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Regional diffusion and adoption effects on HSR demand expansion

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Abstract

High Speed Railway (HSR) has been suggested as one sustainable alternative for acquiring regional and nationwide mobility. In order to maintain the sustainability of HSR also within changing socioeconomic structures, it is important to secure its long-term demand. Therefore this study considered the diffusion theory which explains technology adoption in the marketing area, as a basis for explaining HSR ridership increasing by year. Our target area for study is Taiwan High Speed Rail (THSR). By using the monthly ridership data of THSR between 2007 and 2015, we calculated yearly Adoption Effects which describes the spread of THSR among new users. We consider this effect to be a key element to secure long-term demand. Moreover this study demonstrated that city heterogeneity such as social, economic and geographical characteristics influence the Adoption Effect. Based on our findings, we conclude that specifically improving accessibility should be considered as a policy measure to help stabilizing long-term demand especially in an aging society.

Keywords: High Speed Rail, Taiwan, Diffusion theory, Heterogeneity, Demand adoption

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1. Introduction

As interest in high-speed rail (HSR) rises around the world its network is rapidly expanding across continents. HSR is currently in more than 20 countries in operation (including the UK, France, Germany, Belgium, Spain, Italy, Turkey, Japan, China, Korea, and Taiwan). The predicted demand before construction is often overestimated though compared to the observed HSR ridership in particular in the first years of operation as discussed in Li et al (2016) with Taiwan data and Demizu et al (2017) with data from Tohoku, Japan. They argued this could be the lack of sufficient consideration regarding the time people require adapting to new transportation systems. In the case of the Northeast Japan Shinkansen extension project from Hachinohe (Aomori) to Shin-Aomori (Aomori) which started operation in 2010, the transportation density was 8,300 {(rail passenger-km per day)/rail km-operated} in the initial year but it has grown to 8,800 in 2011 and it reached 9,000 one year later (JR, 2016). To achieve a stable, high demand within a short time period after construction is an important issue though for sustainable HSR planning and its operation.

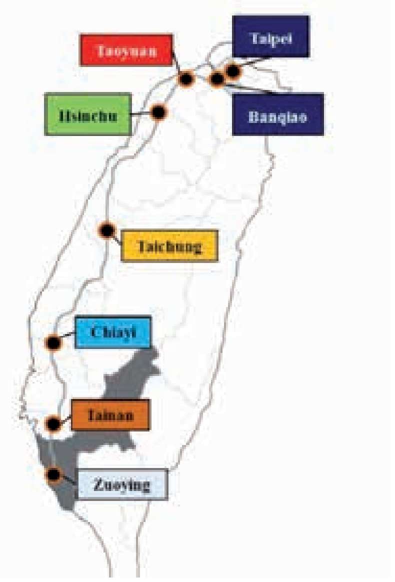

Fig. 1 THSR route and stations

In order to investigate the pure impact of a single HSR project for the country and passenger's travel behavior, we take Taiwan as a case study area. THSR (Taiwan high speed rail) connects the two largest metropolitan areas, Taipei and Kaohsiung, within a travel time of about 90 minutes. The THSR operation between Banqiao (Taipei) and Zuoying (Kaohsiung) started in January 2007. Subsequently, it extended to Taipei Station in central Taipei two months later. The target period of our research is from March 2007 to April 2015. Within this time period no further stations were opened. The eight HSR stations that are operated in this period are shown in Figure 1.

Table 1. Information of city with THSR station

No.	Name	City scale	Distance from capital, Taipei (km)	Travel Time from Taipei Sta. (min)	Population(thousands)		
					2007	2015	Annual Growth Rate
1	Taipei/ Banqiao	L	0	0	6,402	6,672	0.52%
2	Taoyuan	S	36.4	22	1,913	2,062	0.94%
3	Hsinchu	S	66.3	35	883	970	1.18%
4	Taichung	M	159.8	49	2,588	2,742	0.73%
5	Chiayi	S	245.7	89	826	795	-0.48%
6	Tainan	S	308.0	106	1,867	1,885	0.12%
7	Zuoying	M	339.3	94	2,761	2,779	0.08%

