# Demand Adaptation towards New Transport Modes: Case of High Speed Rail in Taiwan

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This study aims to explain the trend and factors affecting ridership changes on new high speed rail in Taiwan. Time-series methodology is used to specify the adaptation effects behind social economics, and competitive modes regarding with time events. The analysis is based on Taiwan High Speed Rail (THSR) monthly ridership data for period January 2007 to December 2012. A seasonal autoregressive integrated moving average (SARIMA) model was applied; showing that the ridership thrives but slightly underestimated from the trend prediction after 2012. Regarding with the impact from social economic factors, adaptation effects and time series parameters; a first ordered moving average model was therefore fitted for this paper to describe a detailed analysis on the potential user adaptation on THSR. The results specified that population, Chinese New Year, summer vacation, fuel price, has a positive effect while gross domestic product (GDP), unemployment, and car ownership could reduce the THSR ridership, a positive trend (adaptation effects) was therefore identified behind THSR ridership.

***Key Words :*** *High Speed Rail; Demand Forecasting; Time Series Modelling; Trend; Adaptation Effect*

## 1. INTRODUCTION: DEMAND FOR NEW PUBLIC TRANSPORT SCHEMES

Demand Forecasting is a key issue for transport planning. Over the last decades various tools have been developed to assess the impact of network changes on the demand. One can observe though that generally model accuracy drops the longer the planning horizon. The reasons for this are obvious in that the uncertainties increase the longer the time horizon. Further, models have most success to predict the demand for small alterations to existing systems. Demand prediction for major infrastructure investments are in most cases far more difficult and often the desired effect does not occur. An explanation is that demand adaptation is influenced by far more factors than usually included in utility estimations that are the basis for mode choice models.

A third issue is that the timing of demand adaptation appears often difficult to predict. Initial demand might be low but only over a fairly long time period the demand might increase to somewhere near the predicted level. Some rail operators for example discount the demand for the first few years for new services compared to their usual demand prediction method.

The problem at stake is though that exactly for large infrastructure investments a planner is in most need for demand predictions as this is a key factor in project appraisal. For example initial demand for the magnetic elevated train considered for construction between Hamburg and Berlin in Germany were estimated at 14 million passengers per year initially. The estimates were later downward revised leading eventually to the rejection of the project. Other sustainable transport policies currently under discussion face similar issues. For example there is a wide range of predictions for the demand of electric cars (Lieven et al. 2011; Link et al. 2012) and bicycle sharing (Fishman et al. 2013; DeMaio, 2009). Also a number of public transport systems have been introduced but services were cancelled after a while when demand did not reach expectations. On the other hand also positive examples are known where demand exceeded predictions (Lee and Senior, 2013; Abrate et al. 2009; FitzRoy and Smith, 1998).

Especially the time duration dimension appears to be under researched. When investments aim to promote mode changes it is reasonable to assume that potential users need time to adapt their behaviour. For example Owen and Phillips (1987) distinguish “short-term” and “long-term” impacts of service changes to railway demand. Therefore the aim of this paper is to discuss factors that influence the demand development for newly introduced public transportation schemes. That is, we would like to know how long does it take for a new system to reach a constant stable demand (if ever). In modelling terms we might phrase this as the time it takes for the system to reach a new equilibrium distribution between the modes (if one exists and if it can be reached).

As a case study we analyse the demand for the Taiwanese High Speed Rail System. The service was introduced in 2007. As will be discussed in the following the service only was altered significantly in the first year of its operation, after that, until today, service attributes have stayed fairly constant. Therefore one might assume that the demand will also be stable after a while which is though not the case. We discuss possible reasons for this and implications as well as general implications for long term demand forecasting.

The reminder of this paper is organised as follows. Section 2 reviews in more detail potential factors influencing the demand adaptation in response to public transport investments. Section 3 introduces the case study. Sections 4 and 5 then present a time series analysis of the demand development. We firstly employ a SARIMA model followed by a simpler MA(1) model where we introduce explanatory variables discussed in previous sections. Section 6 concludes this study and discusses implications.

