High Speed Rail Demand Adaptation and Travellers' Long-term Usage Patterns

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Abstract

Adaptation of behavior is the process of adjusting one's behavior to a change in the environment. In transportation, understanding adaptation towards a new public transportation mode is an important aspect for demand forecasting as well as to understand gradual changes in perception to the new travel mode. However, 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 (user equilibrium) level.

The aim of this dissertation is to understand the adaptation process of high speed rail (HSR) travellers. Especially Asian countries and regions have embraced HSR since the start of the 21st century. In Korea, China, and Taiwan, HSR began its operation and is significantly increasing these years. In Taiwan, the focus of most of this thesis, the HSR service opened in 2007 and cut the travel time from 4 hours to 1.5 hours for a journey from Taipei to Zuoying. This has greatly expanded overall accessibility throughout the whole Western coast region of Taiwan.

In the first stage of this dissertation, the focus is on the HSR monthly aggregated demand in Taiwan. By controlling for economic and seasonal factors, this study aims to explain through econometric time series models the factors affecting ridership changes for the relatively new transportation scheme. The analysis is based on monthly ridership data from January 2007 to December 2013. The impact of THSR on competing modes such as air demand is also discussed. First, a seasonal autoregressive integrated moving average model was applied; showing that the ridership thrives and that the trend prediction fairly well performed if applied to data after 2012. Second, to specify the impact of explanatory variables, a first-order moving average model was fitted. Results show that ridership, population and fuel price have a positive effect, while unemployment and car ownership tend to reduce the THSR ridership. We include as a separate factor 'months since operation start', showing that this factor is significant.

The methodology is then replicated to investigate the HSR local demand. In addition, the thesis assesses the impacts brought by access links for all HSR

stations. Model results show that access links appear to be one stimulus for station demand. For suburban stations, the first-connected public transport connection has been observed to significantly impact travel demand. The result further suggests that access links are important, but operators should not overestimate the impact of such service improvements. This implies that possibly there exists a threshold accessibility in that general accessibility through public transport is important, but further improvements do not generate significant additional journeys in Taiwan.

With aggregate data a more detailed understanding of how such demand adaptation takes place, is though not feasible. Therefore, the study is continued by proposing a new data collection methodology approach to understand the demand adaptation process with data from individuals. Moreover, this dissertation further expands the study area to the other side of Taiwan Strait, the HSR network in China, with a focus on Shanghai. HSR demand were dramatically growing since 2008.

A web-based survey was conducted among HSR travellers. At the heart of the survey is the design of graphical usage patterns to describe individual's HSR usage over several years. These 10 hypothetical graphical usage patterns were finalized after feedback from a pilot survey in both Taiwan and Shanghai were obtained. They are presented to respondents together with a textual description. Respondents are asked to select the abstract pattern that most fits to their actual long-term usage. Comparisons of actual usage frequency and usage patterns (recall frequency) suggest that the patterns fit the usage. The visualized usage pattern allows travellers to reconsider their longer-term travel behaviour (over several years) without concerning the accuracy issues of single answers. Moreover, a descriptive analysis is conducted of the usage pattern explaining the reasons of a) motivation to start HSR usage, b) reasons to increase HSR usage, c) reasons to continue, and d) reasons to drop/stop HSR usage. The analysis has proven that one can extract valuable factors that influence the HSR usage and partly explain the gradual changes in HSR usage over several years.

To further explore the usefulness and limitations of the information obtained from the novel survey, a number of modelling approaches were adopted. Multi-nominal logit (MNL) regression results suggest that we can distinguish and partly explain the behavior of some user groups by attitudinal factors and

perceived perceptions. As alternative to the MNL results, and more in line with the assumption that “choices happen to people” we also test discriminant analysis with the same “explanatory variables” which in this context should be referred to as “predictor variables”. Discriminant analysis is to utilize a set of predictor variables to distinguish the factor of interest in this case the chosen pattern while utility maximization does not have to be assumed in MNL. The results obtain similar conclusions for both types of analysis. Though there are important differences in the estimation process, both models aim to show the explanatory power of the explanatory variables/predictors for the same dependent variable/factor. Moreover, the pattern specific discriminant analysis revealed strong evidence that the formation of long-term usage patterns involve self-planning, initial perceptions of the new mode, receiving further information about it over time and reflecting previous experiences. Therefore, the discussion on the reasons to change HSR usage provide an overview regarding these varies kinds of adaptation processes.

Keywords: Travel Demand Forecasting, High Speed Rail, Usage pattern, Adaptation Effect

Preface

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Chapter 1

Introduction

1.1 Background

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. In some cases demand estimates have been found to be very far from predictions. A notable recent example is the demand for the Incheon Airport Express in Korea which is far below model estimates (KMLIT, 2009)). At the beginning of their projection, demand was estimated to be 210,000 in 2007, the first year of operation. They also predicted the number would jump to 490,000 in 2010 (The Korea Times, 2009). However, approximately 150,000 passengers use the ordinary train every day while only 2,000 use the express train in 2013 (Korea JoongAng Daily, 2013). A part of the explanation is that whether people switch mode to a new system is influenced by far more factors than usually included in utility estimations that are the basis for mode or route choice models.

An additional issue is that the timing of such 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 (user equilibrium) 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. As another 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, Mühlmeier, Henkel, & Waller, 2011; Link, Raich, Sammer, & Stark, 2012); and bicycle sharing (Fishman, Washington, & Haworth, 2013; DeMaio, 2009). Also a number of public transport systems have been introduced but services were cancelled after some time when demand did not reach expectations. On the other hand also positive examples are known where demand exceeded predictions (Lee & Senior, 2013; Abrate, Piacenza, & Vannoni, 2009; FitzRoy & 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 to their travel 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 thesis is twofold, (1) to utilize aggregated ridership data to assess how a population is adapting to a new travel mode, and to discuss factors that influence the demand development for newly introduced public transportation schemes, in this case, high speed rail (HSR); (2) to understand the adaptation process of individuals, the disaggregated perspectives. That is, we want to know how long it takes for a new system to reach a constant stable demand (if ever) and the mechanism of adaptation for travelers. 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 the thesis consists of varies analysis and discussions, we first analyze the aggregated demand and station specific demand for the Taiwanese High Speed Rail. 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.

Furthermore, it is equally crucial to understand the gradual changes in travel behavior over time from a disaggregated perspective to better understand adaptation reasons. However, capturing cause and effect relationships in long-term travel behavior patterns is generally difficult to obtain even with panel data. To this end, this thesis later proposes a different data collection methodology, which aims at analyzing specifically the gradual changes of travel behavior. Continuing the case study, we analyze the usage of HSR in Taiwan and extend our study area to Shanghai, China. The Shanghai HSR schemes had operated over the last 8 years, similar to Taiwan HSR. By a pilot survey in each region, ten graphical long-term usage patterns were developed with detailed usage descriptions. The behavioral and HSR usage dynamics of our sample could be captured and to some degree explained. Further, the growing literature on explaining adaptation to the new travel mode are partially based on concepts involving self-planning, initial perceptions of the new mode, receiving further information about it over time and reflecting previous experiences.

1.2 Research Objective

As explained in previous section, the main objectives in this dissertation are to break down demand adaptation by aggregated analysis as well as the adaptation process formed by individual perspective towards HSR. In specific, the "adaptation process" we interested in, is the gradual change in behaviour over time. This behavioral dynamics is possibly involved with self-planning, initial perceptions of the new mode, past experiences, expectations, as well as diffusion of innovation (consumer behaviour). When a new product comes out, it is likely to first be adopted by consumers who are more innovative than others—they are willing to pay a premium price for the new product and take a risk on unproven technology. Several trends can be identified in the consumer behavior literature: a focus on observed innovativeness, a consideration of adopters to the exclusion of non-adopters, research bias in favor of innovaters and early adopters, and a lack of development of theoretical bases or models (Roger & Schoemaker, 1971; Abou-Zeid, Schmöcker, Belgiawan, & Fujii, 2013; Ball, 2004; Bass F. M., 1969; Bass, Donoso, & Munizaga, 2011; Mahajan, Muller, & Bass, 1995; Norton & Bass, 1987; Mahajan, Muller, & Bass, 1990).

Our focus is to suggest ways to increase the public transport demand, in order to encourage travelers adapting to a new system regarding sustainable

transport policies, especially for the public transport operators and administrations authorities. Public transport demand forecasting is never an easy task and often overestimates the demand. To this end, understanding adaptation process to an existing, but also innovative scheme to that specific region or society is a primary issue for policy makers and public transit operators to support substantial environment. Moreover, the objectives in this thesis are to discover those perception factors that might influence user adaptation and yet have not been noticed before, under researched or discussed. One possible direction suggested by Schmöcker *et al.* (2014) is that the adaptation process may involve varies kinds of *positive* mass effects. They distinguish "real mass effects", "perceived mass effects", "consequential mass effects" and "information mass effects".

In order to propose policies to HSR demand adaptation, this dissertation is started from analyzing the aggregated HSR ridership in Taiwan, controlling social economic factors and try to identify the underlying trend over a prolong time period. Then the study is expanded to station demands which to explore the trend from local (regional) scales. This study then turns to the individual perspectives, where a web-based survey with an unique approach was conducted in two places, Taiwan and Shanghai. By doing the comparative study between these areas, it is hoped that how individual HSR usage pattern can explain the determine factors of mass effects and can be learnt and finally some policies to encourage HSR usage in Taiwan and China can be proposed. To summarize in this dissertation the objectives are:

1. To understand the determining factors from aggregated HSR demand especially social economic factors, seasonal factors and regarding the positive trends, possibly including mass effects; and compared the observed demand with projection.

2. To investigate whether adaptation is similar across the stations and compare with the results from total demand

3. Following objective 2, the analysis further consider accessibilities of accessing/egressing the HSR stations and identify the impacts brought by a number of access links to the eight HSR stations.

4. To obtain long-term HSR travel behavior in order to explain the perceptions and attitudes perceived from HSR travelers; and to show merits and limitations of existing survey approaches to capture cause and effect for long-term behavioural changes.

5. To compare the results and to fill the gap between the traditional predictors (travel time, cost, level of service, and frequency) and predictors from attitudes and perceptions to explore the adaptation process from individual HSR travellers.

1.3 Outline and Structure of the Dissertation

The dissertation is organized by seven chapters. The introduction chapter explaines the motivation and the background and objectives of the study, and research outline of the dissertation. Chapter 2, "Travel Demand Modelling and Innovation and Adaptation of High Speed Rail (HSR)" reviews a number of demand modelling, long-term travel survey, and briefly discuss the development of HSR and its latest related research. Previous studies and papers related to this dissertation are reviewed, including HSR demand forecasting modelling, attidutes towards new mode/technologies and determintants of long-term travel behaviour.

Chapter 3, "Demand Adaptation towards New Transport Modes: Case of High Speed Rail in Taiwan" discusses HSR aggregated ridership demand in Taiwan. Impacts of the introduction of HSR and its compitition; and factors potentially affecting HSR demand are analzed and discussed. Time series modelling was applied to analyze and project the ridership controlling for social economic variables. The results suggest that for a prolong period of time, there exists an adaptation from the HSR users. Chapter 4, "Public Transport Accessibility Impact on Demand for Taiwan's High Speed Rail Stations" further investigated the adaptation effect by applying similar methodology structures to HSR station demand and compares this with the results of the previous total demand in Chapter 3. Moreover, in the second model, the accessibility of HSR stations are taken into account to understand the induced demand from the reduction of access and egress time. In other words, the discussion is continued with impacts brought by the access links to the HSR stations. And finally, we summarize our findings from aggregated data analysis as well as its limitations.

In Chapter 5, "Long-term Travel Behaviour Survey for HSR Usage", based on identified shortcomings of literature discussed in Chapter 2, a new methodology is proposed to obtain long-term HSR travel behavior. A web-based survey was conducted and over 600 respondents were obtained. Details on developing pattern usage, other explanatory variables, overall survey flows, and initial descriptive analysis are also discussed. A comparison between stated usage frequency and our patterns illustrates further the additional information we obtain compared to "traditional" surveys.

Chapter 6, "The Impact of Attitudes and Perceptions on High Speed Rail Usage Uptake in Taiwan and the Shanghai Area (Usage Pattern Analysis)" presents a number of modeling approaches, extracting potential information from the survey data, and analyzed HSR usage. Regression analysis was first performed to find potential factors that influence HSR usage. Multinomial Logit models (MNL) are later tested as well, even though we note that there is an argument as to whether the assumption of utility maximization is realistic for analyzing using long-term patterns, in which decisions are likely to be conditional on previous decisions and other external factors. Analysis of the causes for usage changes further illustrates some marked differences between reasons for initial usage uptake (among others personality related factors), gradual usage increases (particularly service quality) and usage reductions (such as life events). The results are used for policy recommendation especially for HSR operators and countries interested in investing HSR. And finally as an alternative to MNL modelling, we propose discriminant analysis, in order to distinguish the unique feature of each usage pattern. In addition, our results shows that the previous MNL result was in line with our discriminant analysis. All the approaches provide some policy implications as well as recommendation for HSR operators.

Finally, Chapter 7, concludes this study by summarizing and converging the central findings of this study from both aggregated analysis and disaggregated analysis. By following the implication for policy and planning, shortcoming of the study, recommendations for future work, as well as the contribution of this study.

In Appendix A, the questionnaires of long term HSR usage used for Chapter 5 and 6 is presented. However, for brevity, pattern 7 was used as the

example for the overall survey flow as it contains all the sections that were asked to the respondents. Appendix B shows the model specification of the MNL model used for Chapter 6. The structure of this dissertation is shown in Figure 1-1.

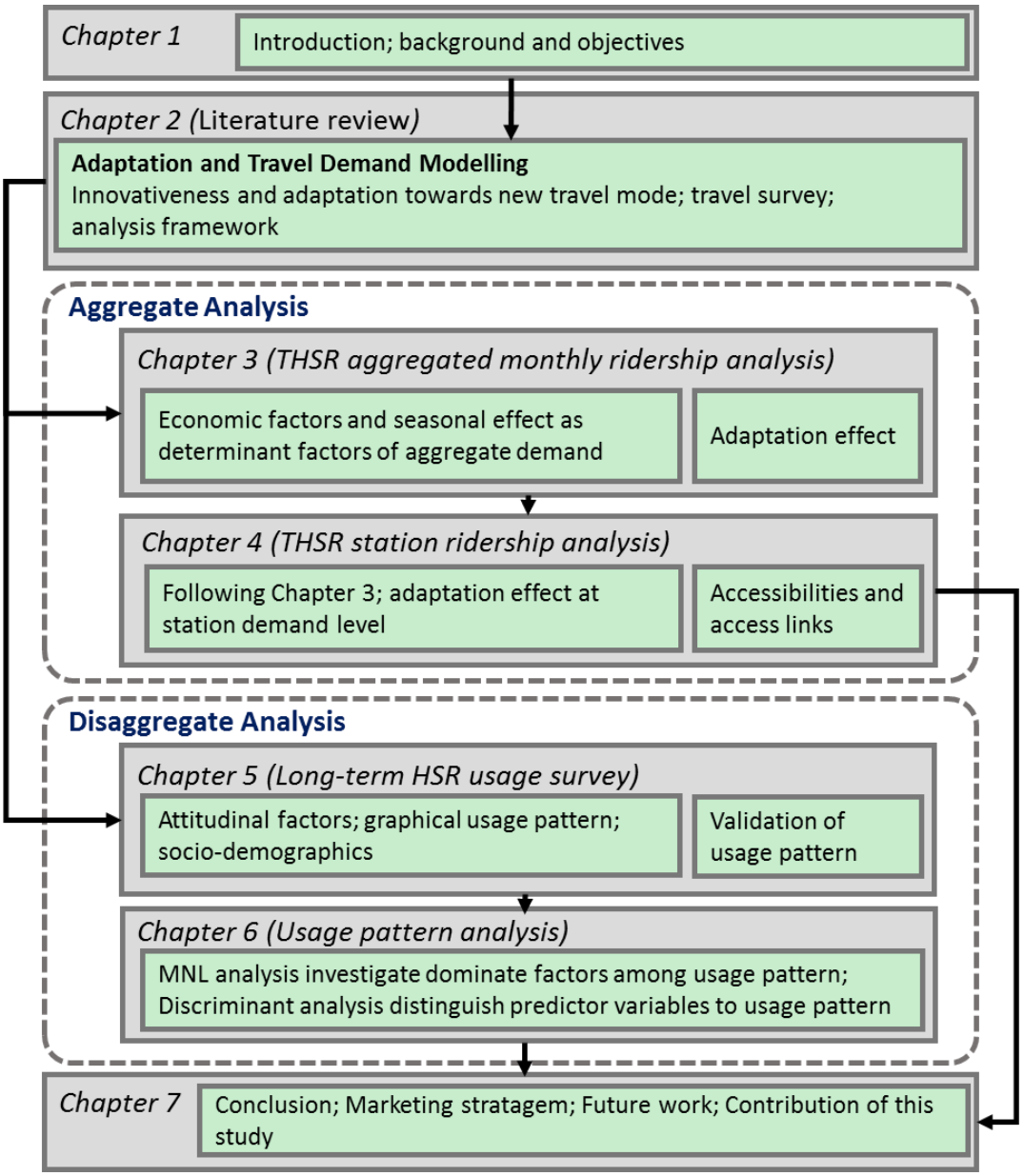


Figure 1-1 Structure Of Dissertation

Chapter 2

Travel Demand Modelling and Innovation and Adaptation of High Speed Rail (HSR)

2.1 Introduction

In this chapter, a number of literature was reviewed and discussed. In the following section, we briefly introduce the development of demand modelling, these approaches were characterized; moreover, the development of long-term travel survey regarding its advantage and draw backs were highlighted and discussed. Section 2.3 will focus on the development of high speed rail and its impact to the modern society. Many HSR researchers had been studying with abundant of different perspectives to HSR. In particular, an example was given to show a classic drawback from traditional methodology approach for HSR demand projection. And finally, the literature were summarized in section 2.4.

2.2 Demand for New Public Transport Schemes

As alternative methods for exploring the demand impacts of transportation investment is to be observed and measured, at a larger scale. Investigating the relationship between investment in transportation infrastructure and indices of economic performance. A range of different methods fall under this general category, including the use of regional economic models, aggregate productivity functions, as well as more disaggregate model specifications that allow for measurement at local and regional levels (Iacono & Levinson, 2008; 2015).

Apparently there is a rich body of literature on factors that explain or predict the demand for new public transport. Those research can be categorized into two levels, aggregate or disaggregate analysis. In this section, we briefly explained the mechanism of existed analysis approaches as well as the general determinant factors that are deemed to be strong predictors for demand forecasting. The ensuing of this section, a number of long-term travel survey methodologies were reviewed and summarized, which also reconfirmed and

anchor our objectives, we further discussed our problems at hand of travel survey issues in Chapter 5.

2.2.1 Aggregated Demand Analysis and Determinant factors

A. Aggregated Demand Analysis

Aggregated forecasting approaches are generally adopted before the actual public transport investments. Numerus methodologies could be identified, such as Four-step models, activity-based models, time series analysis and etc. The Four-step Model (FSM), as a well-developed approach of demand forecasting process: its traffic forecasting methodologies procedures have been developed and implemented by transport planners since early 1950s. Techniques have since evolved, incorporating various critical demographics and economic factors, multi-mode choices, network level of service, tolls and fares and many other variables. The conventional transport modeling attempts to simulate the trip making process into four major stages, "*Trip Generation"*, whereby individual would decide whether or not to make trip; "*Trip Distribution*" would suggest where to go; "*Model Split*", by what kind of transport/mode will be utilized by travelers; "*Assignment*", and by what route to the destination. For detailed model structure could be refer to the book section of "The Four-Step Model" in *Handbook of Transport Modelling* written by McNally (2008).

However, the FSM travel demand forecasting has always "*lacked a valid representation of underlying travel behavior*" (McNally & Rindt, 2008). Especially during a period where "*rapid increases in transportation supply were arguably accommodating*", for instance, the growth in population of post–war boom or economic activity in developing countries might not properly reflect the growth in the following decades. An example of demand forecasting failure of HSR project will be given later in Section 2.3.4.

Therefore, from 1970s, these shortcomings had brought fundamental changes in urban, environmental, and energy policy. It was from that time the Activity-based approach (ABA) was first studied in depth. From the empirical studies, a wealth of behavioral theories, analytical methodologies for travel behavior emerged during the same period that the policy environment was involving. These advances shared "*a common philosophical perspective, whereby the conventional approach to the study of travel behavior... is replaced by a richer,*

more holistic, framework in which travel is analyzed as daily or multi-day patterns of behavior, related to and derived from differences in lifestyles and activity participation among the population" (Jones, Koppelmann, & Orfeuil, 1990). It began as an evolution of research on human behavior, in particular, travel behavior. While trip-based approaches are satisfied with models that generate trips, the discrepancy of activity-based approaches is to focus on what generated the activity that begot the trip and the activity patterns. The activity approach is that "*travel decisions are driven by a collection of activities that form an agenda for participations*" (McNally & Rindt, 2008). Moreover, the combination of trips and activities actually revealed the individual's the decision processes, behavioral rules, activity pattern, and the environment in which they are valid, which together constrain the formation of these patterns, characterize complex travel behavior (McNally & Rindt, 2008; Teo, *et al.*, 2015; Sharmeen, Arentze, & Timmermans, 2010; Pinjari & Bhat, 2011). In summary, from ABA's perspective, the concept of travel/trips could be characterized as:

a) activity participation would derived the travel demand;

b) the travel of individuals was conducted by a sequences of chained-behavior rather than individual trips;

c) household and other socio-economic factors influence travel and activity behavior and;

d) activity-based approaches reflect the scheduling of activities in time and space.

However, the criticism that the activity approach lacks a solid theoretical basis is similar to drawing a conclusion regarding weather or the stock market, which reflects a lack of understating of the incredible complexity despite the universality that is also characteristic as indicated by McNally and Rindt (2008). While attempting to understand such complex (and sometimes even complicated) behavior is essential, this statement of course raised the question of whether such a degree/level of complexity of model structure is necessary to satisfy the initial goals of travel forecasting and policy analysis. In addition, it couldn't explain the demand induced by others specific factors such as information spread from media or public perceptions (though it did considered social structures influence), as the *information mass effects* discussed in Schmöcker *et al.* (2014),

or, the induced demand of public transport may leads to economies of scale that may be passed on to travellers by public transport operators in terms of reduced fares or increased frequencies, namely, *consequential mass effects*. These factors that aren't considered in the ABA model seem still under research.

Other than above mentioned approaches, time series model would become a powerful forecasting model once the new scheme/transport mode began to operate/start for a period of time. For instance, it could be applied to where data in business, economics, engineering, environment, and other area of investigation/observation are often collected in the form of time series, that is, a sequence of observations taken regular intervals of time such as monthly, annual growth rates. The objectives of time series modelling and analysis are, first to understand the dynamics and time-dependent structure of observations of a univariate time series, and secondly, to examine the leading, lagging, and feedback relationship among a number of series-multivariate time series analysis. To be more specific, time series model seeks to establish appropriate values for p (order of autoregressive), d (degree of differencing) and q (order of moving-average) in fitting autoregressive integrated moving average (ARIMA) model. Moreover, seasonal ARIMA model considered the seasonal variation and cyclic effects into the forecasting models. Details of ARIMA identification and estimations can be refer to (Burke, 2011; Peña, Taio, & Tsay, 2001; Enders, 2010).

B. Determinant factors in aggregated analysis

Long-term forecasting, always relies on a range of scenario assumptions, e.g. future sociodemographic composition and spatial distribution, economic growth, fuel prices, train fares and car fleet characteristics (Börjesson, 2014). As the explanatory variables are inextricably tied to these methodology approaches, a number of major determinant factors in aggregated demand modelling that 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, Ito and Lee (2005) reported safety records will influence airline demand over longer time periods and similarly for new rail systems passengers might need some time to adapt to these and gain trust. Fu *et al.* (2014) 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. Kyte *et al.* (1988) apllied time-series analysis to examine the factors affecting changes in transit ridership in Portland. One factor they identify is population size. Similarly, also for large national projects the total population growth should therefore be considered, especially if more specific market size estimation is not available as in Fu *et al.* (2014).

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) reviewed 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. Similarly, Cascetta and Coppola (2014) proposed the HSR induced demand model by considering employment, gender, education, job, level of service, and HSR travel time.

In addition, the transit investments will trigger further economic investments and hence create induced demand as well as having an impact on other determinants of transit ridership such as car ownership. Ahlfeldt and Fedderse (2010) argue that the economic geography framework, such as population distribution, economic activity density, and spatial 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 projects. Connected to economic developments are also gasoline prices. In Lane's (2012) study, gasoline prices have exhibited considerable fluctuation in public transit (PT) demand. On the other side of PT, car ownership is also 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 PT ridership (Belgiawan, Schmöcker, & Fujii, 2012; Beck, Rose, & Hensher, 2013).

A fourth group of factors significant for long term demand might be termed as "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 in developed countries reported by 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 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. Related to our study, Andersson *et al.* (2010), used hedonic price method to evaluate the accessibility changes caused by Taiwan HSR and the effects on the residential property market. The estimation results suggest that accessibility has at most a minor effect on house prices though (just starting HSR operation 3 years so far).

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 investigated by Cheng (2010). Owen abd 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. This exactly one of the most question that enter into endless arguments among travel behaviour researchers.

Similarly to these cyclic effects (modal share competitions), Schmöcker *et al.* (2014) discuss that "mass effects" can be significant determinants of long term demand adaptation. Where one persuades a few to change their behaviour initially in order to encourage a large number of people to fallow later (information mass effects). 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 (consequential mass effects). For example economies of scale may be passed on to travellers by public transport operators in terms of reduced fares or increased frequencies (Mohring, 1972).

2.2.2 Disaggregated Adaptation Modelling

Despite aggregated demand forecasting modelling, the growing body literature of the disaggregated/individual aspect of modelling on travel behaviour, have supplemented the undisclosed details of behaviour changes from the overall ridership or statistical market share analysis and assessment. At a disaggregate level, several methodologies have been carried out to identified factors that affect individual travellers' decisions.

Especially one of the most well adopted modelling by travel behaviour researchers is the discrete mode choice modelling (DCM) (Ben-Akiva & Lerman, 1985; Ben-Akiva, *et al.*, 2002; Ben-Akiva, *et al.*, 2012). Where it consider an individual choosing among the available transportation modes for a specific trip purpose, and the set of available mode is called the individual's *choice set*. The aim of the approach is to understand an individual's behaviour (choice) which mode they selected, in terms of observables, that is, determinants of behaviour which we analysed and can observe, measure, and potentially predicts the changes. The basic concept of DCM is to assume that one has to decide on a travel mode depends on an *utility function*, to assess the maximum utility of each

alternative mode in his/her choice set. The factors/elements in the function could be related to the characteristics of mode itself such as travel time, waiting time, travel cost, level of service and etc., or it could be related to the socio economic status of individual, e.g., income, gender, age, whether owns a car… (Train, 2009) these elements are the ones that can generally be observed. Based on the properties of DCM, a large number of more complicated, advanced modelling were developed to solved issues that have been highlighted by other studies. From the basic binary logit to generalized extreme value family (GVM), which includes nested logit, cross-nest logit as well as the probit model, and mix-logit model (Walker & Ben-Akiva, 2002).

Alternatively, suppose the researchers knew all and only the observables and applied with appropriate model structure, are they confident that they could predict his/her choices each and every time? Of course the answer is no, and the reason is clear. That is, at the meantime there existed such a number of factors that were not easily observed or quantifiable but the individual also takes into account; which factors that they relies on, know about, prefers, and the perceptions from the past experience of certain mode. And moreover, one might argues that the DCM did not answered the process of how travellers adopting to a new travel mode but just recalculate the changes of observable factors to estimate the elasticity of demand for aggregate ridership. From the DCM's perspectives, these unquantified factors appear to be elements of *randomness* in decision making process.

One of the approach to disentangle these randomness is to understand the attitudes, norms, intentions, the role of past behaviour, persuasive communication and etc., which have been discussed in the "Predicting and Changing Behaviour" by Fishbein and Ajzen (2010; 1980), and "The Theory of Planned Behaviour" from Ajzen (1985; 1991). From a good number of literature followed by these guidebooks and theories, it is well know that, for example, the past behaviour/experiences or prior knowledge can be a very good predictor of future action (Bettman & Park, 1980). In fact, the addition of the past behaviours have usually done so under the assumption that the frequency with which a behaviour has been performed in the past can be used as an indicator of *habit strength*. In other words, with repeated usage/behaviour for over prolong period, it is assumed to come under the direct control of stimulus cues, by passing intentions and perceptions of behaviour control (Aarts, Verplanken, & van

Knippenberg, 1998; Triandis, 1977). It could be also be explained as, in a sense that, the decision making process at this phase is under subconscious, travellers would be difficult to explain their decision process of choosing such mode as the option. Another good example is the self-identity that effects on behaviour. Turner (1991) has proposed that people's self-concept can influence their intention and actions. Similarly, one of our focus is the innovativeness in one's self-identity, which we aim to understand the willingness to try, as it's part of one's characteristics, can influence the motivation to try new things, technologies, new travel modes, and etc.

Regarding the concept of self-identity, Hurt *et al.* (1977) proposed an innovativeness scale to measure and define the innovativeness as "a normally distributed underlying personality construct, which may be interpreted as a willingness to change". They claimed that the instrument predicts willingness to adopt innovations across populations which differ in terms of age and socioeconomic status. Via factor analysis, the result converged into four factors from 20 items, namely, willing to try, creative original, opinion leader, and ambiguities and problems. Pallister and Foxall (1988) further validated the scales for the measurement of innovativeness. They tested with internal reliability, dimensionality, and discriminant validity; the results indicate that the innovativeness measure proposed by Hurt *et al.* (1977) exhibits high and acceptable levels of reliability and discriminant validity. Details of full descriptions of innovativeness scale adopted by this thesis will be shown in Chapter 6. For analyzing travellers adpoting to a new travel mode, it would be intersting to see the correlation between personal charateristics of innovation and adaptation process.