THSR monthly aggregated ridership from March 2007 is obtained when for the first time all eight stations were in operation. The ridership in the first month was around 919 thousand and gradually increased by 7.4% per month on average reaching 2.97 million in August 2007. In 2008, passenger numbers almost doubled and the average daily ridership continued to grow to over 138,525 passengers per day in 2015. Figure 2 illustrates though that the growth rates differ by city. The city with the highest growth rate is Hsinchu (1.63%), and the city with the lowest growth rate is Zuoying which is the farthest station from the capital Taipei. This might imply that the needs for HSR is higher in Hsinchu before the opening, though it could also mean that Hsinchu has fast generated additional trips after the HSR opened. In the case of other cities, the THSR ridership is increasing at a relatively higher rate after the opening and the growth rate of cities located between Taipei and Taichung seems to be higher than for cities located in south of Taichung. For more discussion on the general factors influencing Taiwan's HSR demand we refer to Li et al (2015).

In this study we are considering HSR as a new transportation system with which the population might not be familiar with in the beginning. Familiarity here means a general lack of considering HSR in one's choice set which might be due to a wide range of reasons such as lack of information but also issues such as trust in the system. In line with product adoption literature we consider that factors related to information spread through social interaction are important to identify how quickly people adopt to HSR.

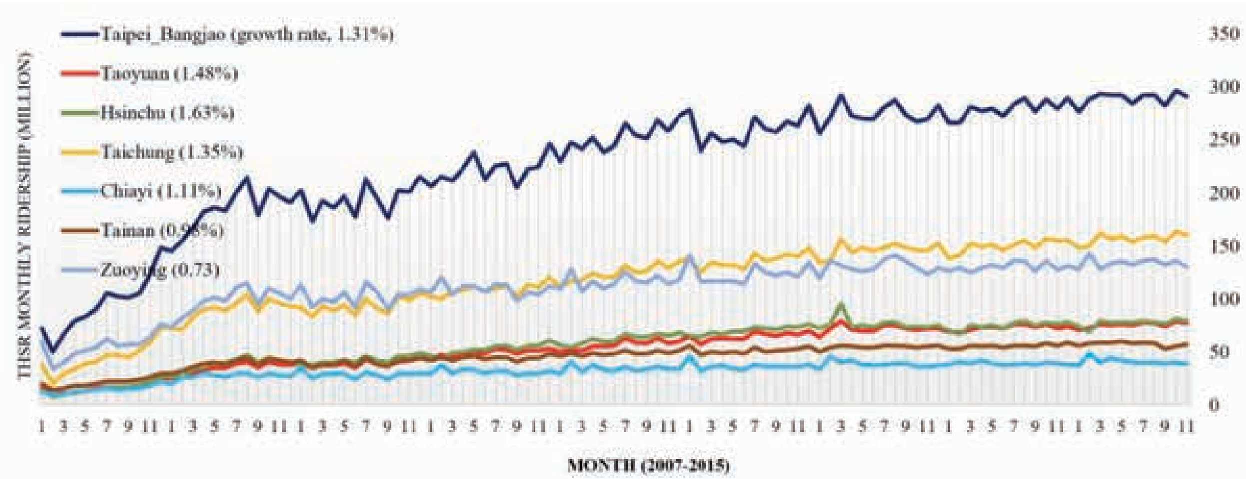

Fig. 2 THSR monthly ridership and averaged growth rate by city

2. Literature Review

The effect of social interaction on decision making has been receiving significant attention. Hartmann et al. (2008) implied that social interactions occur when individuals affect others' choices directly. They suggested that word-of-mouth (WOM) could be considered a key element in social interaction. This is arising through inter-related outcomes which are the factor to represent WOM. Further they noted that WOM is endogenously chosen by individuals, and hence viewed as an action, rather than a characteristic. Park and Chung (2006) also noted that general phenomenon as to how consumer information is spreading through various networks can be referred to as WOM. It has been confirmed through various previous studies that consumers' satisfaction, evaluation, compliments, and complaints related to new product/technology purchasing or using have an effect on other users' choice behaviour and attitudes. Including the effects of mass media and advertisements, Hong and Lee (2014) report that about 80% of buyers are influenced by someone's direct referrals when making decisions.