## 2. LITERATURE REVIEW: DEMAND ADAPTION TO NEW PT SERVICES

A number of major factors influencing (long-term) demand adaptation to public transport investments can be distinguished. For one, obviously the by the population perceived quality and service attributes of the new service will influence the demand as discussed in most of the mode choice literature. Fares, service reliability safety concerns and in-vehicle service will all be determinants. For example safety records will influence airline demand over longer time periods (Ito and Lee, 2005) and similarly for new rail systems passengers might need some time to adapt to these and gain trust. Fu et al. (in press) estimate the demand split between rail and air in Japan if “super high speed rail” is introduced between Osaka and Tokyo. They suggest that passengers will be sensitive to fare and frequency and that eventually air might be driven out of the market.

Further, obviously socio-demographics and their developments will influence the demand. In line with the analysis presented later in this paper, Kyte et al. (1988) used time-series analysis to examine the factors affecting changes in transit ridership in Portland. The market size in their research, population, is used as the measurement for the amount of travel generated. For large national projects the total population might be further an indicator, especially if market size estimation is not available as in the Fu et al. (in press) study.

General economic developments measured by GDP and unemployment rate will play a further role. Important to note are further the cyclic and “endogenous effects” if very large transit investments are considered that make it difficult to estimate their total demand as well as the time when the effect will occur. For example Gwilliam (2008) review the development of thought on the major issues in transit economics over the last half century, in developed and developing countries. He concluded that transit is critical to the achievement of a wider range of social, economic and environmental objectives. Transit investments will trigger further economic investments and hence create induced demand as well as will have an impact on other determinants of transit ridership such as car ownership. Ahlfeldt and Feddersen (2010) argue that the economic geography framework, such as population distribution, economic activity density, and special development structure, can help to derive exante predictions on the economic impact of transport projects and vice versa. The expectation that transport innovations would also lead to sustainable economic growth has long since motivated public investment into large-scale infrastructure investment. Connected to economic developments are also gasoline prices. In Lane’s study (2012), gasoline prices have exhibited considerable fluctuation in PT demand. Further car ownership are driven by economic developments. Bass et al. (2011) for example reports the connection between increasing household income and car ownership particularly in developing countries. With this comes a significant decline in public transit ridership.

A fourth group of factors significant for long term demand might be termed “general perceptions and attitudes”. That is, generally concern for health and environment might have promoted the use of public transport over the least years. The car seems to loose its meaning as status symbol over the last years to some degree (Belgiawan et al. 2012). Also, in particular for new technologies, perceptions of whether the system is safe or convenient will influence demand. Abrate et al. (2009) analysis the impact of Integrated Tariff Systems (ITS) on public transport demand in Italy, and indicate that the introduction of such a system can increase the number of passenger trips both in the short-run (2.19%) and long-run (12.04%). FitzRoy and Smith (1998) investigate the demand of local public transport in German; and argue that although traffic restraint measures and improvements in the quality of the public transit service are significant factors, the main explanation lies in the introduction of low cost environmental travel cards with the key characteristics of transferability across friends and family and wide regional validity across operators. That is, not only the convenience of the card but also the promotion of the service as environmental might have had an effect. Chao et al. (2012) indicate the concept of perceived value from public transport is closely linked to customers' satisfaction. The results show that the satisfaction value could be identified as social, functional, and emotional value. However this group of factors is usually were very difficult to include in demand forecasting.

A fifth group of factors might be called "direct endogenous factors" (in contrast to other more indirect factors such as the above discussed economic impacts).That is, through the introduction of a new system some cyclic effects might be triggered. For example land-use values might change through the introduction of a new public transport system that will lead to changes in the socio-demographics. Andersson et al. (2010) used a hedonic price method to evaluate the accessibility changes through the Taiwanese high speed rail in the residential property market. The estimation results show that HSR accessibility has at most a minor effect on house prices though.

More directly, the competitive modes of the new system might alter their service. For example, in Taiwan, as a consequence of the introduction of the High Speed rail, airlines reduced their prices, while conventional rail changed their timetable and services (Cheng, 2010). Owen and Phillips (1987) mention the wider significant impacts of the introduction of high speed rail in the U.K. on the whole rail demand. In all cases the time duration of the effect is difficult to estimate.

In line with these cyclic effects Schmöcker et al. (2013) discuss that "mass effects" can be significant determinants of long term demand adaptation. One persuades a few to change their behaviour initially in order to encourage a large number of people to fallow later. There is then a potential of enduring significant demand increases as the new service might increase its attractiveness over time if more start to join it. For example economies of scale may be passed on to traveller by public transport operators in terms of reduced fares or increased frequencies (Mohring 1972).

