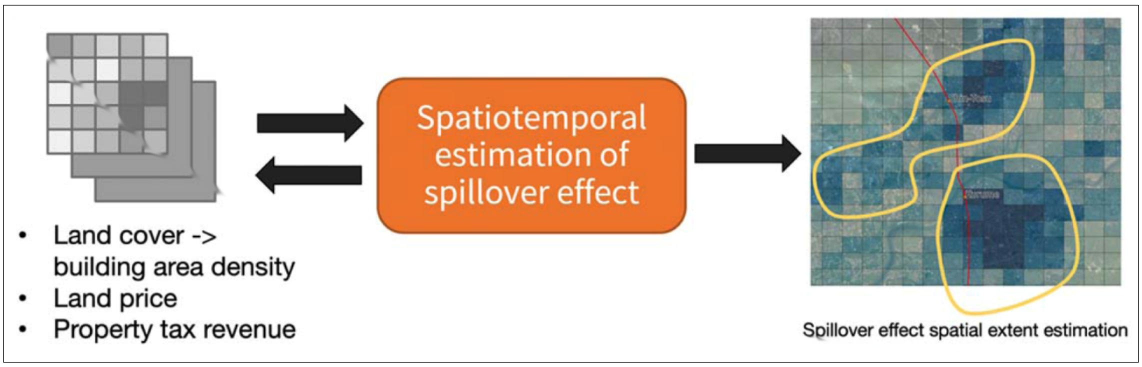
The study introduces and applies the concept of spillover effects to high-speed rail development to formulate the economic impact on increasing the regional tax revenue (Yoshino and Abidhadjaev 2017). It covers the JR-Kyushu's development of the Kyushu Shinkansen (Kagoshima Route) in Kyushu region, Japan. The construction started in 1991, and the operation commenced in 2004, becoming fully operational in 2011. According to the study, the regional tax revenue increased especially during the construction period and after the line became fully operational.

In addition, to ensure the long-term positive effect on the economy, the development needs planning intervention to assure quality-of-life improvement, such as safety and amenity in station areas for the greater transit ridership (Nakamura et al. 2017). This is partially observable in the spatiotemporal change in the land cover and land price, eventually also improving the local property tax revenue. Several studies have investigated the effect of HSR on land values (Chen and Haynes 2015; Kanasugi and Ushijima 2017), and incorporating the land cover change and property tax revenue is also important to understand the more comprehensive state of land development along HSR.

1.2 Key Idea

Figure 1 summarizes the key idea of this work. Our target case is the Kyushu Shinkansen in Kyushu region in Japan, which the Kyushu Railway Company (JR-Kyushu) in Japan has developed. This study aims to extend the idea to spatiotemporal modeling by developing a spillover effect extent estimation model. Our goal is to propose a new policy framework for boosting investment in infrastructure by tapping the spatial spillover effect on the local development and the land market.

Figure 1: Key Idea



Source: Authors' analysis.

This work has the following key characteristics that make it unique compared with previous research.

- Spatial extension of the spillover effect: this study extends the concept of the spillover effect to urban development and the land market to investigate how the effects of the development of the railway propagate spatially.

Also note that this work has the following limitations.

- The statistical evaluation is conducted only on the municipality scale instead of using grid-based modeling, which would require more extensive data processing.
- The study conducts property tax revenue estimation on the municipality level.

The rest of this paper is organized as follows. Section 2 summarizes the related work. Section 3 introduces the data, and Section 4 describes the method. In Section 5, we present the results and discuss the implications, and finally Section 6 concludes the paper.

2. RELATED WORK

2.1 Accessibility

One of the most studied effects of HSR is the impact on regional accessibility. Cao et al. (2013) investigated the accessibility impacts of planned HSR in the PRC by comparing it with other transportation modes. Zhao and Yu (2018) expanded the idea and conducted door-to-door accessibility studies on a proposed HSR route.

2.2 Local Economy

Another prominent area of study is the evaluation of the impact on the local economy. In addition to the aforementioned studies on regional tax revenue (Yoshino and Abidhadjaev 2017), there are studies on industrial location (Han et al. 2012), regional productivity (Wetwitoo and Kato 2017), property prices (Andersson, Shyr, and Fu 2010), and urban area expansion (Long, Zheng, and Song 2018). In particular, Hernández and Jiménez incorporated spatial analysis into the difference-in-difference method in Spain by using a multiple distance buffer for the empirical analysis, arguing that the growth in public revenues and the fiscal gap are most significant in municipalities located within a

5 km radius of HSR stations (Hernández and Jiménez 2014). For the potential impact of an HSR project on the land market, Kanasugi and Ushijima investigated the change in the balanced panel data of the land price (Kanasugi and Ushijima 2017).

2.3 Geospatial Data Processing

For the spatiotemporal modeling of the spillover effect, geospatial data are an essential input. Several related studies have adopted these data. For example, studies have usually created land use classification data from earth observation data, such as satellite imagery. Some studies have combined satellite imagery and auxiliary data to improve land use classifications (Seto and Kaufmann 2003; Hu and Wang 2013). They can then use the land use/cover classification data for several urban planning studies, including urban expansion (Long, Zheng, and Song 2018) and socio-economic trends (Proville, Zavala-Araiza, and Wagner 2017). Panel survey data with geospatial attributes are also useful for spatial analysis/modeling. Land price panel data and property trade data are typical examples that studies have widely adopted for modeling spatiotemporal economic impacts (Kanasugi and Ushijima 2017).

3. DATA

3.1 Infrastructure Development Timeline

The construction of the railway started in 1991. The southern part (from Shin-Yatsushiro Station to Kagoshima-chuo Station) commenced operation in 2004. The northern part (from Hakata Station to Shin-Yatsushiro Station) began operation in 2011, connecting the whole line to the existing Sanyo Shinkansen. We adopt the time frame from Yoshino and Abidhadjaev (2017) and adjust it slightly due to the limited availability of data (Table 1).

Table 1: Time Frame for the Study

Period	Preconstruction	Construction (and Operation I)	Operation I	Operation II
Years	1982–1990	1991–2003	2004–2010	2011–2013
Land cover change (from–to)	1987–1991	1991–2006	2006–2009	2009–2014
Land price change (from–to)	1987–1991	1991–2006	2006–2009	2009–2014
Tax revenue change (from–to)	1989–1991	1991–2006	2006–2009	2009–2014

Source: Authors' analysis.