Numerous models having been developed to assess the role of WOM in the diffusion process (Dodson and Muller, 1978; Mahajan et al., 1990; Mazzarol, 2011). This was first noted by Brooks (1957) as the influence on consumer purchase decisions and the role of opinion leaders in purchasing behavior. Engle et al. (1969) described early adopter of new product and service usually provide positive WOM and this is used to be a combination of media. Therefore a positive relationship between WOM and advertising has been established in marketing literatures according to Day (1971) and Lampert and Rosenberg (1975). Mazzarol (2011) described that the diffusion of innovation is a social process in which interpersonal communication plays a key role. In some transport studies, this diffusion of innovation has been considered. Costa and Fernandes (2012) identified the diffusion of urban public transport modes i.e. trams and trolleybuses, as well as organization of public transport markets across European cities. Jensen et al. (2016) predicted the potential demand for electric vehicles through combining disaggregate choice models and diffusion models based on the assumption that innovation penetrates the market for new product or technology over time through a diffusion process. Wei et al. (2009) conducted a comparative analysis on the traditional vehicles and EV by the forecast model based on diffusion theory which was developed to identify the market expansion of EV in different fields.

One might expand the application range though further to daily travel behaviour. Abou-Zeid et al. (2013) noted that the "informational mass effects" mentioned by Schmöcker et al. (2014) and the "interaction effect in loose social networks" proposed by Ben-Akiva et al. (2012) are related to WOM. These studies describe the effect of WOM on transport behaviour such as illegal parking, unauthorized crossing, mode choice and attitudes. Belgiawan et al (2016) try to quantify social network effects for mode preferences. Abou-Zeid et al. (2013) discuss further resulting examples of social psychological marketing and public effects for transport management.

Related to the methodology chosen in the following, Parkes et al. (2013) presents an analysis of the recent increase in the number of public bike sharing systems in Europe and North America with the data examined through the lens of diffusion theory. In this study we consider HSR demand under the assumption that the individual usage of high-speed railway might be affected by social interaction. We suggest the results could be the basis to predict the demand patterns of a new railway system in the future as well as to manage HSR sustainably.

3. Methodology and Assumption

Bass's diffusion theory has been considered as a good starting point for modeling the long-term penetration pattern of new technologies (Jensen et al., 2016; Lilien et al., 2000). Bass (1969) observed that market absorption of new products or technology can be explained through a model with two groups and then suggested the behavioral theory that an innovative product/technology is usually adopted first by a few people, "innovators", who in turn influence others, "imitators" to adopt it. The innovators can be hailed as a small population group who can adopt new technology as soon as the product is on the market. Then imitators follow by also adopting these slowly after some time until market satisfaction is reached. Generally this leads to an S-shaped curve that describes the diffusion of a new product/technology as shown in Figure 3.

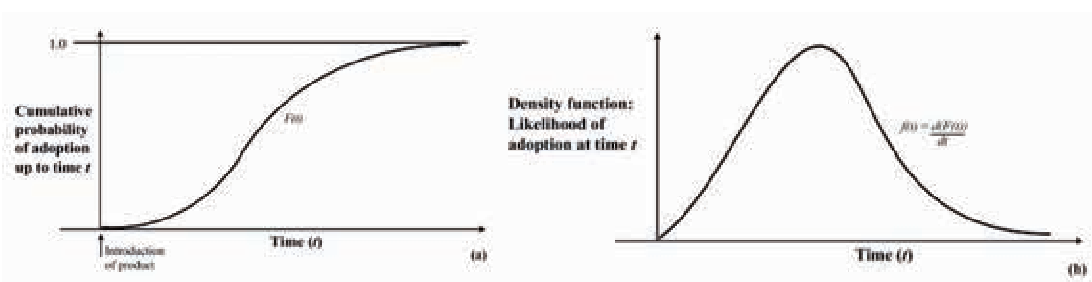

Fig. 3 S-curve (Cumulative curve) (Left) and Density function (Right) in Bass Diffusion Model

The Bass model can also be interpreted by a hazard rate. The interpretation of the hazard is that if it is multiplied by a small time increment it gives the probability that a random purchaser who has not yet made the purchase will do so in the next small time increment (Wang, 2012). The hazard rate indicates "the portion that adopts at t given that they have not yet adopted", thus this formula can be written as follows:

$$h(t) = f(t) / 1 - F(t) \tag{1}$$

The probability of adopting by those who have not yet adopted is regarded as a linear function of those who have previously adopted it, i.e.