As been discussed in the beginning of this section, the disaggregated analysis is a useful tool to disentangle the individual travellers' behaviour changes. Likewise, if one wants to investigate the adaptation process from individual traveller to a new public transportation system, offering an appropriate survey method and adopting modelling ought to be an important topic.

Abundant of literature that looking at adopting to a new system or demand forecasting from disaggregated perspective could easily be found. Shaheen *et al.* (2011) analysed the early adoption, barriers to adoptions, and

behaviour response to bike-sharing in China by intercept survey. From their findings, over 80% of the bike-sharing members agreed the perception of the new scheme is a strong determinants to continue their usage. These perceptions are satisfied by low cost, easy access, station abundance, and minimal problems. Overall they found the bike-sharing is capturing modal share from bus transit, walking, autos, and taxis. Nearly 30% of members adopting the system into their most common commute. Similar work done by Fishman *et al.* (2014), where they looks at the impacts of bike share schemes in U.S., U.K., and Australia. From their result, it involved with adaptation and perceptions towards bike sharing schemes, that is, to optimize the impact on reducing car use, is to encourage those car user to adopting to bike.

Similar to other PT schemes adoption research, Hsiao and Yang (2010) investigate the willingness of taking HSR among college students in Taiwan; the results indicate that attitude, perceived behavioral control, and subjective norm are found to have positive effects on the behavioral intention of taking HSR. Furthermore, novelty seeking and trust also have positive influences on attitude and three antecedents of the intention in taking HSR respectively. In particular, they suggest that novelty seeking has indirect significant influences on students' intention to take HSR via attitude toward HSR. It appears that low intention to take HSR may be attributed to a lack of positive attitude towards HSR, which is influenced significantly by students' tendency of novelty seeking.

To summarize the demand modelling above, one of our objectives is trying to fill the gap between the traditional predictors (travel time, cost, level of service, frequency) and predictors from attitudes and perceptions to explore the adaptation process from individual HSR travellers.

2.2.3 Long-term Travel Survey

Following the discussions of disaggregated modelling, the source of data set to design and create a disaggregate model, the survey methodology certainly plays a critical role for further behaviour analysis and modelling. A number of data collection/survey methodologies on observing long-term behaviour have been used in the literature. The standard approach is to collect data from a cross-section of the population at one point in time. Similarly, "repeated cross-sectional surveys" collect data at several time points from independent samples of the population. A "time series survey" is very similar to a cross-sectional survey, but

distinguished by Pendyala and Pas (2000). In addition to repeated cross-sectional data, it involves the collection of aggregate level data. Further, time series surveys must be carried out at regular intervals for many years or time points. These data are well-developed tools for observing aggregate long term travel patterns. The statistics are typically used to compare travel differences in terms of means and proportions and are reflections of theme differences among the entire population. The advantages of cross-sectional surveys are that they offer a snapshot of conditions present at that instant ("quickly amass data"). While cross-sectional data provide sufficient information for determining overall population characteristics and trends over time, they may not be able to capture underrepresented population segments. As for example Dowling and Colman (1995) examined with household travel survey data from San Francisco, they found that low income groups tend to be underrepresented in most telephone surveys. Moreover, when applied to the problem of estimating the behavioural effects of new infrastructure, critical shortcomings are the difficulty in avoiding bias in the selection of the survey sample and, accounting for persons moving into and out of the presumed "impact" area of the new facility. Controlling for changes in background variables, such as economic and demographic changes would be almost impossible in the reality. Moreover, cross sectional data do not provide sufficient data for detailed behavioural analysis, measurement of change at disaggregated level, and most importantly, the cause-and-effect identification; where two distinct variables are measured at the same point in time. One may find from the modelling analysis that they are correlated, but cannot positively determine if one caused the other.

A possible direction to confront causality problems and to capture the complexity of decision making is panel surveys, also referred to as longitudinal data (Kitamura, 1990; Cheng H. , 2007). Longitudinal surveys differ from the collection of repeated cross-sectional data as the behaviour of independent samples can be tracked over time since at each "survey wave" the same individuals are surveyed. Another advantage of panel data is the simplifying computation and statistical inference. The design of longitudinal data is particularly well suited for stationary populations; in region wide transportation studies, this limits the inference to subjects residing long-term in a closed region. Panel data enable researchers to develop advanced behavioral models such as mixed logit and dynamic discrete choice models. However, one cannot ignore the

additional cost of panel data which generally are much more, or exponentially per se, expensive to collect than cross-sectional data. Time insensitivity is another limitation that makes it very difficult to obtain panel data; the survey would take several years and a good number of the respondents usually drop out during the survey. Another major issue of panel surveys is that repeated measurements are likely to lead to a "survey fatigue problem". For further discussion we refer to a number of literature and books comparing these survey methodologies (Yee & Niemeier, 1996; Pendyala & Pas, 2000; Cheng H. , 2007).

Nevertheless, over the past decade, with the advancement of ICT, "trajectory-based surveys" are increasingly complementing other forms of collecting panel data. GPS log data, smart card data, mobile phone data can all enhance the accuracy of behavioural records and are increasingly used in recent studies. The abundance of the emerging trajectory data has driven a new wave of travel behaviour research, as they introduce new potentials as well as new problems (Yue, Lan, Yeh, & Li, 2014). Travel trajectory properties, such as origins and destinations (OD), departure time, arrival times and travel modes, can be extracted from such digital data and then fed into transport models. Though the majority of trajectory-based surveys focuses on daily/weekly patterns (Gong, *et al.*, 2012; González, Hidalgo, & Barabási, 2008); also capturing longer term behaviour is possible. For instance, de Montjoye *et al.* (2013) utilized the mobile phone records of 1.5 million people to model human mobility uniqueness over 15 months. For trajectory-based data, maintaining privacy is a primary issue. Other challenges such as data sharing (different stakeholders), variation of models and algorithms, data bias, and data limitations are discussed in (Giles, 2012; Yue, Lan, Yeh, & Li, 2014).

Yet, a different approach to capture long-term travel behavioral changes is in-depth personal interviews. Such data can help to fill the gaps left by quantitative techniques. The interview surveys are often used in circumstances when the issues under study are clearly defined and participant responses are, to some degree, anticipated. The survey instruments frame the questions and limit the range of answers to those questions. In-depth interviews have also become more popular since attitudinal factors have been increasingly shown to be important to understand travel behaviour (Clifton & Handy , 2003). The challenges of in-depth interviews are obvious: The survey is easily prone to biases,

not generalizable (small samples, random sampling not available), could be time/labor intensive and the interviewer must be appropriately trained.

As for brevity, we summarized the discussed of survey methodologies with its advantages and drawbacks in Table 2-1, as we will later continue this discussion of long-term travel survey in Chapter 5 and explains the problems and limitation of applying traditional travel survey, and to propose, what we believe, a new survey approach for long-term HSR usage survey.

Table 2-1 Long-Term Travel Behavioral Data Collection Methods

Methods		Advantages	Challenges and Limitations
Cross-sectional data (time series data)		1. A snapshot of conditions present at that instant (quickly amass data) 2. Routinely collected data (large target population) 3. Useful source of information on macroscopic changes; well-developed tools for observing aggregate long term travel patterns exist	1. Causality in changes in environment and behavior often unidentifiable 2. Variation in individual behavior not observable
Panel data	Conventional survey (longitudinal data)	Can overcome disadvantages listed for cross-sectional data: 1. More accurate inference of model parameters; Greater capacity for capturing the complexity of travel behavior 2. Partially can identify causalities	1. More costly than cross-sectional data 2. Time consuming 3. Not well suited if target population changes fast 4. Might miss time point of behavioral changes.
	Trajectory-based (ICT, e.g. GPS log, public transport smart card data)	1. Feasible for travel behavior and disaggregated models 2. Computer-aided, high accuracy of actual behavior recording 3. Much lower cost than traditional panel surveys	1. Privacy issues and data sharing (different stakeholders) 2. Data biases 3. Difficult over very long time periods 4. Limited data depending on source: often lack socio-demographics; smart card data only log a subset of all trips
In-depth personal interviews		1. General approach with qualitative data 2. More detailed information than what is available through other data collection methods 3. Specifically cause and effect relationships can be explored in detail	1. Prone on bias 2. Time/ labour-intensive 3. Interviewer must be appropriately trained in interviewing techniques 4. Difficult to generalize (small samples, random sampling not available)

2.3 Innovation and Adaptation of HSR

2.3.1 Innovation of HSR

HSR is by many regarded as one of the most significant technological breakthroughs in passenger transportation. It was first implemented in 1964 in Japan, and subsequently with technology breakthrough, it was implemented in several western European countries from the second half of the 20th century. Now days, HSR has become a worldwide major intercity transport mode (Nash, 1991; Ahlfeldt & Feddersen, 2010; Albalate & Bel, 2013). In recent years, due to its speed, safety, comfort, low energy consumption and high-capacity, HSR has developed rapidly to stimulate the economic growth Countries in Europe and East Asia and leading this trend through extending HSR networks. Other potential projects were proposed whether in preplanning or construction phases, especially in Asian countries such as China, Singapore-Malaysia, Thailand, and Indonesia. Table 2-2 shows the major HSR Schemes and Descriptive Developments by countries in 2015.

Table 2-2 HSR Schemes and the Descriptive Developments by Country

Country	Length (km)	No. of lines in service	Opening Year	Fare (Euro/km)
Japan (Shinkansen)	2,663*	11	1964	0.22
Italy (ETR500)	923*	6	1977	0.25
France (TGV)	2,036*	8	1981	0.22
Germany (ICE)	1,620*	8	1991	0.27
Spain (AVE)	3,100*	4	1992	0.20
Korea (KTX)	938*	4	2004	0.10
Taiwan (THSR)	339	1	2007	0.12
United Kingdom (Eurostar)	108	1	2007	0.21
China (CRH)	11,927*	8	2008	0.04

Note: Superscript with * denotes HSR network is currently expanding under construction

2.3.2 Overview on HSR related research

As the technological innovative features of HSR, from planning, constructing to operation, its impact may leading these regions not only the travel pattern into a new era, but also influence in various aspects. As the result, there is a rich body of literature which has been studying HSR issues from a range of perspectives. And overlapping with these different topics were commonly found as well as inclusive researches from macroscopic to microscopic scale. A number of topics could be identified and are listed in the following:

- Economical interactions/impacts (Iacono & Levinson, 2015; Chen & Silva, 2013),
- Spatial impacts and land-use patterns (Ahlfeldt & Feddersen, 2010; Albalate & Bel, 2013; Andersson, Shyr, & Fu, 2010; Sasaki, Ohashi, & Ando, 1997; Garmendia, Ribalaygua, & Ureña, 2012),
- Environmental issues or energy efficiency (Cascetta & Coppola, 2014),
- HSR investment assessment (before) and operation research (after) (Yu & Johannesson, 2010; Cheng Y.-H. , 2010),
- Intercity travel pattern (Fu, Oum, & Yan, 2014; Demizu, Li, Schmoecker, Nakamura, & Uno, 2015),
- Ridership forecasting and induced demand (Börjesson, 2014; Fu, Chen, & Chou, 2008; Cascetta & Coppola, 2014; Hsiao & Yang, 2010) and;
- Accessibility/mobility management (Zhong, Bel, & Warner, 2014; Ahlfeldt & Feddersen, 2010; Cao, Liu, Wang, & Li, 2013)

In this thesis some of these issues are addressed such as factors influencing HSR usage are reviewed in more detail in Section 3.2, Section 4.2 and 4.3. Based on the previous fundamental stone of various HSR studies. In this dissertation, we are interested in the mechanism of forming travel's adaptation towards HSR. In particular, apart from traditional sources of uncertainty encountered in forecasting the demand for a project, the effects of induced demand and the dynamic relationship between transportation network improvement, accessibility changes, and development patterns introduce additional sources of uncertainty which may affect estimates of travel demand. There is still a great deal that is not known about the fundamental causal structure underlying the phenomenon of induced demand. Hills (1996) suggests that there are both short-run and long-run effects of induced demand. Demizu *et al.* (2015)'s study on HSR in Japan also confirmed the short-run and long-run demand with adaptation effects existed after the several extensions of HSR networks. However, the research attempting to decompose the complex elements of adaptation effect seems to be under researched.

2.3.3 HSR Demand in China and Taiwan

In this section, the HSR developments were briefly described in our study area, Taiwan and Shanghai Metropolitan area in China. But kindly note that in this dissertation, aggregated analyses only take parts in Taiwan's HSR (Chapter 3 and 4); we further extend the study area to Shanghai after we decided to explore

individual HSR travel behaviour (Chapter 5 and 6). First in this section we discuss the issues of Taiwan HSR, and followed by the Shanghai case.

The Taiwan HSR (THSR) service connecting the eastern part of island from north to south and opened in 2007. The system primarily relies on imported technology and rolling stock from Japan's Shinkansen, supplemented with a European (TGV and ICE) traffic management system; with an investment cost of approximately US$15 billion (Andersson, Shyr, & Fu, 2010). Through connecting its economic corridor north to south, covering almost 90% of population, it brought Taiwan into a new stage of "one-day peripheral circle". Through the nearly 350 kilometres investment, the travel time is cut from 4 hours into 1.5 hours (Taipei to Zuoying). This has greatly expanded overall accessibility throughout the whole Western coast region of Taiwan (see Figure 2-1).

Source: Wikipedia

Figure 2-1 Taiwan HSR Route Map

The THSR ridership despite supply characteristics, such as travel time and cost, staying fairly unchanged over time the demand has been continuously increasing, has increased steadily since the operation. (see Figure 2-2). This is even though the airline had reduced its price so that for some time in 2007 it was cheaper to fly than using THSR. Nevertheless, the domestic airline share continuously reduced since 2008. Eventually, the airline connections among west Taiwanese cities have been suspended since June 2012 (for more detail discussions on modal competitions will be described in Chapter 3).

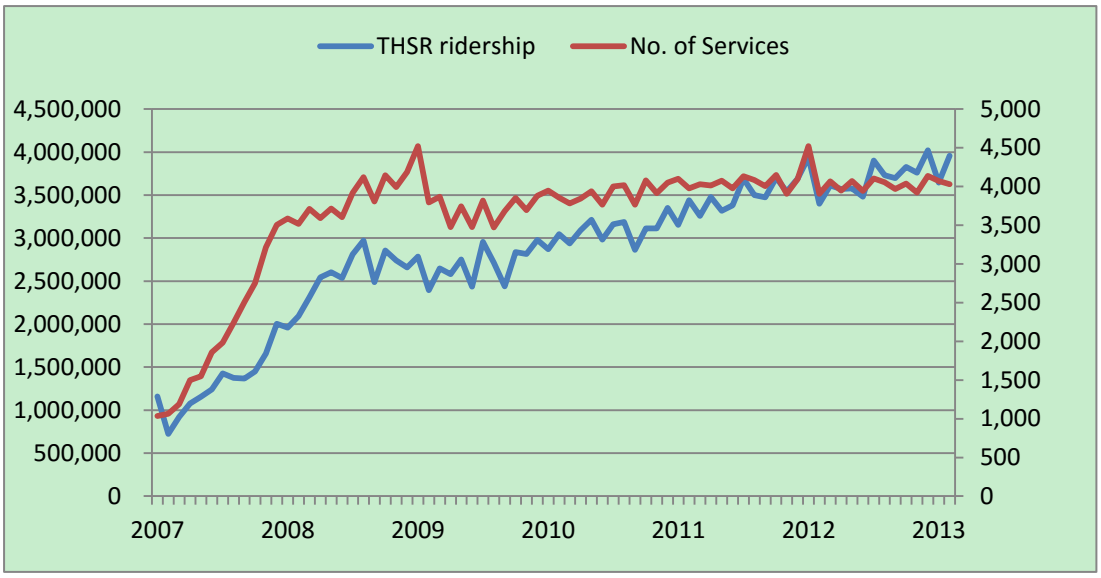


Figure 2-2 Taiwan HSR Monthly Ridership and Services

However, criticism still remains, (Su, Chang, Lu, & Liu, 2012) stated that five out of eight stations are located in suburbs and far away from the CBD area (Taoyuan, 8.4km; Hsinchu, 8.8km; Taichung, 11km; Chiayi, 15.5km; and Tainan, 13.9km away from CBD). This has reduced the travel time benefits in many cases compared to conventional rail (travel cost does not increase as for most of these stations, THSR operates free shuttle buses to the CBD). 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, Shyr, & Fu, 2010).

Another critical issue of THSR operator is that the demand projections made before the opening of Taiwan HSR have though continuously overestimated the total demand. We note that all demand estimations are far below initially predicted levels. For a more detailed discussion on discrepancy between forecasted and actual demand will be discussed in the next section 2.3.4.

Based on these discussions above, it given us the motivation to investigate the HSR demand in Taiwan. Details of the impacts from HSR will be discussed in Chapter 3, where we controlling for socio-demographic and economic factors and conclude that the increase (on a below estimate level) is a mix of mode shift and induced demand. And by following Chapter 3, the accessibility issue will be further examined in Chapter 4.

On the other side of Taiwan Strait, HSR is currently rapidly growing in China, the HSR network keeps rapidly extending, where the first passenger-dedicated HSR service in China opened in 2008 between Beijing and Tianjin. By the end of 2013 China has built a network of about 10,000 route-km of HSR. In order to find a similar case for comparison, we carefully considered the economic scales (IMF, 2013; World Bank, 2014) and HSR development, and Shanghai metropolitan choose area as the case study in China, the time period of starting HSR operation started in 2008, just one year behind THSR opened. Though accurate HSR demand data for Shanghai demand is not available (to us), we found a report stating that there are 132 thousand passengers per day in 2011 which has increased to 252 thousand passengers in 2014 (Ollivier, Sondhi, & Zhou, 2014). In the Shanghai Megapolitan area, the service has been keeping attracting numerus inter-city travels from the congested air traffic and conventional rail services.

Though China has by now a widespread HSR network, a comprehensive demand analysis does not appear to be available (at least not in the openly accessible literature). Detailed official ridership figures for the HSR services generally are not available but indirect evidence suggests ridership is broadly favourable compared to international experience (Bullock, Salzberg, & Jin, 2012). Only a few studies looking at specific HSR routes are currently available and open to HSR researchers. These studies focus mostly on how HSR competes as well as cooperates with road and air passenger transport. The studies mostly use disaggregate modelling approaches to study the choice of individual passengers after their choice sets are updated to also include HSR. As an example we note the work by Chen (2013)studying the competition between HSR, conventional rail, bus, and private vehicles in Chengdu. Further, Liu and Zhang (2012) investigate the intercity passengers' travel behavior before and after the introduction of high-speed rail among Beijing-Tianjin. The result suggests that HSR users are mainly attracted among conventional rail users. Trip activities have changed from single to multiple trips due to considerable increase in round-trip frequency and a decrease in round-trip return time. Ye and Wang (2010) examined the Shanghai-Hangzhou passenger line based on hypothetical, stated preference (SP) and observed, revealed preference (RP) survey data and established a disaggregate multinomial logit (MNL) model as the passengers' mode choice model. They estimate the change in share rates for various transport

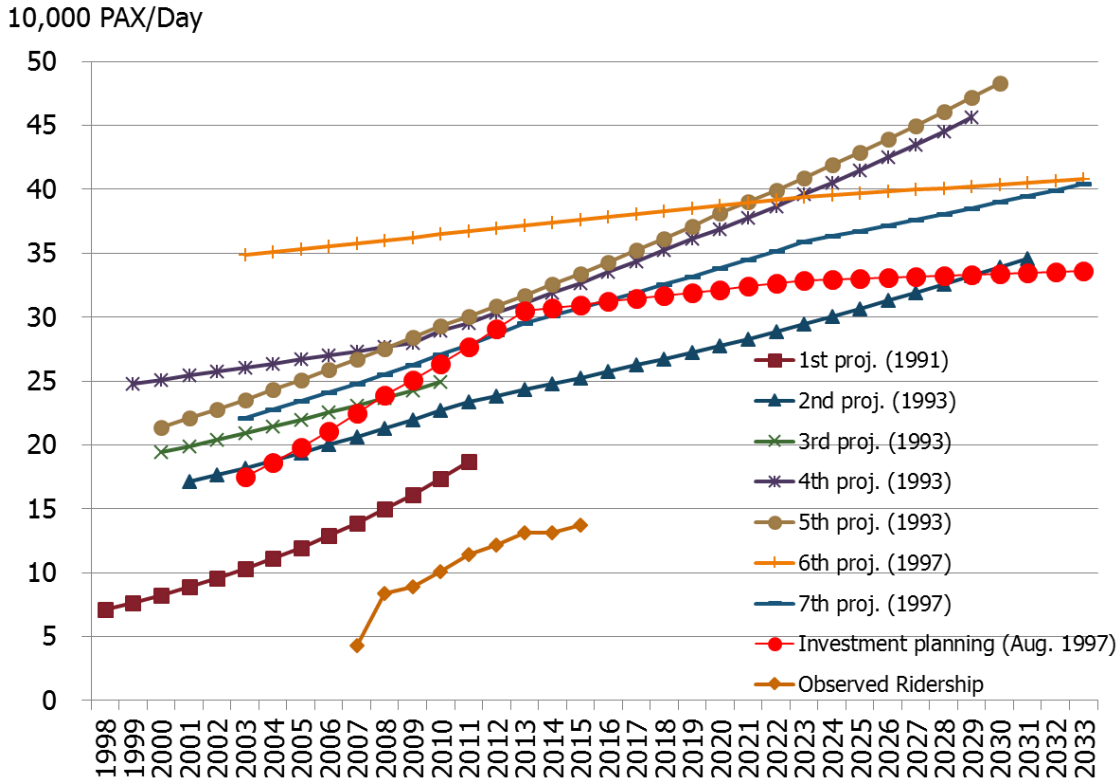
modes after the opening of the Shanghai-Hangzhou service. A key feature observed in HSR demand to date has been the high level of generated trips, i.e. trips made by those who have been induced to travel by the improved service levels (speed, frequency, reliability, and comfort) of HSR.

In general, previous HSR studies in China found that not surprisingly HSR had a strong impact on air demand for travel distances of approximately 500 km. As has been widely reported, some short-distance air services have been completely withdrawn after an HSR line has opened. In contrast to longer routes where the chief competition in terms of travel speed and cost is air, the main competitors for shorter intercity routes are bus and private vehicles (car and minibus). Systematic volume data for both of these modes is unfortunately not often available but, based on evidence collected from bus service operators, they have often been hard-hit (Bullock, Salzberg, & Jin, 2012; Cao, Liu, Wang, & Li, 2013).

To this end, this study intends to understand the HSR usage uptake among travellers in these areas after several years of operation. As discussed in our following study in Chapter 3 and 4, with THSR aggregate demand data, demand adaptation to a new travel mode appears to require a longer time horizon especially if it encompasses significant changes in lifestyle and if travelers first have to get used to considering a new transport system in their choice set. Therefore we decided to extend the study area to Shanghai and with disaggregate approach (will be described in Chapter 5 and 6).

2.3.4 Demand Forecasting Failure in THSR and its Adjustment on Demand Prediction

During THSR planning and construction phases, patronage forecasts have been analysed by various institutes and authorities, including Taiwan's High Speed Rail Corporation (THSRC) itself (see Figure 2-3). Since the HSR rail is a whole new mode in Taiwan, the forecasts were mostly relying on observed traffic data, references to government studies concerning Taiwan traffic patterns and expected future macroeconomic and demographic developments. Conventional four-stage transport modelling based on a SP survey were carried out to simulate THSR ridership in 2003; with the ridership estimated to be initially 200,000 passengers / day, which would be doubled by 2036.



Source: Taiwan High Speed Rail Corporation (2014), the Control Yuan, R.O.C. (Taiwan) (2009)

Figure 2-3 Taiwan HSR Demand Projections and Actual Ridership

However, when the operation first started, daily trips were merely 43,000 in 2007 and 84,000 passenger per day in 2008. The latest daily ridership in 2014 was 130,000 which does not even achieve the initial goals. The lower-than-expected predictions means that revenues are still insufficient to handle the financial, operational and depreciation costs of assets and infrastructure Yu and Johannesson (2010). Cheng (2010) pointed out that this is a major concern for the THSR operator as well as the government authorities. Albalate and Bel (2013) propose two explanations for this discrepancy between predicted and actual demand. The first one is the optimism of predictions on which estimates were based prior to the 1997 financial crisis. Although the estimates after 1997 were subsequently modified, the estimates continue to too high though. A second (subtle) explanation according to their report might be the government's desire to obtain better offers in the bidding for the concession.

Similarly, based on our own discussions with the THSR operator in 2014, we suggest four reasons for the drastic over predictions: a) The predictions were based on a SP survey which usually overestimate the willingness of people to change their behaviour b) as also pointed out by Albalate and Bel (2013) using

historical data for from the 1960s to 1990s for demand predictions turned out to be not suitable as these are the period when Taiwan was experiencing a highly economic growth period; c) The mode choice modelling of travellers was based on an over prediction in congestion on expressways. Particularly the second north-south bound expressway project was entirely completed in 2004 and has eased the congestion on the 1st highway; d) The effect of inconvenience in access to some stations located outside of the CBD, especially during the beginning operation, has been underestimated. This fourth point is further investigated in Chapter 4.

Another phenomenon, and potentially fifth reason for the low demand, that has been observed was the negative perception of the travellers of the service quality at the beginning of the operation. Survey respondents had safety concerns, or were frustrated about unreliable ticketing and the reservation system that prohibited some potential users to taking rides (Cheng Y.-H. , 2010)o-. This general perception might possibly have been improved over time though due to some service improvements and travel time advantages becoming more obvious though. As in Chapter 5, an HSR usage survey was conducted later will be discussed in detail. In Chapter 5 and 6, where we suggests that initial HSR uptake was driven more by personality related factors, later gradual usage increases were more related to positive perceptions from service quality, i.e., travellers' perception to HSR may change over time.

Nevertheless, during the interviews with THSR operator, they claimed that the forecasting mechanism had adjusted, according to their estimation of modal shares, the HSR has now capture 70% of long distance travel demand (Taipei-Zouying), but short distance trip were still competing with expressway buses, conventional rail, and private cars. Furthermore, the THSR operator applied two type of forecasting in their operation, namely, the short-term and long-term prediction on HSR demand. For Short-term forecasting, THSR operator now could capture 95% of the demand on daily average, and even 97% of the demand could be captured in Chinese New Year. And the Long-term predictions are for financial purpose.

2.4 Summary

To summarize, all of the literatures discussed above mention about the development of demand modelling, these approaches were characterized into aggregated and disaggregated analysis; moreover, the development of long-term travel survey regarding its advantage and draw backs were highlighted and discussed. The innovation and adaptation of HSR, and the interview of demand failure learnt from Taiwan HSR, apparently modelling of demand for new public transport modes is important but underresearchd issue. In particular, this study finds a rich body of HSR literatue but not much on how usage of people changes over time, the focus has been rather on mode choice competitions, fare structures, regional impacts and etc. This thesis therefore aims to reduce the literature gap in accordace objectives described in section 1.3.

Chapter 3

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

3.1 Introduction

As already discussed in Chapter 2, the introduction of Taiwan High Speed Rail was recognized as a game changer in inter-city travel market in Taiwan among the west coast. The introduction section will discuss the impacts in details and the competitions among other alternative travel modes. The impact of intercity market share was revealed regarding the HSR competition. Section 3.2 further explained the exogeneous factors that would possibly affect HSR ridership in Taiwan as discussed in Chapter 2 but with more details. Sections 3.3 briefly explain the function and notation of with our function, we firstly employ a SARIMA model, and execute the model specification and identification. Section 3.4 followed by a simpler model structure to further presents a time series analysis of the demand development by controlling the social economic factors in order to compare the actual HSR demand, where we introduce explanatory variables to discuss with the previous sections. Section 3.5 concludes the findings in this chapter from time series analysis.

3.1.1 Impacts for Inter-city Ridership and Market Share

As a consequence of the THSR introduction the ridership and inter-city market share shifted between different travel modes between 2005 and 2013 are shown in Table 3-1. To further illustrate this impact of inter-city travel market share, traffic volumes of individual modes have been obtained from Taiwan's Ministry of Transportation and Communications (MOTC, Taiwan, 2015). Private cars, expressway buses, and domestic airlines experience negative trends while conventional rail demand (Taiwan railway, TRA) remained stable during the first year of THSR operation and has since then been increasing. The average growth ratio for each mode since 2005 is 0.53% for cars, -4.46% for buses, 3.76% for Taiwan rail, and -6.47% for domestic airlines respectively; while excluding the outlier in the 1st year of THSR, with an average annual growth ratio comes to

9.26% since 2008. (Fu, Chen, & Chou, 2008) applied discrete choice modelling for intercity travel soon after THSR opened, the results suggested that intercity mode choice was significantly affected by service performance factors such as in-vehicle time, out-vehicle waiting time, travel cost, and accessibility of access transport to THSR.

Table 3-1 Aggregated Inter-City Ridership of Travel Modes in Taiwan

Travel Mode	Unit (market share)	2005	2006	2007	2008	2009	2010	2011	2012	2013
Private Vehicle	million cars	479.1	480.6	475.5	453.9	457.1	464.8	479.6	482.8	498.9
	(%)	(52.0)	(52.7)	(51.9)	(49.4)	(49.9)	(49.8)	(50.1)	(50.5)	(52.1)
Bus	million Pax	252.8	245.2	242.3	246.4	237.8	232.8	220.6	197.1	173.9
	(%)	(27.5)	(26.9)	(26.5)	(26.8)	(26.0)	(24.9)	(23.0)	(20.6)	(18.2)
Conventional Rail	million Pax	169.6	169.0	169.7	178.7	179.4	189.8	205.8	220.3	227.3
	(%)	(18.4)	(18.5)	(18.5)	(19.4)	(19.6)	(20.3)	(21.5)	(23.1)	(23.7)
Domestic Airlines	million Pax	19.29	17.36	12.71	9.85	9.23	9.73	10.48	10.68	10.55
	(%)	(2.1)	(1.9)	(1.4)	(1.1)	(1.0)	(1.0)	(1.1)	(1.1)	(1.1)
THSR	million Pax	-	-	15.56	30.58	32.35	36.94	41.63	44.53	47.49
	(%)			(1.7)	(3.3)	(3.5)	(4.0)	(4.3)	(4.7)	(5.0)
Total	million Pax	920.8	912.2	915.8	919.5	915.9	934.1	958.1	955.4	957.9

Source: Ministry of Transportation and Communications (MOTC)
Note: No. of cars were been counted by the toll stations, and therefore it not available to reflect the realistic traffic volume.