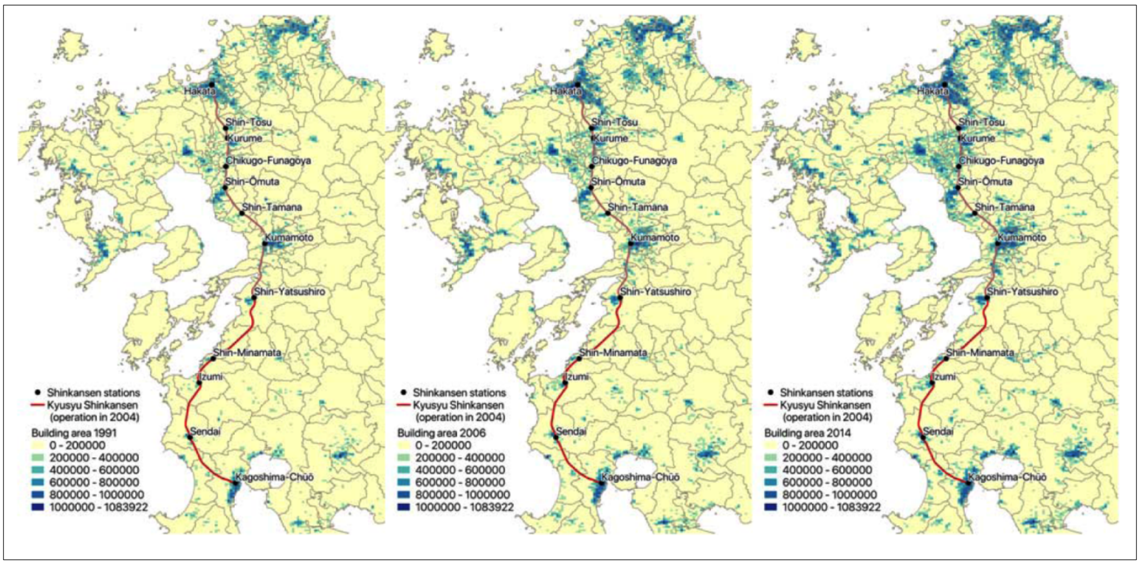
3.2 Land Cover

We assume that different land uses affect the economic impact on the area. We downloaded the land use class data from the National Land Numerical Download service [1] of the National Land Information Division, National Spatial Planning and Regional Policy Bureau, Japan.

[1] http://nlftp.mlit.go.jp/ksj-e/index.html.

The bureau has produced these data every few years (in 1976, 1987, 1991, 1997, 2006, 2009, and 2014) using multiple satellite images for each year. It is a 1 km grid-based dataset in which each grid contains the area values (in m^2) of different land cover classes (Table 2) based on manual classification.

Figure 2: Building Area Density in 1991, 2004, and 2014



Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Table 2: Land Cover Class

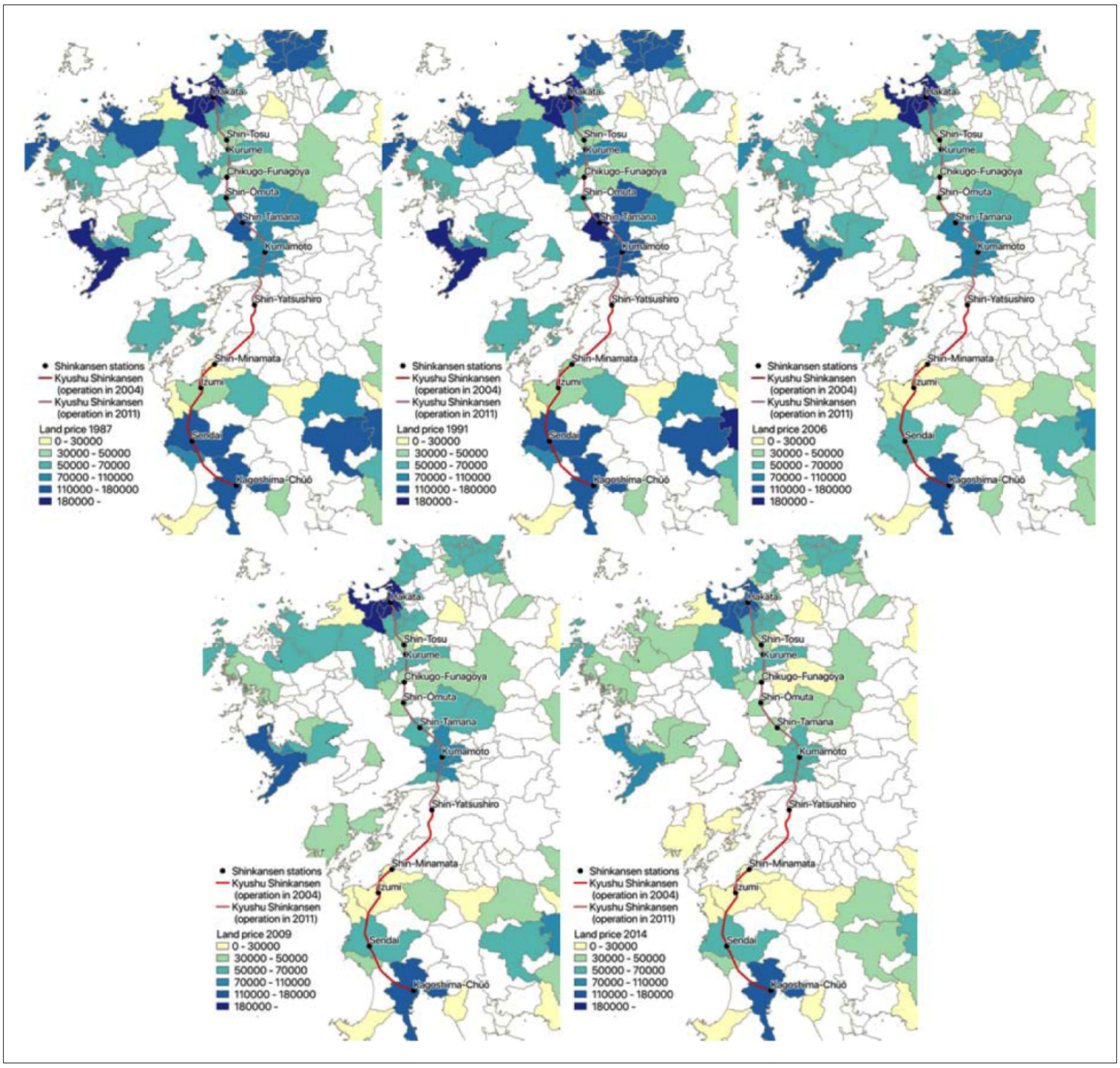
Code	Corresponding Details
1	Paddy Fields
2	Other Agricultural Land
5	Forest
6	Wasteland
7	Land for Building
9	Trunk Transportation Land
A	Other Land
B	Rivers and Lakes
E	Beach
F	Body of Seawater
G	Golf Course

Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

3.3 Land Price

As one proxy for property tax revenue, we use the publication of land price data, also from the National Land Numerical Download service. This is the annual sample panel data from the national government to regulate the property value and resulting property tax revenue for municipalities. Each year, there are new or discontinued points for the panel data. However, we only use the points available in the 2014 data and the historical values for the points.

Figure 3: Average Land Price in Each Municipality in 1987, 1991, 2006, 2009, and 2014