$$f(t)/(1 - F(t)) = p + qF(t)$$

$$h(t) = p + qF(t) = p + q \cdot Y_t / N, \quad t > 0 \tag{2}$$

Where *h(t)* means the conditional likelihood that HSR users will adopt the innovation at exactly time *t* since introduction, given that the users has not adopted before that time *ft* is the likelihood for any randomly selected individual to adopt at time *t* (Rate at which the probability of adoption is changing at time *t*), and *F(t)* is the market saturation at time *t* (Probability density function of adoption at time *t*). *Yt* is the accumulated number of customers who have already adopted the innovation by time *t* and *N* is a parameter representing the total number of HSR users in the adopting target segment, all of whom will eventually adopt HSR. *p* is the "innovation coefficient"' and *q* is the "imitation coefficient". Bass (1969) calibrated the curve and parameters *p* and *q* for a range of products ranging from lawn moreover to microwaves.

We hypothesize that we can use the product adoption model also to improve estimates regarding HSR demand uptake. It is important to note that our interpretation of *p* and *q* changes. Originally in the model, the interpretation of these coefficientscan be directly associated with "innovators" and "imitators". In the case of HSR travel though it is not a "single purchase" we are interested in but the general increase in using HSR. We therefore re-interpret *p* as "innovative diverted demand" and *q* as "diverted and induced demand" considering features of transport demand in this study as shown in Figure 4. Therefore *p* means here that demand plus some initially diverted demand from other transport modes and *q* could be interpreted as later diverted demand as well as newly induced demand through the existence of HSR.

In the following, considering HSR utilization as demand of new transportation, we confirm the diffusion phenomenon and further the rates of innovation and imitation are calculated on the basis of a diffusion model based on the hypothesis as mentioned in above. We further estimate a model to verify that there would be influences of city heterogeneity on diffusion phenomenon of HSR ridership.

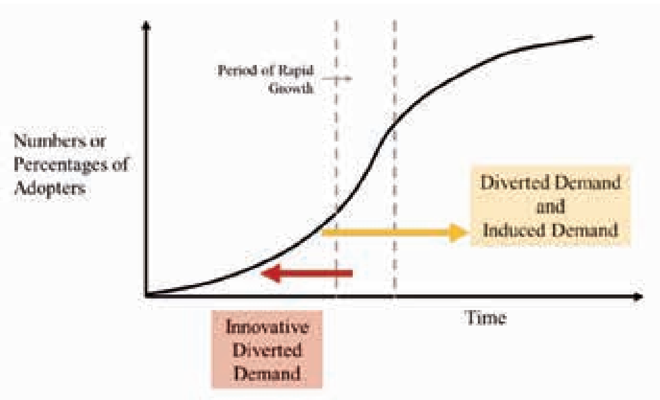

Fig. 4 S-curve representing rate of HSR adoption over time

4. Adoption Ratio and City Heterogeneity

We assumed that diffusion effects are different by year after opening as well as by city. Based on diffusion model, the city-specific annual values of and are obtained as following.

$$y_t = Nf(t) = \left(p + \frac{q}{N}Y_t\right)(N - Y_t)$$
$$= pN + (q-p)Y_t - \frac{q}{N}Y_t^2,\ \ t > 0 \qquad (3)$$

Equation (3) could be regarded as quadratic equation Y_t of thus the coefficients could be estimated by a *Least Square Method.* This estimation was carried out by city and year with the results shown in Appendix. All estimates by city and year are significant at 0.01% error level, except for 2007. Table 2 shows the mean value of diffusion rates by city. Here, the diffusion rates in 2007 were not calculated due to small sample size, therefore we assumed that *Adoption Effects* in 2007 is the same as in 2008 for model estimating. Chiayi is showing the highest *p* value followed by Taipei/Banciao and Taichung. Taoyuan has the lowest rate of innovative diverted demand among the cities. For diverted and induced demand, Hsinchu has a high value followed by Taichung and Taoyuan. Zuoying and Tainan, the cities farthest from the capital, show the lowest rates of *q*.