3.1.2 HSR Monthly Ridership and Competition with Air Service

Figure 3-1 Taiwan HSR Annual RidershipFigure 3-1 shows the monthly pattern in THSR ridership (THSR, 2014) over the 8.5 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 an annual perspective, the ridership increases steadily and the seasonal pattern became stable after 2008. To explain the annual increase, in line with our literature review, a number of factors are investigated in section 3.2.

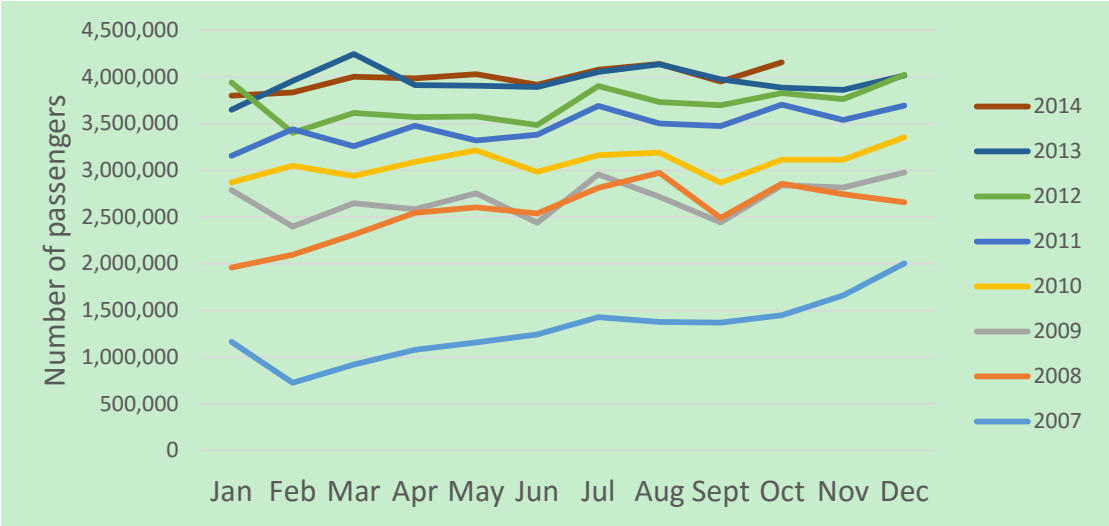


Figure 3-1 Taiwan HSR Annual Ridership

On the other side, the competition with air service is always an interesting topic. Comparing the THSR ridership and the domestic airline demand within the west coast of Taiwan in more detail, had illustrateed that the airline share dramatically decreases after the opening of THSR (see Figure 3-2, note that the airline data is different from the previous Table 3-1, due to the airline ridership data only accumulates the domestic airlines ridership within Taiwan's west coast). This likely shows the advantages for high speed rail within 600 km travel distance, or travel time within 2 hours as suggested in (Cascetta & Coppola, 2014). 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.

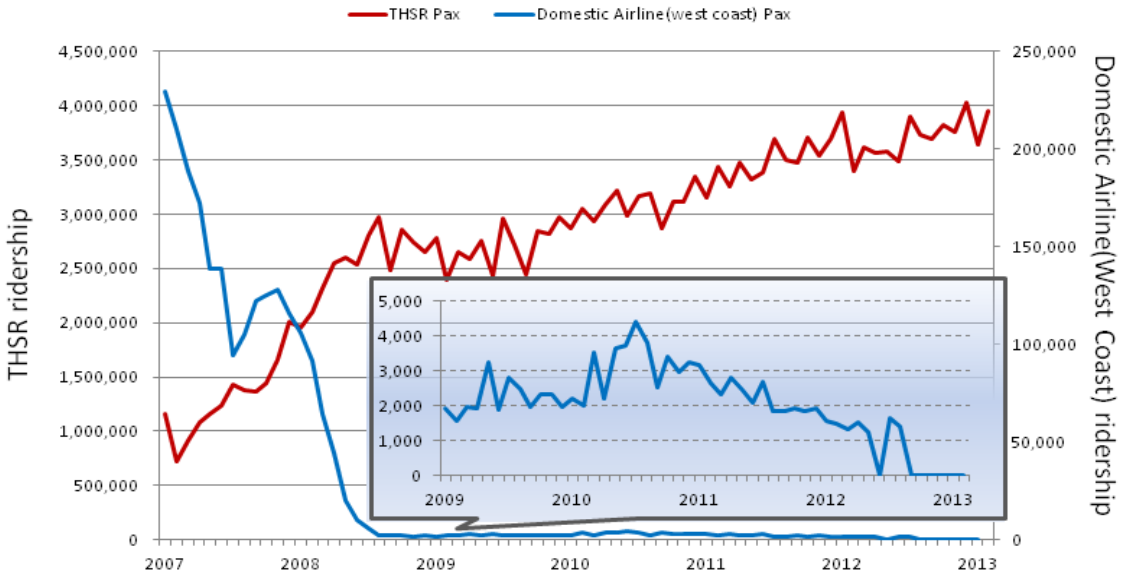


Figure 3-2 Air (West of Taiwan) and Taiwan HSR Competitions

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 as long as there is spare capacity. 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 (the reason behind the low service frequency is because the lack of qualified HSR drivers at the beginning of the operation) within the first two years of service operation after which the service frequency remained comparatively stable (see Figure 2-2). This cyclic effect in increased market share for high speed rail, increasing service frequency and less attractive services for competing modes is certainly one explanation for the growth curve in (THSR, 2014), but not the main one. For one, only a low percentage of high speed rail passengers are former air passengers. This illustrates that the demand keeps increasing disproportional to air ridership decrease. It is further important to emphasise that since 2008 the supply characteristics of THSR and other competing modes have been staying nearly unchanged so that indeed other (slow) adaptation effects appear to be important.

3.2 Exogeneous Factors Potentially Affecting THSR Ridership

Besides the above discussions on air competitions, clearly 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 (2009) 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 directly affects the travel cost of private vehicles. Whereas in the 2007 fuel prices remain relatively stable with a price of around NT$31~35 per litre, in July 2008 fuel prices reached a peak of NT$36.1 and then quickly dropped to NT$21.1 at the end of 2008 due to the global financial crisis (see Table 3-2).

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 aggregated into monthly averages.

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 3-1) except for travel by expressway buses. The reason might be that this service provides the lowest travel cost among the mode choice options and not capturing much business travels. 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 macroeconomic impacts become visible in the demand as suggested by (Kyte, Stoner, & Cryer, 1988; Lane, 2012).

We further note that we find a high correlation between fuel price and GDP (0.794 for Pearson test) thus in our subsequent analysis in Section 3.3, 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 collected from the webpage of the Taiwan National Statistics (National Unemployment Statistics, 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 as suggested by (Owen & Phillips, 1987; Kyte, Stoner, & Cryer, 1988; Gwilliam, 2008; Lane, 2012; Cascetta & Coppola, 2014). We note that the Taiwan west coast holds about 90% of the total population, thus using nationwide population data appears acceptable. The population shows a slow but steady increase from 22.87million in January 2007 to 23.33million in December 2012. It should be noted that it is predicted that from 2018 Taiwan will face a population decline due to the low birth ratio (Wang, Lo, Fan, & Chao, 2009).

As a second related measurement to "market size" as well as economic development we include the population's car ownership ratio. Our data 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 rising again and has reached 30% by the middle of 2011.

For a seasonal demand analysis, holidays should be considered as an important factor (Quddus, Bell, Schmöcker, & Fonzone, 2007) which creates additional demand. Reflecting our observations in section 3.1, 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.

Table 3-2 Definition, Expected Sign and Descriptive Statistics of Variables

Variables		Definition/Notes	Expected sign in model	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 Services	High speed rail train services per month		Service frequency	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			USD / L	Continuous / Monthly	0.69	1.19	0.98
	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 (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 / 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

3.3 SARIMA Time Series Model

In order to distinguish seasonal from overall trends, a time-series seasonal autoregressive integrated moving average (SARIMA) model is used to estimate the demand for THSR 2013 monthly ridership based on data from January 2007 to December 2012. The type of SARIMA model is usually denoted by SARIMA (p,d,q)(P,D,Q)s model: p and P represent the order of the non-seasonal and seasonal autoregressive (AR) process; d and D 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 the annual repetitive character of some demand, such as new year festivities related journeys.

A fuller description of SARIMA modelling can be found in (Andreoni & Postorino, 2006). Examining the autocorrelation function (ACF) and the partial autocorrelation function (PACF) from time series data we could identify the values of each of these parameters. Based on this preliminary analysis we suggest to employ a SARIMA model of the order $(0,1,2)(0,1,1)_{12}$. The model is given by:

$$\hat{Y}(t) = \mu + Y(t-12) + \big(Y(t-1) - Y(t-13)\big) - \theta_1 e(t-1) - \theta_2 e(t-2)$$
$$-\Theta e(t-12) + \theta_1 \Theta e(t-13) + \theta_2 \Theta e(t-14) \qquad (1)$$

Besides the mean μ the model includes three parameters to be estimated. The two non-seasonal moving average terms θ_1 and θ_2 as well as the seasonal moving average Θ. The model form hence suggests that the ridership can be estimated by considering the ridership estimates in the last month and the ridership one year (season) ago. The three parameters describe the "smoothing process" due to past outliers and the double exponential smoothing for the non-seasonal part suggests that there is some underlying non-stationary trend.

Table 3-3 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 predicted ridership is compared with observed ridership in Figure 3-3. Note that for illustration of the predictive power of the model we only estimate the parameters

with data up to December 2012. The values starting from January 2013 are predicted by our model. We find a fairly good fit, though the February 2013 peak was not predicted by the model. This peak can be explained by a non-recurring large event, the Lantern festival, which was held next to THSR Hsinchu station that month (see also Figure 4-2).

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

Parameters	Coeff.	t-statistics	p-value
Moving Average MA(1), θ_1	0.69	6.30	≤0.01
Moving Average MA(2), θ_2	-0.55	-4.50	≤0.01
Seasonal Moving Average SMA(1), Θ	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		

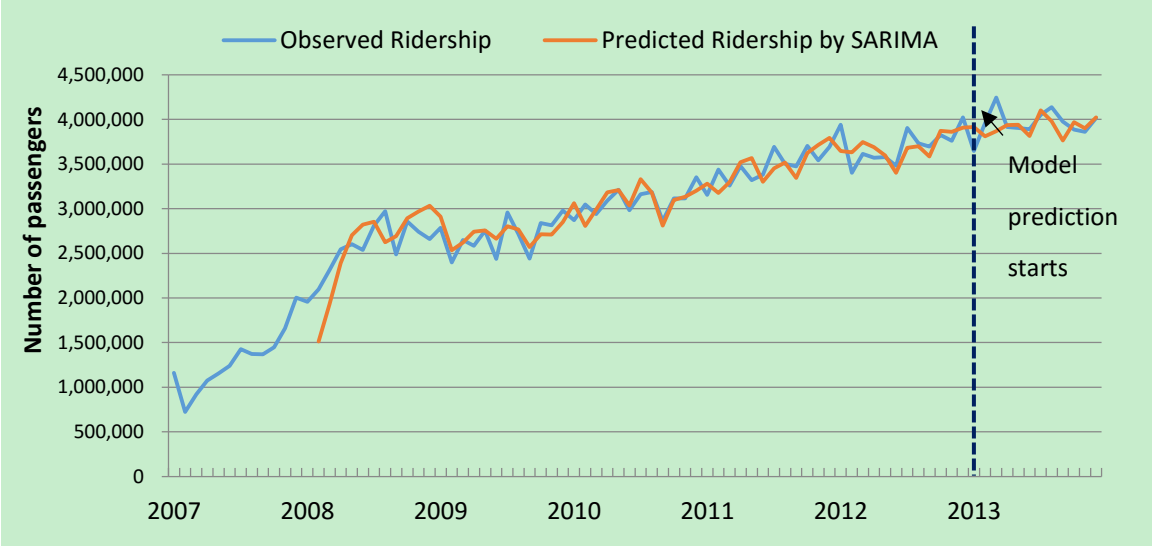


Figure 3-3 SARIMA Projection and Observed ridership

3.4 Time Series Model with Explanatory Variables

To further identify the existence of a trend that can be explained with an adaptation effect in this section, we further use a number of explanatory variables as exogenous factors discussed in Section 3.2 and summarised in Table 3-2. The table also includes the expected sign for each variable. Our aim is to

understand whether there are residual ridership adaptation effects if we control for other explanatory factors.

The dependent variable remains THSR ridership. To avoid over fitting, we choose for this analysis a simpler model structure. Log-linear and linear versions of AR(1) and MA(1) models have been tested. Log-linear MA(1) models are found to provide slightly better model fits. Therefore, two first-ordered moving average model MA (1) are discussed in the following. The models are given by:

$$\ln y_t = \alpha + \beta \ln \boldsymbol{X}_t + \theta \boldsymbol{D}_t + \varepsilon_t \quad (2)$$

where the error term satisfies:

$$\varepsilon_t = \rho \ \varepsilon_{t-1} + \eta_t \quad (3)$$

In this model y_t 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, ε t are the white noise or error terms, ρ ($-1 < \rho < 1$) is the moving average coefficient, where η is independent and identically distributed with mean zero and variance σ 2. Finally, β and θ 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 3-4 and the explanatory power of both models are illustrated in Figure 3-4Figure 3-4 ARIMA Forecasting and Observed HSR Ridership . 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 in 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 excluded from our model specifications.

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, Stoner, & Cryer, 1988) and (Lane, 2012) who also discuss 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 show 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. The relationship between THSR and car ownership is found to be, as expected, 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 since operation (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 possibly some of the endogenous effects not captured in the model as well as some of the "information mass effects" discussed in (Schmöcker, Hatori, & Watling, 2014). 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 trips 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 executives 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 culture" of private as well as business people of the country.

Table 3-4 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	

Note: Bold denote sig. at 1%, italic denote sig. at 10%

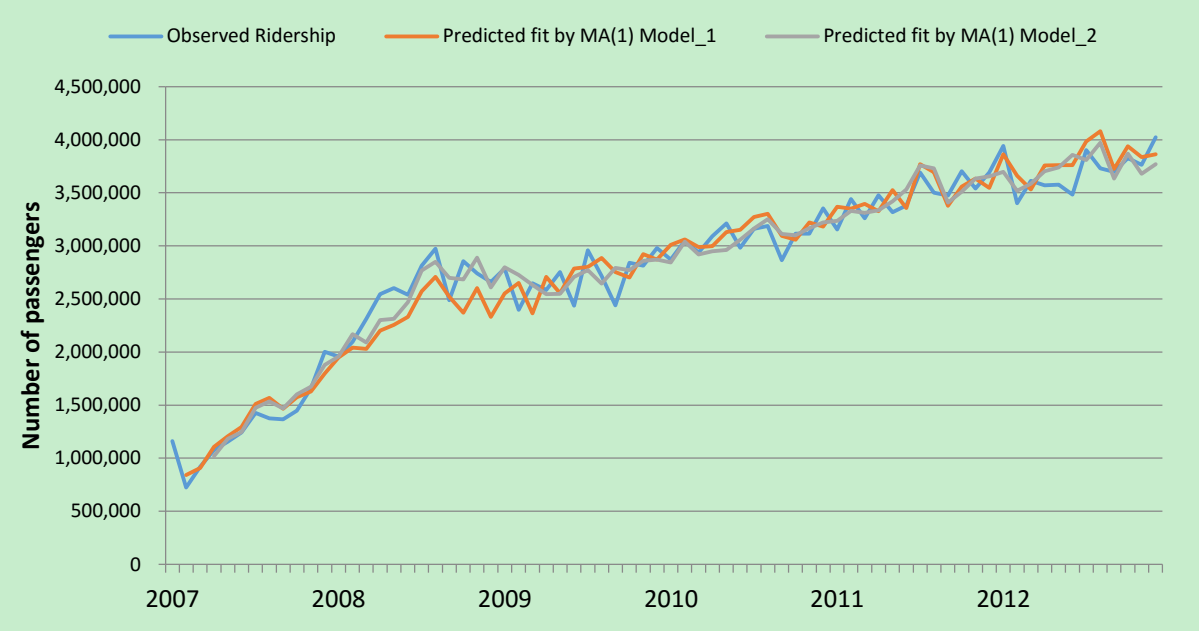


Figure 3-4 ARIMA Forecasting and Observed HSR Ridership

3.5 Discussion

In this paper we reviewed demand uptake of the newly introduced Taiwan High Speed Rail since 2007. 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 and two specific scale of data to test our model performance. Our fitted SARIMA model appears suitable for demand forecasting whereas our simpler MA(1) models help us understanding the role of specific exogenous factors for aggregate as well as station specific demand.

For aggregate forecasting 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 take into account a mixture of long-term predictable factors (such as population growth) as well as short term fluctuating factors (such as fuel price). For station specific demand socio-demographics, GDP, fuel price, and car ownership may not always be significant. Rather it is important to understand the composition of the trip purposes of the travellers as our analysis of demand patterns for Hsinchu and Taipei suggests.

The focus of our study has been on the adaptation effect. We estimate this with continuous log-linear dummy variable representing the duration since operation. Even after seven years of operation it is not obvious when and whether 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". Our analysis of Hsinchu versus Taipei ridership patterns further tentatively suggests that adaptation effect might be stronger for business than for private travel. We acknowledge though that further work is needed to confirm this by disentangling the different factors combined in the adaptation effect. This is though not possible with the data currently available. Instead we suggest one might need to look into individual personal trip patterns, and in addition to conduct a more qualitative

study interviewing business as well as private travellers on when and why they started using the high speed rail service.

In discussions on the cost-effectiveness of potential high speed rail projects often expected ridership data are published. We propose that adaptation effects to new systems might take a significant time and initial low ridership might not be a sign of "wrong estimates". Demand estimation for new systems that potentially significantly change the mobility patterns of a wider region might have to be treated very differently than demand estimation for system extensions. For example, data from German rail suggest that for recently built or upgraded high speed routes it takes around three to four years for demand to stabilise. Also data from the recently opened high speed rail extension in Kyushu, Japan, suggest that total ridership appears to stabilise fast. In both cases the population will have been already used to the high speed rail concept and fairly easily adapt their behaviour.

Clearly the present study leaves ample room for further work besides the already mentioned issues. One extension of the present study would be to continue with a detailed comparison of ridership between all eight THSR stations. This could be used to better understand the role of local and regional factors as well the importance of station location and access possibilities. Connected with this, as our Table 3-1 Aggregated Inter-City Ridership of Travel Modes in Taiwan shows, there appears to be a general shift away from bus to rail in Taiwan. Though we believe in some sense non-high speed rail also profits from this, further analysis should clarify the interdependencies between demands for these modes. In particular, it appears worthwhile to investigate in how for THSR rail profits or losses by improvements to other rail lines.

Chapter 4

Public Transport Accessibility Impact on Demand for Taiwan's High Speed Rail Stations

4.1 Introduction

Following previous chapter, we replicate the proposed time series methodology in Chapter 3 to examine the predictors in total demand into local scale, by looking at 8 THSR stations' demand. A few stations were located in the centre of downtown and others in peripheral locations; for the latter stations, THSR continues to improve its access infrastructures to the corresponding downtown areas. In this chapter, demand impact via the access links to the THSR stations and "adaptation effects" were examined. (Su, Chang, Lu, & Liu, 2012) Monthly ridership data from 2007 to 2013 have been obtained from the 8 stations that are currently in operation. Time series models were applied to examine how accessibility improvement and adaptation effect would impact on station demand. As discussed in section 2.3.3, the nearly 350 kilometres investment has cut the travel time from 4 hours into 1.5 hours (Taipei to Zuoying), which the interregional accessibility of the Western coast Taiwan has naturally improved (see Figure 4-1 and Table 3-1).

Figure 4-1 Taiwan HSR Stations and Conventional Railway

Cheng (2010) investigated the initial stage of THSR operation; he concluded that overestimated ridership is one of the major issues for THSR system operator and the authorities. Though the ridership, service frequency,

load factors (seat occupancy) is continuously growing, it's still under expected from their demand prediction. The original ridership forecasts estimated an initial daily ridership of around 200 thousands, which would be doubled by 2036. However, when operation first started, were merely 43 thousands in 2007 and 84 thousands in 2008 of observed daily trips; and, the latest daily ridership in 2014 was slightly over 140 thousands which does not yet even achieve the initial figures predicted by THSR.

4.2 Determinants of HSR Station Demand

4.2.1 Regional Economic Impacts

The economics and spatial impacts of high-speed rail are quite varied and mixed, especially the time horizon for observing change is often distant. Loukaitou-Sideris *et al.* (2013) review studies that examine predicted HSR impacts related to job growth, real estate development, regional restructuring, and other economic activities. Where they concluded the projective literature seeks to predict the impacts on cities from the enhanced accessibility afforded by HSR. Yet, neither of these patterns are universal and depend on a number of other factors. Some simply offer an informed prediction about the magnitude of effects, while others use sophisticated forecasting models. Nevertheless, they nearly uniformly predict positive outcomes and overshooting demands (Yu and Johannesson, 2010). Empirical studies, on the other hand, tells us that HSR impacts are varied and largely contingent on a variety of social-spatial and economic factors as well as planning and policy. Owen and Phillips (1987) examined the effects on rail demand by considering Gross Domestic Product (GDP), car usage, local levels of economic activity, and regional growth in population as economic factors. Though not directly connected to HSR demand, Kyte *et al.* (1988) examined factors affecting changes in transit ridership in Portland. The "market size" which denote the amount of travel generated related to the amount of activities that takes place in the area, are generally considered as the number of population in that area and the number that are employed. Lane (2012) analyzed the relationship between public transit ridership and gasoline price by applying time-series regression. The result indicated that the consistently amount of the demand fluctuation is influenced by gasoline price. Cascetta and Coppola (2014) suggested HSR induced demand can be distinguished as two components: which depends either a) endogenous factor,

"directly" on the generalized travel cost, i.e. changes in travel frequency and patterns or destination, e.g. the trip becomes more frequent because traveling with HSR is faster, cheaper and/or more comfortable; or b) exogenous factors, "indirectly" due to adjustment of the mobility decisions and choices. For instance, travellers conducted more business trips or commuting due to the obtaining of a new job, changes of the residence location, new activities of urban development (land use changes). They also indicated "economic-based" factors should be considered as exogenous factor to explain the increase of the overall accessibility due to economic growth. Demizu *et al.* (2015) applied time-series analysis in order to examine mode share impacts from HSR construction, rail, and air demand in North-East Japan by considering a number of socio-economic activity factors such as population, gasoline price, GDP, company income, unemployment, and car ownership as well as extreme events, namely, the Tohoku earthquake and tsunami. They found the "standard" HSR extension would immediately increase rail share and total public travel mode, and gradually generates additional rail demand over longer term.

Though a number of economic factors that are considered to have an impact of HSR demand are discussed in the literature. One should keep in mind that the economic geography framework, such as socio-demographic, economic activity density, and spatial development structure, can help to derive extant predictions on the economic impact of transport projects and vice versa. Holmgren (2007) concluded these demand forecast studies often use the same methods that been used for a long time, and apply them to the new data (schemes). It's interesting and necessary; preferences might vary between countries and over time. A number of good works on comparison studies can refer to Albalate and Bel (2013); Campos and de Rus (2009); and Garmendia *et al.* (2012).

Finally, as an important foundation of research structure in this thesis, a number of significant factors were verified from Chapter 3 that impacted HSR demand in Taiwan with aggregate demand. Where in previous chapter, we proposed an econometric time-series model to predict aggregated THSR ridership on long-term demand based on monthly ridership and general explanatory variables.

To this end, a continuous log-linear dummy variable was estimated representing the duration since operation, from the results; we further argued that various types of adaptation effects would possibly include general population's perception of the new scheme. However, if looking at local level of demand, one should also take into account of accessibility changes over time. In the following section, we will investigate the adaptation effects and impacts from access links to HSR station demands.

4.2.2 Impacts of Intermodal Accessibility on HSR Station Demand

Considering the heavy bit of former studies, impacts of accessibility to HSR regional demand seems not yet fully investigated. Which of local HSR demand forecasting becomes a valuable topic and appears to be under researched. In particular, the overall assessment of the impact of access improvement to HSR demand is limited. Zhong *et al.* (2014) discussed HSR accessibility by using four measures defined as: population, population density, employment and income. An accessibility function was proposed to quantify the accessibility of HSR stations across metropolitan areas in the US and Spain. They assessed socioeconomic and spatial characteristics over different urban structures that may affect HSR accessibility. The result further indicated that urban structure and station allocation have important implications for HSR competitiveness. For instance, new infrastructures were required in remote cities for parking at terminals or, improvements in intermodal connectivity (Cheng Y.-H. , 2010). The vital importance of urban spatial form of the accessibility of HSR reflects the spatial distribution of population, employment and income across the metropolitan area. As also addressed in their study, to access HSR accessibility are often to be found challenging, where measurement unit/criteria such as urban geography, data series (normalization) might be not comparable/available.

Looking at Taiwan HSR, a little research related to HSR station accessibility was founded. Fu *et al.* (2008) model the travel behaviour changes of two stations after HSR was opened in Taiwan by SP and RP survey. The results suggested accessibility of access transit is one of the significant factors in intercity mode choice. Moreover, the result revealed the preference of access time is larger than access cost, implied the poor condition to access HSR station at the beginning of HSR operation. Similarly, Cheng (2010) indicated that although THSR relatively competitive against air traffic, the observed ridership barely

meets the previous demand projections. One of the critical reasons is the extended access/egress travel time to HSR stations results in travel time from origin to destination does not significantly reduced in several remoted stations.

As Su *et al.* (2012) investigated the transferring system between THSR stations and conventional rail; they classified all THSR stations into three categories and proposed a suggestion for using public transportation systems regarding different station groups. The first group is the stations located in a populated area with a well-connected public transportation network. The following group is those stations located in the suburb, but connected with rail services, and finally the one without rail services. Yet, data on intermodal distribution and modal split in their analysis are limited to only two observation time point, also economic impacts were not taken into account as they are specifically looking at transferring between HSR and conventional rail mode. Therefore, in this study, given the general sparse literature on the effect of station access to HSR demand, we replicated the methodology and factors identified from previous chapter and extended to HSR station demand with regional economic factors and access link improvements.

Clearly, the issues at stake would be intraregional station accessibility for THSR; (Kuo & Tang, 2013) indicate the importance and condition of accessibility does not only affect the level of service, but also the corporate image of THSR. Su *et al.* (2012) discusses that five out of eight stations are located in suburbs and far away from the CBD (central business district) area (except Taipei, Banciao, and Zuoying); where they found inter-city travellers from around these stations are less willing to use THSR. In terms of this, the THSR stations which located in peripheral location did not have a direct transit connection with its corresponding CBD at the beginning. This has reduced advantage of travel time benefits in many cases compared to intercity buses and conventional rail (TRA). For example, the HSR traveling time from Taipei to Tainan is slightly less than two hours, but from Tainan HSR station to downtown would requires an extra travelling time of 25 mins by TRA. Therefore, THSR operators realized that pursuing a seamless transfer for those remoted HSR stations were essential and the lack of access to these stations needs to be further improved. A THSR usage survey in late 2007 published by MOTC has disclosed the poor accessibility of THSR stations by reporting that over 60% of HSR travellers access/egress these suburban stations by private vehicles. Moreover, from the same survey, for those

who had chosen not to continue their HSR usage, over 40% of the travellers reported inconvenience of access to HSR stations as the reason to drop from HSR.

4.3 THSR Stations Accessibility Improvements

As described in previous section, eight out of the eleven THSR stations, including the three newly opened stations in late 2015, are located in suburbs, far out from its corresponding CBD. To this end, the THSR operator and MOTC have been aware accessibility issues of these stations, by proposing new access link/connection between HSR station and city centre is a critical issue. By collaborating with other stakeholders, THSR increased the level of service of transit access links and implemented new feeder lines. Table 4-1 shows the (planned) opening time and types of access links to THSR stations. Four categories of access mode should be distinguished: Mass rapid transit (MRT), Taiwan Railway (TR), bus rapid transit (BRT) and free shuttle buses offered by THSR. Considering the low cost and efficiency of deployment, THSR attempted to use BRT and shuttle buses to provide a direct connection between THSR stations and their corresponding CBD during the initial years of operation. The BRT and Shuttle buses had been usually offered with a frequency of every 20 minutes. MRT and new feeder lines constructed by TR took longer construction time/cost, but provide higher capacity and are offered with higher frequency. We notice that at a few stations, the shuttle bus had been suspended soon after the railway links (MRT and TR) began their operation.

For the three newly opened stations in December 2015, THSR apparently has reacted to past experiences and free shuttle buses are already in place in accordance with the possible access demand of additional HSR stations. Moreover, for Miaoli a new TR station is under construction and will be opened in 2016. There is also an ongoing feasibility assessment for a TR branch line connecting Changhua HSR station to the TR network.