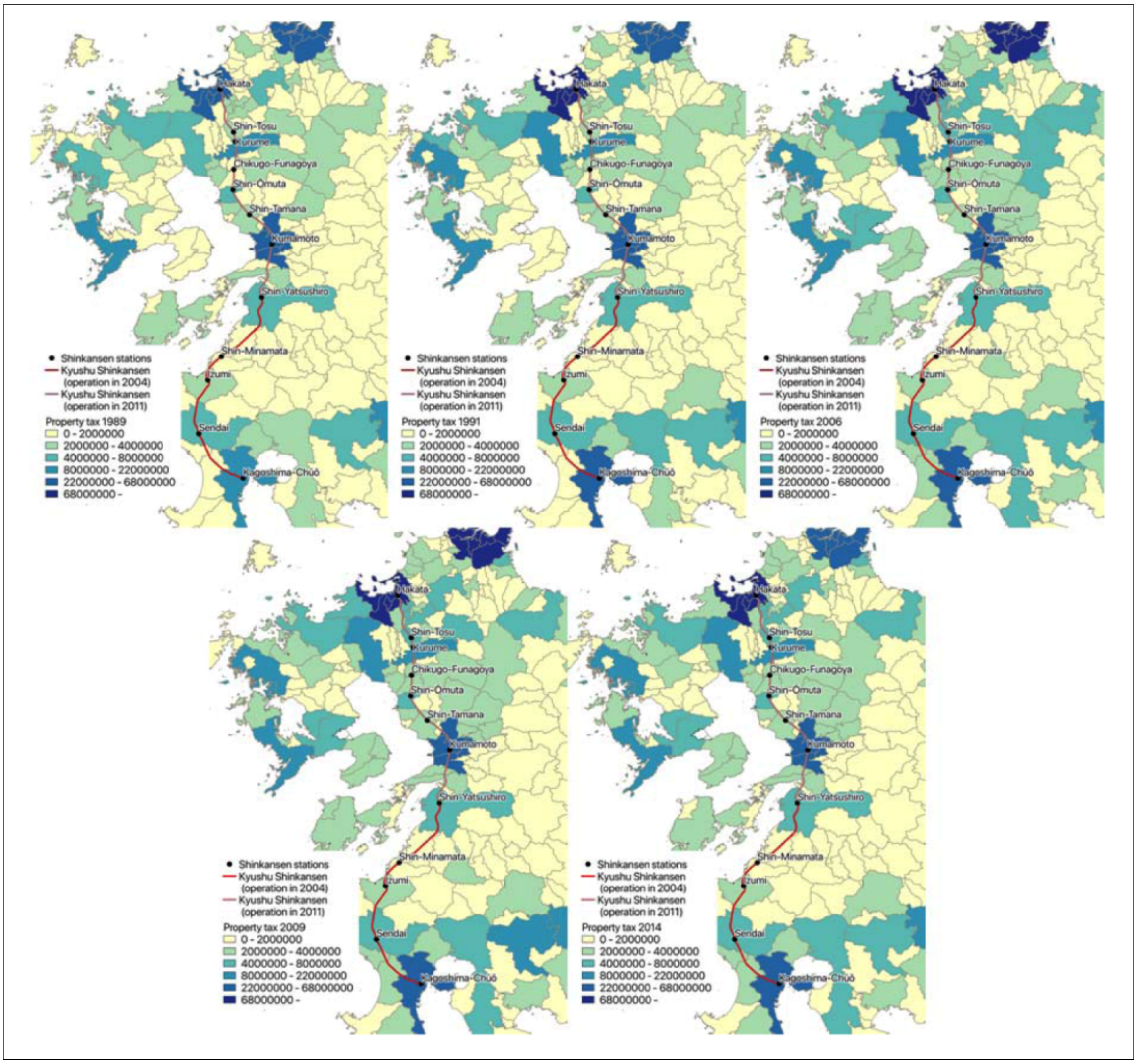
Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

3.4 Property Tax Revenue

We use the annual reporting of the property tax "settlement" revenue data of municipalities from e-Stat.[2] The settlement revenue represents the ideal value of the revenue, which excludes any delinquency or overdue payment from the previous year. Some municipalities have merged with neighboring municipalities over the years. To aggregate the tax revenues of those merged municipalities, we use the administration boundary in 2014 and perform a spatial join to summarize the revenues for the merged municipalities.

2 https://www.e-stat.go.jp/en.

Figure 4: Property Tax Revenue of Each Municipality in 1989, 1991, 2006, 2009, and 2014



Source: Ministry of Internal Affairs and Communications, Japan.

4. METHOD

4.1 Compound Annual Growth Rate

Since each time span in the time frame is different, we convert each input value into the compound annual growth rate (CAGR) using the following definition:

$$CAGR(t_1, t_2) = \left(\frac{V_{(t_2)}}{V_{(t_1)}}\right)^{\frac{1}{t_2 - t_1}} - 1 \quad (1)$$

where t_1 and t_2 are the start year and the end year, respectively. After each aggregation, we calculate the CAGR from the aggregated values.

4.2 Aggregation to the Municipality Boundary

To show the broad spatial trend, we aggregate the building density, land price, and property tax revenue to the municipality boundary. In 1987, there were 520 (including different "wards") municipalities in Kyushu region; following several mergers, there are 249 municipalities as of 2014.

4.3 Aggregation to the Station Buffer

Then we conduct a buffer analysis on the areas around each station to compare the trend of station areas. To start, we create buffers around each station and aggregate the values that intersect with the buffer. By comparing the trends, we can identify the characteristics of each station area.

4.4 Difference-in-Difference Estimation Model

To evaluate the statistical significance of the spillover, we employ the difference-in-difference (DID) method (Card and Krueger 1994). Under the parallel trend assumption, DID estimates the effect of a policy (i.e., the introduction of HSR).

We can formalize the model as follows:

$$Y_{it} = \beta_0 + \beta_1 c_i + \beta_2 t_t + \beta_3 DID_{it} + \boldsymbol{\theta\delta_{it}} + \varepsilon_{it} \quad (2)$$

where

Y_{it} = the dependent variable in region *i* in year *t*;
c_i = the treatment effect: 0 if *i* belongs to the control group and 1 if *i* belongs to the treatment group;
t_t = the time effect: 0 if *t* is before the policy introduction and 1 if *t* is after the policy introduction;
DID_{it} = the DID effect, which equals $c_i \times t_t$;
$\boldsymbol{\delta_{it}}$ = a vector of control variables in region *i* in time *t*;
$\beta, \boldsymbol{\theta}$ = unknown coefficients; and
ε_{it} = error component.

We estimate the parameters using the ordinary least square (OLS) method. The estimated coefficients ($\beta, \boldsymbol{\theta}$) indicate the effect of DID on the control variables in the model.

In this paper, we analyze the effect of the introduction of HSR in Kyushu region on the property tax revenue per area (¥/m^2) of each municipality. We also use the aforementioned building area density and land price values as the control variables.

The empirical model is as follows:

$$Y_{it} = \beta_0 + \beta_1 c_i + \beta_2 t_t + \beta_3 DID_{it} + \theta_1 BA_{it} + \theta_2 LP_{it} + \varepsilon_{it} \quad (3)$$

where

Y_{it} = the ln tax revenue in municipality *i* in year *t*;
c_i = the treatment effect: 0 if *i* belongs to the control group and 1 if *i* belongs to the treatment group;
t_t = the time effect: 0 if *t* is the beginning of the period and 1 if *t* is the end of the period in the time frame (Table 1);

DID_{it} = the DID effect, which equals $c_i \times t_t$;
BA_{it} = the ln building area density of municipality *i* in year *t*;
LP_{it} = the ln average land price of municipality *i* in year *t*;

Among 232 target municipalities, we select the treatment group based on the distance from Kyushu HSR stations, *DistHSR*. We experimentally set *DistHSR* = 5 km first. We label the municipalities located within the distance from Kyushu HSR stations as the treatment group and the other municipalities as the control group. The treatment group has several subgroups to investigate the spillover effect on particular stations (Table 3). For all of the treatment groups, the control group only includes municipalities other than those in treatment group 1.

Table 3: Treatment Groups

Name	Description	Included stations
Treatment group 1	All Kyushu HSR stations	Hakata, Shin-Tosu, Kurume, Chikugo-Funagoya, Shin-Omuta, Shin-Tamana, Kumamoto, Shin-Yatsushiro, Shin-Minamata, Izumi, and Kagoshima-Chuo
Treatment group 2	Non-terminal stations	Shin-Tosu, Kurume, Chikugo-Funagoya, Shin-Omuta, Shin-Tamana, Shin-Yatsushiro, Shin-Minamata, and Izumi
Treatment group 3	Southern part (operational in 2004)	Kumamoto, Shin-Yatsushiro, Shin-Minamata, Izumi, and Kagoshima-Chuo
Treatment group 4	Northern part (operational in 2011)	Hakata, Shin-Tosu, Kurume, Chikugo-Funagoya, Shin-Omuta, Shin-Tamana, and Kumamoto

Source: Authors' analysis.