For our focus on expected long-term demand growth, we now suggest the concept of "Adoption Ratio" obtained as the ratio between *p* and *q*:

$$\text{Adoption Ratio} = \frac{\text{Diverted and Induced Demand}}{\text{Innovative Diverted Demand}} = \frac{q}{p}$$

The "Adoption Ratio" shows how strong the latent impact for increasing a long-term demand is compared to the initial demand growth during the first few months since HSR operation starts. The higher the ratio the more we can expect a continuous, fairly steady growth. Therefore a high "Adoption Ratio" means strong *Adoption Effects.*

As shown in Table 2, Taoyuan and Hsinchu both show high adoption ratio. We note that both cities can be classified as comparatively small cities and both are located close to the capital. Also when we see Figure 5, we observe that roughly two city groups are divided that lie above or below the curve for Taipei/Banqiao. Each group has a strong *Adoption Effects* the order of city size, Small, Small and Middle i.e. Based on the line of Taipei/Banqiao(L), Taoyan(S) and Hinchu(S) as well as Taichung(M) are belong to the group above. And the group below include Tainan(S), Chiayi(S) and Zuoying(M). From these observations we hypothesize that the city characteristic elements such as size and distance from Taipei, the capital and economic centre of Taiwan, affect *Adoption Effects*. Therefore, in the next section we analyse what factors, which reflect city heterogeneity, determine the level of *Adoption Effects*.

Table 2. Result of diffusion rates by city

Nº	City	Averaged Rate of Innovative Diverted Demand ($\bar{p}$)	Averaged Rate of Diverted and Induced Demand ($\bar{q}$)	Averaged Adoption Ratio ($\bar{p}/\bar{q}$)
1	Taipei/ Banqiao	0.0005815	0.043152	108.4584
2	Taoyuan	0.0004741	0.047560	155.2722
3	Hsinchu	0.0005012	0.052259	152.0790
4	Taichung	0.0005663	0.044495	124.1517
5	Chiayi	0.0006310	0.042222	98.0602
6	Tainan	0.0005522	0.038128	101.3215
7	Zuoying	0.0005516	0.036622	91.5447

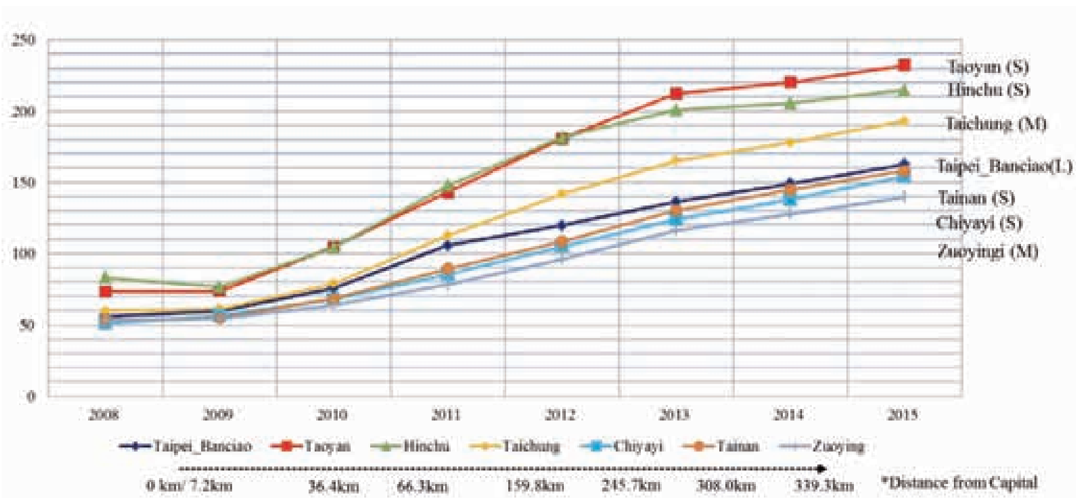

Fig. 5 Plot of Adoption Ratio by City (S: small sixe city, M:middle size city, L:Large size city)

5. Factors affecting on HSR Adoption Effects

5.1 Model Structure and Factors

Our data set consist of the panel data set $\mathbf{X}_k$ with observations x_{itk}. i is the city index and t denotes the year. Therefore this study uses a fixed effect (FE) one-way error component model. We then associate the *Adoption Effects* y_{it} by city and year using the following model;

$$y_{it} = \mu + x_{it}\beta + e_{it}, \quad i = 1,2\cdots,7, \quad t = 0,1,\cdots,8 \qquad (4)$$