## 3. TAIWAN HIGH SPEED RAIL AND ITS IMPACT ON MODE SHARE

### (1) THSR Demand

On January 2007, Taiwan high speed rail (THSR) opened its operation. The system primarily relies on imported technology and hardware from Japan's Shinkansen line, supplemented with a European (TGV and ICE) traffic management system; with an investment cost of approximately US$15 billion (Andersson et al. 2010). Through connecting its economic corridor north to south, covering almost 90% of population and making Taiwan into a new stage of "one-day peripheral circle", it brings a whole new era of travelling style to Taiwan. Through the nearly 350 kilometres investment, the travel time is cut from 4 hours into 1.5 hour (Taipei to Zuoying). This has greatly expanded overall accessibility throughout the whole Western coast region of Taiwan (see Figure 1). However, criticism still remains


**Fig.1** THSR route map.

as several stations (5 out of 8) are located in suburbs and far away from the CBD area (e.g., Taoyuan, Hsinchu, Taichung, Chiayi, and Tainan). This has reduced the travel time benefits in many cases compared to conventional rail (travel cost does not increase as in most of these station free shuttle buses are operated to the CBD by THSR). This has also led the access to these stations being often confined to motor vehicles, resulting in minimum travel time of between 20 to 40 min from downtown areas (Andersson et al. 2010).

**Table 1** Aggregated Inter-City Ridership of Travel Modes in Taiwan

| Travel Mode | Unit | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|---|---|---|---|
| Expressway (Private Vehicle) | million cars | 479.14 | 480.59 | 475.50 | 453.93 | 457.10 | 464.82 | 479.55 | N/A |
| Expressway (Bus) | million Pax | 252.80 | 245.20 | 242.30 | 246.40 | 237.80 | 232.80 | 220.60 | 197.05 |
| Taiwan Rail (TR) | million Pax | 169.60 | 169.00 | 169.70 | 178.70 | 179.40 | 189.80 | 205.83 | 220.30 |
| Domestic Airlines (Air) | million Pax | 19.29 | 17.36 | 12.71 | 9.85 | 9.23 | 9.73 | 10.48 | 10.68 |
| Taiwan High Speed Rail (THSR) | million Pax | - | - | 15.56 | 30.58 | 32.35 | 36.94 | 41.63 | 44.53 |

N/A: not available.

Source: Ministry of Transportation and Communications (MOTC)

As a consequence of the THSR introduction the ridership and inter-city market share shifted between different travel modes as shown in Table 1 between 2005 and 2012. Private cars, expressway buses, and domestic airlines experience negative trends while non high speed rail demand (Taiwan rail, TR) remained during the first year of THSR operation and has since then been increasing. The average growth ratio for each mode since 2005 is 0.04% for cars, -3.43% for buses, 3.86% for Taiwan rail, and -7.22% for domestic airlines respectively; while THSR shows is "booming", with an average annual growth ratio of 19.45% since 2007.

Figure 2 shows the monthly pattern in THSR ridership over the 6.5 years of operation. There are three peaks within each year relating to Chinese New Year, which varies from January to February due to the lunar calendar; the beginning of the summer vacation in July; and the final peak, December, for Christmas and New Year. The figure further illustrates that, from a annual perspective , the ridership increases steadily and seasonal pattern became stable after 2008.

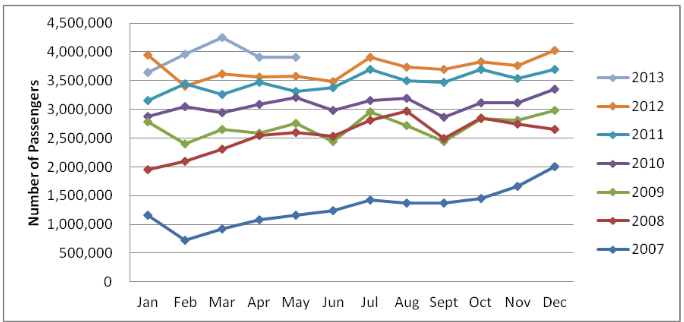


**Fig. 2** THSR monthly ridership.

**(2) Air Service and THSR Service Frequency Adjustments (Largely Endogeneous Effects)**

If we look closer to compare the THSR ridership and the domestic airline within the west coast of Taiwan (see Figure 3, note that the airline data is different from the previous Table 1. Figure 3 airline ridership data only refer to domestic airlines within Taiwan's west coast), the airline share dramatically decreases after the opening of THSR. This likely shows the advantages for high speed rail within 600km travel distance. In fact fares between TSHR and airlines have been fairly similar with around USD$50 from Taipei to Zuoying (Kaohsiung) on TSHR and USD$55~$70 for airline depending on sales and peak days. After losing market shares some airlines tried for a while to remain in business by offering specially reduced sales, however, by June 2012 flights along Taiwan's west coast had been suspended.