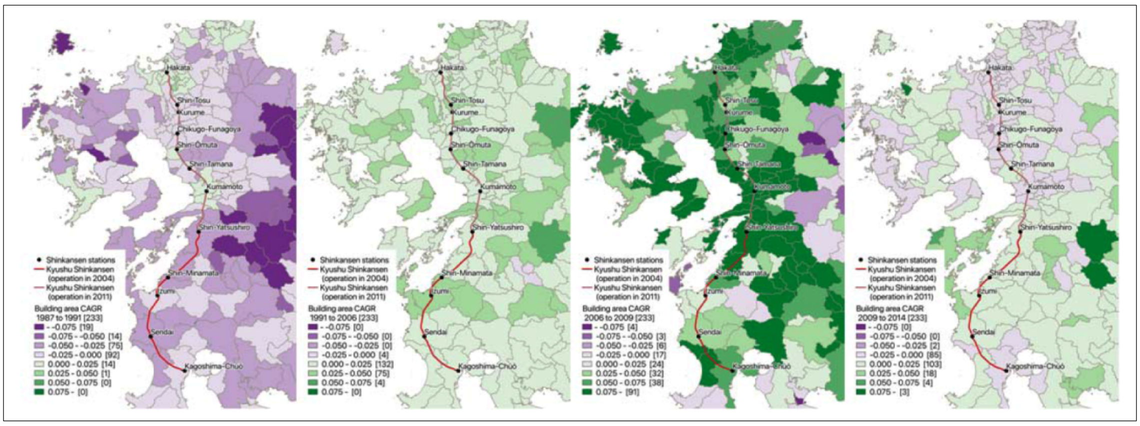
5. RESULT

5.1 Aggregation to the Municipality Boundary

5.1.1 Building Area

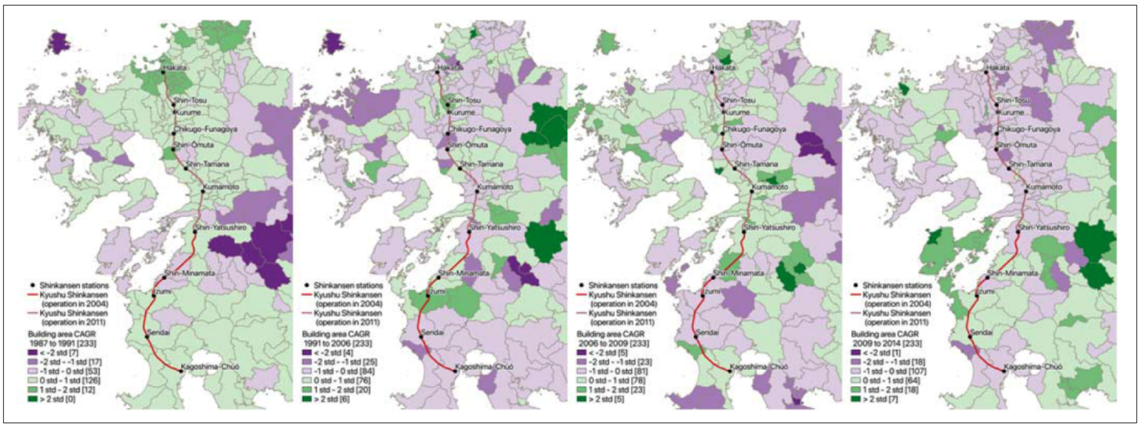
Figure 5 shows the compound annual growth rate of building area density in each phase. During the preconstruction phase, only small parts of Kyushu region experienced positive building area growth (e.g. Fukuoka and Kumamoto). During the construction and operation I phases, a larger area experienced significant growth. After the connection of Kyushu Shinkansen to larger cities, the growth around the southern part of Kyushu stayed positive. Note that, since the land cover classification involves different datasets for each year, the overall trend of the CAGR from the data might not reflect the actual change in the building area. For example, as the resolution of satellite imagery increases, physical structures become clearer, making the classification more precise. This could result in both increasing and decreasing the total area depending on the surroundings. On the other hand, as Figure 6 shows, the classification of the CAGR based on the mean and standard deviation values highlights the spatial difference. During the preconstruction phase, the CAGR of the building area around the rail was significantly higher than the average of the region. In addition, in the following phases, the CAGR of the building area around smaller stations, such as Shin-Tosu and Shin-Tamana, was significantly higher than the average.

Figure 5: Compound Annual Growth Rate of the Building Area



Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Figure 6: Compound Annual Growth Rate of the Building Area Classified Based on the Mean and Standard Deviation



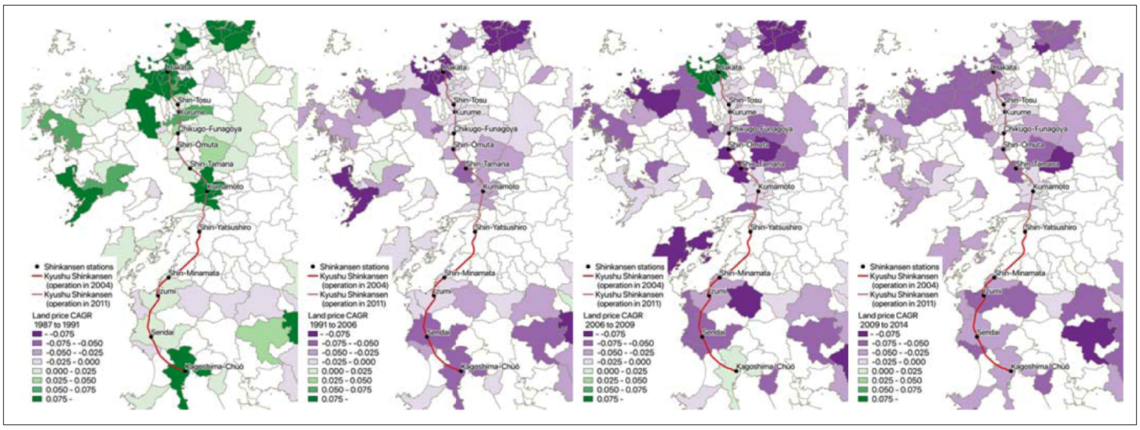
Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

5.1.2 Land Price

Figures 7 and 8 show the compound annual growth rate of the land price in each phase. The overall trend is positive in the preconstruction phase and negative in the following phases. The aggregation based on the mean value in each municipality (Figure 7) and the maximum value (Figure 8) shows trivial differences. Large cities (Fukuoka, Kumamoto, and Kagoshima) tend to have a more positive trend than the rest of the region.

