Appendix

A. Estimation of distance-decay parameters for different transportation modes

Travel time decay parameters (β in equation (1)) for road and railroad transportation are estimated as in equation (A1), an equivalent of the gravity-type equation form in (A2)

$$lnOD_{ij} = \alpha_i lnM_i + \alpha_j lnM_j - \beta T_{ij} \tag{A1}$$

$M_{i(j)}$: Population of zone i (j)

OD_{ij} : The number of travelers between zone i and zone j

$$OD_{ij} = M_i^{\alpha_i} M_j^{\alpha_j} \exp(T_{ij})^{-\beta} \tag{A2}$$

To compare the strength of spatial interaction against travel time by transportation mode, the equation (A1) is estimated for different modes of transportation. Inter-zone travel demand (OD_{ij}) information is obtained from inter-zone O-D travel matrixes distinguished by the mode of transportation, and travel time is driven by the operation of shortest route algorithm in GIS using national road and railroad network data.

The estimation results in Table A1 shows that trip demand using road is more sensitive to travel time compared to railroads. The likelihood of interaction between regions within a 45-minute distance decreases by half for road users, whereas decay of 50% is generated between regions within a 90-minute distance for those who mainly use railroad transport. The degree of decay is almost indifferent over a 300-minute distance for the case of road transportation, implying that road transportation is barely used for travel of more than a five-hour distance. On the other hand, time decay exists even at more than a seven-hour distance in railroad transportation. These figures suggest that the likelihood of road travel is more time-sensitive and railroad transportation is preferred by intermediate- or long-distance travelers. It is notable, however, since our estimates for spatial decay are based on the quantity of passenger travel, not a freight travel. Given that spatial decay in human interaction-related spatial spillovers is relatively strong (Ahlfeldt and Feddersen, 2017), the relative size of travel time decay for road and railroad transportation might be reversed if we estimate them using freight travel data.

Compared to Ahlfeldt & Feddersen (2017) showing that the strength of spillovers cult in half in about 30 minutes and diminishes to around 1% in 200 minutes and other studies finding even higher rate of spatial decay (for example, Ahlfeldt et al., 2015; Ahlfeldt and Wendland, 2013), much lower spatial decay in this study seems to attribute to 1) difference in spatial scope (our spatial coverage is whole nation), and 2) difference in the subjective of the decay (number of travelers is dependent variable in our spatial decay function).

Table A1 Estimation results of decay parameter for road and railroad transportation

		Road	Railroad
Estimates	α_i	0.347^{***} (0.004)	0.160^{***} (0.007)
	α_j	0.178^{***} (0.004)	0.154^{***} (0.006)
	β	0.017^{***} (0.000)	0.009^{***} (0.000)
Adjusted R-Square		0.879	0.345
Number of O-D pairs observed		51,706	20,473

***: statistically significant at 1% level

B. Estimation result of production function for manufacturing sectors

Table B1 Estimation result of production function for manufacturing sectors

Variable	Estimate	S.E.	Variable	Estimate	S.E.
lnL	0.813^{***}	0.008	lnPop	0.029	0.023
lnK	0.187^{***}	0.008	lnPop*lnRoad	-0.004	0.013
$(\ln L)^2$	0.109^{***}	0.002	lnPop*lnRail	-0.029^{***}	0.009
$(\ln K)^2$	0.109^{***}	0.002	Region	-0.061^{***}	0.019
lnL*lnK	-0.109^{***}	0.002	Intercept	2.215^{***}	0.116
lnRoad	0.366^{***}	0.128	Restriction 1	1210.904^{***}	224.4
lnRail	-0.101^{*}	0.060	Restriction 2	3836.238^{**}	1902.9
lnRoad*lnRail	0.066^{**}	0.034	Restriction 3	9627.061^{***}	2424.3
$(\ln Road)^2$	-0.068^{**}	0.034	Adj. r-square	0.919	
$(\ln Rail)^2$	0.016	0.018	Sample size	2,108	

C. Comparison of the CGE simulation result with observed data

To convince the validity of our CGE model, we compare the result of CGE simulation with observed data for the GRP growth rate. We take two different approach to compare our analysis outcome with actual data. First, we check growth rates of Gross Regional Product (GRP) in 2016 (the latest year of data availability) published by the Statistics Korea (http://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1YL20571&conn_path=I3), where the growth rate is calculated as:

$$\frac{GRP_{2016} - GRP_{2015}}{GRP_{2015}} \times 100$$

As shown in the Table C1, the observed GRP growth rate in 2016 (column B) is positively correlated (Pearson's r=0.588) with simulated GRP growth rate in our CGE model (column A).