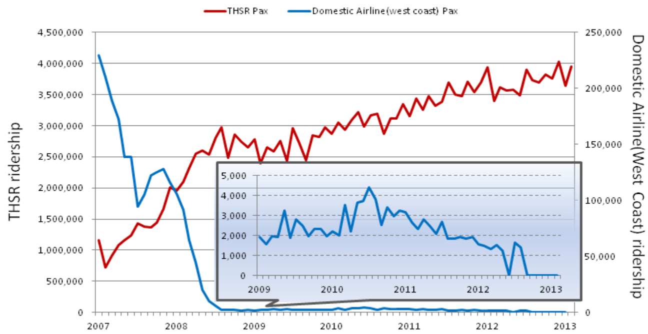


**Fig. 3** Comparison of THSR and airline (West Coast of Taiwan) monthly ridership.

To explain the annual increase, in line with our literature review, a number of factors are in the following investigated. As service attributes such as travel speed and fares remain stable over the years, these cannot be used as explanatory variables. Service frequency will be to a large degree an endogenous factor as the operator reacts to increased demand. The THSR has reported that the number of services has risen from 1,034 (January 2007) to 4,032 (February 2013) per month. However, this was not a gradual increase but rather there was a nearly 400% increase in service frequency within the first two years of service operation after which the service frequency remained comparatively stable (Figure 4).

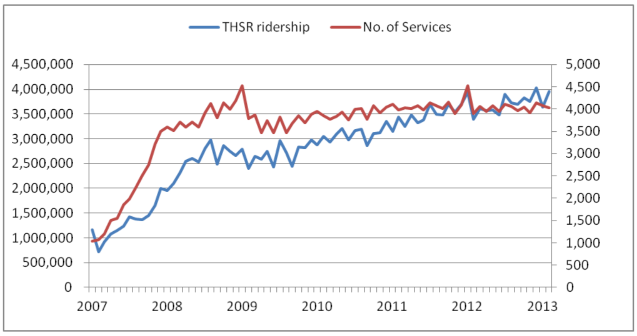


**Fig.4** THSR Monthly service and ridership.

**(3) (Largely) Exogeneous Factors Potentially Affecting THSR Ridership**

Besides the above discussed air developments, clearly also transport developments for other modes might have impacted the modal split. For instance the extension or lane widening of the expressway increased capacities for both private vehicles and buses which could have a negative impact on rail demand. The expressway network in Taiwan extended from 373 km in 1978 to 989 km in 2009. Guo and Feng (2008) argue that this well connected network (3 north-souths orientated and 17 east-west orientated expressway networks) has induced 5% car volume each year in the last 15 years, and forced conventional rail to reduce service frequency on some routes. Also the fuel price may lead to fare changes for buses, domestic airlines, and the travel cost of private vehicles as well. Over the last years prices remain relatively stable with a price around 31 to 35 NTD per litre, we also note that in July 2008 had a 36.1 peak and quickly drop to 21.1 in the end of 2008 December due to global financial crisis.

Most studies and previous literature examining gasoline prices have used real gasoline prices (Lane 2012). In reality, gasoline prices in Taiwan are supervised by Ministry of Economic Affairs, but authorized by the Chinese Petroleum Corporation, Taiwan (CPC, Taiwan) to determine changes in prices. The gasoline price varies frequently and unpredictably between weeks. Thus in this paper, fuel prices was adjusted into monthly averages from real gasoline prices per week.