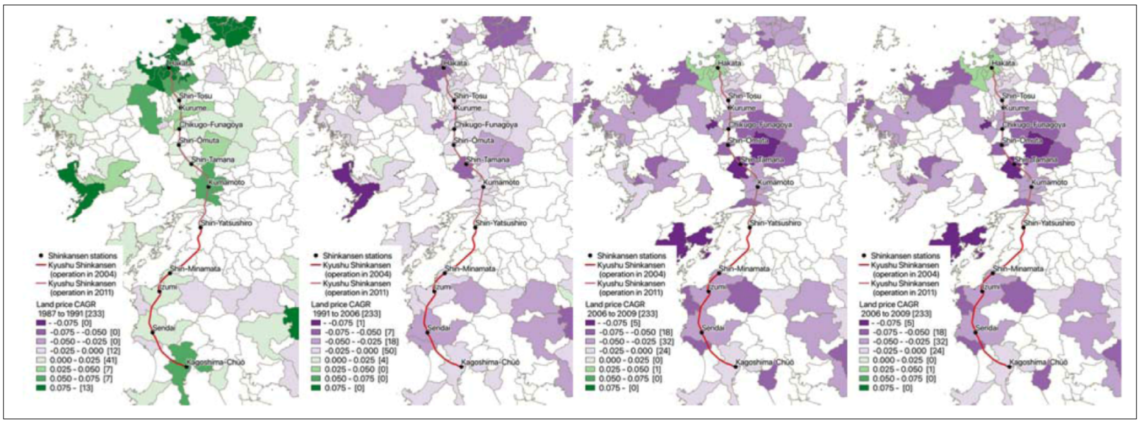
Figures 9 and 10 show the classification CAGR based on the mean and the standard deviation. Here, the figures show that the growth in smaller cities around Kyushu Shinkansen was more positive than that in some larger cities during construction and the following phases. This suggests that the construction and operation of HSR may have stimulated investment in the land market of those smaller cities.

Figure 7: Compound Annual Growth Rate of the Land Price (Max.)



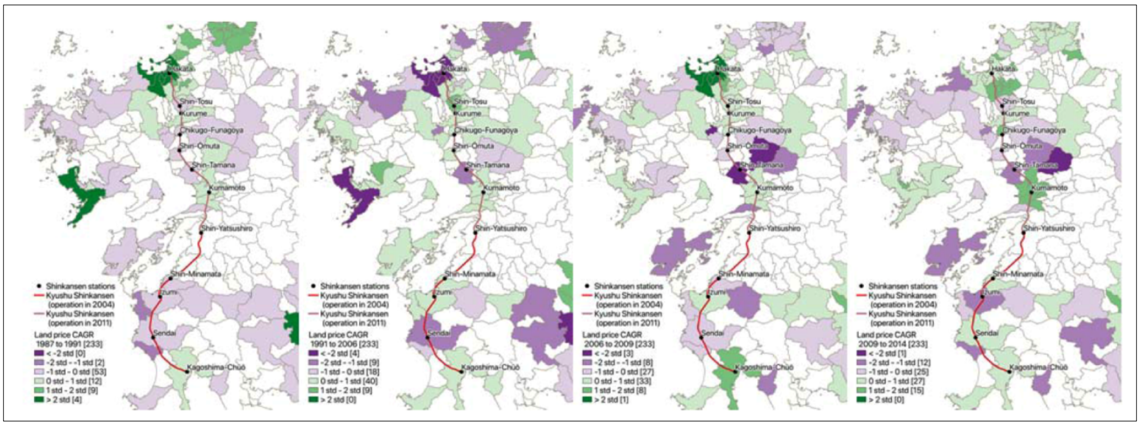
Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Figure 8: Compound Annual Growth Rate of the Land Price (Average)



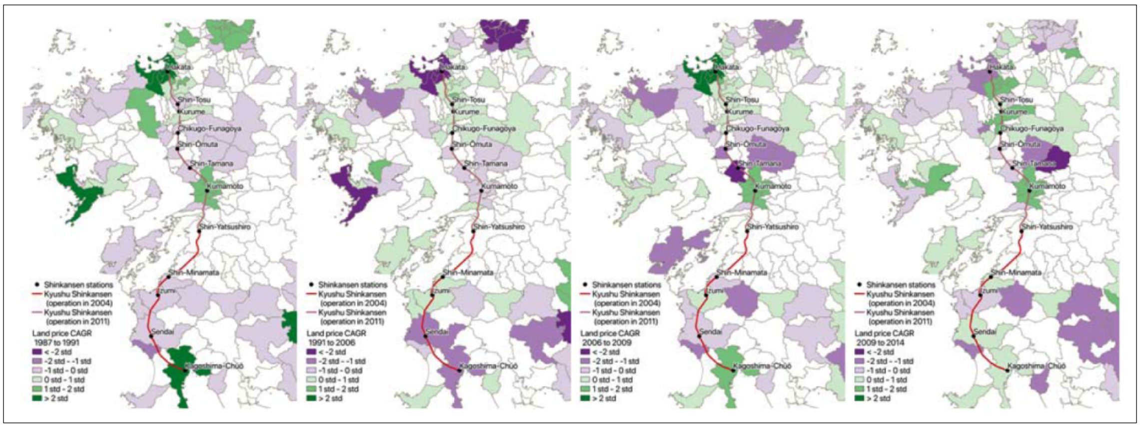
Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Figure 9: Compound Annual Growth Rate of the Land Price (Mean) Classified Based on the Mean and Standard Deviation



Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Figure 10: Compound Annual Growth Rate of the Land Price (Max.) Classified Based on the Mean and Standard Deviation