Table C1 Comparison of the GRP growth rate (%) simulated using the CGE model and observed in 2016 (without/with control of the growth rate of labor and capital)

		A. CGE simulation (simulation option 1: assuming immobile factor mobility)	B. Observed data (without control of labor and capital growth rate)	C. Observed data (with control of labor and capital growth rate)
Capital area	Seoul	0.005	2.4	-0.029
	Inchon	0.014	3.6	-0.028
	Kyunggi	0.084	5.1	-0.011
Central area	Daejon	0.001	3.3	-0.022
	Chungbuk	0.033	6.4	0.008
	Chungnam	0.052	4.0	-0.016
Southwest area	Kwangju	-0.02	0.8	-0.045
	Jeonbuk	-0.001	0.6	-0.055
	Jeonnam	-0.024	2.6	-0.031
Southeast area	Daegu	-0.005	-0.3	-0.058
	Kyungbuk	0.006	2.5	-0.032
	Busan	-0.004	1.5	-0.040
	Ulsan	-0.053	0.3	-0.055
	Kyungnam	-0.003	0.2	-0.055
Mountain area	Kangwon	0.003	2.8	-0.031
Island	Jeju	0.002	7.3	-0.029
Correlation with CGE simulation results (Pearson correlation coefficient)			0.588 (p<0.001)	0.693(p<0.001)

However, there might be a possibility that the regional variation in the observed GRP growth rate could be dependent on the regional difference in the labor and capital growth. So, to avoid the problem, we estimated a GRP growth equation to control growth rates of the labor and capital inputs with dummy variables for post period of HSR completion and localities as follow:

$$\frac{\Delta GRP_{rt}}{GRP_{rt}} = \alpha_0 + \alpha_1 \frac{\Delta L_{rt}}{L_{rt}} + \alpha_2 \frac{\Delta K_{rt}}{K_{rt}} + \alpha_3 \mathrm{T}_{2016} + \sum_{r=1}^{15} \alpha_{4r} Region_r + \sum_{r=1}^{15} \alpha_{5r} \mathrm{T}_{2016} Region_r \quad \text{(eq. C1)}$$

$\frac{\Delta GRP_{rt}}{GRP_{rt}}$: GRP growth rate of region r in year t (t: 2004~1016)

$\frac{\Delta L_{rt}}{L_{rt}}$: Labor (employment) growth rate of region r in year t

$\frac{\Delta K_{rt}}{K_{rt}}$: Capital growth rate of region r in year t

T_{2016}: Dummy variable indicating year 2016 (post period of HSR completion)

$Region$: Dummy variable indicating region r

$\mathrm{T}_{2016} Region_r$: Dummy variable indicating region r in year 2016 (post period of HSR completion)

Table C2 shows the estimation result. The column A indicates that the GRP growth is significantly associated with the change in labor endowment of the region. Taking into account the growth impact of the factor endowments and the time fixed effect, we could find that the regional variation in GRP growth rates after the HSR completion (represented by those observed in 2016) is equal to the sum of α_{4r} (regional average GRP growth rate during 2004~2016) and α_{5r} (difference in the GRP growth rates in 2016 from those in previous years). These regional values for $\alpha_{4r} + \alpha_{5r}$ are reported in column C of table C1. Compared to the observed GRP growth rate in 2016 published by the Statistics Korea (column B), the values in the column C is smaller and mostly negative. This can be explained by that the GRP growth rate in 2016 is 0.5% lower than the average growth rates in previous years (as shown in column B of table R2). The Pearson correlation coefficient in this case, 0.693, is higher than that between the simulated GRP growth rate and the observed GRP growth rate without controlling of variables. Such high correlation between simulated and observed GRP growth rate seems to support the validity of our CGE model.

Table C2 Estimation results of equation C1

	A. Full model	B. Restricted model (dummy variables for regional variation are omitted)
Labor growth rate	0.383*** (0.121)	0.533*** (0.109)
Capital growth rate	0.003 (0.003)	0.002 (0.003)
Dummy(year=2016)	0.018 (0.023)	-0.005* (0.003)
Seoul	-0.014 (0.009)	-
Inchon	-0.016* (0.009)	-
Kyunggi	0.001 (0.009)	-
Daejon	-0.021* (0.009)	-
Chungbuk	0.003 (0.009)	-
Chungnam	0.018* (0.009)	-
Kwangju	-0.012 (0.009)	-
Jeonbuk	-0.016 (0.009)	-
Jeonnam	-0.014 (0.009)	-
Daegu	-0.013 (0.009)	-
Kyungbuk	-0.006 (0.009)	-
Busan	-0.016* (0.009)	-
Ulsan	-0.017* (0.009)	-
Kyungnam	-0.006 (0.009)	-
Kangwon	-0.014 (0.009)	-
Dummy(year=2016) * Seoul	-0.015 (0.032)	-
Dummy(year=2016) * Inchon	-0.012 (0.032)	-
Dummy(year=2016) * Kyunggi	-0.012 (0.032)	-
Dummy(year=2016) * Daejon	-0.001 (0.033)	-
Dummy(year=2016) * Chungbuk	0.006 (0.033)	-
Dummy(year=2016) * Chungnam	-0.033 (0.032)	-
Dummy(year=2016) * Kwangju	-0.033 (0.033)	-
Dummy(year=2016) * Jeonbuk	-0.039 (0.032)	-
Dummy(year=2016) * Jeonnam	-0.016 (0.032)	-
Dummy(year=2016) * Daegu	-0.045 (0.032)	-
Dummy(year=2016) * Kyungbuk	-0.026 (0.032)	-
Dummy(year=2016) * Busan	-0.024 (0.032)	-
Dummy(year=2016) * Ulsan	-0.039 (0.032)	-
Dummy(year=2016) * Kyungnam	-0.049 (0.032)	-
Dummy(year=2016) * Kangwon	-0.017 (0.032)	-
Intercept	0.038 (0.007)	0.029*** (0.002)
Adj. R-squared	0.169	0.102
Number of observations	192	192