Further, since we are discussing nationwide intercity travel demand, global economic events such as the 2008 crisis cannot be ignored. Most of the inter-city travel demand generally decreased in the later half of 2008 and early 2009 (see also 2008 data in Table 1 and Figure 4) except for travel by expressway buses. The reason might be that this service provides the lowest travel cost among the mode choice option and not capturing much business travel. As a macroeconomic indicator for this study we therefore collected information on the Gross Domestic Product (GDP) in Taiwan. GDP data could be obtained as seasonal data from the first quarter of 2007 (2007Q1) to the fourth quarter of 2012 (2012Q4). Annual comparison shows that in 2008 and 2011 the GDP declined by 3.26% and 0.02%, while 2007, 2009, 2010, and 2012 the GDP increased by 2.23%, 3.99%, 2.84% and 1.12% respectively. We note that it might take some time before the

**Table 2** Variables Definition, Expected Sign, and Descriptive Statistics

| Variables | | Definition | Expected Sign | Unit | Type | Minimum | Maximum | Mean |
|---|---|---|---|---|---|---|---|---|
| THSR | THSR Ridership (Dependent) | Total ridership per month | | person | Continuous / Monthly | 724,784 | 4,023,302 | 2,826,824 |
| | Number of Service | High speed rail train services per month | | car | Continuous / Monthly | 1,034 | 4,524 | 3,620 |
| Social Economic Factors | Total Population | | + | person | Continuous / Monthly | 22,879,132 | 23,328,602 | 23,102,882 |
| | Unemployment Ratio | | - | % | Continuous / Monthly | 3.78 | 6.13 | 4.61 |
| | GDP | Transformed into GDP / Fuel Price as 1 independent variable due to high correlation | - | USD / person | Continuous / Seasonal | 3,823 | 5,398 | 4,592 |
| | Fuel Price | | + | NTD / L | Continuous / Monthly | 21.15 | 36.10 | 30.32 |
| | GDP / Fuel Price | Substitution for both explanatory variables, GDP and Fuel Price | - | | Continuous / Monthly | 120.14 | 196.27 | 152.15 |
| Airline | Airline Ridership | Total ridership along west coast (Including Taipei-Taichung, Taipei-Chiayi, Tapei-Tainan, Taipei-Kaohsiung, Taipei-Pingtung) | - | person | Continuous / Monthly | 0 | 288,599 | 33,915 |
| Private Vehicles | Car Ownership Ratio | cars per 100 persons | - | % | Continuous / Monthly | 29.10 | 31.00 | 29.74 |
| Holidays & Vacations | Chinese New Year | Winter vacation, based on lunar calendar | + | | Dummy / Monthly | 0 | 1 | 0.31 |
| | Summer Vacation | Every July to August | + | | Dummy / Monthly | 0 | 1 | 0.37 |
| | Consecutive Holidays | Holiday over 3 days off in a row, e.g., Spring Break, Christmas, and New Year Holiday | + | | Dummy / Monthly | 0 | 1 | 0.23 |
| Adaptation effects | | Assumed that effects grow larger after the operation | + | | Continuous / Monthly | 1 | 72 | 36.5 |

macroeconomic impacts become visible in the demand as suggested by Kyte (1988) and Lane (2012).

We further note that we find a high correlation between fuel price and GDP (0.794 in Pearson test) thus in our subsequent analysis in Section 5 we use the ratio of the GDP and fuel price for a given month as a measure of "disposable income for petrol". The expected sign for the impact of (GDP) / (Fuel Price) on rail demand should hence be negative, i.e. the more disposable income for petrol, the less attractive rail is.

As a further economic indicator for effects not captured with the seasonal GDP we consider the monthly unemployment ratio in Taiwan. The monthly unemployment data could be also collected from the webpage of the Ministry of Economic Affairs (2013). The ratio varies between 3.78% and 6.13% with a mean of 4.61% for the time period in question.

Besides these economic factors total population data was collected from the Ministry of the Interior as a proxy-measurement for THSR market size (Owen and Phillips, 1987; Kyte, 1988; Gwilliam, 2008; Lane, 2012). We note that the Taiwan west coast holds about 90% of the total population, thus using nationwide appears acceptable. The population shows a slow but steadily increase from 22.87million in January 2007 to 23.33million in December 2012 (Figure 5). It should be noted that it is predicted that from 2018 Taiwan will face a population decline due to the low birth ratio (Wang et al. 2009).