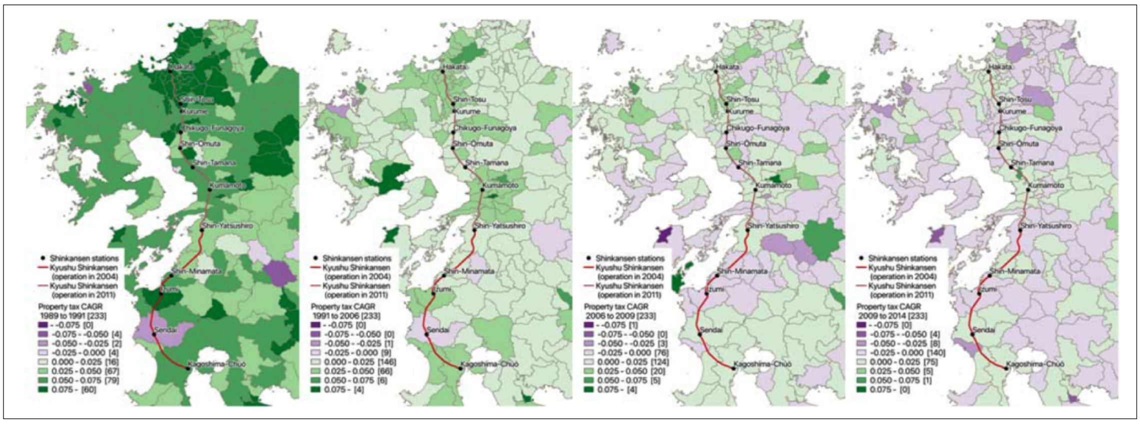


Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

5.1.3 Property Tax

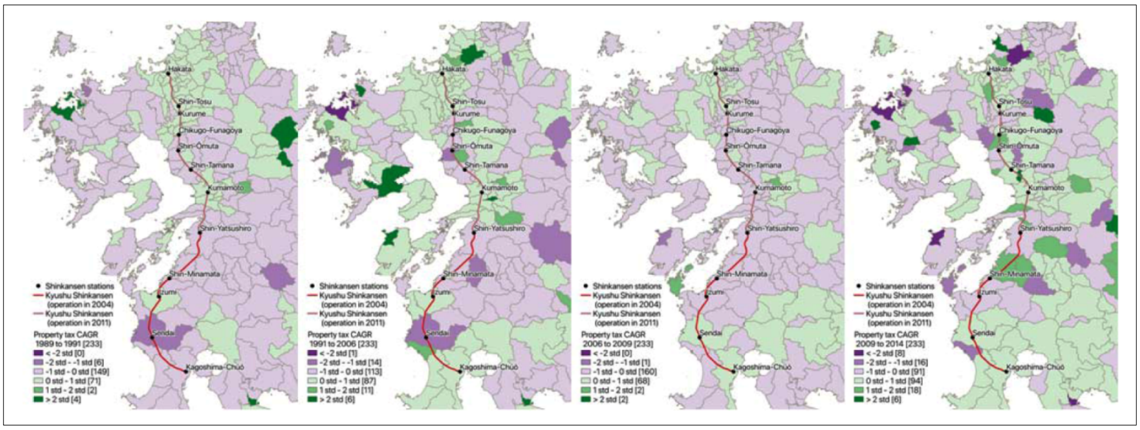
Figures 11 and 12 show the compound annual growth rate of property tax and its classification based on the mean and the standard deviation value, respectively. The overall trend is the transition from positive growth to negative growth; however, some of the municipalities maintained positive growth in recent phases. One notable feature is that, during the construction phase, most of the municipalities with the highest growth rate are those around the Kyushu Shinkansen. The significant development is observable in the same phase in Figure 5, while the negative trend apparent in Figure 7 may have contributed significantly to the positive growth in total.

Figure 11: Compound Annual Growth Rate of Property Tax



Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Figure 12: Compound Annual Growth Rate of Property Tax Classified Based on the Mean and Standard Deviation

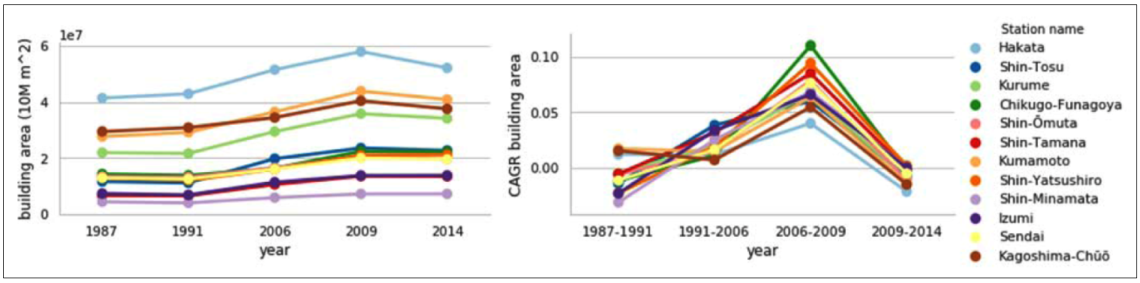


Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

5.2 Station Buffer Analysis

Figure 13 shows the aggregated building area and the compound annual growth rate (CAGR) of the building area within 5 km around each station. Large stations, such as Hakata, Kumamoto, and Kagoshima-Chuo, have more building area than other stations throughout the time period; however, the CAGR around most smaller stations (e.g. Shin-Tosu) surpassed that of the large stations during the construction phase (1992–2006) and remained higher after the operation phase.

Figure 13: Aggregated Building Area and the Compound Annual Growth Rate of the Building Area within 5 km around Each Station

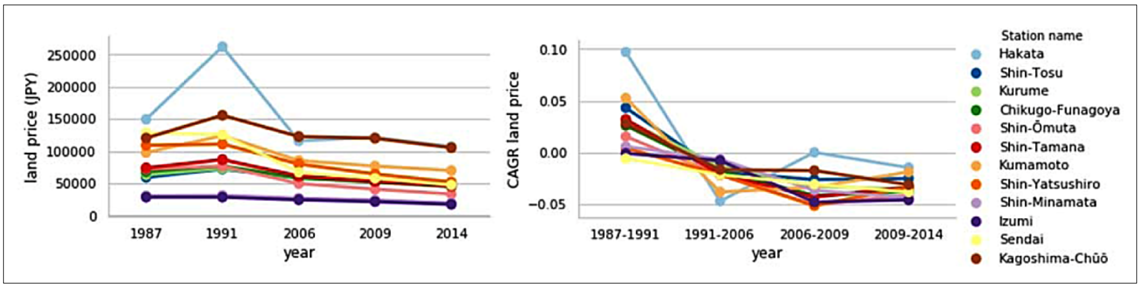


Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Figure 14 shows the aggregated land price and the compound annual growth rate of the land price within 20 km around each station. We chose 20 km as the buffer size to ensure that the buffers cover all the HSR stations. Here too the overall growth trend became negative; large cities, such as Hakata and Kumamoto, experienced a sharp dip during construction, but the long-term growth was better than that of other cities.

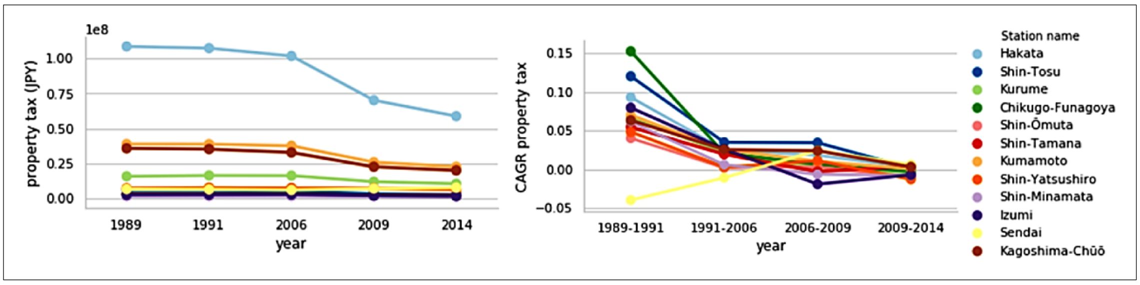
Figure 15 shows the property tax revenue and the compound annual growth rate of the property tax of the municipalities where the stations are located. Interestingly, the CAGR of the property tax revenue during the preconstruction phase varied significantly (mostly positive) but became very similar over time. From this result, it is hard to identify the biggest beneficiaries among the stations.

Figure 14: Aggregated Land Price and the Compound Annual Growth Rate of the Land Price within 20 km around Each Station



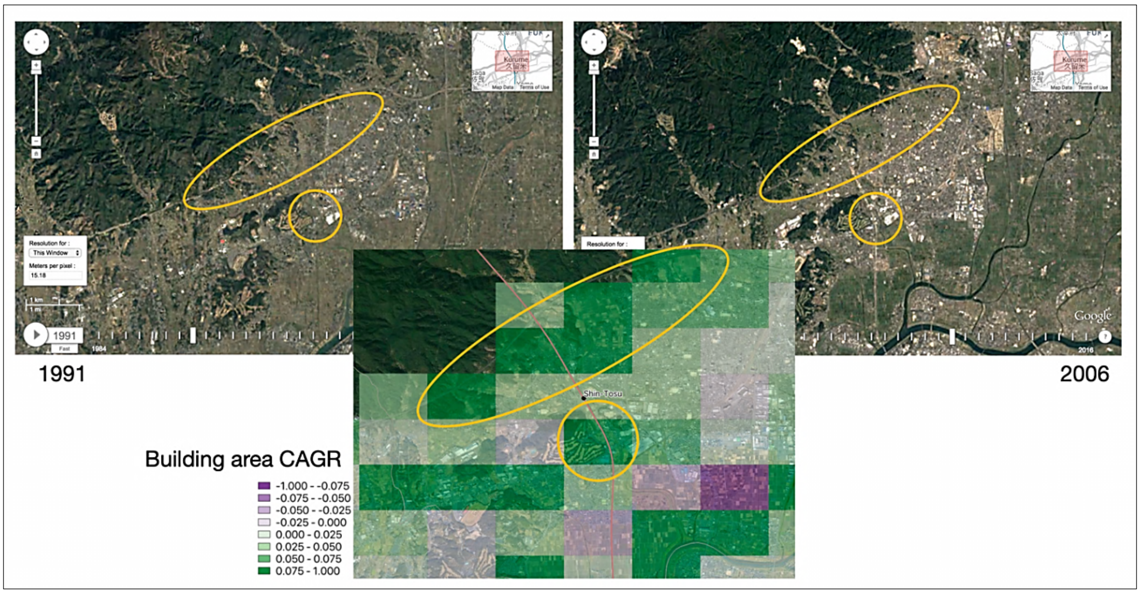
Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Figure 15: Property Tax Revenue and the Compound Annual Growth Rate of the Property Tax of the Municipalities Where Each Station is Located



Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

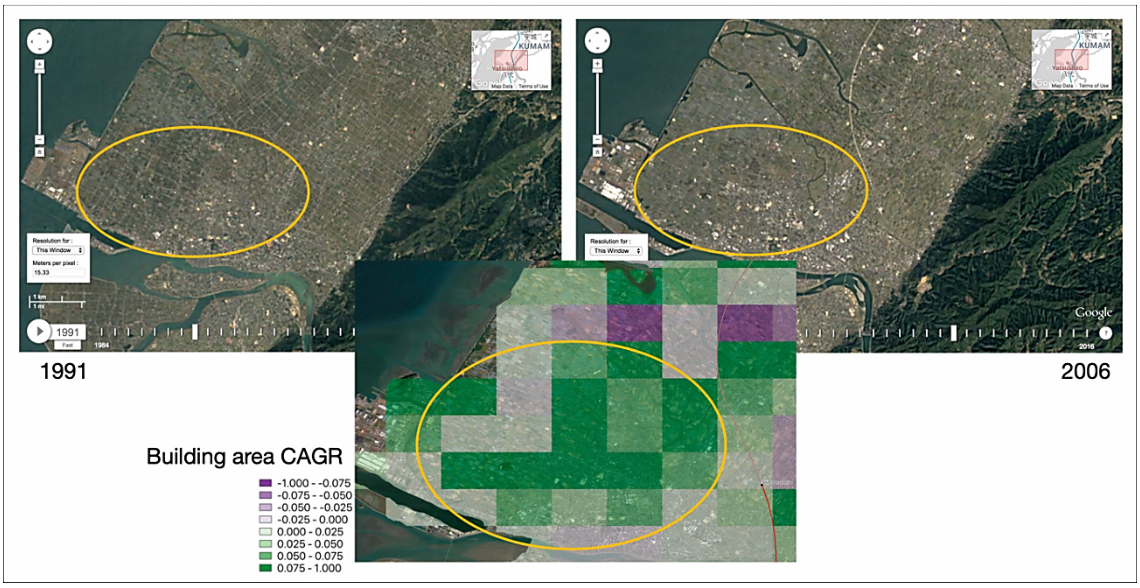
Figure 16: Building Area Compound Annual Growth Rate around Shin-Tosu Station during 1991 and 2006



Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

Figures 16 and 17 show the building area CAGR in a 1 km grid and historical satellite imagery from Google Earth Engine Time Lapse.[3] The yellow shapes indicate the same locations. Some significant development can be observed in areas with a high building area CAGR during the period. It suggests the potential validity of the method, even though more extensive statistical modeling would be necessary for comprehensive evaluation.

Figure 17: Building Area Compound Annual Growth Rate around Shin-Yatsushiro Station during 1991 and 2006



Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan.

5.3 Difference-in-Difference Estimation Model

Tables 4–7 summarize the result of the DID model. The correlation with BA_{it} and LP_{it} is less than 0.5 for all the models. Overall, the adjusted R^2 is consistently high, with high significance of the building area and land price values for all the groups. Still, the DID effect is not significant in any model. We also test different distances from Kyushu HSR stations *DistHSR* from 5 km to 50 km, but the statistical significance of the DID effect never changes. This implies that the spillover effect that the previous analyses suggest is not statistically significant in the whole Kyushu region or is even a smaller scale effect than the municipality scale (Figures 16 and 17).

[3] https://earthengine.google.com/timelapse/.

Table 4: Estimation Results of the DID Model for Treatment Group 1

	Preconstruction			Construction		
Period	**Estimate**	**t-stat.**	**Sig.**	**Estimate**	**t-stat.**	**Sig.**
Const.	–3.070	–7.963	***	–3.064	–7.510	***
c	0.096	1.695	*	0.075	1.385	
t	0.187	2.518	**	0.056	0.763	
DID	–0.018	–0.241		–0.029	–0.386	
BA	1.246	28.401	***	1.251	30.402	***
LP	0.167	5.805	***	0.183	6.026	***
Adj. R^2		0.889			0.905	
N			156			
	Operation I			**Operation II**		
Period	**Estimate**	**t-stat.**	**Sig.**	**Estimate**	**t-stat.**	**Sig.**
Const.	–3.642	–8.889	***	–4.077	–10.767	***
c	0.039	0.808		0.037	0.834	
t	–0.203	–3.220	**	0.022	0.373	
DID	0.000	0.006		0.013	0.219	
BA	1.263	35.338	***	1.264	37.609	***
LP	0.243	7.347	***	0.264	8.498	***
Adj. R^2		0.928			0.938	
N			156			

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

Source: Authors.

Table 5: Estimation Results of the DID Model for Treatment Group 2

	Preconstruction			Construction		
Period	**Estimate**	**t-stat.**	**Sig.**	**Estimate**	**t-stat.**	**Sig.**
Const.	–3.032	–7.833	***	–3.034	–7.391	***
c	0.083	1.290		0.078	1.276	
t	0.181	2.454	*	0.065	0.873	
DID	–0.004	–0.056		–0.063	–0.743	
BA	1.259	0.043	***	1.262	31.503	***
LP	0.167	5.771	***	0.1835	5.985	***
Adj. R^2		0.888			0.904	
N			144			
	Operation I			**Operation II**		
Period	**Estimate**	**t-stat.**	**Sig.**	**Estimate**	**t-stat.**	**Sig.**
Const.	–3.599	–8.692	***	–4.053	–10.566	***
c	0.014	0.251		0.021	0.422	
t	–0.208	–3.320	***	0.025	0.665	
DID	0.007	0.096		0.007	0.104	
BA	1.273	36.40	***	1.273	38.562	***
LP	0.242	7.254	***	0.265	8.420	***
Adj. R^2		0.927			0.937	
N			144			

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

Source: Authors.

Table 6: Estimation Results of the DID Model for Treatment Group 3

	Preconstruction			Construction		
Period	**Estimate**	**t-stat.**	**Sig.**	**Estimate**	**t-stat.**	**Sig.**
Const.	–2.940	–6.639	***	–2.968	–6.308	***
c	0.283	1.441		0.229	1.204	
t	0.189	2.446		0.053	0.675	
DID	–0.048	–0.174		–0.148	–0.551	
BA	1.256	24.291	***	1.250	25.716	***
LP	0.157	4.865	***	0.175	5.058	***
Adj. R^2	0.862			0.880		
N	130					
	Operation I			**Operation II**		
Period	**Estimate**	**t-stat.**	**Sig.**	**Estimate**	**t-stat.**	**Sig.**
Const.	–3.470	–7.404	***	–3.832	–9.023	***
c	0.065	0.395		0.096	0.648	
t	–0.205	–3.132	**	0.017	0.296	
DID	0.037	0.160		–0.005	–0.025	
BA	1.262	30.281	***	1.270	33.260	***
LP	0.227	6.071	***	0.243	7.042	***
Adj. R^2	0.911			0.928		
N	130					

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

Source: Authors.