Table 4-1 Access Modes for THSR Station

Access Modes / Station	MRT	Taiwan Railway (TR)	BRT	THSR free Shuttle Bus
Taipei[1]	●	●		
Banciao[1]	●	●		
Taoyuan[2]	○ (2016)			◎(Feb. 2008)
Hsinchu[2]		◎(Nov. 2011)		◎(Feb. 2008 – May 2012)*
Miaoli[3]		○ (2016)		◎(Dec. 2015)
Taichung[2]	○ (2017)	◎(Nov. 2007)		◎(Nov. 2007)
Changhua[3]		Planning		◎(Dec. 2015)
Yunlin[3]				◎(Dec. 2015)
Chiayi[2]			◎(Feb. 2008)	
Tainan[2]		◎(Nov. 2010)		◎(Feb. 2008)
Zuoying[1]	◎(Mar. 2008)	●		◎(Nov. 2007 – Apr. 2008)*

Note: Superscript[1] denotes stations which are located within / close to the CBD
Superscript[2] denotes stations located in suburb areas
Superscript[3] denotes new stations opened in December 2015 and located in suburbs area, were later omitted in model analysis due to data were yet not available
Data within parentheses indicates actual or scheduled year/month of opening
Superscript* denotes links suspended after a new link connects to stations
●: Connection existed before THSR
◎: New connection after THSR opened
○: Links/Stations currently under construction

For the stations close to the CBD, access links had been integrated with THSR before opening. Taipei and Banciao station are both located within the Taipei metropolitan area and are integrated nodes in the TR and MRT networks, the MRT network extended the network length from 74.4km in 2007 to 112.8km in 2012. While Zuoying station was constructed with Xinzuoying station (TR) at the beginning of the operation, the number of TR services increased from 117 per day to 159 in end of 2012. On the other side, Taichung HSR station later constructed pedestrian flyovers to nearby Xinwuri stations (TR) in later 2007. Smaller metropolitan areas such as Hsinchu and Tainan instead implemented new TR feeder lines (Luijia line and Shalun line) to its HSR station in 2010 and 2011. These improvements induced THSR ridership demand as well as reduced HSR station access/egress by private vehicles from 59.5% in 2008 to 51.5% in 2010 as reported in Su *et al.* (2012). Furthermore, Taoyuan has a MRT project that connects to its CBD, THSR station, and Taoyuan International Airport which expected to be open in 2015 (See Figure 4-1 and Table 4-1). Based on the

aforementioned effort improved by THSR, the impact of intraregional accessibility to THSR station ridership need to be further examined.

Another issue that has been observed was the negative perception of the traveller at the beginning of operation, such as safety concerns, unreliable ticketing, or the reservation system that prohibited some potential users to taking rides reported by Cheng (2010). However, this general perception might possibly have been changed over time, where more travellers recognized the advantages of HSR, travel time saving, level of services, easier to access than before and other advantages related with perception. The time duration dimension on THSR demand appears to be under researched. These conversions of perceptions would enlarge THSR travellers from a small number of population group penetrates into majority. This was resonated by Schmöcker *et al.* (2014) who discussed 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. As this research proposed an econometric time-series model to predict aggregated THSR ridership on long-term demand in Chapter 3, based on monthly ridership from 2007 to 2012 and general explanatory variables. They estimated a continuous log-linear dummy variable representing the duration since operation, from the results, they further argue that various types of adaptation effects would possibly including general population perception of the new scheme and 'information spread'. Regarding with previous research, this study takes into account on THSR local demand to understand the impact of adaptation effects as well as access link regarding other general explanatory variables.

Passed on our objectives and limited approach to accurate data, we firstly continue the study by in Chapter 3 that the aggregated demand model can likewise explain the demand for each of the eight stations Taiwan HSR is serving, i.e., three new stations denoted in Table 4-1 were omitted. We then quantify the service improvement in station access and add these as explanatory variables in our model. We discuss the impact on specific situations and suggest some general conclusions.

4.4 Data Description and Methodology

4.4.1 THSR Station Ridership and Data Description

Based on previous studies, parameters that significantly influence aggregated THSR demand had been specified, a full detailed description of factors, inference process, and methodology can be found in Chapter 3. Figure 4-2 illustrates THSR ridership of all eight stations that are currently in service. Taipei is the capital and largest city of Taiwan with a population of around 6.6 million at the end of 2012. The station was dominated by all kinds of travellers including business travellers as well as local and some foreign tourists. Zuoying (located in Kaohsiung city) and Taichung station represent the 2nd and 3rd largest metropolitan areas located in the south and middle of Taiwan's west coast respectively. The rest of the stations listed in order of ridership are Hsinchu, Taoyuan, Tainan, and Chiayi, which are considered as second or third-tier city, form the 3rd group in the figure. Note that Banciao is located in Taipei metropolitan area as a satellite station dispersing the mass demand from Taipei.

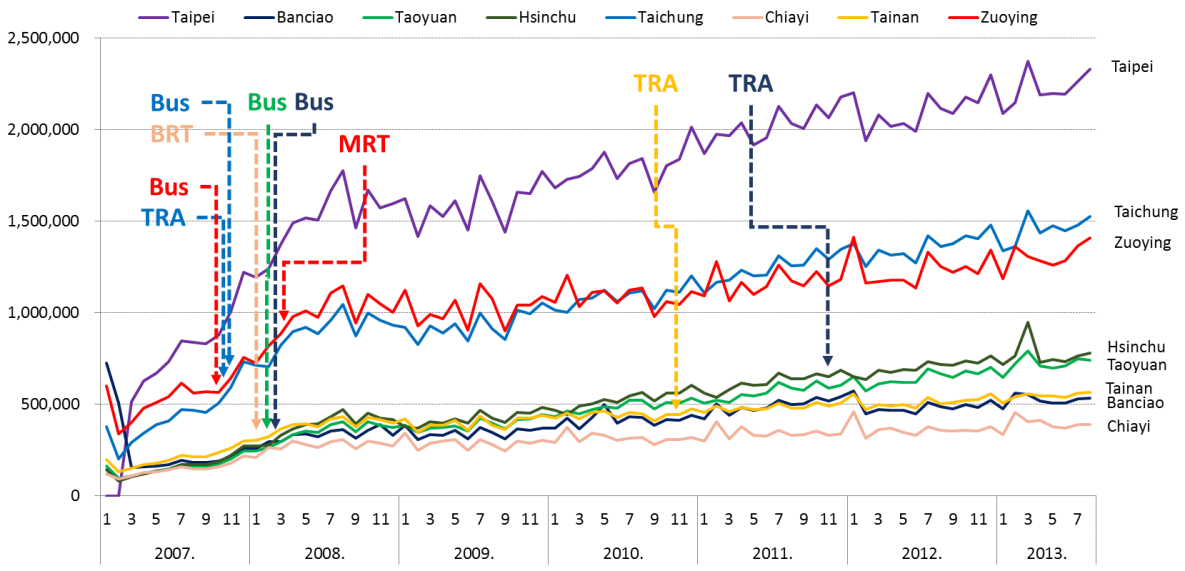


Figure 4-2 Monthly Ridership of Taiwan HSR Stations and Its Access Links

Regarding explanatory variables which explain THSR total demand, estimated a number of major factors including population, unemployment ratio, GDP, disposable income of petrol, car ownership, Chinese New Year, summer vacation, and a continuous dummy variable, "time since operation" were found to be significant on aggregated THSR demand. Looking at a regional level, we

replaced national economic statistics with regional ones. The ridership, population, unemployment ratio, and car ownership were obtained and calibrated into the regional scale of monthly data, descriptive variables were summed up in Table 4-2 Descriptive Statistics of Variables.

One of the limitations of this paper is that access link measures for all THSR station are complex and may results in difficulty of comparing their impact across different stations. Ideally, the access link could be measured as continuous variables from the service frequency, extension of the network (length in operation), number of bus routes, or, it could be defined as dummy variables which indicate the specific month when access links connected to THSR stations as proxy due to difficulties from available sources. The continuous variables that have been obtained in our models were, Taipei (MRT), Banciao (MRT), Taoyuan (shuttle bus), Taichung (shuttle bus), and Zuoying (TR). The dummy variables been defined in our models were, Hsinchu (shuttle bus and TR), Taichung (TR), Chiayi (BRT), Tainan (shuttle bus and TR), and Zuoying (MRT and shuttle bus). Note that we excluded the TR parameters from Taipei and Banciao because of the parallel service with THSR between Taipei-Banciao.

Table 4-2 Descriptive Statistics of Variables

Variables	Definition/Notes	Unit	Station	Type	Min.	Max.	Mean
THSR Station ridership	(Dependent Variable) Station ridership per month	person	Taipei	C	516,115	2,299,498	1,663,122
			Banciao		155,332	724,251	388,593
			Taoyuan		95,538	700,689	432,540
			Hsinchu		82,539	764,880	469,034
			Taichung		203,128	1,479,497	992,092
			Chiayi		92025	460752	288076
			Tainan		133124	559313	405185
			Zuoying		338427	1411649	1007024
Regional Population	1. Taipei and Banciao are considered to test with the same economic parameters in the modeling due to difficulty in defining a separate measurement for 2 individual station. 2. Numbers after second decimal are omitted for better reading.	person	Taipei and Banciao	C	6,401,666	6,642,531	6,493,898
			Taoyuan		1,913,145	2,030,161	1,977,237
			Hsinchu		883,483	949,064	918,426
			Taichung		3,904,386	3,984,761	3,946,124
			Chiayi		804,943	826,056	818,053
			Tainan		1,867,005	1,881,645	1,874,006
			Zuoying		2,760,571	2,778,659	2,770,492
Regional Unemployment Ratio		%	Taipei and Banciao	C	3.7	5.8	4.5
			Taoyuan		4.0	6.0	4.7
			Hsinchu		3.7	5.9	4.5
			Taichung		3.9	5.9	4.6
			Chiayi		3.1	5.7	4.2
			Tainan		3.8	5.8	4.5
			Zuoying		4.1	5.9	4.7
Regional		%	Taipei and	C	20.3	25.3	24.0

Car ownership			Banciao				
			Taoyuan		27.1	29.9	27.8
			Hsinchu		26.0	30.6	28.9
			Taichung		24.3	29.8	27.6
			Chiayi		24.6	28.2	25.6
			Tainan		25.5	31.2	26.7
			Zuoying		24.0	27.3	24.8
GDP /Fuel Price	variables, due to high correlation been founded in GDP and fuel price, substitution for both explanatory (from Chapter 3)			C	120.14	196.27	152.15
Chinese New Year (Spring vacation)	Winter vacation, based on lunar calendar			D	0	1	-
Summer Vacation	Every July and August			D	0	1	-
Time Since Operation (adaptation effect)	Assumed that adaptation effects grow larger after the operation			C	1	72	36.5
Access links	Depending on observation data obtained, if possible the variables are measured as continuous variable from the service frequency, extension of the network (length in operation), or it could be defined as dummy variables which indicate the time when access links connected to THSR stations.		Taipei and Banciao (MRT)	C			
			Taoyuan (Bus)	C			
			Hsinchu (Bus)	D			
			Hsinchu (TR)	D			
			Taichung (Bus)	C			
			Taichung (TR)	D			
			Chiayi (BRT)	C			
			Tainan (Bus)	D			
			Tainan (TR)	D			
			Zuoying (MRT)	D			
			Zuoying (Bus)	D			
			Zuoying (TR)	C			

Note: Type C denotes continuous variable; Type D denotes dummy variable.

4.4.2 Methodology

In order to compare the findings in Chapter 3 and to understand whether parameters estimates vary significantly depending on the location, we use the same methodology as proposed for the aggregated ridership. To further identify the existence of adaptations and demand impact from access links, we used the explanatory variables as exogenous factors described above and proposed a first order of moving average time-series model (MA(1)) to avoid over-fitting. Linear and log-linear model have been tested and log-linear MA(1) are found to provide better model fit. The models are given as follows:

$$\ln y_s t = \alpha + \beta_1 \ln \boldsymbol{X} t + \beta_2 \ln \boldsymbol{X}_s t + \theta_1 \boldsymbol{D} t + \theta_2 \boldsymbol{D}_s t + \varepsilon t \quad (4)$$

where the error term satisfies:

$$\varepsilon t = \rho\ \varepsilon t\text{-}1 + \eta t \quad (5)$$

In this model, y_{st} is the THSR ridership for station s on month t where we measure months continuously since operation began. $\boldsymbol{X}$ is a k*1 vector of common continuous explanatory variables that apply for all stations where $\boldsymbol{X}_s$ denote station-specific continuous variables, e.g. regional population, regional car ownership. $\boldsymbol{D}$ is a m*1 vector of common dummy variables where $\boldsymbol{D}_s$ denote station-specific dummy variables. ε_t are the white noise or error terms, ρ ($-1 < \rho < 1$) is the MA coefficient, where η is independent and identically distributed with mean zero and variance σ^2. Finally, $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ represent the coefficients of continuous variables $\boldsymbol{X}$ and dummy variables $\boldsymbol{D}$, respectively, which are to be estimated.

4.5 Time Series Model Analysis

4.5.1 Comparison of THSR Aggregated and Station Demand

The estimated models for the eight THSR stations and comparison with aggregate results are presented in Table 4-3. Coefficients significant at the 1% level are denoted in bold, those significant at the 5% level are designated in bold with italic, and those significant at the 10% level are in italics. The result suggested that station specific socio-demographics, GDP, fuel price, and car ownership may not always be important but generally explain THSR station demand. The population, as a proxy for market size, is a positive factor in some areas, specifically in the northern part of Taiwan, where the population is more concentrated (Taipei and Taoyuan). However, we also note that the population

may not always explain the positive trend in THSR station demand as we find in Chiayi, a county struggling from emigration these years, that ridership gradually increased despite shrinking population (population parameter is negative but not significant).

Table 4-3 Comparison of THSR Aggregated and Station Demand

Variables	Lag	Total ridership		Taipei		Banciao		Taoyuan		Hsinchu	
		Coef.	t	Coef.	T	Coef.	t	Coef.	t	Coef.	t
Population	0	**190.54**	**2.81**	***529.76***	***2.14***	585.59	1.63	*313.90*	*1.81*	-82.07	-1.23
	1	***178.06***	***2.64***	***551.10***	***2.19***	600.30	1.65	*319.58*	*1.83*	-70.69	-1.07
unemployment	3	**-0.65**	**-4.35**	**-0.48**	**-4.95**	***-0.27***	***-2.05***	***-0.25***	***-2.24***	**-0.44**	**-3.15**
GDP / Fuel	1	**-0.31**	**-2.76**	*-0.21*	*-1.80*	-0.21	-1.29	*-0.24*	*-1.87*	**-0.39**	**-3.13**
Car Ownership	0	**-7.52**	**-2.99**	0.31	1.24	-0.09	-0.24	1.44	1.35	0.09	0.37
Chinese New Year	0	***0.06***	***2.37***	0.01	0.39	**0.11**	**3.06**	***0.05***	***2.12***	***-0.05***	***-2.09***
Summer Vacation	0	*0.04*	*1.87*	**0.06**	**2.73**	*0.06*	*1.99*	**0.09**	**3.60**	**0.07**	**2.84**
Month since operation (Adaptation)	0	**0.51**	**6.27**	**0.61**	**12.45**	**0.56**	**9.53**	**0.77**	**10.34**	**0.95**	**13.66**
Constant		170.63	-0.57	**346.89**	**4.54**	**243.26**	**2.66**	*85.75*	*1.93*	**168.29**	**4.91**
MA(1)		***-0.26***	***-2.01***	-0.21	-1.51	**-0.27**	**-2.80**	**-0.57**	**-5.13**	**-0.52**	**-4.44**
No. of observation		72		70		72		72		72	
Adj R-squared		0.96		0.94		0.95		0.98		0.98	
Variables	Lag	**Total ridership**		**Taichung**		**Chiayi**		**Tainan**		**Zuoying**	
		Coef.	t	Coef.	T	Coef.	t	Coef.	t	Coef.	t
Population	0	**190.54**	**2.81**	-205.43	-0.66	-13.29	-0.11	-154.99	-0.56	-390.26	-0.68
	1	***178.06***	***2.64***	-165.25	-0.52	-24.96	-0.20	-86.88	-0.30	-286.81	-0.48
unemployment	3	**-0.65**	**-4.35**	**-0.64**	**-3.43**	*-0.26*	*-1.68*	***-0.46***	***-2.21***	***-0.35***	***-2.16***
GDP / Fuel	1	**-0.31**	**-2.76**	***-0.32***	***-2.43***	***-0.38***	***-2.10***	***-0.33***	***-2.30***	-0.26	-1.63
Car Ownership	0	**-7.52**	**-2.99**	0.12	0.61	0.02	0.02	*-0.44*	*-1.75*	-0.68	-1.52
Chinese New Year	0	***0.06***	***2.37***	-0.01	-0.25	**0.20**	**4.69**	*0.05*	*1.70*	**0.11**	**3.44**
Summer Vacation	0	*0.04*	*1.87*	*0.05*	*1.95*	0.05	1.55	*0.05*	*1.95*	**0.09**	**3.21**
Month since operation (Adaptation)	0	**0.51**	**6.27**	**0.78**	**10.33**	**0.49**	**10.22**	**0.59**	**8.96**	**0.58**	**5.49**
Constant		170.63	-0.57	**623.33**	**4.13**	***-145.89***	***-2.09***	**999.47**	**2.89**	***1552.20***	***2.25***
MA(1)		***-0.26***	***-2.01***	**-0.35**	**-2.71**	*-0.21*	*-1.68*	**-0.44**	**-3.65**	**-0.36**	**-2.88**
No. of observation		72		72		72		72		72	
Adj R-squared		0.96		0.96		0.87		0.92		0.89	

Note: Taipei was opened two month later compared to other stations, so that its data point is 70.

Bold denotes sig. level at 1%; Bold with Italic denotes sig. level at 5%; Italic denotes sig. level at 10%.

Unemployment appears to be more applicable in predicting station demand, for all THSR stations, as this predictor factor was negatively significant. This result is also in line with other studies on HSR demand (Loukaitou-Sideris *et al.* 2013; Cascetta and Coppola, 2014; Demizu *et al.* 2015). The GDP/fuel price represents a measure of disposable income for petrol and was found significant to explain demand changes for 6 stations (except Banciao and Zuoying). We further found car ownership does not perform well in explaining local demand.

Interestingly, our seasonal factors, Chinese New Year and summer vacation can partly explain urban and economic characteristics. We find that in

Hsinchu, Chinese New Year has a negative impact on demand, whereas for five other stations it has a positive impact and for Taipei and Taichung the factor is not significant. This can be explained with Hsinchu station being located outside of its CBD but close to its well-known world leading IT industry cluster, emphasizing the primary importance of this station for business travel. In contrast, the exodus of rural population has impacted HSR demand in Chiayi, as its ridership was strongly derived from Chinese New Year (mostly composed of return-home trips from other trip purposes). One can also easily observe the return-home peaks for Chiayi ridership in Figure 3. That Chinese New Year is not significant for Taipei and Taichung indicates that these two stations have a sufficiently broad range of both business and leisure travellers. Note that these stations are the stations with the highest overall demand, generating 47.6% of all trips at the end of 2013.

Though not directly observed from our model result, summer vacation in some sense implies that trips generated by students, related activities such as leisure trips, travel to popular places (Taipei, Tainan, and Zouying), or seeking for oversea travel (Taoyuan, a station which closely located to the international airport) and return-home trips (Hsinchu, has bigger portions of students from whole population). We suggest that stations with smaller demand, are more likely to be influenced by specific/singular trip purpose (as business trips reduced in Hsinchu and return-home trips in Chiayi). From the two seasonal predictors, we emphasized that the composition of different trip purposes may have influenced station demand.

Adaptation effects are included as a continuous log-linear variable for months since the operation. The effects are found to have a statistically significant positive sign in all estimated models and in line with aggregated result. This factor likely captures a combination of various effects, possibly including a bit of perception changes from THSR travellers, indicating the positive tendency of growing ridership in THSR. We also note that this possibly includes some of the other endogenous effects not captured in the model as well as possibly some of the 'information mass effects' discussed in Schmöcker *et al.* (2014).

4.5.2 Impacts from HSR Station Access Links

A. HSR Stations in CBD

In discussion on the demand impact from THSR access links, our initial analysis suggests that improvement of access links that existed before start of the THSR operation does not seem to affect ridership. Both MRT network extension (Taipei and Banciao) and new TR station (Zuoying) are not significant in our model results (see Table 4-4). We emphasize though that our model cannot capture if these access links that existed prior to THSR operation per se have had influence. Our models capture the effect of changes in the level of service here measured with the continuous variables (length in operation over time as measurement for MRT and service frequency for TR).

As the case in Taipei metropolitan (including Taipei and Banciao station), though several MRT lines were opened after THSR operation, one might expected MRT extensions would encourage those who were not within MRT services/hinterland before to start taking HSR by MRT. One possible explanation is the spatial location of these two HSR stations, which suited in the center of the CBD. These new MRT extensions are mostly expecting with lower demand compared to prior ones. As the result, it seems that there existing a marginal benefit of network extensions from an already well-developed public transport network, the induced demand might be difficult to observe. The marginal effect also appears from the growth rate of mode share (PT share 37% from total trips in 2014), with a growth ratio of 8.50% in PT travellers from 2009 to 2014 reported by MOTC (2015).

On the other hand, the Zuoying case, in turn of connecting to HSR station are as follows: TR (a new union station integrated to HSR), free shuttle bus, and MRT. While TR continues to increase the train frequency and designate Xinzuoying station as the terminal for southbound services. However, the MRT in Kaohsiung which opened one year after, turns out significant from the result. It's not so surprised that the commuter rail (MRT) are generally much more attractive than conventional rail (TR) and shuttle buses as transfer mode, the frequently MRT had attracted more travellers to access HSR. This possibly indicates the efficiency (travel time) of shuttle bus that did not increase accessibility significantly as previous and latter railway connections, thus this led to bus service suspension soon after MRT opened. Moreover, the MRT

expected to capture demand from metropolitan area with delivering high dense frequency and loadings to where we suggest if such network would still induce THSR ridership. We also noticed that compared with Taipei, mode share of public transport is much lower (PT share 8.2% from total trips in 2014), but increased 32.25% from 2009 to 2014.

Table 4-4 Model Estimation Results for THSR Access Links

Variables		Lag	Taipei		Banciao		Taoyuan		Hsinchu	
			Coef.	t	Coef.	t	Coef.	t	Coef.	t
Population		0	***529.84***	***2.11***	*600.11*	*1.70*	**112165.38**	**2.99**	-94.94	-1.47
		1	***552.04***	***2.17***	*607.06*	*1.70*	**108947.41**	**2.89**	-89.62	-1.41
Unemployment		3	**-0.50**	**-3.68**	-0.14	-0.79	**-96.54**	**-3.92**	**-0.63**	**-3.71**
GDP / Fuel		1	*-0.21*	*-1.75*	-0.23	-1.40	-42.11	-1.48	**-0.39**	**-3.18**
Car Ownership		0	0.31	1.24	-0.07	-0.19	***530.86***	***2.35***	0.35	1.28
Chinese New Year		0	0.01	0.37	**0.11**	**3.06**	*11.67*	*1.92*	***-0.06***	***-2.62***
Summer Vacation		0	**0.06**	**2.68**	***0.06***	***2.04***	**19.08**	**3.97**	**0.06**	**2.86**
Month since operation (Adaptation)		0	**0.61**	**11.18**	**0.53**	**7.95**	**64.25**	**4.31**	**0.81**	**9.32**
Access Links	MRT	0	0.04	0.16	-0.39	-1.09	-	-	-	-
	Bus	0	-	-	-	-	9.73	0.96	***0.09***	***2.26***
	TR	0	-	-	-	-	-	-	-0.07	-1.07
	BRT	0	-	-	-	-	-	-	-	-
Constant			**105.95**	**3.26**	37.38	0.88	**-17616.89**	**-7.21**	*28.63*	*1.67*
MA(1)			-0.21	-1.51	*-0.24*	*-1.80*	*-0.25*	*-1.90*	**-0.48**	**-4.01**
No. of observation			70		72		72		72	
Adj R-squared			0.95		0.95		0.98		0.99	
Variables		Lag	**Taichung**		**Chiayi**		**Tainan**		**Zuoying**	
			Coef.	t	Coef.	t	Coef.	t	Coef.	t
Population		0	-82413.79	-1.32	**-153.65**	***-2.32***	4.18	0.02	**172890.31**	**3.25**
		1	-90459.68	-1.42	**-160.96**	***-2.40***	35.46	0.13	**170795.42**	**3.17**
Unemployment		3	**-108.55**	**-2.87**	**-0.34**	**-3.77**	***-0.41***	***-2.32***	16.28	0.81
GDP / Fuel		1	***-72.30***	***-2.60***	**-0.35**	**-2.82**	***-0.27***	***-2.07***	-16.44	-0.94
Car Ownership		0	-89.57	-1.66	0.00	0.68	0.17	0.45	**146.73**	**3.24**
Chinese New Year		0	-3.00	-0.47	**0.12**	**2.90**	0.03	1.15	**21.91**	**4.92**
Summer Vacation		0	***10.30***	***2.12***	0.01	0.21	0.04	1.65	**10.06**	**3.44**
Month since operation (Adaptation)		0	*41.91*	*1.95*	**0.31**	**6.38**	**0.45**	**6.43**	**29.10**	**2.77**
Access Links	MRT	0	-	-	-	-	-	-	**46.80**	**7.82**
	Bus	0	-3.53[c]	-0.50	-	-	**0.16**	**2.86**	4.05	0.89
	TR	0	**43.35**	**2.73**	-	-	-0.10	-1.07	-9.34	-1.13
	BRT	0	-	-	**0.29**	**6.05**	-	-	-	-
Constant			**-35987.96**	**-3.01**	*-27.49*	*-1.81*	148.83	1.39	-10387.14	-0.47
MA(1)			-0.11	-0.77	**0.37**	**2.88**	*-0.25*	*-1.85*	**0.30**	**2.12**
No. of observation			72		72		72		72	
Adj R-squared			0.97		0.92		0.95		0.94	

Note: Taipei was opened two month later compared to other stations, so that its data point is 70.

Bold denotes sig. level at 1%; Bold with Italic denotes sig. level at 5%; Italic denotes sig. level at 10%.

B. HSR Stations located in Peripheral Locations

For the other HSR stations which mostly do not have any public transport access link at the beginning of THSR operation, we find that the first public transport service connecting the station from downtown significantly stimulates demand. That is, THSR shuttle buses for Hsinchu and Tainan, BRT in Chiayi and TR in

Taichung were found to be strongly significant. The accessibility developments in Hsinchu and Tainan are in fact similar, where the first access link is a THSR shuttle bus and later TR constructed a branch line connecting the CBD to the distant station. Though shuttle buses connecting to Hsinchu CBD and IT industrial park were suspended soon after the TR branch line opened in 2012, our model suggests that it induced Hsinchu HSR demand as travellers therefore had much easier demand to access to HSR stations from downtown. The demand shifted to TR later, but no further increase could be observed. In the case of Tainan, shuttle buses are strong competitors even though TR opened a branch line here in 2010. One possible reason is the level of service (travel time and frequency) to access Tainan HSR did not significantly improve. In the case of Chiayi, it is not surprising that the BRT (the only option for public access) is found to be significant. Looking at Taichung, (Xinwuri) TR station is able to plug into the hinterland of the development region due to its wide reaching rail network (connecting Taichung line, the costal line and other sections of TR West Trunk line), i.e. it is not like the branch line in Hsinchu and Tainan where frequency and capacity are generally limited. Passengers accessing/egressing via Xinwuri station can easily reach a number of recent developments along the coastline and cities as well as inland regions.

Interestingly, we find the induced demand by public transport access in Taoyuan not to be significant. We notice that Taoyuan Station, to some degrees, bears the oversea travel demands as it located quite close to the international airport. The THSR shuttle bus offers access to two regional cities (Taoyuan and Zhongli) instead of airport transit. The travel time to the airport is around 20 minutes, much shorter than travel to Taoyuan city, but operated by another bus operator. As we controlled our observations to THSR shuttle buses, the station demand stimulated by airport transit demand cannot be observed in our model. One might anticipate additional demand though by the airport MRT opening later in 2016. The new MRT system will connect the Taoyuan HSR station and the Taoyuan International airport in 2016, and further connects to Zhongli in 2018, as the extension of airport MRT.

In summary, the eight HSR stations tell different stories that need to be analysed carefully case by case. What is clear though is that we observe differences between the impacts of access improvements for city centre versus peripheral stations. For peripheral stations access via public transport is one of

the significant factors to induce HSR station demand. In particular establishing some connection appears to be important, whereas upgrading to better connections does not always generate additional demand.

Our results suggest that differences in regions economic developments would influence the annual station's demand pattern. We further show that access links appear to be one of the stimulus to station demand. For suburbs stations, the first-connected public transport connection has been observed to significantly impact travel demand. We suggest that access links are important but their impact should also not be overestimated. Possibly there exists a threshold accessibility. Tentatively we suggest that general accessibility through public transport is important but further improvements do not necessarily generate additional journeys.

4.6 Discussion and Summary of Aggregate Data Analysis

4.6.1 Discussion of Station Demand Analysis

In this chapter, we examine how station accessibility impacts high speed rail demand. Based on analysis and methodology in Chapter 3, I apply this to explain THSR station demand. A number of explanatory parameters are obtained and fitted. From the finding on economic factors, unemployment ratio and "disposable income for petrol (GDP/fuel price)" are more applicable for explaining regional HSR demand, whereas regional population and car ownership may not always be significant but generally explain the trend. By including seasonal factors, we find that it is important to understand the composition of the trip purposes of the travellers as our analysis of local demand patterns. The results suggest that stations with smaller demand, are more likely to be influenced by specific/singular trip purpose as in the cases of Hsinchu and Chiayi shows.

The focus has been though on the demand impact of station access improvements. As discussed, the eight HSR stations tell different stories that need to be analysed carefully case by case. What is clear though is that the observed differences between the impacts of access improvements for city centre versus peripheral stations. For peripheral stations access via public transport is one of the significant factors to induce HSR station demand. THSR shuttle buses (Hsinchu and Tainan), BRT (Chiayi), and TR (Taichung) were found to be strongly significant. From the results, it further conclude that in particular

establishing some connection appears to be important, whereas upgrading to better connections does not always generate additional demand. One might tentatively even express it as follows: Station access quality is important, but operators should also not overestimate their impact, possibly there might exist a threshold accessibility. That is, general accessibility through public transport is important, but further improvements do not necessarily generate additional journeys.