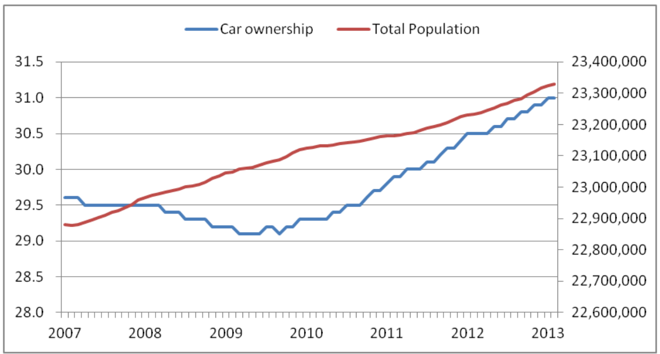


**Fig.5** Total population and car ownership in Taiwan.

As a second related measurement to "market size" as well as economic development we include the population's car ownership ratio. Figure 5 shows that in 2007 there were 29.6 cars per 100 Taiwanese, then ownership declined in 2008 until nearly the end of 2009. Since 2010 the ownership has been raising again and has reached 30% by the middle of 2011.

For a seasonal demand analysis, holidays should be considered as a important factors (Quddus et al., 2007) that it induce the demand and eventually had a higher peak than usual weekends. Reflecting our observations in Figure 2 we consider Chinese New Year (winter vacation), summer vacation and all three day consecutive holidays (Spring breaks, Dragon Boat Festival, Moon Festival, Christmas and New Year Holiday) as potential sources of high speed rail demand. For Chinese New Year, many will travel to visit families whereas for summer and other holidays significant travel to island and festivals held across the country is generated.

Finally, in line with our aforementioned discussion that demand adaption is likely to require some time and that cyclic effects might encourage more shift of demand after some initial users have been attracted we include a trend or "adaption effect" variable which we specify as being related to the time since service operation and presume to have a positive effect.

## 4. SARIMA TIME SERIES MODEL

The estimation was based on data from January 2007 to December 2012 while keeping the data from 2013 as control group. The type of SARIMA model is usually denoted by SARIMA $(p,d,q)(P,D,Q)_s$ model. In the SARIMA model, $p$ and $P$ represent the order of the non-seasonal and seasonal autoregressive (AR) process; $d$ and $D$ represent the order of the non-seasonal and seasonal difference process; $q$ and $Q$ represent the order of non-seasonal and seasonal moving average (MA) processes. The subscript $s$ denotes the length of seasonality, i.e., in this model $s$ =12 in case of monthly time series data and due to annual repetitive character in some demand types. A fuller description of the model could be found in Andreoni and Postorino (2006). Examining the autocorrelation function (ACF) and the partial autocorrelation function (PACF) from time series we could identify the values of each of these parameters.

The ACF and PACF from time series ridership data suggest to employ a SARIMA model of the order $(0,1,2)(0,1,1)_{12}$. Also Table 3 illustrates the high significance of first and second order moving averages and that the seasonal moving average is significant at 10% level. The model can thus be used to forecast 2013 monthly ridership and the prediction ridership can then be compared with observed ridership (see Figure 6, note that the model prediction start from 2013). The fitted model shows that the predictions are slightly below observed ridership, which illustrates the continuously positive trend behind THSR ridership.

**Table 3** SARIMA Model Estimation Results for THSR Monthly Ridership

| Parameters | Coeff. | t-statistics | p-value |
|---|---|---|---|
| Moving Average, MA(1) | 0.69 | 6.30 | $\leq$0.01 |
| Moving Average, MA(2) | -0.55 | -4.50 | $\leq$0.01 |
| Seasonal Moving Average, SMA(1) | 0.84 | 1.81 | 0.08 |
| Differencing: 1 regular and 1 seasonal of length 72 | | | |
| Constant | -10439.18 | -1.20 | 0.24 |
| Observation | 72 | | |
| R-square | 0.85 | | |
| Adjusted R-square | 0.53 | | |
| Ljung-Box Q test | 0.63 | | |

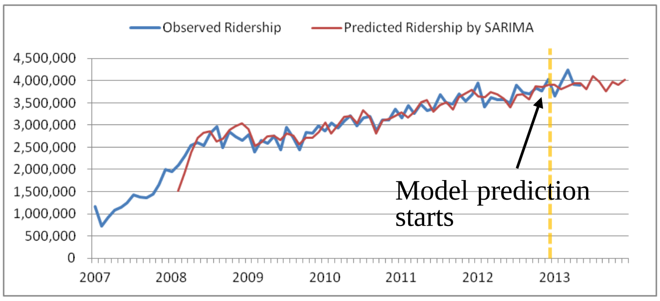


**Fig.6** Comparison of THSR observed and predicted monthly ridership

## 5. TIME SERIES MODEL WITH EXPLANATORY VARIABLES

Unlike previous SARIMA model in which we used only THSR ridership data itself, two first ordered moving average model (MA (1)) with explanatory variables discussed in Section 3 and summarised in Table 2. The dependent variable remains THSR ridership. AR(1) and MA(1) models have been tested with loglinear, MA(1) models providing slightly better model fit. The model is given by:

$$\ln y_t = \alpha + \beta \ln \boldsymbol{X}_t + \theta \boldsymbol{D}_t + \varepsilon_t \quad (1)$$

where the error term satisfies:

$$\varepsilon_t = \rho \varepsilon_{t-1} + \eta_t \quad (2)$$

In this model yt is the THSR ridership for month t where we measure months continuously since operation begin. $\boldsymbol{X}$ is a $k$ * 1 vector of continuous explanatory variables, $\boldsymbol{D}$ is a $m$ * 1 vector of dummy variables, $\varepsilon$ is the white noise or error terms, $\rho$ ($-1<\rho<1$) is the moving average coefficient, where $\eta$ is independent and identically distributed with mean zero and variance $\sigma$ 2. Finally, $\beta$ and $\theta$ represent the coefficients of continuous variables X and dummy variables D respectively which are to be estimated.

Results of both models are shown in Table 4 and the explanatory power of both models is shown in Figure 7. We firstly note that in both models we exclude endogenous variables such as service frequency as we presume that demand drives the increase in service frequency and not vice versa. Our two models differ in terms of the included explanatory variables. Model 1 is a minimal model excluding any multi-collinearity problems among the explanatory variables. Coefficients significant at the 5% level are shown in bold, whereas coefficients significant at the 10% are indicated by italic.

We find that, as expected, Chinese New Year and summer vacation have a positive effect on THSR ridership while consecutive holidays does not have a significant sign and is included from our final model specification.

GDP / fuel price has the expected negative sign. Further, in our model specification we tested lag effects of the socio economic factors. For the GDP/ fuel price factor we find that a lag of one month provides the best model fit which is in line with Kyte (1988) and Lane (2012) who also discusses that such lagged responses are reasonable and important behavioural components in consumer response to changes in marketplace. The lag can be explained by the fact that fuel prices as well as GDP take time to influence people's decision.

In model 2 we added the other socio economic factors such as total population, unemployment ratio and car ownership. The model results have shown that population has a significant positive effect both on lag 0 and lag 1. Unemployment ratio was suggested to have a 3 month lag on THSR ridership with significant negative effect as expected. Car ownership in this paper was considered as potential alternative mode choice for travellers, whereby they (car owner) have alternative choice between public transport and private vehicles. The relationship between THSR and car ownership is found to be negatively significant, suggesting that if one owns a car this has also influence on inter-city travel mode choice. Note that the model fit only slightly increases by adding the additional variables though the significance of the constant vanishes in Model 2.

The adaptation effect is included as a continuous variable for months (from January 2007 to December 2012) in both models. The effect is found to have a strongly statistically positive sign. We note that the adaptation effect is likely to capture a combination of various effects. That is, it includes possible some of the in the model not captured endogenous effects as well as possibly some of the "information mass effects" discussed in Schmöcker et al (2013). For example it might take some time before the population gets fully aware of the service quality and gets convinced it is safe to use. Also businesses might have only over time adjusted their schedules. From personal experience the first author of this paper knows that since a few years now more one-day business trips between Tainan and Taipei are conducted. Whereas before the introduction of THSR one would arrange for longer, infrequent meetings, nowadays company bosses can conduct morning meetings in Taipei and same day afternoon meetings in Tainan or Taichung. Thus, one might conclude that the TSHR is slowly changing the "mobility

**Table 4** Model Estimation Results for Time-series Models

| Model: Loglinear with MA(1) | | Model 1 | | Model 2 | |
|---|---|---|---|---|---|
| Parameters | lag | Coeff. | t-statistics | Coeff. | t-statistics |
| Total Population | 0 | | | **190.54** | 2.81 |
| | 1 | | | **178.06** | 2.64 |
| Unemployment Ratio | 3 | | | **-0.65** | -4.35 |
| GDP/Fuel Price | 1 | **-0.30** | -2.03 | **-0.31** | -2.76 |
| Car Ownership | 0 | | | **-7.52** | -2.99 |
| Chinese New Year | 0 | *0.05* | 1.82 | **0.06** | 2.37 |
| Summer Vacation | 0 | **0.08** | 2.77 | *0.04* | 1.87 |
| Adaptation Effects | 0 | **0.44** | 28.48 | **0.51** | 6.27 |
| Constant | | **14.82** | 19.82 | -170.63 | -0.57 |
| Observation | | 72 | | 72 | |
| R-square | | 0.96 | | 0.97 | |
| Adjusted R-square | | 0.95 | | 0.96 | |
| Moving Average Coeff. | | -0.51 | -4.63 | -0.26 | -2.01 |
| Ljung-Box Q test | | 0.00 | | 0.06 | |