Here μ is a scalar representing the intercept, β is κ a 1 vector. Thus note that χ_{it} is fixed over i. The error component e_{it} is decomposed as below;

$$e_{it} = \alpha_t + u_{it} \qquad (5)$$

Where α_{it} denotes the unobservable year specific effect and U_{it} denotes the remaining disturbance. Combining Eqs.(3) and (4), we have a region-fixed effect one-way error component regression model

$$y_{it} = \mu + x_{it}\beta + \alpha_t + u_{it} \tag{6}$$

Considering the data for all the samples, this model may be written as

$$\begin{pmatrix} y_{\sim 1} \\ \vdots \\ y_{\sim i} \end{pmatrix} = \begin{pmatrix} \mu 1_t \\ \vdots \\ \mu 1_t \end{pmatrix} + \begin{pmatrix} X \\ \vdots \\ X \end{pmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} + \begin{bmatrix} 1_t & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1_i \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_t \end{bmatrix} + \begin{pmatrix} u_{\sim 1} \\ \vdots \\ u_{\sim i} \end{pmatrix}$$

$$\rightarrow \mathrm{y} = \mu(1_i \times 1_t) + X\beta + Z\alpha + u, \tag{7}$$

Where

$$y_{\sim 1} = (y_{i1}, y_{i2}, \cdots y_{it}), u_{\sim 1} = (u_{i1}, u_{i2}, \cdots u_{it}), \mathrm{Z} = I_t \times 1_i$$

is the matrix of dummy variables associated with α. *X* represents the matrix of time-varying regressors on *t* samples for i^{th} repeat and is of the form

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{t1} & \cdots & x_{tk} \end{bmatrix} \tag{8}$$

Here the *X* matrix is same for all the repeats. Since α_t are assumed to be fixed year specific effects with remainder disturbance stochastic, this fixed effects model is an appropriate specification if we are focusing on a set of cities where THSR stations located.

Since we also hypothesized *Adoption Effects* of HSR ridership is quite influenced by status of social and economic situation by time as well as city heterogeneity, the estimated model considers six independent variables i.e. X_{1it} , distance from capital of Taipei to city *i* at year *t* (km); X_{2i}, city size of city *i* (Large:3, Medium:2, Small:1); X_{3it}, distance from city center to HSR station(km) of city *i* at year *t*; X_{4it}, Total length of road network (km) of city *i* at year *t* ; X_{5it}, Aging population ratio of city *i* at year *t* (%); X_{6it}, Business scale (Total amount of sales (Taiwan dollar)/ Number of enterprise) of city *i* at year *t*.

5.2 Modelling Results

Table 3 shows the results of the model estimation which considers *Adoption Effects* as dependent variable and the model is found to be statistically significant. Moreover it is shown that all considered six independent variables are statistically significant at 95% confidence level.

A positive (negative) coefficient of the independent variable represents a greater probability for larger (smaller) *Adoption Effects*. Only the explanatory variable of business scale has a positive coefficient and this means that as the economy grows, the size of *Adoption Effects* also increases. In line with the results in previous section, the farther from Taipei and the larger the city, the lower the *Adoption Effect* tends to be. In addition, it is verified that cities with a good accessibility to HSR station close to city center have a strong *Adoption Effects*. Instead, the higher the supply of road network, the lower the value of Adoption Effects. This illustrates that cars are the competitive transport mode of high-speed railway in Taiwan due to country size. Among the explanatory variables, the variable which has the greatest influence on *Adoption Effects* is aging. The proportion of the elderly population has a negative impact on the level of *Adoption Effects*.

Table 3. Model estimation results

Variables		Coef.	Std. Err.	Z	p-value
Dependent var.	y: Log(Adoption Effect)				
City scale characteristics var.	x_1: Log(Distance from Taipei)	-0.068	0.007	-9.31	0.000
	x_2: City size	-0.065	0.021	-3.06	0.002
HSR station access var.	x_3: Log(Station location)	-0.225	0.016	-13.92	0.000
	x_4: Log(Road length)	-0.067	0.032	-2.13	0.033
Socioeconomic var.	x_5: Log(Aging ratio)	-0.737	0.058	-12.65	0.000
	x_6: Log(Business scale)	0.089	0.023	3.96	0.000
Year dummy var.	α_1: 2008	0.016	0.026	0.62	0.538
	α_2:2009	0.062	0.026	2.37	0.018
	α_3:2010	0.299	0.026	11.41	0.000
	α_4:2011	0.605	0.027	22.77	0.000
	α_5:2012	0.831	0.027	30.67	0.000
	α_6:2013	1.015	0.028	36.45	0.000
	α_7:2014	1.118	0.029	38.67	0.000
	α_8:2015	1.205	0.029	41.87	0.000
Constant		2.611	0.288	41.87	0.000
Random variables	sd(Residual)	0.049	0.004	-	-
Log likelihood		101.202			
Wald chi square		5627.40			
Prob>Chi2		0.000			