It will be very interesting to observe if the findings also hold for the new stations opened in December 2015. In further work also the model could be improved if time series data on modal split of how people access HSR would be available. Finally, current work also aims to understand the importance of access links and other factors through surveys asking HSR users about their reasons to gradually increase (or decrease) their use of HSR as will be discussed in Chapter 5 and 6.

4.6.2 Summary of Aggregated Demand Analysis

With aggregate data as used in Chapter 3 and 4, though the strong significance of adaptation effects have been revealed in total and station demand; however, more detailed of understanding how such demand adaptation takes place, is though not feasible. In particular it is not feasible to understand how long, if ever, it takes for the demand to reach the predicted levels. The results also suggest that though further work is needed to confirm this by disentangling the different factors combined in the adaptation effect; however, this is though not possible with the current aggregate data. Instead, one might need to look into individual personal trip patterns, and in addition to conduct a more qualitative study interviewing business as well as private travellers on when and why they started using the high speed rail service.

Therefore, in the next Chapter, the study is continued by proposing a new data collection methodology approach to understand the demand process from individual aspect. Moreover, this dissertation further expands the study area to the other side of Taiwan Strait, the HSR network in China. HSR demand were dramatically growing since 2008. Especially the Shanghai Megapolitan area, the heart of China's economics activities, the HSR services have been keeping attracting numerus inter-city travels from the congested air traffic and conventional rail services.

Chapter 5

Long-term Travel Behaviour Survey for HSR Usage

5.1. Introduction

Long term travel behaviour is difficult to observe and even more difficult to explain. Using survey methods respondents might recall key decisions, such as when they bought cars, when they changed their commuting pattern, but it is difficult to recall more detailed decisions. Such information is though of interest if one wants to understand the gradual change in behaviour over time. In particular planners are interested in understanding the "adaptation process" of travellers to infrastructure investments and technology advances. In this paper we focus on the effect of introduction of high speed rail. However, the market entry of low cost airlines, the recent rise in usage of various shared mobility schemes or the near advent of autonomous vehicles are all further examples where one tends to expect an, over time, growing usage uptake. For each of these three cases, the reasons are manifold and vary but can all be at least partially linked to changing (or adapting) user attitudes and preferences.

Memory, habit, and past experiences form our preferences over time. Similarly, looking at long term usage patterns of a specific mode is the outcome of a (sometimes lengthy process) involving self-planning, initial perceptions of the new mode, receiving further information about it over time and reflecting previous experiences. Developing appropriate methodologies to capture long term behavioral dynamics is hence essential for transportation planners to understand the gradual changes of individuals to able to make population wide predictions.

The remaining of Chapter 5 is structured as follows. In section 5.2, we hence describe the limitation to the existing survey methods from Section 2.2 and 4.6.2 for our objectives, which are to collect data about long-term behavioural adaptation to high speed rail usage. Section 5.3, we describe the problem at hand that triggered our survey analysis and proposed a new methodology to confront the issue. Details on other explanatory variables in the survey and the overall

survey flow are discussed. Section 5.4 reveals the usage pattern distribution from travellers and descriptive analysis on socio-demographics, in addition, we discuss the validation of proposed usage pattern via actual usage frequency. The initial descriptive analysis of reasons on behaviour changes is discussed in section 5.5. Finally, the chapter concludes by discussing findings from the proposed survey and will further discuss the usefulness and limitation of this approach in the next chapter.

5.2. Limitation of Existing Data Collection Approaches for Observing Long-Term HSR Usage

Based on the literature review on long-term survey methodology in Section 2.2.3; we find that, the discussed data collection types differ with regard to the degree of behavioural dynamics observed and the potential analysis methodologies. Especially for our main interest, that is explaining gradual changes of travel behaviour over several years, the discussed survey approaches all have some drawbacks. The objective of this chapter which we partially aim to overcome with a, what we believe, new survey approach where we ask users to choose between graphically represented patterns and to report initial findings on high speed rail (HSR) travel behaviour from the proposed survey; and discuss the usefulness and limitations of our approach, for obtaining (very) long term behavioural data; in this case, the usage of HSR over the last eight years. Table 2-1 summarizes the characteristics of the discussed methodologies; details of our proposed approach will be discussed in Sections 5.3 and 5.4.

5.3. Developing Long-Term High Speed Rail Usage Survey for Individuals

5.3.1 Survey Distributing Area and Survey Method (HSR in Taiwan and Shanghai)

As discussed the development and introduction of HSR in Taiwan and China in Chapter 2, consider the significant difference of population and geographic scales in two countries, we choose the target area as Shanghai from China. The reason to choose Shanghai, which is China's most populous city and the largest city proper in the entire world (Urban Construction and Communications Commission, 2010). It's both a major financial center and a global city, Shanghai's population in 2013 is estimated at 23.9 million, which means it has finally surpassed the entire population of nearby Taiwan of 23.4 million.

Similarly, not only the population, both economics performance/index are the closest compare to other big megacities in China (World Bank, 2014; IMF, 2013). Therefore on the other side of the Taiwan Strait, we took Taiwan as the whole sampling area.

With aggregate data as used in previous Chapter 3 and 4 a more detailed understanding of how such demand adaptation takes place, is not feasible. In particular it is not possible to understand how long, if ever, it takes for the demand to reach the predicted levels. Further, at this stage, obtaining cross-sectional or panel data for retrospective observations seems not feasible. In particular, if we ask for HSR travel at specific points in the past, the respondent might not be able to answer, or, if s/he could answer, we might miss detailed information on events that might have occurred between the data collection points and triggered the change. Personal in-depth interviews could capture these variables and characteristics mentioned above, but efficiency consideration must be taken into account, especially as we aim to compare data collected from two specific regions. As such, we aim for our survey to be carried out via the internet, especially since our objectives are clearly defined but we want to reach a wide population group. We therefore develop a survey tool as described in the following section.

5.3.2 Graphical Usage Patterns

The proposed questionnaire consists of three main parts. At the heart of the survey is the design of graphical usage patterns to describe individual's HSR usage over several years. In particular, our pattern selection was finalized only after a pilot survey and obtaining feedback from 50 samples in Taiwan and Shanghai. We then simplified and grouping them into 10 graphical hypothetical HSR usage patterns, and been defined following with a detailed description for respondents to select the abstract pattern that most fits to their actual long-term usage (see Figure 5-1). In other words, respondents were asked to choose that specific pattern that best represents their usage pattern over time. We note that it might be difficult for respondents to recall their memory of HSR experience by just looking at each graphical hypothetical pattern; therefore, before asking about the patterns we ask some "usage recall questions" as discussed in Section 5.4.1.

Once recall questions are answered, 10 graphical hypothetical HSR usage patterns with text descriptions are displayed to respondents. The figures were defined as a coordinate system. The *y*-axis denotes HSR usage frequency without explicit numbers of trips; the *x*-axis from left to right denotes the timeline since the first time when the traveller starts using HSR until now, without the exact time period nor interval to represent time duration; therefore the virtual x-coordinate zero represents the time when the individual starts using HSR. In order to examine the dynamic usage over time, the description of the patterns intents to split the timeline into several time periods depending on usage pattern. The main information that we aim to obtain from the pattern selection are following:

1. Did the 1st time taking HSR trigger subsequent usage or was it a one-off usage?
2. In particular, did it take some time before a significant increase of HSR usage occurred?
3. If ever, did the usage significantly drop at some point?
4. If ever, does the traveller describe HSR usage as fairly stable or constant over a prolonged time period?
5. What is the current HSR usage?

Furthermore, based on the chosen pattern, a set of specific questions (items) could be assigned to respondents;

A. Motivation to start using HSR
B. Reason/motivation to increase HSR usage, and, the type of HSR trip that mostly increased.
C. Reason for continuous, fairly stable usage of HSR over a prolonged time period
D. Reason/motivation to drop HSR usage, and, the type of HSR trip that mostly reduced.

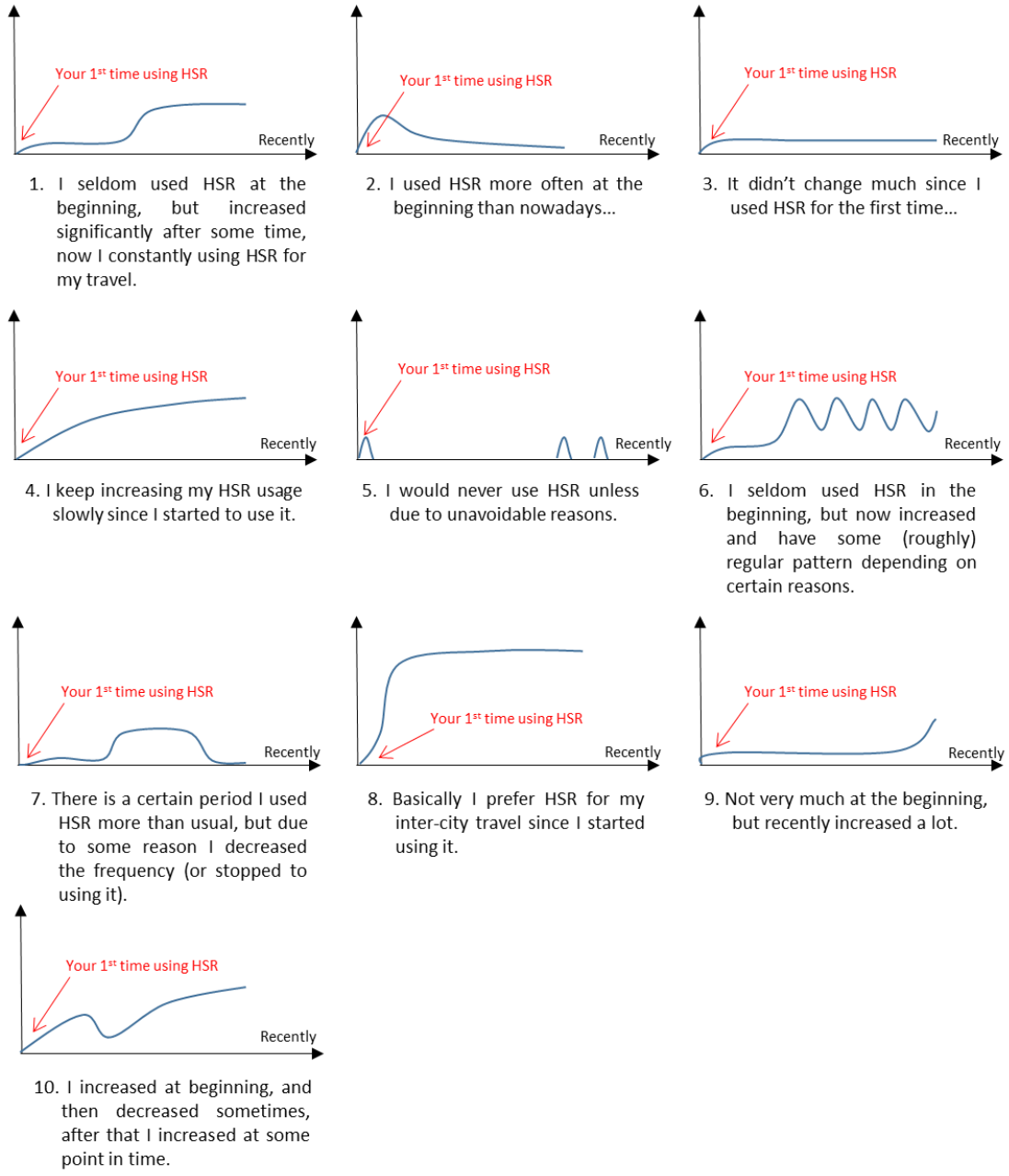


Figure 5-1 Hypothetical HSR usage patterns.

The set of questions corresponding to A are perception related items such as "I expected HSR to be more convenient" and "friends encouraged me to use HSR", as well as factors related to perception on service attributes such as "speedy, time saving". Some sections among B to D were then skipped depending on the chosen pattern. For example, if one chose Pattern 1 as his/her experienced HSR usage, Section A, B, and C will be included but section D (reduced HSR usage) is skipped; if Pattern 2 is chosen, sections A, B, and D will be included but Section C is skipped. The sections assigned to individual patterns see Table 5-1. The table shows that only if the respondent selects patterns 7, all four sections

will be included. Using this pattern 7 as an example, in the survey when answering the questions related to these four sections the time period the section refers to will be highlighted in the selected graphical pattern (see Figure 5-2). Note that Pattern 10 has a second period of usage increase which is denoted as 2B.

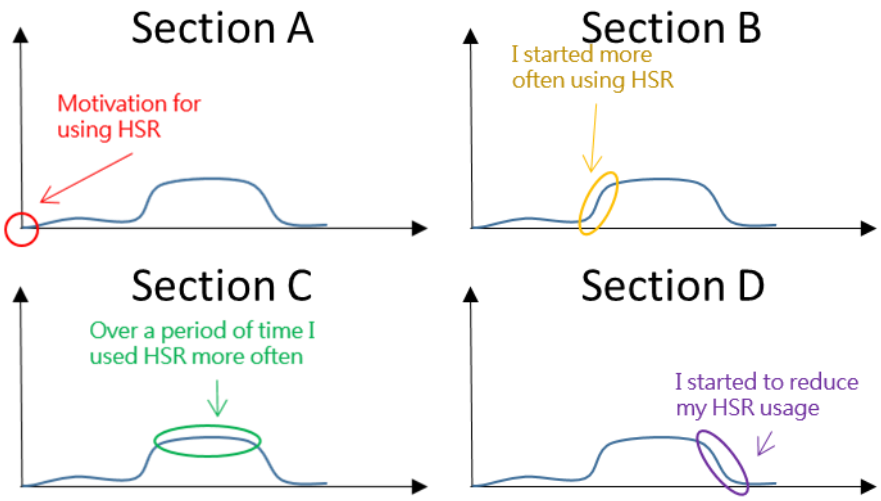


Figure 5-2 Examples of Section Assigned To Graphical Pattern

Table 5-1 Section Assigned to Graphical Patterns

Pattern	1	2	3	4	5	6	7	8	9	10
Section	ABC	ABD	A	ABC	AD	ABC	ABCD	ABC	AB	ABD2B

Each item in sections A, B, C, and D is posed on a 5-level Likert scale question to identify the importance of that item from 1 to 5 and are verbally described as: "Absolutely not the reason", "Unimportant reason", "Moderately important reason", "Important reason", and "The most important reason [to start using HSR/ to use HSR more/ to keep using HSR/ to reduce HSR usage]".

5.4 Other Explanatory Variables and Overall Survey Flow

To explain the chosen pattern and to better describe the usage frequency associated with the patterns other variables such as attitudinal factors, recall questions, and socio-economic factors are obtained. This section discusses the detailed descriptions of these and the overall survey flow.

5.4.1 Recall Questions (Frequency and Trip Purpose), and Socio-Economic Factors

Regarding the usage patterns, we ask respondents to recall their HSR usage frequency and trip purpose during each two year period since opening of HSR. We ask these questions before asking for the usage patterns to arouse the respondent's memory in order to be able to identify the graphical pattern that describes their usage best. The questions are similar to the survey given in cross sectional and panel survey but less accurate since we suggest it is difficult to recall once precise usage frequency of a mode several years ago. Based on their vague impressions/memories, the HSR usage frequency and the type of trip mostly conducted during each time frame (period) were investigated. The usage frequency are rephrased as: can't remember, never, once/a round trip, a few times, monthly/almost monthly, weekly/almost weekly, daily/almost daily. Trip purpose was defined as commuting, business, return-home, and leisure trips.

The respondents were firstly asked about usage of in 2014 (the period when survey was distributed), then followed by the question of when they started using HSR. According to their answer, recall questions in chronological order are then assigned and continue till the last 2 years (2012~13). These questions are expected as "warm-up questions" for the following graphic usage patterns.

Socio-economic factors were obtained in the survey as well. The respondents are asked regarding their most frequently HSR origin and destination (station), alternative travel mode, as well as socio demographics including gender, marital status, age, personal income, family income, level of education, car license, occupation, and residence. In addition, the survey includes attitudinal measures at the beginning of the survey, where innovativeness might also explain the usage pattern. A subscale of the commonly used scale proposed by Hurt *et al.* (1977) is included in our survey; and the full description of the innovativeness measures considered in this study and further analysis will be discussed in the next Chapter.

5.4.2 Overall Survey Flow and Survey Implementation

The overall survey flow chart is shown in Figure 5-3. After a brief introduction about the purpose of the survey we firstly ask the innovativeness scale. We decided to pose these questions first, to avoid the influence of answers given to

HSR usage on answers to this part. Next, a filter question is asked for screening those who had HSR experience and are eligible to continue the survey. Following are the recall questions about the HSR usage frequency and the type of trip mostly conducted at each time frame (period). Then the ten hypothetical HSR usage patterns shown in Figure 5-1 are displayed to the respondents. According to the selected pattern, corresponding sections of items are than assigned as shown in Table 5-1. Finally, we asked travellers about their most frequently used HSR stations, their alternative travel mode in case HSR is not available as well as socio demographics.

The survey was coded via an online questionnaire website and responses collected from September to October 2014. In order to reach a wide population range, in Taiwan we recruited via an announcement in a popular Bulletin Board System (Ptt.cc). As an incentive, we awarded those completing the survey with virtual points that are commonly used as currency on the bulletin board. 500 "P points" were given which can also be purchased for the equivalent of about 0.5$ USD. Similarly, in China, we recruited via an internet forum with a small incentive in the form of a mobile phone voucher for those who completed the survey.

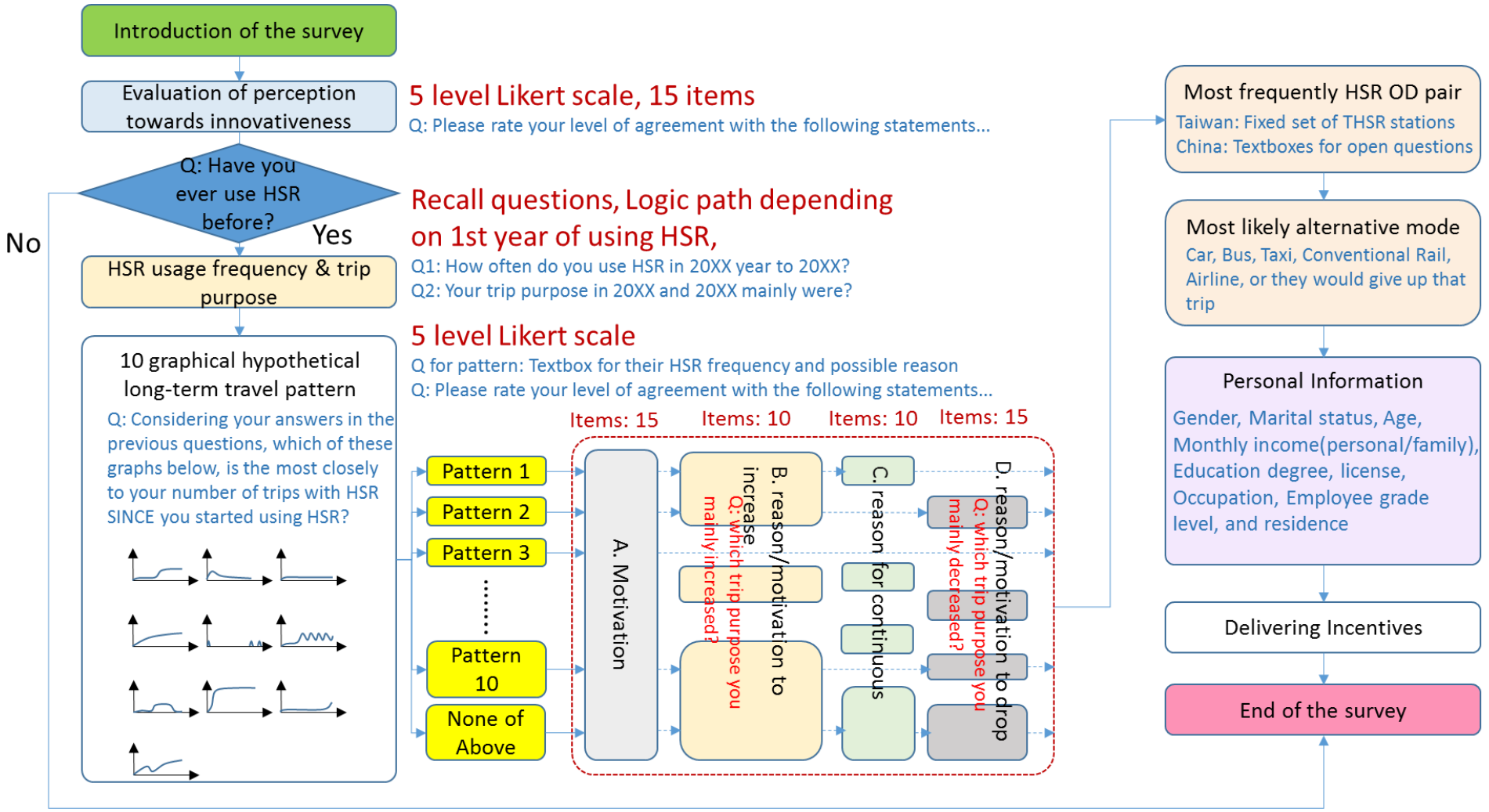


Figure 5-3 HSR usage survey flowchart.

5.5 Initial Descriptive Analysis

5.5.1 Socio-demographics

We collected a total of 693 valid responses: 309 from Taiwan and 384 from Shanghai. Table 5-2 shows the distribution of our sample in terms of socio-demographics. Clearly in particular male students are found to be overrepresented in this choice-based sample, possibly due to their higher likelihood of frequenting internet bulletin boards and answering online surveys. These biases should be kept in mind for our subsequent analysis. If one wants to obtain population representative statistics on adaptation behaviour, a significantly larger sample size will be required.

Table 5-2 Descriptive Statistics of Socio-demographics

Socio-demographics		No.	Percentage	Socio-demographics		No.	Percentage
Gender	Male	436	65.5%	Monthly personal income (USD)	0 - 500	340	51.1%
	Female	230	34.5%		500 - 1,000	194	29.1%
Marital status	Unmarried	493	74.0%		1,000 - 1,500	75	11.3%
	Married	169	25.4%		1,500 - 2,000	41	6.2%
	Other	4	0.6%		above 2,000	16	2.4%
Education Degree	No university degree	34	5.1%	Monthly household income (USD)	0 - 1,000	75	11.3%
	Bachelor	344	51.7%		1,000 - 2,000	197	29.6%
	Master	243	36.5%		2,000 - 3,000	158	23.7%
	PhD	45	6.8%		3,000 - 4,500	107	16.1%
Age	under18	6	0.9%		4,500 - 6,000	57	8.6%
	18 - 25	271	40.7%		6,000 - 8,000	24	3.6%
	26 - 30	231	34.7%		8,000 - 10,000	11	1.7%
	31 - 35	94	14.1%		above 10,000	37	5.6%
	36 - 40	31	4.7%	Occupation (industrial sectors)	Primary	2	0.3%
	41 - 45	14	2.1%		Secondary	85	12.8%
	46 - 50	8	1.2%		Tertiary	341	51.2%
	51 - 55	7	1.1%		Students	207	31.1%
	56 - 60	3	0.5%		Household/Others	31	4.7%
	over 65	1	0.2%	Car license	Y	431	64.7%
					N	234	35.3%

5.5.2 Pattern Distribution

Looking at the pattern distribution in both regions, it seems that most respondents could identify themselves with one of the ten patterns. A chi-square test was performed suggesting the pattern distribution is similar between the two regions except for patterns 4, 5 and 10. We find that only 2% of the respondents answered “none of above patterns fit to my experiences” (see Table

5-3). Pattern 8 receives the biggest share whose verbal description is "basically I prefer HSR for my inter-city travel since I started using it". This pattern represents 21% of our survey respondents and these people can be classified as "fast adopters". We remind that we filter those who answer that they do not use HSR, in other words this percentage does not reflect population usage percentages. We find though that only 1.2% answer that they have never used HSR which is clearly lower than the actual percentage of population who never used HSR. This is though not surprising given that the survey title will have attracted mostly HSR users to the survey webpage.

25.6% of our sample, that is those choosing patterns 3 or 5, can be classified as low HSR usage travellers. We note that these two patterns have higher proportions in Taiwan. Another difference between Taiwan and Shanghai is pattern 10. We included this pattern considering specifically the HSR accident in 2011 in mainland China. The public safety concerns may have decreased the HSR demand for a period of time, but users might have restarted taking HSR after some time passed. The distribution indeed shows a higher portion of travellers from China who chose pattern 10.

Table 5-3 HSR Usage Pattern Distribution

Pattern	**Taiwan**		**Shanghai**		**Total**	
	No.	Percentage	No.	Percentage	No.	Percentage
1	34	10.5%	51	11.8%	85	11.3%
2	28	8.6%	24	5.6%	52	6.9%
3	53	16.4%	53	12.3%	106	14.0%
4*	13	4.0%	59	13.7%	72	9.5%
5*	58	17.9%	37	8.6%	95	12.6%
6	15	4.6%	21	4.9%	36	4.8%
7	21	6.5%	25	5.8%	46	6.1%
8	66	20.4%	95	22.0%	161	21.3%
9	15	4.6%	25	5.8%	40	5.3%
10*	15	4.6%	34	7.9%	49	6.5%
None of above	6	1.9%	7	1.6%	13	1.7%
Total sample	324		431		755	
Valid sample	309		384		693	

Note: * denotes the proportions of patterns differ significantly from each region at 5% level.

5.5.3 Grouping into Aggregate Patterns

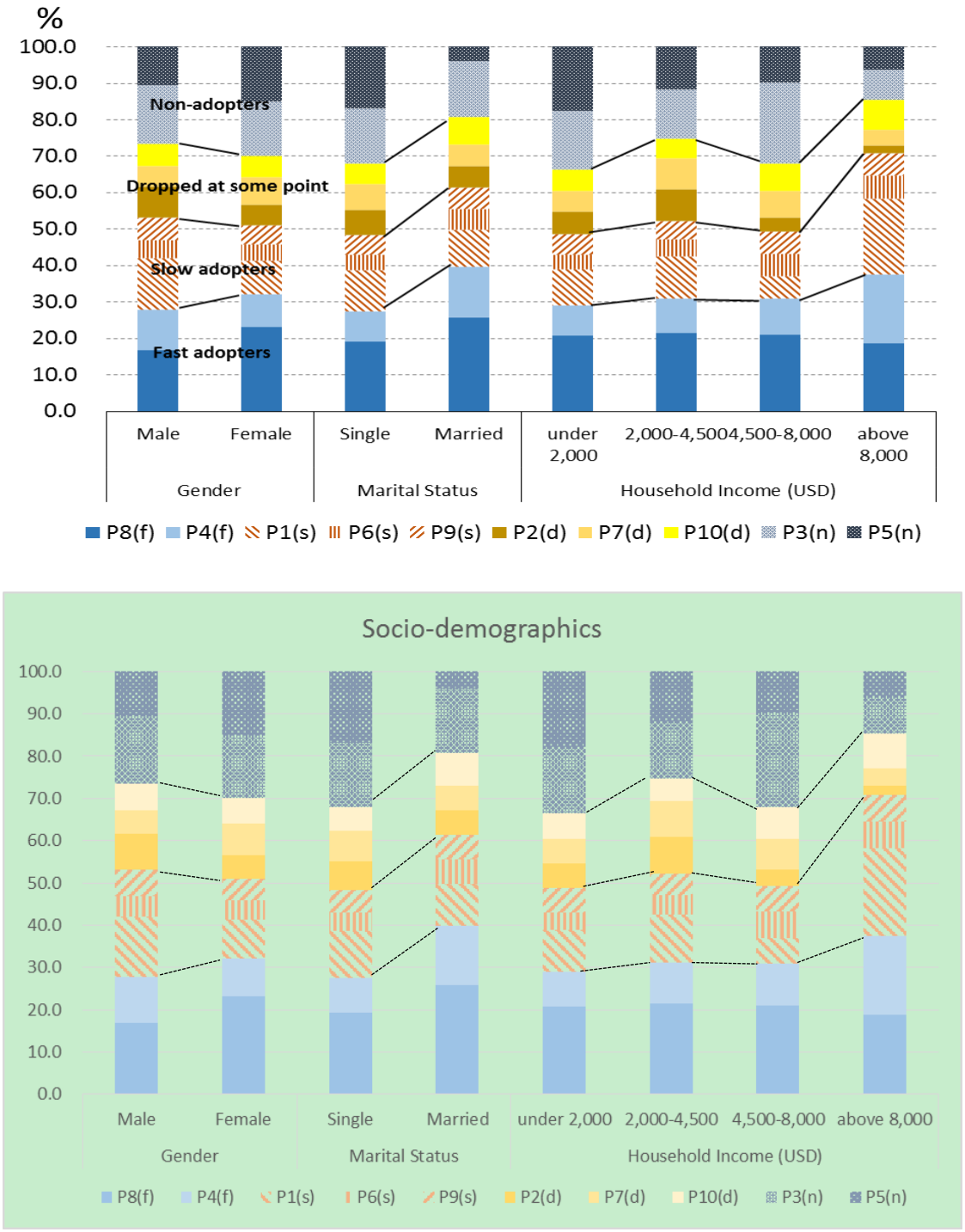
For the subsequent analysis we group the ten original patterns into four groups of travellers based on the speed of the adaption process according to its verbal and graphical description, namely: fast adopters, slow adopters, those who once adopted but dropped usage at some point (dropped group), and non-adopters. Unanswered/skipped questions and those who answered "none of above" patterns, were excluded, which leaves us with 655 valid samples for our subsequent analysis that can be fairly well distributed into four groups as shown in Table 5-4.

Table 5-4 Aggregate Patterns

Groups (pattern No.)	Samples	Percent
Fast adopter (4,8)	201	30.7%
Slow adopter (1,6,9)	138	21.1%
Adopted but dropped at some point (2,7,10)	128	19.5%
Non-adopter (3,5)	188	28.7%
Total	655	100.0%

5.5.4 Distribution of Patterns among Socio-demographic Groups

Considering socio-demographics, we find that female respondents are more likely to become fast adopters, and less likely to become slow adopters (see Figure 5-4). We find less non-adopters from households with higher income which might be expected as income is likely to positively influence the affordability of behavioural adaptation in this case higher HSR usage over time. Similarly we find that marital status has an effect on the usage pattern in that married travellers adapt faster to HSR than those being single. We can explain this with the correlation of income and age with marital status (we remind that a large proportion of our respondents are students).