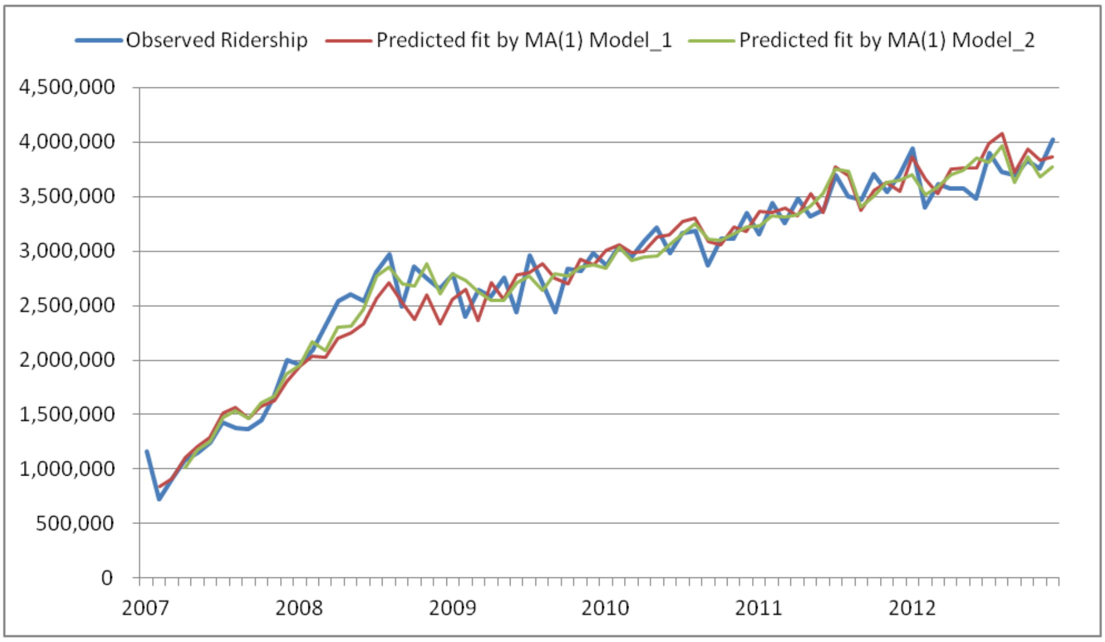


**Fig.6** Comparison of THSR observed and predicted monthly ridership

culture" of private as well as business people of the country.

## 6. CONCLUSIONS/ IMPLICATIONS

In this paper we reviewed demand uptake of the in 2007 newly introduced Taiwan High Speed Rail. We discuss its effect on competing modes such as air and highway traffic showing that the new system has slowly driven domestic air transport out of market. This might be an encouraging message for other countries aiming to introduce more sustainable rail transport for medium long distance travel. However, one also has to remember the specific geography of Taiwan, where a single high speed rail line can capture most of the air demand.

We present two types of time series modelling. Our fitted SARIMA model appears suitable for demand forecasting whereas our simpler MA(1) models with explanatory variables allow us to understand the role of some exogeneous variables better. We find that total population, GDP, unemployment and fuel prices as well as seasonal effects are significant determinants of demand all with the expected sign. This suggests that to estimate demand precisely one needs to consider a mixture of long-term predictable factors (such as population growth) as well as short term fluctuating factors (such as fuel price) into account.

A main result of our analysis is that adaption to the new system might take a much longer time than often predicted. Even after seven years of operation it is not obvious when and whether an equilibrium might be reached, which has possibly implications for demand modelling of any kind of new transport system such as electric cars or shared car schemes. Policy makers should be careful in over predicting the short term demand a new scheme might generate. We argue that this is possibly due to various types of "adaptation effects" including general population perception of the new scheme and possibly "information spread". An obvious extension for future work is hence a more detailed analysis of individuals as well as businesses and their adaptation behaviour to new travel demand services.

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