In addition, the estimated dummy variable's coefficients show that temporal changes after THSR opening also influenced on *Adoption Effects* positively. Figure 6 could be interpreted that *Adoption Effects* increases gradually as time goes. However, this is not likely to last, as according to diffusion theory, at some point we would expect a decrease. This result also supports our hypothesis for defining of *Adoption Effects* as the latent impact for increasing a long-term demand since HSR operation starts. When we see the changes in exponential function[1] of dummy coefficients, there was a sharp increase in 2011 (after 4 years from opening). This remains at similar levels until 2013, but decreases from 2014. This, in turn, implies that the effect of temporal changes on *Adoption Effects* can be weaker over time. Therefore, in order to maintain a high level of *Adoption Effects* for securing long term sustainable HSR ridership as well as a high level of continuous demand growth, it may be necessary to pursue additional policy strategies considering the factors which are considered in our estimated model.

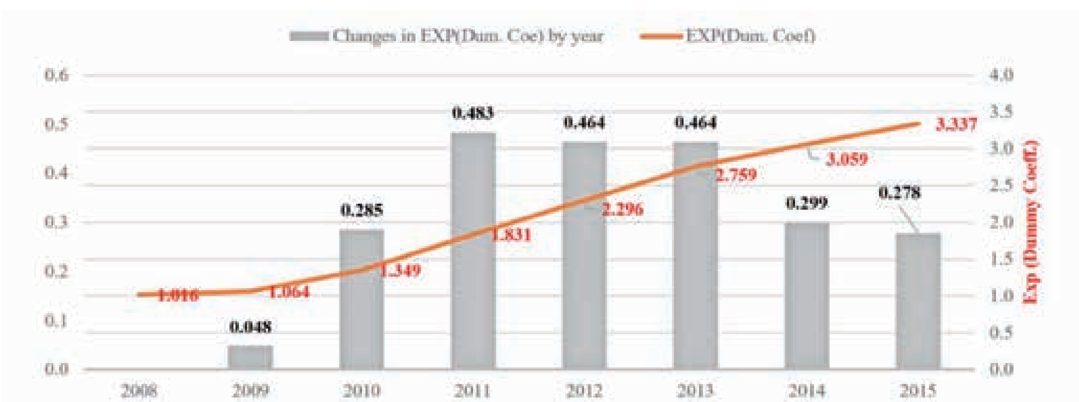

Fig. 6 Impacts of temporal change on Adoption Effects

1 *In the estimated model, the dependent variable is Log(Adoption Effects).*

6. Discussion and Conclusions

Sustaining demand growth especially for new introduced transportation system has been becoming an important concern and issue over the world. HSR has been suggested as one alternative for acquiring sustainability in mobility to car and air travel of the decade. Moreover, there is no doubt that HSR can promote economic development. In this study we investigated how to promote HSR sustainably focusing on its long-term demand. Our major findings are detailed as following.

First of all, with adopting a diffusion modeling in marketing study fields, we identified that there is diffusion effects on HSR demand and this was different by city. Therefore, it is suggested that new transport systems could be compared to other new products or technologies and their market penetration patterns. Secondly, we calculated the impacts of "innovative diverted demand" and "diverted and induced demand" on HSR demand by city. It was verified that degree of impacts differed by city. Therefore, one of main conclusion of this paper can be that the demand growth pattern might be significantly related to urban regional characteristics. By estimating a fixed effect (FE) one-way error component model, it was demonstrated that city heterogeneity such as social, economic and geographical characteristics influence *Adoption Effect* which explain long-term demand and are a key factor to promote sustainable transport. Therefore, in order to operate the sustainable HSR system, it is necessary to understand the characteristics of each city and to establish policy measures to reflect them. Here, by estimated model, it was presented that accessibility to the station could be an important element to raise *Adoption Effects*. Our study implies that an accessible station is not only likely to generate a large initial demand but also leads to continuous increase of demand. This we suggest is an important finding. From this result, it could be implied that it is important to improve the accessibility and psychological distance to HSR use which citizens have, although geographical and social factors should be taken into consideration when determining the station location. Therefore, some policy approaches which forward reducing public's psychological distance and increasing accessibility to HSR station should be urged in order to secure to long-term HSR demand.