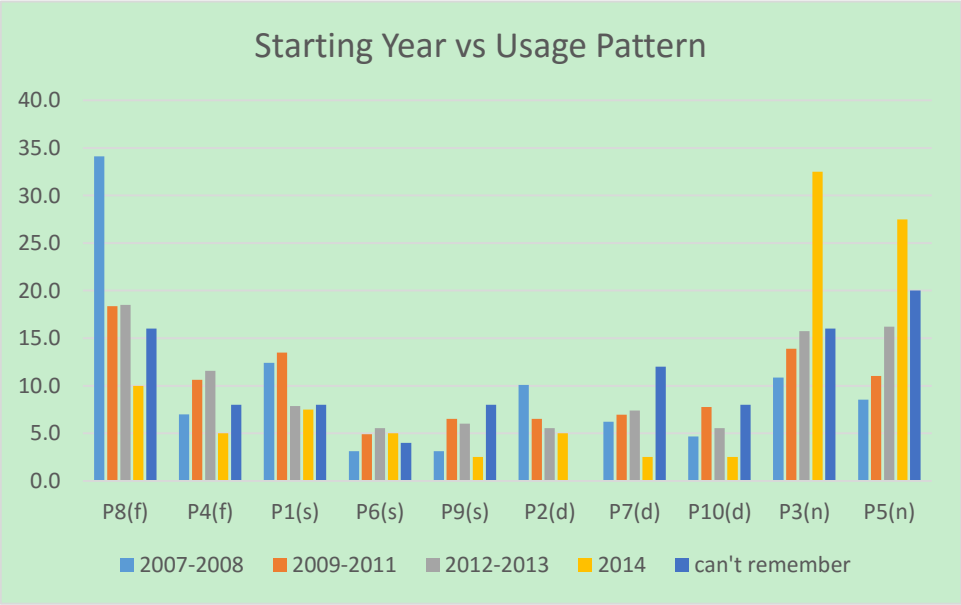
Note: (f) denote as fast adopters, (s) slower adopters, (d) dropped at some point, (n) non-adopters.

Figure 5-4 Socio-demographics and usage pattern.

The survey also investigated for the year when the respondent started to use HSR in usage recall questions. By comparing the year that respondents started to use HSR with the usage pattern distribution, we find that nearly 35% of the travellers who started using HSR in 2007 or 2008, choose pattern 8

("Basically I prefer HSR for my inter-city travel since I started using it.") as their HSR usage as shown in Figure 5-5. In contrast, among those who just begun using HSR in 2014, we find that more than 30% choose pattern 3 and in total 60% choose a "non-adopter" pattern. Considering that the x-axis of the graphical patterns does not indicate absolute time, this probably indicates that those starting to use HSR only recently are not likely to consider these recent trips as enough to be called "continuous HSR usage" as described in pattern 5 or, at a lower level, in pattern 3. Instead the current pattern of these users might "evolve" also into a pattern distribution similar to those who started using HSR earlier. In line with our previous observation this suggests that adaptation process seems to require time and are possibly time-homogeneous.

Importantly though, the 2007 observations of a large proportion of pattern 8 fast adapters, suggests one exception. There seems to have been a significant proportion of travellers "who have been waiting for the opening of the HSR" and are ready to shift their travel habits once the service is open. We suggest that identifying the size of this group among a target population is important to understand how much stable demand a new transportation system will be attracting.

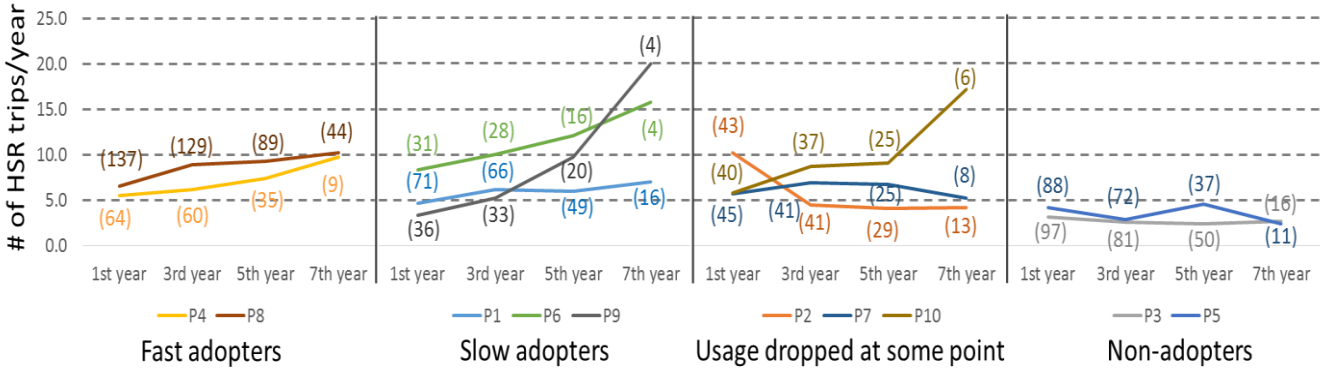


Note: (f) denote as fast adopters, (s) slower adopters, (d) dropped at some point, (n) non-adopters.

Figure 5-5 Starting year and pattern distribution.

5.6 Comparison of Pattern with Usage Frequency

In order to examine how actual HSR usage corresponds to the chosen graphical usage pattern, usage frequencies for different time periods were estimated from the recall questions. Since the HSR recall usage frequency in the different time periods has been obtained from a choice between {never, once/a round trip, a few times, monthly/almost monthly, weekly/almost weekly, daily/almost daily} these categories had to be transformed into estimated usage frequency per year. We applied following weights: 0 trips if one answered "never"; 1 trip if the answer was "once/a round trip"; 4 if "a few times"; 9 for "monthly/almost monthly"; 36 for "weekly/almost weekly"; and finally, 100 trips if answered "daily/almost daily" (We tested the resulting graphs also with different weights, but the conclusions discussed in the following appear to be fairly robust). Moreover, data was grouped according to the time passed since the traveller starting to use HSR. Therefore we are obviously losing more data the longer the usage. Finally, for better visualization and to distinguish different characteristics among patterns, in Figure 5-6 the patterns are displayed in four graphs according to the grouping defined in "Grouping into Aggregate Patterns".



Note: Numbers in brackets denote number of samples corresponding to years of HSR experience and chosen patterns

Figure 5-6 Weighted annual HSR frequency since 1st time using HSR by usage pattern.

The non-adopter patterns are found to have a lower usage frequency compared to other patterns over times, where the average annual usage is below 5 HSR trips. Further, in line with our verbal descriptions and proposed pattern figures, pattern 5 travellers appear to have more fluctuation in their HSR usage compared to pattern 3 travellers. We note that we even found one of the pattern 5 respondents reporting his frequency as daily/almost daily during the first year of his HSR usage but his usage dropped during his 3rd year period into "a few

times". In other words, even daily HSR users may not always be considered as having adapted to the system as the high usage frequency was just occurring during a certain "once-off" period during the respondents life. We suggest that it is among others such findings that are possible to obtain with our survey.

For the dropped group we find also on aggregate level a distinguished usage drop at different time points. Whereas pattern 2 respondents have a higher usage frequency at the beginning, with an annual average of 10.2 HSR trips, this significantly drops to 4.5 trips per year during the 3rd year of their HSR usage. Pattern 7 respondents have a higher usage at a certain period of time (3rd year and 5th year) but reduce their usage later. Though pattern 10 does not show the drop from actual usage at any time point, but the early trend is similar to pattern 7 and the second increase in usage is also visible.

We further observe that slow adopters are found to have a lower usage at the beginning compared to fast adopters (except pattern 6), but increased usage frequencies over time. The initial high usage frequency of pattern 6 needs further investigation, but we suggest the overall frequent usage possibly is stemming from the perceptions of cyclic/seasonal effects as described in the verbal description of the pattern as: "have some (roughly) regular pattern depending on certain reasons". Among the slow adopters those in pattern 9 indeed adapt particularly slow as we would expect from our graphical figures and we also find that pattern 6 has higher usage in recent years.

The fast adopter group, namely, patterns 4 and 8, have a higher usage frequency average at the beginning of their HSR usage. Pattern 8 increases from 6.6 trips in their first year to 8.9 trips during the 3rd year of their usage. This initial increase in usage is much higher than for other patterns. Pattern 4 has lower usage but gradually increased over time, which is in line with our verbal pattern description.

In conclusion, these findings suggests that the recall frequency, given the inaccuracy inherent in our categorization, fit the proposed pattern. As the above discussion though shows the numbers obtained from the frequencies alone give us much less information about the (perceived) gradual changes in usage behaviour. Furthermore, the graphical patterns allows us to directly ask participants about reasons for changes during different periods of time which is the focus of the analysis in the next section.

5.7 Reasons for HSR Usage (All Patterns)

5.7.1 Scale Parameter

We examine the HSR travellers' reasons for their gradual behaviour changes through analysis of the answers to the items in sections A, B, C, and D as explained in "Graphical usage patterns" and with Figure 5-1 and Figure 5-2 (Note that in pattern 10 respondents answer section B twice, but for brevity and since there are only few samples with pattern 10 we omit this discussion here). Mean of items and standard deviations are estimated to identify which items have more impact for behavioural changes. For brevity in the subsequent tables we only report a selection of items with highest mean ratings. In addition, we report how many items on average a respondent rates with "4. important reason" and "5. the most important reason" to understand the importance of a single item being rated highly. Further, a generalized scale parameter r was estimated for each section, as follows:

$$r = \sum_j \frac{\left[\frac{\sum_i \delta_{ij}}{M}\right]}{N_j} \qquad (6)$$

$$\text{with } \delta = \begin{cases} 1, \text{if respondent i rates item j as 4 or 5} \\ 0, \text{otherwise} \end{cases}$$

Nj denotes the sum of respondents i for which item j is available and M denotes the number of items in that section. The scale parameter r can hence be considered as the likelihood of respondents choosing items as the reasons of their current behaviour at that time. When r is close to 1, every respondent rates most of the items as the reasons; whereas r close to 0 indicates that respondents choose fewer items to be their reasons for explaining the usage changes.

5.7.2 Motivations to Start HSR Usage

Not surprisingly we find that "HSR is speedy" has the highest score among the items in section A, with over 77 % considering this as an important motivation to start using HSR (see Table 5-5). In decreasing order, further comfort (45 %), reliability (34 %), safety (32 %), curiosity (30 %), and the improved frequency (30 %) of HSR are selected by respondents. Among all the items in section A, we find hence that the service quality features of HSR are embraced by the population including those with low HSR usage. In addition, we find that curiosity is a frequently mentioned reason for people to start using HSR. Such a

factor is generally difficult to be included in demand projections, but supports that attitudinal factors may play a significant role, particularly during the initial years of operation. Further noteworthy is that timetable improvements was mentioned frequently among the main reasons for starting to use HSR. Hence, it seems that, even for HSR, some customers would only consider it, if a certain frequency is guaranteed.

Table 5-5 Reasons to Start HSR Usage

Ranking	Items descriptions (Section A)	Mean	Std. Deviation	Important reason	Most important reason	% from sample
1	I expected HSR to be speedy and to save me time.	4.11	1.06	207	306	77.03%
2	I expected it should be more comfortable than other travel options	3.28	1.09	219	82	45.20%
3	I thought it should be more reliable than other travel options	2.98	1.15	162	67	34.38%
4	I thought it is the safest travel option and therefore started using HSR.	2.89	1.17	151	59	31.53%
5	I was curious about HSR, it sounded exciting and cool	2.81	1.24	129	72	30.18%
6	Once the timetable improved I started using HSR.	2.78	1.24	156	53	31.38%
7	I was often stuck in traffic and therefore wanted to try HSR	2.67	1.25	133	55	28.23%
8	I was encouraged by my friends' / family's experience	2.57	1.22	125	44	25.38%
9	A lot of positive feedbacks from media / internet encouraged me to try it out	2.50	1.18	116	34	22.52%
10	Only when the other modes / options became worse (e.g. flights) I started using HSR	2.45	1.24	101	44	21.77%
11	I wanted to work while travelling	2.37	1.26	116	37	22.97%
12	HSR had a sales campaign and the price was so attractive (TW)/ compare to the fare, HSR was more attractive than other modes (SH)	2.37	1.28	98	48	21.92%
13	When accessing the HSR station became easier, I started using the service	2.36	1.19	89	32	18.17%
14	My company / organization sent me on a business trip	2.27	1.39	70	74	21.62%
15	I made a trip that I would not have done without HSR	2.05	1.24	58	44	15.32%
	n=666					
	avg. items answering 4 and 5 in section/respondent				4.476	
	scaled parameter				0.298	

5.7.3 Reasons to Increase HSR Usage

We find that accessibility improvements is the most important reason that leads to significant increase in HSR usage (47%). This entails that the access and egress time to the HSR stations are essential to induce HSR trips, as specified access links are one of the important factors that induced HSR ridership in Taiwan as discussed in Chapter 4.

However, we also find evidence that HSR has been increasingly attracting trips due to gradual changes in the respondents' perceptions (see Table 5-6). For example 42% rate previous experiences and service experience as reasons to further increase their HSR usage after some time. These are both factors that show that the (slow) build-up of trust in the service attracts over time new demand.

The sales campaign is another important reason to attract travellers using HSR in Taiwan, as over 46% of the respondents mention this item as important factor. The flexible fare may reduce 5%~35% from the original price during off-peak periods or for "early bird bookings". (The demand of discount tickets has even led to the creation of a web-based platform for HSR users to transact/enquiry discounted tickets in Taiwan.) Note that this item was not included in the survey conducted in China as no such discounts are available there currently.

Finally, we find that services of alternative modes are considered by many to be an important reason to increase HSR usage. This is likely due to dynamics in the competition between modes as HSR enforces other modes to adjust their operation strategies such as fare and frequency. In particular in Taiwan, HSR has driven domestic air transport along the west coast out of market. Asking for reasons in frequency increase over time as done in our survey might help understanding these complex long-term dynamic demand-supply interactions better. For brevity we omit also in Table 6 items with lower means. We find that there is a clear gap in that means of all other items are less than 2.4.

Table 5-6 Reasons to Increase HSR Usage

Ranking	Items descriptions (Section B)	Mean	Std. Deviation	Important reason	Most important reason	% from sample
1	HSR had improved its access to the station, therefore I started using HSR more	3.22	1.20	165	61	47.28%
2	I was satisfied with my initial HSR experiences	3.18	1.13	152	50	42.26%
3	I realized HSR has a sales campaign and the price is so attractive (TW, 180 valid sample)	3.17	1.40	44	39	46.11%
4	The frequency improved, making it feasible for me to travel more often	2.91	1.24	114	51	34.52%
5	I realized the service is better than I thought	2.83	1.13	99	36	28.24%
6	The other modes / options became worse (e.g. flights), so I used HSR more	2.73	1.26	113	38	31.59%
7	I was encouraged by my friends' / family's experience	2.36	1.17	71	21	19.25%
8	A lot of positive feedbacks from media / internet encouraged me to use the service more regularly	2.25	1.13	51	20	14.88%
9	I moved to another place.	2.17	1.34	52	42	19.67%
10	I have changed my job / got a different job (including getting your 1st job)	2.15	1.34	60	39	20.71%
	n=478					
	avg. items answering 4 and 5 in section/respondent		3.045			
	scaled parameter		0.294			

5.7.4 Reasons to Maintain/Continue HSR Usage

To also understand why usage stabilizes over a time period, we included a separate set of questions for this. We find that the average scores are comparably higher than for other sections as indicated by the scale parameter. This suggests that it is generally more difficult to distinguish a single reason why a respondent keeps using HSR (see Table 5-7).

Not surprisingly we find that the experienced speed advantages of HSR are one of the main reasons for respondents to remain HSR usage. Furthermore, comfort was rated highly. Interesting is though that nearly 49% of respondents commit to no specific reason but "just got used to HSR". This highlights that not only analysts but even respondents themselves find it often difficult to disentangle the reasons for usage adaptation. Another specific finding is that discount tickets, that were possibly meant to encourage travellers to start using the service, have in fact been used by Taiwanese to travel regularly over a longer term basis.

Table 5-7 Reasons to Maintain HSR Usage

Ranking	Items descriptions (Section C)	Mean	Std. Deviation	Important reason	Most important reason	% from sample
1	It's speedy, it has proven to save my time	4.04	1.03	117	148	73.82%
2	I feel comfortable when traveling with HSR	3.47	1.12	126	65	53.20%
3	I just got used to HSR	3.36	1.18	108	67	48.75%
4	I am satisfied with the service	3.31	1.12	115	51	46.24%
5	I regularly book discount ticket (TW, 135 valid sample)	3.21	1.40	30	33	46.67%
6	Because I feel safe	3.11	1.17	100	42	39.55%
7	I now prefer HSR rather than driving cars	3.01	1.33	96	50	40.67%
8	My way of travel is decided by others and they keep using HSR	2.73	1.26	71	34	29.25%
9	My business now strongly depends on HSR	2.63	1.29	65	33	27.30%
10	I simply have to though I don't like it	2.08	1.16	33	16	13.65%
	n=359					
	avg. items answering 4 and 5 in section/ respondent			4.191		
	scaled parameter			0.416		

5.7.5 Reasons to Reduce/Drop HSR Usage

We firstly note that the number of respondents answering section D is less as only 227 respondents chose a pattern that involved a usage drop (see Table 5-8). We find that the price of HSR is the most important reason to drop/reduce HSR trips as 39% of the respondents agreed that this has been an important or the most important reason. Connected to price is also the item with the second highest mean as a significant number of Taiwanese travellers would drop their usage in periods with less or no discount tickets being available. This item indicates that almost 40% of our sample who reduced HSR usage can be considered as price sensitive travellers. Interestingly we find nearly the same percentage for both Taiwan and China. We remind in this context that young people are overrepresented in our sample.

Followed by fare reasons are life course events such as job changes (22%) or "I moved to other places" (20%) become important reasons to reduce HSR usage. The life event items are corresponding to those listed in section B (usage increase) but in contrast were found to be among the least mentioned items in Section B as other reasons are more important for usage increase. In general we find that our scale parameter suggests that for usage reduction it is easier to distinguish items that cause the change in behaviour. There is a large list of items that was mentioned by only a few people as reasons for change in behaviour, including bad service experiences and safety concerns (which we expected to be more significant for travellers in China). Nevertheless, in the next section, we find interesting findings where the travellers who has increased HSR usage again, possibly partly answered our assumption here.

Table 5-8 Reasons to Reduce HSR Usage

Ranking	Items descriptions (Section C)	Mean	Std. Deviation	Important reason	Most important reason	% from sample
1	The fare has become too expensive for me	3.00	1.43	44	45	39.21%
2	I only used HSR when there's a discount, otherwise HSR wouldn't be my preferred option (TW, 110 valid sample)	2.85	1.55	20	23	39.09%
3	I have changed my job and now don't need HSR so much anymore	2.23	1.41	27	24	22.47%
4	I don't use HSR so much anymore since I moved to other places	2.19	1.35	25	21	20.26%
5	I now prefer other public transportation	1.90	1.01	15	3	7.96%
6	I now prefer to drive	1.82	1.04	13	5	7.93%
7	Access to the HSR station became worse	1.80	1.07	17	5	9.69%
8	I switched to other modes / options due to their improvement on its service	1.77	0.98	12	2	6.17%
9	The timetable changed and was not convenient for me anymore	1.72	1.02	10	5	6.64%
10	I heard a lot of negative feedback from media / internet discussion	1.71	1.00	13	4	7.49%
11	The service quality decreased (crowding, cleanness, and etc.)	1.61	0.86	8	1	3.96%
12	I felt HSR wasn't safe	1.58	0.91	9	3	5.31%
13	It became unreliable	1.56	0.93	10	4	6.17%
14	My friend / family had some terrible experience on taking HSR	1.49	0.80	3	2	2.20%
15	In general, I am NOT satisfied with my previous HSR experiences	1.47	0.83	6	2	3.52%
16	I have had a particular terrible experience	1.43	0.78	4	2	2.64%
	n=227					
	avg. items answering 4 and 5 in section/ respondent			1.906		
	scaled parameter			0.110		

5.7.6 Reasons to Second Increase in HSR Usage (Specific Section for Pattern 10)

Though number of sample for respondent whom chosen pattern 10 is limited with 49 samples. It is still very interesting to investigate these reasons that leads travellers to increase HSR usage again. As described in Section 5.5.2 pattern distribution, most of these respondents are from Shanghai with a number of 34 versus 15 from Taiwan. The ranking was listed by order of mean of answered by all respondents (see Table 5-9). The first thing we noticed is the reasons for second increase are more related to business purpose, coming at the first (36.7%) and (26.5%) second place in the rank, but we also notice promotion is a significant reason to induce HSR usage (it was ranked by mean as no.8) also shared a portion of 20.4%, which means that indeed business related factors have significant impacts to second increase in HSR usage. On the other side, item ranked as No.3, "The reason I drop had gone", though not shown in the table, but we find the answers ranking as important reasons were all from Shanghai's respondents. This finding partly supported our hypothesis that the collision accident in 2011 in Wenzhou China, have influence to the perception of safety. The sadly tragedy had cause 40 deaths and more than 210 people were injured. However, many critics and depute to the authority during the rescue stage and the clean-up procedure afterward. In particular, due to "technical" reason, we did not explain the descriptions more specific to connect it with this HSR accident, but we do believe the negative perception from massive publics would impact HSR usage and need more time to change traveller's perception. And eventually, travellers reconsidered HSR as their travel option again.

Another interesting finding is the reasons that least respondents choose. The improvement of access links (ranked as last second) to HSR stations does not seems to have a strong motivation to increase traveller's usage. Moreover, the second increase did not have a significant influence by others around the traveller, where convincing other to use HSR again is not very effective, only 8.6% reported as important reason. This may suggest that in the later adaptation process, influence from others would be less effective. Where if we compare the motivation stage, influenced by other (25.4%), positive perception from media (22.5%); and the increase usage stage, encouraged by other (19.3%) and positive feedback from media (14.9%). The reduced trend of influenced by other factors

shows that as the longer the HSR traveller are adopting to HSR, the less influence from others.

Table 5-9 Reason to Increase HSR Usage Again

Ranking	Items descriptions (Section 2B)	Mean	Std. Deviation	Important reason	Most important reason	% from sample
1	I realized that HSR was good for my business	3.23	1.17	13	5	36.73%
2	I have changed / got my job (including getting your 1st job)	2.83	1.36	7	6	26.53%
3	The reason I drop had gone	2.78	1.27	6	5	22.45%
4	The sale campaign that HSR now had become affordable for me	2.73	1.20	7	3	20.41%
5	The traffic condition became worse	2.63	1.19	6	3	18.37%
6	The frequency improved, make it feasible for me to depart at anytime	2.60	1.06	7	1	16.33%
7	I moved to other places	2.53	1.30	4	5	18.37%
8	I got promoted in my career, which generates more business trips	2.48	1.32	7	3	20.41%
9	The other modes / options became worse (e.g. flights)	2.35	1.21	7	1	16.33%
10	The reason I drop still existing, but my work made me have to use HSR more often	2.35	1.27	5	3	16.33%
11	HSR had improved its access to station, I felt now it has better connection	2.33	1.02	4	1	10.20%
12	Others whom are closed to me convinced me to use HSR again	2.13	0.99	4	0	8.16%
	n=49					
	avg. items answering 4 and 5 in section/ respondent		2.825			
	scaled parameter		0.235			

5.8 Discussion

We suggest that asking users for their long-term travel behaviour with graphical patterns including questions on the reasons that lead to significant changes in usage might be one way to collect data that are otherwise difficult to obtain. Our methodology will be particularly helpful when recall questions on precise numbers of trips (frequency) or usage in general during specific time periods in the past might not be feasible as the respondent might not be able to answer these. The visualized usage pattern allows travellers to reconsider their longer-term travel behaviour (over several years) without concerning the accuracy issues of single answers. Clearly such data is not fully accurate but, on the positive, might reflect the perceived usage trend. One might argue that these perceptions also drive the image of the transport mode in question and help to explain future decisions. Especially in the panel data often missing detailed information on events likely to occur between the data collection points that triggered (gradual) changes in usage have been the focus of our study. We show how the survey can distinguish different adaptation types. We find that for our case study four traveller groups can be distinguished according to their adaptation pattern and that reasons for change in usage can be extracted. In addition, the proposed usage patterns and its descriptions were found consistent to the usage obtained by revealed preference questions also on aggregate level. Nevertheless, clearly further validation of the accuracy of the approach and the usage patterns are needed. One possible approach is the comparison of panel data on actual usage with our patterns.

Our HSR case study with Taiwanese and Chinese samples we believe further illustrated some interesting tentative findings. We note that the findings are tentative and not representative for the whole population in both countries due to limited and biased sample sizes. Nevertheless, we demonstrate that the proposed graphical patterns capture most usage patterns from travellers since less than 2% of the respondent answered “none of above pattern fit to my experiences” in both China and Taiwan. If one wants to apply the graphical patterns to other applications we emphasize also the need for reconsidering the specific patterns. Our pattern selection was finalized only after a pilot survey and obtaining feedback from 50 samples in each region.

By aggregating patterns we find that at least 31% of users adapt fast (more depending on how one classifies those stabilizing their usage soon but dropping their usage later) and that there are at least 21.1% of travellers who adapt slow and some of these might be expected to further increase their usage in the future. We further analyse the reasons given by respondents that motivated them to start using, to increase, to keep using and to drop HSR usage. We find that starting to use HSR is mostly based on travel time savings as well as "positive expectations" whereas increases in service usage is mostly due to other service quality factors, in particular station access. Reductions in usage seem easiest to explain and are mostly based on life course events.

In this chapter, the focus is on the survey description and the descriptive analysis of reasons for changes in behaviour. In the next chapter, further analyse pattern choice by applying varies type of adaptation modelling; such as discriminant or regression type analysis with socio-demographics and motivations to start using HSR as explanatory variables.

Chapter 6

Taiwan and Shanghai HSR Usage Pattern Analysis

6.1 Introduction

6.1.1 Data Description

Following the discussion and data obtained in Chapter 5 with our initial descriptive analysis. In this chapter a number of modelling approaches were proposed to seek the potential and limitation of the obtained usage pattern data. In the following section, the dependent variable, explanatory variables will be defined and discussed.

6.1.2 Explanatory Variables and Pre-processing Data

Our explanatory variables can be grouped into measures of a person's innovativeness, general stated motivations to start using HSR, trip purposes, modes used for similar trips before HSR opened as well as the aforementioned sociodemographic factors. In this section we describe the pre-processing of some of these variables.

A. Innovativeness Measures

In order to obtain a reliable measure of a person's innovativeness we conducted a factor analysis by principal component method on the measured items. We found the results from our survey are in line with previous findings, where "creative original" and "willingness to try" are specified from our data (see Table 6-1); however it also suggests that "willingness to try" could be further distinguished into two components, more details on factor analysis and guidance could be refer to Hershberger (2005), DiStefano *et al.* (2009), and Fabrigar *et al.* (1999). From the item descriptions, we can verify the concept of "willingness to try" can be further explained and defined as "observations from others or living experiences" and "personality" (separated by dashed line). The Cronbach's alpha test suggests that the former two constructs are reliable whereas "personality" is not and which is hence also not used in our further analysis.

Table 6-1 Factor Analysis and Cronbach's Alpha of innovativeness scale

Factors	Innovativeness scale measurements	Component			Cronbach's Alpha
		1	2	3	
Creative original	I am an inventive kind of person	.752			0.831
	I consider myself to be creative and original in my thinking and behaviour	.739			
	I enjoy trying out new ideas	.716	.225		
	I frequently improvise methods for solving a problem when an answer is not apparent	.713			
	I seek out new ways to do things	.700	.242	-.130	
	I am receptive to new ideas	.650		.151	
	I find it stimulating to be original in my thinking and behaviour	.579	.279	-.256	
Willingness to try	I am reluctant about adopting new ways of doing things until I see them working for people around me	.133	.784	.189	0.806
	I tend to feel that the old way of living and doing things is the best way		.749		
	I am aware that I am usually one of the last people in my group to accept something new		.742		
	I rarely trust new ideas until I can see whether the vast majority of people around me accept them	.139	.673	.284	
	I must see other people using new innovations before I will consider them	.121	.638	.353	
	I often find myself sceptical of new ideas		.205	.664	0.482
	I am suspicious of new inventions and new ways of thinking	-.347		.656	
	I am generally cautious about accepting new ideas		.319	.614	
KMO value					0.835
Bartlett's Test of Sphericity (Approx. Chi-Square)					3085.265
Sig.					0.000

In addition, to determine the factorability of this intercorrelation matrix, two tests were performed, namely, Barlett's test of Sphericity and Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO). The Barlett's test of sphericity calculates the determinate of the matrix of the sums of products and cross-products (S) from which the intercorrelation matrix is derived. The determinant of the matrix S is converted to a chi-square statistic and tested for significance. The null hypothesis is that the intercorrelation matrix comes from a population in which the variables are noncollinear (i.e. an identity matrix). And that the non-zero correlations in the sample matrix are due to sampling error.

The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) was to test if two variables share a common factor with other variables, their partial correlation will be small, indicating the unique variance they share. The KMO function was given as below:

$$KMO = \frac{\left(\sum\sum r_{ij}^2\right)}{\left(\sum\sum r_{ij}^2 + \sum\sum a_{ij}^2\right)} \quad (7)$$

where the partial correlation, $a_{ij} = (r_{ij} \cdot 1, 2, 3, \ldots k)$. If $a_{ij} \cong 0.0$, the variables are measuring a common factor, and KMO $\cong$ 1.0; if $a_{ij} \cong 1.0$, The variables are not measuring a common factor, and KMO $\cong$ 0.0. The result shows the KMO value is 0.835, which the value between 0.80-0.89 in the interpretation as characterized by Kaiser, Meyer, and Olkin is "Meritorious".