Table 7: Estimation Results of the DID Model for Treatment Group 4

	Preconstruction			Construction		
Period	**Estimate**	**t-stat.**	**Sig.**	**Estimate**	**t-stat.**	**Sig.**
Const.	–3.060	–7.532	***	–3.127	–7.276	***
c	0.143	1.102		0.112	0.894	
t	0.188	2.514	*	0.058	0.771	
DID	–0.040	–0.235		–0.016	–0.096	
BA	1.267	26.738	***	1.258	28.405	***
LP	0.170	5.676	***	0.190	5.978	***
Adj. R^2	0.891			0.906		
N	148					
	Operation I			**Operation II**		
Period	**Estimate**	**t-stat.**	**Sig.**	**Estimate**	**t-stat.**	**Sig.**
Const.	–3.733	–8.596	***	–4.157	–10.313	***
c	0.084	0.766		0.061	0.601	
t	–0.202	–3.163	**	0.023	0.394	
DID	–0.017	–0.118		0.037	0.277	
BA	1.263	32.691	***	1.265	34.731	***
LP	0.251	7.187	***	0.272	8.236	***
Adj. R^2	0.928			0.938		
N	148					

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

Source: Authors.

6. CONCLUSION

In this paper, we introduced the spatial extension of the spillover model and demonstrated the potential contribution of our method to spatial analyses. This study extends the concept of the spillover effect to urban development and the land market to investigate how the effects of the development of the railway propagate spatially. The spatial analysis shows the regional trend of Kyushu and highlights some significant small-scale trends around HSR stations. To sum up, the building area around smaller HSR stations has increased significantly compared with larger cities and areas without HSR stations. The land price has decreased regionally, except in a few large cities, such as Fukuoka and Kagoshima. The growth in property tax revenue in most municipalities with HSR stations has stayed positive, although the regional trend is turning negative. The difference-in-difference model results show no statistical significance of the DID effect. Future work requires the application of a clustering algorithm to 1 km grid data to highlight the smaller-scale differences in the spatiotemporal spillover effect. It is also important to evaluate the scalability of the model with a more globally available dataset.

REFERENCES

ADBI. 2018. *Financing Infrastructure in Asia and the Pacific: Capturing Impacts and New Sources*. Asian Development Bank Institute.

Albalate, Daniel and Bel, Germa. 2012. "High-Speed Rail: Lessons for Policy Makers from Experiences Abroad." *Public Administration Review* 72 (3): 336–49. https://doi.org/10.1111/j.1540-6210.2011.02492.x.

Andersson, David Emanuel, Oliver F. Shyr, and Johnson Fu. 2010. "Does High-Speed Rail Accessibility Influence Residential Property Prices? Hedonic Estimates from Southern [Taipei,China]." *Journal of Transport Geography* 18 (1): 166–74. https://doi.org/10.1016/j.jtrangeo.2008.10.012.

Cao, Jing, Xiaoyue Cathy Liu, Yinhai Wang, and Qingquan Li. 2013. "Accessibility Impacts of China's High-Speed Rail Network." *Journal of Transport Geography* 28: 12–21. https://doi.org/10.1016/j.jtrangeo.2012.10.008.

Card, David., and Krueger, Alan B. 1994. "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania." *American Economic Review* 84 (4): 772–93.

Chen, Zhenhua., and Haynes, Kingsley E. 2015. "Impact of High Speed Rail on Housing Values: An Observation from the Beijing-Shanghai Line." *Journal of Transport Geography* 43: 91–100. https://doi.org/10.1016/j.jtrangeo.2015.01.012.

Han, Ji. Hayashi, Yoshitsugu. Jia, Peng. and Yuan, Quan. 2012. "Economic Effect of High-Speed Rail: Empirical Analysis of Shinkansen's Impact on Industrial Location." *Journal of Transportation Engineering* 138 (12): 1551–57. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000467.

Hernández, Aday., and Jiménez, Juan Luis. 2014. "Does High-Speed Rail Generate Spillovers on Local Budgets?" *Transport Policy* 35: 211–19. https://doi.org/10.1016/j.tranpol.2014.06.003.

Hu, Shougeng. and Wang, Le. (2013). "Automated Urban Land-Use Classification with Remote Sensing." *International Journal of Remote Sensing* 34 (3): 790–803. https://doi.org/10.1080/01431161.2012.714510.

Kanasugi, Hiroshi., and Ushijima, Koichi. 2017. "The Impact of a High-Speed Railway on Residential Land Prices." *Papers in Regional Science* 596: 1–38. https://doi.org/10.1111/pirs.12293.

Long, Fenjie, Zheng, Longfei. and Song, Zhida. 2018. "High-Speed Rail and Urban Expansion: An Empirical Study Using a Time Series of Nighttime Light Satellite Data in China." *Journal of Transport Geography* 72 (June): 106–18. https://doi.org/10.1016/j.jtrangeo.2018.08.011.

Nakamura, Kakuki. Morita, Hiroyoshi. Vichiensan, Varameth. Togawa, Takuya. and Hayashi, Yoshitsugu. 2017. "Comparative Analysis of QOL in Station Areas between Cities at Different Development Stages, Bangkok and Nagoya." *Transportation Research Procedia* 25: 3192–206. https://doi.org/10.1016/j.trpro.2017.05.361.

Proville, Jeremy. Zavala-Araiza, Daniel. and Wagner, Gernot. 2017. "Night-Time Lights: A Global, Long Term Look at Links to Socio-Economic Trends." *PLoS ONE* 12 (3): 1–12. https://doi.org/10.1371/journal.pone.0174610.

Seto, Karen C. and Kaufmann, Robert K. 2003. "Modeling the Drivers of Urban Land Use Change in the Pearl River Delta, China: Integrating Remote Sensing with Socioeconomic Data." *Land Economics* 79 (1): 106–21. Retrieved from http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?db=pubmed&cmd=Retrieve&dopt=AbstractPlus&list_uids=2413477376606001905related:8doKCuNkfiEJ.

Wetwitoo, Jetpan, and Kato, Hironori. 2017. "High-Speed Rail and Regional Economic Productivity through Agglomeration and Network Externality: A Case Study of Inter-Regional Transportation in Japan." *Case Studies on Transport Policy* 5 (4): 549–59. https://doi.org/10.1016/j.cstp.2017.10.008.

Yin, Ming. Bertolini, Luca. and Duan, Jin. 2015. "The Effects of the High-Speed Railway on Urban Development: International Experience and Potential Implications for China." *Progress in Planning* 98 (2): 1–52. https://doi.org/10.1016/j.progress.2013.11.001.

Yoshino, Naoyuki. and Abidhadjaev, Umid. 2017. "Impact of Infrastructure on Tax Revenue: Case Study of High-Speed Train in Japan." *Journal of Infrastructure, Policy and Development* 1 (2): 1–20. https://doi.org/10.24294/jipd.v1i2.69.

Zhao, Yun. and Yu, Hongbo. 2018. "A Door-to-Door Travel Time Approach for Evaluating Modal Competition of Intercity Travel: A Focus on the Proposed Dallas-Houston HSR Route." *Journal of Transport Geography* 72 (August 2018: 13–22. https://doi.org/10.1016/j.jtrangeo.2018.07.008.