In addition, we also find that an increase of elderly population would influence on securing long-term demand of HSR negatively. This finding could be interpreted as "Since the elderly may not be able to make business trips, the increase of elderly population rate can have a negative impact on long term demand growth for high-speed railways". Chen and Haynes (2015) noted that HSR has been increasingly attractive mode for business traveler who have a high value of time than other travelers. Our analysis suggests that it is difficult to "gradually persuade" and to create continuous demand growth among an older, non-working, population. Especially among an ageing population that dislikes public transport for various reasons such as fears of safety (Schlag, 2008; Karthaus and Falkenstei, 2016) it might hence be difficult to create a large demand if the initial acceptance has not been large. Further research on confirming this is though needed.

More generally, we suggest one implications of our findings is that it illustrates that not only hard measures such as fare adjustment and network expansions are needed to secure long term. We might postulate that the coefficient p is also related to advertising effect and q presents word-of-mouth effect (Mahajan et al., 1995). Therefore, the study results can be interpreted as showing that marketing strategies to transportation service is possible for sustainable operation of the transportation system. Indeed, according to Kim (2008), various marketing strategies to KTX (Korea Train eXpress) have been implemented over the past several years in order to successfully enter the high-speed railway transportation market. To support this conclusion further, it would be important though to understand if the *p* and *q* differences among the cities can be also explained with attitudinal factors and/or regional specific HSR promotion efforts.

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8. Appendix

Index and city		1	2	3	4	5	6	7
		Taipei/ Banqiao	Taoyuan	Hsinchu	Taichung	Chiayi	Tainan	Zuoying
Rate of Innovative Diverted Demand (p)	2008	0.001906	0.001496	0.001619	0.001922	0.002054	0.001661	0.001497
	2009	0.001233	0.001085	0.001122	0.001241	0.001301	0.00123	0.001218
	2010	0.000586	0.000448	0.00046	0.000563	0.000682	0.000616	0.000692
	2011	0.000286	0.00025	0.000244	0.000271	0.000371	0.000325	0.000384
	2012	0.000222	0.000167	0.00017	0.000179	0.000236	0.000216	0.000234
	2013	0.000169	0.000127	0.000144	0.000137	0.000167	0.000149	0.000156
	2014	0.000137	0.000117	0.000134	0.000118	0.000133	0.00012	0.000128
	2015	0.000112	0.000103	0.000117	9.93E-05	0.000105	0.0001	0.000105
Rate of Diverted and Induced demand (q)	2008	0.10753	0.110378	0.135075	0.115986	0.105102	0.089316	0.080044
	2009	0.074225	0.080327	0.086243	0.076407	0.074112	0.068017	0.066531
	2010	0.04464	0.046999	0.048286	0.044735	0.046684	0.042229	0.044421
	2011	0.03035	0.035767	0.036039	0.030603	0.031864	0.029107	0.030151
	2012	0.026669	0.030134	0.030834	0.025466	0.024793	0.02348	0.022589
	2013	0.023066	0.026982	0.028857	0.02259	0.020742	0.019501	0.01821
	2014	0.020509	0.025881	0.027595	0.020982	0.018336	0.017454	0.01636
	2015	0.018228	0.024014	0.025141	0.01919	0.016142	0.015922	0.014669
Adoption rate $(\frac{q}{p})$	2008	56.41449	73.78651	83.45631	60.33129	51.15934	53.78259	53.47707
	2009	60.2088	74.00546	76.85228	61.58675	56.9441	55.28747	54.63313
	2010	76.11386	105.0194	104.8553	79.43253	68.49952	68.53677	64.22159
	2011	105.9876	143.3079	147.7062	112.9444	85.88177	89.64759	78.53006
	2012	119.9717	180.8442	181.8714	142.0875	105.1915	108.7815	96.53571
	2013	136.5497	212.4424	201.004	165.4063	124.1764	130.7404	116.7347
	2014	149.4149	220.4313	205.7258	178.1118	138.2544	145.2074	128.0983
	2015	163.0062	232.3404	215.1608	193.3128	154.3745	158.588	140.1268