B. Trip purpose and HSR Travel Time Calibration

In addition, trip purpose and HSR travel time may also influence traveller's usage during their adaptation process, as such; these factors were calibrated and taken into account for model estimation. From the previous descriptions in section 3.2, trip purpose over each time period was obtained from recall questions since the first time HSR usage. One could then easily distinguish HSR travellers who do not change their travel purpose from those who utilize HSR also for different purposes. For example, some travellers may initially conduct mainly business trips by HSR, but over time appreciate the convenience by HSR so that HSR also induces them to make more long distance leisure trips. We refer to these travellers as "Mixed-trip purpose" travellers and also include it as dummy variable in our model. We find nearly 35% of the respondents have changed their dominant type of trip purpose over time (see Table 6-2). The travellers who do not change their trip purpose over time, were defined as single trip purpose travellers and are distinguished into commuters, business travellers, return-home travellers and leisure trip travellers. Trip purposes were defined and calibrated as dummy parameters in modelling.

Table 6-2 Distribution of HSR trip purpose

Trip purpose	Total		Shanghai		Taiwan	
	No.	%	No.	%	No.	%
Commuting	12	1.8	5	1.3	7	2.5
Business	111	16.9	72	19.2	39	13.9
Return-home	139	21.2	72	19.2	67	23.9
Leisure	168	25.6	101	26.9	67	23.9
Mixed	225	34.5	125	33.4	100	35.8

The predominant HSR travel time could be estimated from the question of "most frequent HSR OD stations" in the survey. HSR travel time was estimated and calibrated as dummy variables to for the non-linear effect different trip

distances have on pattern choice. We distinguish travel within 1 hour, between 1~2 hours, 2~3 hours, and more than 3 hours. These segments could be regarded as short, medium, long, and ultra-long-haul distance travellers respectively. We also note that in Taiwan all travel times are within 2 hours, therefore an additional regional dummy variable was assigned to the utility function for those with travel times over 2 hours.

C. Correlation with HSR usage and Socio-Economic Factors

In this sub chapter, the correlation for HSR usage and socio-economic factors obtained from the respondents are shown in Table 6-3. The result indicates that marital status and age were correlated with most of the socio-economic variables, this is in line with life course experience which incomes, job status, whether holding a licence and etc., possibly should be taken care of if it has impacts to usage pattern in further analysis. Education and income related variables seems to be fairly distributed among usage pattern. These variables from correlation table could be taken into account on whether to leave or to abandon while iterating behaviour modelling on HSR usage.

Table 6-3 Correlation among HSR Usage Pattern, Frequency and Socio-economic factors

Factors and Variables		HSR Usage Pattern	HSR Usage Frequency				Gender	Marital Status	Age	Incomes		Edu.	Licenses			Job Status		Alternative mode for HSR
			2014 (390)	2008~09 (51)	2010~11 (203)	2012~13 (349)				Personal	Household		Car	Scooter	Heavy bike	Occupation	level of employment	
HSR Usage Pattern		1	.196**	-.049	.169*	.128*	-.134**	.035	-.026	-.014	-.071	-.034	-.031	-.046	.007	-.094	.030	.c
HSR Usage Frequency	2014		1	.129	.443**	.539**	-.054	-.003	-.048	.106*	.143**	.075	-.143**	-.078	-.003	-.148**	.171*	-.103
	2008~09			1	.601**	.074	-.049	.404**	.364**	.092	.022	.078	.000	-.192	-.154	-.044	-.308	.c
	2010~11				1	.351**	-.025	.161*	.048	.078	-.045	-.084	.010	-.058	-.040	-.105	-.063	-.269
	2012~13					1	.048	.046	.016	.090	.062	.003	-.141**	-.010	.027	-.132*	.028	.041
Gender							1	-.013	.012	.062	-.008	.016	.195**	.135**	.099	.110*	-.025	-.302
Marital Status								1	.566**	.234**	.166**	-.069	-.080	-.144**	-.168**	-.278**	.266**	.334
Age									1	.202**	.142**	-.135**	-.064	-.198**	-.165**	-.228**	.218**	.552**
Personal Income										1	.518**	-.025	-.074	-.096	-.075	-.213**	.283**	.291
Household Income											1	.014	-.135**	-.112*	-.097	-.171**	.355**	.069
Edu.												1	-.154**	.034	.071	.007	.151*	.018
Car license													1	.169**	.154**	.179**	-.261**	-.301
Scooter license														1	.659**	.132**	-.249**	-.230
Heavy bike license															1	.118*	-.248**	.c
Occupation																1	-.116	-.441*
level of employment																	1	.184
Alternative mode for HSR																		1

Note: **. Correlation sig. at 0.01% (Two tails); *. Correlation sig. at 0.05% (Two tails); c. Unable to estimate due to one of the variable is constant

6.2 Multinomial Logit (MNL) analysis to explain pattern choice

6.2.1 Arguments for and against MNL modelling

In this section we want to explain pattern choice by the above introduced potential explanatory variables. To analyze pattern choice by applying regression type analysis on explaining the choice between all respondents, requires further discussion on whether the assumption of utility maximization is realistic for analyzing using long-term patterns, in which decisions are likely to be conditional on previous decisions and other external factors. In other words one might phrase this as: Do people choose patterns or do they happen to one?

If people choose patterns we can possibly express this as a utility maximization process. However, patterns are an agglomeration of single trips over a longer time period. Most probably not all of these single trips have been conscious decisions of the traveler. For example, a traveler might choose a household location or a job and with that comes a whole set of HSR trips. In other words, the HSR trips might just have been a "side effect" of a different decision in which the HSR usage has just been a small part in the deliberation process. Therefore we are aware that modelling the pattern choice as a conscious utility maximization process might have its limitations. On the other hand, considering it a utility maximization process allows us to possibly extract that larger life style decisions also includes to some degree a preference or dislike for travel modes such as high speed rail. Furthermore, clearly some trips are not a result of constraints by other decisions but are expressions of mode preferences. In particular, our attitudinal factors, such as perceived safety or comfort are likely to show the perceived attractiveness of HSR.

Given these pros and cons, we do employ a utility maximization model in the form of a Multi-nominal Logit model (MNL), as it has been the most widely used structure for modelling discrete choices in travel behavior (Ben-Akiva and Lerman, 1985). Further, as one of our interests, it is capable of investigating behavioral differences between regions by interaction between behavioural or attitudinal and regional specific variables. Moreover, it is able to jointly estimate common characteristics factors among groups of travelers, e.g., higher income may have positive influence on HSR adopters (either fast or slow) compared to non-adopters.

As alternative to the MNL results, and more in line with the assumption that "choices happen to people" we also test discriminant analysis with the same "explanatory variables" which in this context should be referred to as "predictor variables". The objective of discriminant analysis is to utilize a set of predictor variables to distinguish our factor of interest in this case the chosen pattern. Utility maximization does not have to be assumed. The discriminant results of this analysis will be discussed in the next section. But not surprisingly we obtain similar conclusions for both types of analysis. Though there are important differences in the estimation process both models aim to show the explanatory power of the explanatory variables/predictors for the same dependent variable/factor.

6.2.2 Aggregated Pattern (Dependent Variable)

In the initial model, we analyze the behavioral characteristics among HSR usage pattern. As in previous section we also use here the grouping of patterns as discussed in Table 5-4 namely, fast adopters, slow adopters, adopted but dropped at some point, and non-adopters. We note that we also estimated separate models for both Taiwan and Shanghai samples and find that most variables share similar effects which increases our confidence in the results. For brevity, in the following we only report the analysis of the HSR usage pattern jointly estimated from both data sets.

6.2.3 Variables Estimated in MNL

Our explanatory variables were discussed in Section 6.1, which can be grouped into measures of a person's innovativeness, trip purposes, modes used for similar trips before HSR opened as well as the aforementioned sociodemographic factors. In particular, items stated motivations to start using HSR (section A in the survey) were considered in the MNL model. The detailed descriptions and descriptive analysis of answers given by all respondents on their motivations to start using HSR are already discussed in Chapter 5, Table 5-5.

In the following section, we will briefly discussed the Taiwan and Shanghai result, then primary focus on the report of the analysis of the HSR usage pattern jointly estimated from both data sets. In our initial model we grouped the 10 original patterns into four groups of travelers, namely: fast adopters, slow adopters, those who once adopted but dropped usage later (dropped group), and non-adopters. Multi-nominal logit modelling (MNL) was

applied in order to examine the behavioral characteristics among each group. After excluding unanswered/skipped questions, 655 valid samples were tested in an MNL framework (Table 5-4).

Following the aggregated pattern groups, the non-adopter group (Patterns 3 & 5) was defined as reference group in the MNL analysis. The model is estimated using maximum likelihood in Biogeme. Explicit formulations of MNL models and implementation in Biogeme are available from Bierlaire (2003) and Bierlaire and Fetiarison (2009). In the MNL analysis, converted innovativeness variables from principle component analysis (PCA), Section A items (motivations for start using HSR), and socio demographics are tested.

6.3 MNL Model Results

6.3.1 Taiwan and Shanghai Results

Firstly, both Taiwan and Shanghai samples were estimated in separate models and find that most variables share similar effects which increases our confidence in the results. Table 6-4 shows the estimated result of Taiwan and Shanghai. Note that the table kept those variables that are either significant in other region or closely to significant in the model iteration. In brevity, the discussion of how these explanatory variables influence usage pattern were addressed in the latter section.

Table 6-4 Separated MNL Estimation (Taiwan and Shanghai)

Region	Taiwan			Shanghai			Description
Factors	Fast & Dropped	Slow adopters	Non-adopter	Fast & Dropped	Slow adopters	Non-adopter	
ASC	-2.49***	-2.55***	ref.	-1.52*	-1.55*	ref.	Alternative specific constant
WtT	0.595***		ref.	0.411***		ref.	Perceptions perceived from others or living experiences
STA	-0.446***		ref.	-0.680***		ref.	Starting year of HSR
INCP	0.411***		ref.	0.346**		ref.	Personal income
EDU	0.328		ref.	0.595***		ref.	Education degree
A02	0.206		ref.	0.312**		ref.	Comfortable than other travel options
A14	0.493***		ref.	-0.0196		ref.	Timetable improved
A05	0.197	ref.		0.129	ref.		Safest travel option
A07	-0.178	ref.		-0.118	ref.		Encouraged by others
A15	-0.0062	ref.		0.138	ref.		Other modes / options became worse
A12	ref.	-0.303**	ref.	ref.	-0.165	ref.	Working efficiently
A11	0.0257		ref.	0.387***		ref.	Travel cost, HSR is more attractive
Log_0	-295.53			-396.60			
Final_log	-244.13			-331.09			
ρ	0.17			0.17			
ρbar	0.13			0.13			

Note: *** sig. at 1%; **sig. at 5%; * sig. at 10%

6.3.2 Combined Result

A. Four groups MNL analysis

From the previous Table 6-4 suggested that HSR travelers from Taiwan and Shanghai, shared some common characteristics. The further analysis intent to combine both data set, after several model iterations, the estimated results are shown in Table 6-5. It suggests that one's innovativeness of willingness to try has a positive influence on HSR usage. We also find, (though this is not self-evident), that the year when a respondent starts to use HSR is a significant determinant of the pattern, therefore the adaptation process does not seem to be time-homogeneous (not that this is not self-evident as the starting point in Figure 5-5 is "chosen" by the respondent).

The result indicates that comfort (A02) and timetable improvement (A14) seems to be the most significant reason among HSR adopters to start using HSR. What distinguishes fast adopters from other groups is the perception of safety (A05): If one considered HSR to be a safe mode to travel, then that individual is more likely to become a fast adopter. Slow adopters, on the other

hand, do not consider working while travel (A12) as the reason to start using HSR compared with other groups.

Table 6-5 MNL Estimation (4 Groups of Usage Pattern)

Factors	Fast adopters	Slow adopters	Dropped	Non-adopters
ASC	-2.94***	-2.11***	-2.34***	ref.
WtT	0.511***			ref.
STA	-0.454***			ref.
INCP	0.327***			ref.
EDU	0.43***			ref.
A02	0.283***			ref.
A14	0.223***			ref.
A07	-0.134*	ref.		ref.
A15	0.13*	ref.		ref.
A05	0.24***	ref.		
A12	ref.	-0.215**	ref.	
A11_S	0.258***		ref.	
Log_0	-873.365			
Final_log	-794.691			
σ	0.09			

Note: *** sig. at 1%; **sig. at 5%; * sig. at 10%

In terms of fare, the fare policy was quite different in both countries. According to an investigation released from China railway authority in 2014, HSR travel cost in China was the cheapest compare to the existing HSR system worldwide; Taiwan HSR lies on the 3rd place of 0.12 €/km just behind KTX, Korea of 0.1 €/km and China, 0.04 €/km. In order to attract travelers from the existing market, Taiwan HSR operator offered a ticket discount of 50% at the initial stage of operation, and quite flexible on ticket pricing afterwards. While in Shanghai, the fare is well fixed correspond to its railway policy in China. The fare issue apparently is one of our interest and was included as one of the motivations (A11) for traveler to start using HSR. The descriptions were modified due to the circumstance regarding region differences. As for Taiwan version, we described the item as "HSR had a sales campaign and the price was so attractive". For Shanghai version, we modified this into "Compared with other travel mode cost, HSR is more attractive". An interesting finding from here is that, for those who are currently adapted to HSR, that is, the fast and slow adopters; it was found that the discount ticket in Taiwan is not significant as the motivation to start using HSR. As the result suggested, the fare discount may not be an effective policy or marketing strategy to attract people "keep using" Taiwan HSR. Instead,

it's significant for Shanghai area though there's no fare campaign, but, HSR fare was considered as relatively attractive.

In this model, the result shows that the common characteristics been shared among fast adopters and once adopted but dropped group; which suggesting that HSR operators should carefully examine the specific reason for travelers to drop from HSR. The result may implies that most of the dropped group originally could be came from the fast adopters, where slow adopters react slower in HSR adaptation process and vice versa.

B. Three Groups MNL analysis

In a number of initial model tests we observed that the fast adopter group and dropped group are found to have a number of common variables that share similar effects compared to slow adopters and non-adopters as discussed in previous section. One obvious reason is that "reason to drop" items could not be taken into account in the utility function given our MNL model structure. The results imply though also that most of the dropped group is likely to be originally fast adopters. Instead, slow adapters use HSR in the beginning less but are also less likely to reduce the service frequency over longer time periods again. Two MNL models are proposed in this section. The first model analyzed the preprocessed variables including innovativeness factors, motivations to start using HSR and socio demographics as well as the year they started HSR usage. HSR trip purpose and travel time is then added in the second model.

In the following we therefore continue the estimation by combining the fast adopter and dropped group into one group and the model results only using attitudinal variables and socio-demographics are shown in Table 6-6. The results suggest that one's innovativeness of willingness to try (WtT) has a positive influence on HSR usage. We also find that the year when a respondent starts to use HSR (STA) is a significant determinant of the pattern. The starting year of HSR in the survey was measured in chronological order, therefore, the negative sign indicates that those who start HSR usage earlier, are more likely to become HSR adopters (fast and slow group). As for socio-demographics, not surprisingly, higher education degree (EDU) and personal income (INCP) would encourage travelers adopting HSR compared to non-adopters. As education arguably should be treated as a categorical variable, we tested if this changes the model results

but found similar variable estimates and model fits. To reduce the number of variables, we therefore keep it as a continuous variable in the model.

As for the motivation items shown in Chapter 5, Table 5-5, we omit non-significant attitudinal variables which also ensures that all remaining variables are not significantly correlated. The result further indicates that comfort (A02) and timetable improvement (A14) seem to be the most significant reasons among HSR adopters to start using HSR. One of the factors that distinguishes the fast adopters and dropped group from others, is the perception of safety (A05): If one considers HSR to be a safe mode to travel, then that individual is more likely to choose a pattern from the fast/dropped group. Fast adapters are further less influenced by others, though we find A07 to be significant only at 10% level. This could also be correspondingly explained as that the slow adopter and non-adopter groups are more susceptible, which is understandable in that taking into account the opinions and experiences of others means that one is less likely to react quickly. We further find that slow adopters do not consider working while travel (A12) as the reason to start using HSR compared with other groups. This is also reasonable in that it suggests that those who value the time savings of the HSR are more likely to adapt fast if ever.

In terms of fare, the fare policy was quite different in both regions, therefore the description was slightly modified for item (A11). Though items regarding fare were rated as important reasons to "increase/reduce" HSR usage, it was found that "discount tickets" are not a significant motivation to start HSR usage in Taiwan which we suggest has policy implications in that campaigns are not likely to permanently attract new users. In contrast, we found the fare in Shanghai is a significant factor to adapt so that the HSR fare can be considered as relatively attractive compared to prices for other travel alternatives in China.

We notice that the significance and signs of each variable, are in line with the result of discriminant analysis except for influence by others (A07), which is weakly significant in the MNL model but not significant in the discriminant analysis. Also, (A11), i.e., the sales campaign/fare is less significant than other predictor variables possibly due to regional differences that could not be specified in the discriminant analysis.

Table 6-6 MNL Model Estimation (3 Groups of Usage Pattern)

Factors	Fast & Dropped	Slow adopters	Non-adopter	Descriptions
ASC	-2.100***	-2.260***	ref.	Alternative specific constant
WtT	0.502***		ref.	Willingness to try (inverse of factor related to perceptions or experiences by others)
STA	-0.512***		ref.	Starting year of HSR
INCP	0.357***		ref.	Personal income
EDU	0.480***		ref.	Education degree
A02	0.269***		ref.	I expected it should be more comfortable than other travel options
A14	0.242***		ref.	Once the timetable improved I started using HSR.
A05	0.167*		ref.	I thought it is the safest travel option and therefore started using HSR.
A07	-0.128*		ref.	I was encouraged by my friends' / family's experience
A12	ref.	-0.234***	ref.	I wanted to work while travelling (working efficiently)
A11_SH	0.416***		ref.	Compared with other travel mode cost, HSR is more attractive (Shanghai specific)
Log_0	-692.126			
Final_log	-581.519			
ρ	0.160			
ρbar	0.142			

Note: * sig. at 10%; ** sig. at 5%; *** sig. at 1%

In Table 6-7 we further include HSR trip purposes and travel time into the model. We observe that the model fit slightly increases though not as much as one might expect. For the effect of trip purpose, it suggests that having mixed trip purposes (TP_Mixed) has a very strong positive effect for HSR travelers to adapt, where the coefficient was estimated as 0.616. Further, among those who use HSR consistently over time dominantly for the same purpose; we find a negative parameter for leisure trips (TP_L) and slow adopter. The result might be interpreted in that leisure travelers either adapt fast or not at all, but that they do not tend to continuously, slowly increase their leisure trips. Contrary, we find that commuting is rather a slow adaptation process, though we only find the variable to be significant if it is interacted with a dummy denoting Shanghai respondents. As one might expect we find a positive significant variable for business trips and "fast & dropped" (TP_B_SH) as business travelers will have in general a higher value of time, though it is only weakly significant and only significant for Shanghai respondents. That it is not more highly significant might be due to the slowly developing cyclic effects between HSR extension and business development.

In terms of travel time, the results suggest that compared to other travel segments, HSR travelers whose most frequent journey takes between 1~2 hours are more likely to be fast adopters, this finding is also in line with Cascetta and

Coppola (2014) where they estimated the threshold of HSR travel time is 120 minutes (2 hours). One can explain this by considering that for short distance trips possibly a number of competitors such as buses, conventional trains exist. Compared to this HSR travel costs are considerable higher and hence people require more time to commit to a change in their usual travel mode (if ever). Similarly, for long haul trips flying becomes a feasible option. Also here the decision making progress of mode choice sets among these segments may took longer. Only for travel distances of between 1 to 2 hours HSR is so attractive that many are likely to adapt fast.

Table 6-7 Revised MNL Estimation Considering HSR Trip Purpose and HSR Travel Time

Factors	Fast & Dropped	Slow adopters	Non-adopter	Descriptions
ASC	-2.460***	-2.410***	ref.	Alternative specific constant
WtT	0.501***		ref.	Willingness to try (inverse of factor related to perceptions or experiences by others)
STA	-0.423***		ref.	Starting year of HSR
INCP	0.334***		ref.	Personal income
EDU	0.419***		ref.	Education degree
A02	0.263***		ref.	I expected it should be more comfortable than other travel options
A14	0.254***		ref.	Once the timetable improved I started using HSR.
A05	0.174**	ref.		I thought it is the safest travel option and therefore started using HSR.
A07	-0.145*	ref.		I was encouraged by my friends' / family's experience
A12	ref.	-0.220***	ref.	I wanted to work while travelling (working efficiently)
A11_SH	0.410***		ref.	Compared with other travel mode cost, HSR is more attractive (Shanghai specific)
TP_Mixed	0.616***		ref.	Mix trips
TP_B_SH	0.497*	ref.		Business trip in Shanghai
TP_L	ref.	-0.543**	ref.	Leisure trips
TP_C_SH	ref.	1.670**	ref.	Commuting trip in Shanghai
TT_2	0.194*	ref.		HSR travel time between 1~2hr
Log_0	-692.126			
Final_log	-571.159			
ρ	0.175			
ρbar	0.150			

Note: * sig. at 10%; ** sig. at 5%; *** sig. at 1%

6.3.3 Discussion on MNL Approach

Our primary objective in this study has been to explain which users adapt fast, slow or not at all to the introduction of HSR in Taiwan and China. For this we analyzed the impact of attitudes and perceptions as well socio-demographics and travel characteristics. MNL was applied as methodology as we found it best suitable for this purpose despite also being aware that associating pattern choice with utility maximization has its drawbacks. We believe our findings help understanding long term travel behaviour and include several policy implications. We note that the findings are tentative and not representative for the whole population in both samples due to limited and biased sample sizes.

We find it noteworthy that the pattern distribution in both samples are fairly similar. A good 30% of all respondents adapt fast to the new service. This percentage increases to around 50% if one also include those adapting fast but at one point dropping usage again. Further for more than 21% of its customers, the HSR operator might be able to expect a gradual increase in usage over time. The reminder are likely to stay occasional users. Some of the existing differences (such as higher proportion of pattern 4 and pattern 10 in Shanghai) between the regions can be explained by the gradual extension of HSR network these years in China.

The MNL model jointly estimates HSR usage pattern from Taiwan and Shanghai travelers. We note that we also estimated separate models for both samples and find that most variables share similar effects. Nevertheless, the results suggested that fare policy and trip purpose brought different impact to both regions. The combined parameters from MNL result suggests that fast adopters and the dropped group shared similar characteristics compared to slow adopters. This possibly indicates that the travelers in the dropped group are mostly from fast rather than slow adopters.

As for socio-demographics, not surprisingly, higher education degree and personal income would encourage travelers adopting HSR. Clearly business and time conscious travelers are likely to adapt faster as for example the significance of timetable improvements and the value of being able to work on the train suggests. The perspective of HSR adopters towards fare discounts seems different across the strait. In Taiwan, where the standard fare kept fairly constant over our analysis period, but discounts were available sometimes, these were not found to be significant in our model. This should not be over-interpreted as meaning that the discount was not attractive, but to emphasize that fare discount was not effective to influence long term adaptation. The Shanghai case illustrates that HSR adaptation is depending on the fare. Travelers in mainland China very much rely on the low cost fare controlled by the railway authority. In line with previous literature we find that it is particular travelers who often travel distances of around 150-400km (or 1-2 hour travel time) find HSR attractive. We add to previous findings by concluding that these travelers are also often those who start to develop regular travel patterns fastest.

6.4 Discriminant Analysis

The discriminant analysis approaches are well known to learn discriminative feature transformations in the statistical pattern recognition literature and have been successfully used in many recognition tasks. The concept of discriminant analysis is closely related to regression analysis and analysis of variance (ANOVA), which attempt to express one dependent variable as a linear combination of other features or measurements. However, ANOVA uses categorical independent variables and a continuous dependent variable, where discriminant analysis has continuous independent variables and a categorical dependent variable. In the proposed usage pattern, apparently it should be regards as categorical variables though the study tried to "group" the patterns into 4 types (or says the status/duration of adapting to HSR) of adaptation process. In particular, the motivation to apply discriminant analysis that seems promising, was the assumption that "choice happen to people", where the utility maximization of MNL does not have to be assumed. The MNL treats the accumulated trips (forming the usage pattern) choices as a conscious decisions of the travellers yet in discriminant analysis, these parameters were treated as classify predictor variables and distinguish items that are most effective for pattern choice classification. The discriminant analysis performs canonical linear discriminant analysis which is the classical form of discriminant analysis in SPSS. More importantly, applying discriminant analysis from the information obtained in section B, C and D could not be estimated in MNL modelling due to the survey design, a number of respondent compulsory skipped these questions. The discriminant analysis could supplement the drawback of MNL models and investigate the reason behind the gradual usage changes over time.

At the beginning of the section, the discriminant analysis attempted to validate result from previous MNL analysis, the explanatory variables were estimated according to the parameters from the previous modelling. Following with pattern specific analysis, in order to investigate the differences of reason at each stage of usage among each individual pattern, namely, the reasons that classify the reasons to start using HSR, reasons to increase, reason to continue and reason to drop from HSR usage. For brevity, detail description of each question (reasons at that current usage state) was simplified.

6.4.1 Comparison to MNL combined result

Based on the previous MNL analysis, a number of extracted variables were identified and the result suggested that it has different influence among different group of HSR travelers (Fast and Dropped group, Slow adopter and Non-adopter). Table 6-8 shows the classification function coefficients from discriminant analysis, the coefficient could be explained as how strong the predictors influence among each group. From the table, it shows that most of the variables are significant and the sign are in line with MNL analysis (denoted in bolt). The result suggests that HSR adopter group has stronger influence from WtT than those non-adopters. In line with the previous finding, STA indicates HSR adopters started to take HSR earlier than non-adopters. Socio-economic related factors illustrate HSR users are more likely to have higher income and education degree. Motivation items suggest that HSR adopters perceived higher positive perceptions towards HSR than those non-adopters. In summary, this alternative approach confirmed that the variables tested in MNL analysis were well-performed. The MNL model can distinguish and partly explain the behavior of some user groups by attitudinal factors and perceived perceptions.

Table 6-8 Classification Function Comparison with MNL model

Predictors	Classification Function Coefficients			TEGM		Descriptions
	Fast & Dropped	Slow adopters	Non-adopter	F	Sig.	
Constant	-20.765	-21.918	-18.980	-	-	Alternative specific constant
WtT	0.821	1.070	0.388	13.287	**.00**	Perceptions perceived from others or living experiences (Willingness to try)
STA	3.139	3.241	3.464	10.008	**.00**	Starting year of HSR
INCP	1.233	1.216	0.914	8.722	**.00**	Personal income
EDU	5.767	6.064	5.492	8.003	**.00**	Education degree
A02	2.871	2.763	2.588	12.810	**.00**	I expected it should be more comfortable than other travel options
A14	1.026	1.006	0.772	6.652	**.00**	Once the timetable improved I started using HSR.
A05	0.576	0.489	0.392	11.726	**.00**	I thought it is the safest travel option and therefore started using HSR.
A07	0.023	0.164	0.227	0.112	.89	I was encouraged by my friends' / family's experience
A12	-0.089	-0.294	-0.146	6.785	**.00**	I wanted to work while travelling (working efficiently)
A11	0.772	0.813	0.670	3.813	**.02**	HSR had a sales campaign and the price was so attractive (TW ver.) / compare to the fare, HSR was more attractive than other modes (SH ver.)

Note: TEGM denotes Tests of Equality of Group Means

6.4.2 Individual Pattern Analysis

From this section, this study begin to assess the difference of the perceived perceptions and reason that cause the changes of behavior at each usage status. The dependent variables is the pattern which had answered that specific set of question set. The result of motivation items (Section A) which answered by all respondents were tested and as shown in Table 6-9; patterns which assigned to answer the reason to increase HSR usage (Section B) are as shown in Table 6-10; patterns which assigned with reason to continue the usage (section C) are as shown in Table 6-11; and Table 6-12 illustrate the result of usage patterns which assigned with reason to reduce/drop from HSR (section D). From the four tables, a number of predictors indicate that it can classified the differences among usage patterns. The classification function coefficients illustrate the attitude of each predictor and the magnitude of influence to individual usage pattern. The result revealed that even with different types of usage pattern, some perception might share similar effects and some would have less impact compared with other patterns. This could be easily identified from a number of coefficients among usage patterns, are close to each other.

A. Fast Adopter (Pattern 4, 8)

Pattern 4 and 8 were grouped as fast adopter, from the graphical figure with description of HSR usage, these pattern adapted to HSR faster than others. The motivation suggested that these users along with pattern 6 and pattern 10 users, evaluate HSR as a safer travel options than other patterns. In particular, pattern 4 users rated accessibility (A13) and other options became worse (A15) higher compared with pattern 8. Moreover, both of them are less likely to use HSR due to traffic congestions. For the reason to increase, the timetable improved (B08) has similar positive effect for most of the pattern except pattern 7 and 9. Interestingly, Table 6-10 suggests that pattern 8 users were satisfied with their initial HSR experiences (B03), similar to pattern 1 and pattern 6 users in slow adopters, where pattern 4 users has less influence from this reason. Regarding the graphical usage of pattern 4, most of the predictors in section B did not stand out as a strong predictor to identify pattern 4. This could be explained as the description of this pattern, where phrased as “I keep increasing my HSR usage slowly since I started to use it”. The gradual increase seems reasonable that the

predictors might be difficult to identify since the respondent choose this pattern. When asking the reason to continue their usage, it seems that "Safer than other modes (C04)" is a very strong predictor that distinguish them from other HSR user.

B. Slow Adopter (Pattern 1, 6, 9)

The slow adopter group includes pattern 1, 6 and 9, the classification is from the usage graphics that it takes a while before a significant increase. From the motivation to start HSR usage, the experience of been stuck in the traffic (A04) is more likely the reason that pattern 6 and pattern 9 users to start HSR. "I made a trip that I would not have done without HSR (A10)" was found to be a strong predictor to classify pattern 6 users from all other patterns. In particular, the motivation predictors seems to distinguish pattern 9 users quite well, where they are more likely to consider travel cost (A11), accessibility to the HSR stations (A13), when other modes/options became worse (A15) as the motivation compared with the rest of the slow adopter. This finding might suggest that pattern 9 user were more sensitive to the level of services, self-planning, and traffic condition before their travel. This is also supported from the reason to increase HSR usage (see Table 6-10) that "Service is better than I thought (B04)" has a very outstanding power to predict pattern 9 user, where meanwhile it has no such influence to the rest of the slow adopter group. Another strong predictor to classify pattern 9, was "I was encouraged by my friends' / family's experience (B05)", this might suggests that pattern 9 user may listen to the opinions/experience from others, taking others' suggestions into account. On the other hand, this study finds that the reason to increase for pattern 1 and pattern 6 user, they shared similar characteristics (B3 and B7) with the fast adopter group. The reason to continue HSR usage, pattern 1 users stick to the reason of "I am satisfied with the service (C01)", same as the reason of why they increase their HSR usage. While pattern 6 users answered a number of reason including "I feel comfortable when traveling with HSR (C02)", "I now prefer HSR rather than driving cars (C03)", and a very strong predictor among other patterns "My business now strongly depends on HSR (C09)". This could be explained as difference of continuous usage between pattern 1 and 6; where pattern 6 contains some (roughly) regular pattern depending on certain reasons, while pattern 1 usage is fairly stable. The variations of the continuous demand implies the traveler of pattern 6 has more awareness of taking HSR than pattern 1 users.

C. Adopted but Dropped at Some Point (Pattern 2, 7, 10)

Since this group was grouped as the dropped group, the classification is for those who answered the reason to drop from HSR usage (except pattern 5). It contains the reduced usage at different of time duration, no such common predictors or similar effects from section A, B, and C to distinguish the difference within the group. However, Table 6-12 shows very interesting findings. Essentially, the difference among pattern 2, 7, and 10 were that pattern 2 user adapted very fast at the beginning of HSR usage but quickly dropped out; pattern 7 and 10 has a period of time that they use HSR more often but later pattern 7 dropped and did not increase the usage again, instead pattern 10 has a significant increase after the drop. Among the reasons, "I have changed my job and now don't need HSR so much anymore (D11)" could identify the dropped group compare to those respondent answering pattern 5 as their HSR usage. Pattern 2 user could be distinguished from the two predictors as follow: "I now prefer other public transportation (D06)" and "Access to the HSR station became worse (D14)". Regarding the other sections answered by pattern 2 users, they admitted that using HSR is comfortable (A02), fare campaigns is attractive (A11), service is better than expected (B04), and time table improved (B07) are the reasons to utilized HSR at the beginning, but later there either due to the bad accessibility or other travel options is more preferable, they soon changed their decision and dropped from HSR usage. Looking at pattern 7 users, which adopted to HSR longer than pattern 2 users; the results from these tables indicate that HSR indeed is one of the options in their mode choice set, considering fare (A11), other travel options (A15), HSR services (B04), however, in the continuous usage, they were less agree with the reasons listed in section C. The predictors were either significantly less impact from comfort (C02), HSR trips were decided by others (C07), and business travel (C09). In addition, pattern 7 users argued and disagreed that they were adapting to HSR (C05, see the stronger coefficient). Pattern 10 users is one of the interesting findings, where they shared a number of similar predictors with other HSR adopter, and even work while travel was a significant predictor from other patterns. They seem like much sensitive to time saving (A04, A12, A14, B07) and safety issues (A05). But the reason to reduce HSR usage, is exactly the bad experience/information from others (D08). This is the largest variation among other predictors. At the meantime, the reasons to drop were less likely from the level of services including travel cost (D12) and

accessibility (D14). These travllers are possibly a heavy user themselves, and well-fitted with the proposed pattern and description. The safety issue supported the assumption of the serious HSR collision took place in China on 2011, the tragedy has caused more than 210 people injured and 40 more were killed. The public safety concerns may have decreased the HSR demand for a period of time, but users might have restarted taking HSR after some time passed.

D. Non-adopter (Pattern 3, 5)

The non-adopter group were found less influence from the questions comparing to other HSR users. Pattern 3 users are more likely to consider reliability (A03) and accessibility (A13) than others while no other sections were assigned to this pattern, further investigation of this pattern is not feasible. Pattern 5 users showed less interest in comfort (A02), timetable improvement (A14) and prefer other travel mode (D06), sensitive to fare (D12), poor accessibility (D14), and other modes have improved (D15). These reason indicates that this pattern of travellers, are the one who does not need HSR at all or the HSR is not reachable, though they had experience of using HSR at a point of their life, but HSR is not in their travel mode choice set. Although this group of HSR users were obviously not the main subjects foe the research, however, it is essential to include these non-adapted pattern in the survey in order to increase the chance of reaching a good number of observation as well as taken as a reference group in the analysis.

Table 6-9 Motivation Predictors

Predictors (Section A)	Usage Pattern (Classification Function Coefficients)										F	Sig.
	1 (S)	2 (D)	3 (N)	4 (F)	5 (N)	6 (S)	7 (D)	8 (F)	9 (S)	10 (D)		
A01 Curiosity	.943	.855	1.008	.960	1.135	1.335	1.023	1.133	.865	1.200	.95	.48
*A02 Comfort	1.346	1.681	1.038	1.227	.803	1.003	1.045	1.293	1.204	1.150	4.01	**.00**
A03 Reliability	-.345	-.031	-.472	-.333	-.121	-.308	-.261	-.383	-.379	-.605	3.17	**.00**
A04 Stuck in traffic	-.143	-.084	.056	-.064	.049	.246	.070	.066	.296	.263	2.56	**.01**
*A05 Safety	.209	.102	.366	.599	.034	.533	.016	.516	.252	.533	4.53	**.00**
A06 Speedy	3.464	3.496	3.481	3.457	3.651	3.670	3.517	3.713	3.644	3.247	2.16	**.02**
*A07 Encouragement from close ones	-.075	-.005	.081	-.112	.244	.132	-.211	-.124	.247	-.173	.49	.88
A08 Encouragement from media	.192	-.230	.151	-.009	-.027	-.536	.406	.049	-.093	-.018	.71	.70
A09 Business trip	.647	.580	.616	.673	.660	.723	.579	.701	.555	.484	1.04	.40
A10 It's a must	1.679	1.711	1.676	1.818	1.802	2.037	1.603	1.587	1.529	1.733	1.74	**.08**
*A11 Fares campaign	.091	.230	-.049	.174	.132	.063	.228	.086	.272	-.076	1.81	**.06**
*A12 Work while travel	-.470	-.281	-.418	-.203	-.088	.008	-.100	-.218	-.445	.268	3.67	**.00**
A13 Accessibility	.161	.116	.293	.310	.110	.033	-.014	.146	.284	-.172	1.70	**.09**
*A14 Timetable was improved	.125	.169	-.067	-.005	-.252	-.213	-.123	.049	-.067	.323	2.18	**.02**
A15 Other options became worse	.385	.384	.356	.593	.425	.386	.628	.405	.514	.487	1.87	**.05**
(Constant)	-14.991	-17.158	-14.230	-17.213	-15.491	-18.346	-15.756	-16.875	-17.118	-16.489		

Note: * denotes the significant variables in MNL analysis;

(F) denotes the pattern was defined as Flow adopter;

(S) denotes the pattern was defined as Slow adopter in previous analysis;

(D) denotes the pattern was defined as Used to be adopter but dropped at a time point;

(N) denotes the pattern was defined as Non-adopter in previous analysis

Table 6-10 Induced Usage Predictors

Predictors (Section B)	Usage Pattern (Classification Function Coefficients)								F	Sig.
	1 (S)	2 (D)	4 (F)	6 (S)	7 (D)	8 (F)	9 (S)	10 (D)		
B01 Job changed	.559	.653	.450	.585	.376	.626	.858	.572	.794	.59
B02 Moves to other places	.391	.170	.304	.351	.212	.087	-.051	.289	1.090	.37
B03 Satisfied with initial HSR experiences	1.749	1.415	1.326	1.680	1.130	1.622	1.217	1.385	2.053	**.05**
B04 Service is better than I thought	.118	.725	.578	-.002	.706	.425	.926	.395	1.867	**.07**
B05 Encouraged by closes one's experience	.287	.083	.349	.173	-.185	.260	.542	.247	2.231	**.03**
B06 Positive media feedbacks	-.291	-.258	-.142	-.092	.142	-.136	-.390	.073	1.215	.29
B07 Timetable was improved	1.029	.956	.941	.952	.761	1.076	.668	1.010	2.197	**.03**
B08 Accessibility	.708	.877	.637	.845	.449	.732	.758	.723	1.682	.11
B09 Other options became worse	.617	.495	.832	.683	.744	.532	.493	.583	1.202	.30
(Constant)	-10.940	-11.051	-10.813	-11.772	-9.324	-10.396	-10.942	-11.339		

Note: (F) denotes the pattern was defined as Flow adopter;
(S) denotes the pattern was defined as Slow adopter in previous analysis;
(D) denotes the pattern was defined as Used to be adopter but dropped at a time point in previous analysis.

Table 6-11 Continuous Usage Predictors

Predictors (Section C)	Usage Pattern (Classification Function Coefficients)					F	Sig.
	1 (S)	4 (F)	6 (S)	7 (D)	8 (F)		
C01 Satisfied with previous HSR experiences	1.537	1.321	1.044	1.221	1.528	4.591	**.00**
C02 Comfort than other modes	.277	.136	.498	.034	-.037	3.710	**.01**
C03 Prefer HSR than cars for long distance travel	.207	.373	.473	.275	.427	4.356	**.00**
C04 Safer than other modes	.597	.988	.575	.646	.888	6.151	**.00**
C05 Adapted to HSR	-.143	-.123	-.126	-.351	-.004	5.159	**.00**
C06 Proven time saving	3.504	3.308	3.476	3.485	3.473	1.984	**.10**
C07 Decided by others and they keep using HSR	.072	.162	.135	.051	.270	2.172	**.07**
C08 I simply have to though I don't like it	1.750	1.956	1.913	1.905	1.563	2.773	**.03**
C09 My business now strongly depends on HSR	.132	.116	.182	-.074	-.001	2.324	**.06**
(Constant)	-14.903	-15.433	-16.232	-12.967	-14.842	-	-

Note: (F) denotes the pattern was defined as Flow adopter;
(S) denotes the pattern was defined as Slow adopter in previous analysis;
(D) denotes the pattern was defined as Used to be adopter but dropped at a time point in previous analysis.

Table 6-12 Reduced Usage Predictors

Predictors (Section D)	Usage Pattern (Classification Function Coefficients)				F	Sig.
	2 (D)	5 (N)	7 (D)	10 (D)		
D01 A particular terrible experience	2.118	1.841	1.480	1.799	.407	.75
D02 NOT satisfied with previous HSR experiences	-1.541	-.696	-1.061	-1.692	.763	.52
D03 Unreliable	-.538	-.534	.001	-1.045	.139	.94
D04 Not safe	.017	.151	-.346	.206	.461	.71
D05 Service quality decreased	.501	-.515	.449	-.411	.147	.93
D06 Prefer other public transportation	.862	1.044	.287	.497	4.030	**.01**
D07 Prefer to drive	.317	.142	.406	.305	.304	.82
D08 Close one's terrible experience	.435	.099	.816	2.302	2.125	**.10**
D09 Negative feedback from media	-.425	-.215	-.427	.262	1.430	.24
D10 Move to other places	.439	.585	.700	.345	.312	.82
D11 Job changed	.818	.399	.698	.776	2.609	**.05**
D12 Expensive fare	1.070	1.575	1.366	.931	10.707	**.00**
D13 Inconvenient timetable	.720	.431	.938	.814	.032	.99
D14 Poor accessibilities	.136	.209	-.428	-.260	2.234	**.09**
D15 Other modes have improved	-.419	.321	-.468	-.226	3.082	**.03**
(Constant)	-7.091	-7.280	-7.725	-7.210	-	-

Note: (D) denotes the pattern was defined as Used to be adopter but dropped at a time point;
(N) denotes the pattern was defined as Non-adopter in previous analysis

6.5 Overall Discussion on Survey Results

In this chapter, this thesis particularly focused though on the impact of attitudes and perceptions. Several variables has been processed and calibrated in order to reduce the modelling dimensions and correlations. These results suggest that these factors explain adaptation in fact more than travel characteristics and socio-demographics. It also suggests that these partially difficult to quantify factors are important for demand forecasting. Possibly the Taiwan HSR forecasting errors could have been reduced by better understanding of the populations' expectations and perceptions of the system to be built.

Specifically we find that perceived comfort is found to be an important reason to attract people to start using HSR. Further our results suggests, HSR operators should keep in mind that perception of safety is crucial for travelers' adaption process, as higher perception of safety is associated with fast adaptation. We also find though that one's "willingness to try" has a positive impact on a

person's likelihood to start using HSR regularly, suggesting that personality factors beyond control of an operator are also important for demand prediction.

The two MNL results suggest that the models can indeed distinguish and partly explain the behavior of some user groups by attitudinal factors and perceived perceptions. We acknowledge though that our model fit is low even after trip purpose and travel time were further included in the model. One of the major issues is that factors related to usage increase, reasons to keep using, and reasons to reduce HSR usage over time, were not considered in our MNL analysis estimation. Including these items (despite being available from our survey) in an MNL framework is not possible as the questions were not answered by all respondents. One might formulate the problem instead as a joined or nested choice model between one of the groups defined in Table 4 and one of the 10 specific patterns which would then possibly allow including those questions. Doing so emphasizes though the issue of the limited alternative (pattern) specific variables. Alternatively, one might use Sections B to D to model the choice between specific patterns in a separate model, using discriminant analysis, as the usage pattern are known a priori. This could classify predictor variables and distinguish items that are most effective for pattern choice classification.

The alternative approach, discriminant analysis has provided two contributions in the overall analysis. Firstly it is the supplemental analysis to confirm the result from MNL is solid. Secondly, it revealed the characteristics among different usage pattern and offer possible reason behind the accumulated patterns without adding burdens to recall long-term memories and avoiding accuracy issues. In addition, this approach is able to utilize the parameters extracted from the survey. The visualized usage pattern allows travellers to reconsider their longer-term travel behaviour (over several years) without concerning the accuracy issues of single answers. The discussion argues that the assumption of utility maximization is doubtful for models analyzing long-term patterns in which the decisions are likely to be conditional on previous decisions and other external factors as revealed from the discriminant analysis and discussion.

Chapter 7

Conclusions

7.1 Summary of Findings

The overall objective of this thesis, i.e. explaining the demand adaptation and usage pattern towards HSR, have been broken down into five tasks, which are: a) To understand the determining factors for aggregated observed HSR demand with social economic factors, seasonal factors and positive trends due to mass effects; b) to replicate the analyses to further investigate the adaptation effect at station level and to compare these with the results regarding the previous total demand; c) to consider the impacts of accessibility to the eight HSR stations in Taiwan; d) to develop a new survey methodology to obtain long-term HSR travel behaviour; and e) to compare the results and to fill the gap between the traditional predictors (travel time, cost, level of service, frequency) and predictors from attitudes and perceptions to explore the adaptation process from individual HSR travellers.

To accomplish the first objective, Chapter 3 presents two types of time series models to test our model performance. The fitted SARIMA model (first model) appears suitable for demand forecasting whereas the simpler MA(1) (second model) helps us understanding the role of specific exogenous factors for aggregate demand. The SARIMA model was estimated by using Taiwan HSR monthly ridership, it suggests that employ a $(0,1,2)(0,1,1)_{12}$ model specification is appropriate, which indicates that HSR ridership was influenced by not only the short-term effects but also seasonal effects. Therefore, a simplified ARIMA model with MA(1) was adopted with a number of explanatory variables, the results suggesting that the "total" Taiwan HSR demand was influenced by total population, GDP, unemployment and fuel prices as well as seasonal effects (Chinese New Year and Summer Vacation) are significant determinants of demand, and all with the expected sign. The findings further suggest that to estimate demand precisely, one needs to take into account a mixture of long-term predictable factors (such as population growth) as well as short term fluctuating factors (such as fuel price).

The second and third objectives are accomplished by replicating the previous modelling with a detailed comparison of ridership between all eight THSR stations. For "station specific" demand, socio-demographics, GDP, fuel price, and car ownership may not always be significant. Rather it is important to understand the composition of the trip purposes of the travellers as the analysis of station demand patterns. As the analysis of station ridership patterns further suggests, adaptation effects might be stronger for business than for private travel. Stations with smaller demand are more likely to be influenced by specific/singular trip purposes as the cases of Hsinchu and Chiayi shows. Moreover, in Chapter 4, we examine how station accessibility impacts local HSR demand. The explanatory parameters mentioned above are taken as control variables and we assess the demand impact of access links improvement to the eight HSR stations. As discussed, the eight HSR stations tell different stories that need to be analysed carefully case by case. What is clear though is that we observe differences between the impacts of access improvements for city centre versus peripheral stations. For peripheral stations access via public transport is one of the significant factors to induce HSR station demand. THSR shuttle buses (Hsinchu and Tainan), BRT (Chiayi), and TR (Taichung) were found to be strongly significant. We further conclude that in particular establishing some connection appears to be important, whereas upgrading to better connections does not always generate additional demand.

In the reminder, the results also suggest that though further work is needed to confirm this by disentangling the different factors combined in the adaptation effect; however, this is though not possible with the current aggregate data. Thus, the thesis has then focus on detangling the role of adaptation process with perceived perceptions, the past experiences, memories, and influence from others as the literature review emphasized the potential importance of such "internal" elements.

In Chapter 5, the fourth objective is accomplished by assessing the possibility of obtaining individuals' long-term HSR travel behaviour with a new survey methodology considering usage patterns. The patterns were developed and compared with the "conventional" survey methodologies to explore the potentialities and limitations by adopting a number of discrete choice modelling approaches with extracted variables from the survey. The results suggest that

asking users for their long-term travel behaviour with graphical patterns including questions on the reasons that lead to significant changes in usage might be one way to collect data that are otherwise difficult to obtain. The methodology is particularly helpful when recall questions on precise numbers of trips (frequency) or usage in general during specific time periods in the past might not be feasible as the respondent might not be able to answer these. The visualized usage patterns allow travellers to reconsider their longer-term travel behaviour (over several years) without concerning the accuracy issues of single answers. From the descriptions of the usage patterns, the survey can distinguish different adaptation types i.e., four traveller groups can be distinguished according to their adaptation pattern and that reasons for change in usage can be extracted.

To validate the proposed usage patterns and its descriptions, it was found consistent to the usage obtained by revealed preference questions also on aggregate level. The proposed graphical patterns capture most usage patterns from travellers since less than 2% of the respondent answered "none of above pattern fit to my experiences" in both China and Taiwan.

The reasons of each usage periods (including the reasons that motivated them to start using, to increase, to keep using and to drop HSR usage) were analysed. The result suggests that starting to use HSR is mostly based on travel time savings as well as "positive expectations" whereas increases in service usage is mostly due to other service quality factors, in particular station access. Reductions in usage seem easiest to explain and are mostly based on life course events.

The final objective is partly accomplished in that this research explains the duration of the adaptation process among different types of HSR travellers. In Chapter 6, the focus was on the impact of attitudes and perceptions. We find that these factors explain adaptation in fact more than travel characteristics and socio-demographics. The result suggests that these partially difficult to quantify factors are important for demand forecasting. The MNL was found best suitable for this purpose despite also being aware that associating pattern choice with utility maximization has its drawbacks. Also noteworthy is that the pattern distributions in both samples are fairly similar. A good 30% of all respondents adapt fast to the new service. This percentage increases to around 50% if one also

includes those adapting fast but at one point drop usage again. Further for more than 21% of its customers, the HSR operator might be able to expect a gradual increase in usage over time. Some of the existing differences (such as a higher proportion of pattern 4 (continuous increase) and pattern 10 (continuous increase, with usage drop in between) in Shanghai) between the regions can be explained by the gradual extension of the HSR network these years in China. In addition, the results also suggest that fare policy and trip purpose brought different impact to both regions. The combined parameters from MNL result indicates that fast adopters and the dropped group shared similar characteristics compared to slow adopters; which implies that the travellers in the dropped group are mostly coming from fast rather than slow adopters.

As for socio-demographics, not surprisingly, higher education degree and personal income would encourage travellers adopting HSR. Clearly business and time conscious travellers are likely to adapt faster as for example the significance of timetable improvements and the value of being able to work on the train suggests. The perspective of HSR adopters towards fare discounts seems different across the strait.

In Taiwan, where the standard fares kept fairly constant over our analysis period, but discounts were available sometimes, these were not found to be significant in our model. This should not be over-interpreted as meaning that the discount was not attractive, but to emphasize that fare discount was not effective to influence long term adaptation. The Shanghai case illustrates that HSR adaptation is depending on the fare. Travellers in mainland China very much rely on the low cost fare controlled by the railway authority. In line with previous literature we find that it is particular travellers who often travel distances of around 150-400km (or 1- 2 hour travel time) find HSR attractive. We add to previous findings by concluding that these travellers are also often those who start to develop regular travel patterns fastest.

Moreover, the results also suggest that HSR operators should keep in mind that perception of safety is crucial for travellers' adaption process, as higher perception of safety is associated with fast adaptation. The one's "willingness to try" was found to have a positive impact on a person's likelihood to start using HSR regularly, suggesting that personality factors beyond control of an operator are also important for demand prediction. In summary, the MNL

results suggest that it can indeed distinguish and partly explain the behaviour of some user groups by attitudinal factors and perceived perceptions.

Finally, by applying discriminant analysis with the usage patterns known a priori, the results suggest that it could classify predictor variables and distinguish items that are most effective for pattern choice classification. In conclusion, this study found strong evidence the formation of long-term usage patterns involve self-planning, initial perceptions of the new mode, receiving further information about it over time and reflecting previous experiences. The discussion on the reasons to change HSR usage have provided an overview of varies kinds of adaptation processes and usage pattern.

7.2 Implications for Policy and Planning

From the general conclusion above, some policy implications related to significant influence of perceptions and one's innovativeness on HSR usage can be derived. Based on the aggregated analysis of HSR ridership in Taiwan, we suggest that adequate transport demand policy can contribute to induce a trend towards a continuous increase in HSR demand.

The findings, in Chapters 3 and 4, from the intercity travel market share, the effect on competing modes such as air and highway traffic show that the new HSR in Taiwan 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.

The focus in the thesis has been on the adaptation effect. The dummy factor indicating this effect in the econometric analysis is highly significant for both aggregate as well as local HSR demand. Even after seven years of operation it is not obvious when and whether equilibrium might be reached, which has possibly implications for demand modelling of any kind for new transport systems such as electric car or shared car schemes. Policy makers should be careful in not over predicting the short term demand a new scheme might generate. Indeed it's arguable that possibly due to various types of "adaptation effects" including general population perception of the new scheme and possibly "information spread".

Still related to the results and projections of THSR demand, the discussions on the cost-effectiveness of potential high speed rail projects often expected ridership data are published. We propose that adaptation effects to new systems might take a significant time and initial low ridership might not be a sign of "wrong estimates". The demand estimation for new systems that potentially significantly change the mobility patterns of a wider region might have to be treated very differently than demand estimation for system extensions. For example, data from German rail suggest that for recently built or upgraded high speed routes it takes around three to four years for demand to stabilise. Also data from the recently opened high speed rail extension in Kyushu, Japan, suggest that total ridership appears to stabilise fast. In both cases the population will have been already used to the high speed rail concept and can fairly easily adapt their behaviour.

Looking at the access links improvements of HSR, the results suggest that HSR station access quality is important, but operators should also not overestimate their impact, possibly there might exist a threshold accessibility. That is, general accessibility through public transport is important, but further improvements do not necessarily generate additional journeys.

The findings also reveal some understanding regarding long term travel behaviour and include several policy implications from disaggregate perspectives. Though the proposed survey methodology does not provide highly accurate data but, on the positive, might reflect the perceived usage trend. Such survey approach could be easily applied to an existing transport scheme with lesser costs and consumptions of time and labour compared with other long-term "conventional" travel survey. For example, the survey may also be adopted to investigate an existing scheme of highway usage, bike sharing, and etc. Nevertheless, clearly further validation of the approach and the usage patterns are needed. One possible approach is the comparison of panel data on actual usage with our patterns.

Based on these findings, it is suggested that the critical factors for demand forecasting, other than travel time, cost, and "typical" quantified factors identified from literature, psychological factors such as perception, information spread as well as consumer (traveler) behavior diffusion factors that influence acceptability, or "adaptation" to a new travel mode should be considered. This

also encourages the endorsement of soft policy measures such as "mobility management".

7.3 Recommendations for Future Works

While in parts explorative, this research made use of both aggregated and disaggregated data, seeking their possibility and potentials to provide insight into a wide variety of reasons and processes that form the HSR demand adaptation process.

A main limitation of the aggregate analysis as used in Chapters 3 and 4 is that, though the strong significance of adaptation effects have been revealed in total and station demand; a more detailed understanding how such demand adaptation takes place, is though not feasible. In particular, it is not feasible to understand how long, if ever, it takes for the demand to reach the predicted levels. The results also suggest that further work is needed to confirm this by disentangling the different factors combined in the adaptation effect; however, this is also not possible with the current aggregate data. Another issue, a minor one, is obtaining the data of accessibility measurements of THSR access links, the limitation of such detailed data is not accessible due to different stakeholder and operators. In addition, if research are interested in the effect of access links, one possible direction is to establish a separate model by splitting the data into two segments according to the time when the access service start operation, as a before and after analysis.

We believe that as discussed in this chapter our survey reveals some interesting findings. It has to be noted though that the findings are tentative and not representative for the whole population in both countries due to limited and biased sample sizes. This issue can be properly solved together with another shortcoming in the later discussion on additional survey.

Furthermore, in Chapter 6, it is acknowledged that the MNL model fit is low even after trip purpose and travel time were included in the model. One of the major issues is that factors related to usage increase, reasons to keep using, and reasons to reduce HSR usage over time, were not considered in our MNL analysis estimation. Including these items (despite being available from our survey) in an MNL framework is not possible as the questions were not answered by all respondents. Doing so emphasizes though the issue of the limited

alternative (pattern) specific variables. Alternatively, one might use Sections B to D to model the choice between specific patterns in a separate model. Another way to confront the issues is to expend the population size with conducting the survey and implement to the other regions in China, Korea or Japan. The extended HSR user survey might take into account of adding additional question sets to obtain the alternative specific variables. This can further support developing alternative modelling structures to improve mode fit. That is, to create a set of items aiming to the group specific pattern, namely to assign a unique set of questions targeting the fast adopter, slow adopter, dropped group and non-adopter group. Ideally, by obtaining these alternative specific parameters, the cross-nested logit model (CNL) could possibly be established. More generally, one might further have to discuss though the assumption of utility maximization for such models using long-term patterns in which decisions are likely to be conditional on previous decisions and other external factors. In other words further work might answer the question: "Do people choose patterns or do they happen to one?" better.

Regarding socio-economic factors obtained from the survey, the changes of the incomes, education degree, ages, purchasing a car, or even having children, such life course events and socio-economic factors might be another interesting topic. How do these factors effect the mode choice and adaptation over time? Asking these personal related factors in more detail in each section, this could be another (easy to implement) extension.

Besides the already mentioned issues and discussion, clearly the thesis leaves ample room for further work as methodologies on collecting long-term behaviour are arguably still under research. For future work, if one wants to apply the graphical patterns to other applications such as new expressway or public transport demand, it is essential that the usage patterns should be reconsidered. As discussed in Chapter 5, the pattern selection was finalized only after a pilot survey and obtaining feedback from 50 samples in each region. The pilot survey relies heavily on local knowledge in order to create efficient usage patterns. In particular, the experience learnt from this research is that asking people to draw their usage among different regions, may create a very different patterns. A simple example is that asking HSR usage in Japan, where the HSR already existed over 50 years, and asking people their HSR usage in a region

that just introduced HSR less than 10 years, the graphical usage patterns were found to be difficult to integrate.

7.4 Contribution of the Study

There are four significant contributions from this dissertation. First, this study is the first to assess the HSR demand impact considering adaptation effects explicitly. In addition, it is the first study that tries to investigate the overall impacts from access links in Taiwan. These findings can be employed and be considered by other countries in planning HSR projects or implementing related policy. Especially the South East Asia countries such as Indonesia, Thailand, Singapore-Malaysia, where currently the HSR project is under debates.

Despite the limitations found in aggregate analysis and the current method approaches on obtaining long-term travel behaiour, the second main contribution of this research, is to propose a different data-collection approach to grasp progressive changes in mobility systems. The methodological contribution is essential in order to understand the gradual changes in travel behaviour over time, and, to comprehend the connection between traveller's adaptation process and travel demand. Capturing cause and effect relationships in long-term behaviour patterns is generally difficult to obtain under limited resources and time. The proposed methodology specifically aims analysing the gradual changes of travel behaviour. The approach hinges on asking users for their long-term travel behaviour with graphical patterns including questions on the reasons that lead to significant changes in HSR usage. This dissertation demonstrated that the behaviour dynamics of the samples could be captured and to some degree explained. It is also believed that the allocation of travellers to long-term usage patterns, provides a view of future use, sheds light on the perceived future and therefore helps explaining fluctuating demand.

Related to the second contribution, the third contribution of this dissertation is proposing two types of well-developed modelling approaches, to seek the potential and limitation of the obtained usage pattern data. The analysis of the pattern choice in Chapter 6 was carried out by applying MNL analysis and discriminate analysis, explaining the choice between all respondents. From the results, an important discussion that emerged was the advantage and limitation from both modelling in detecting how attitudes (including innovativeness) and perceptions among traveller can explain choice

pattern. It is believed that these findings can shed further doubt on the assumption of utility maximization for models analysing long-term patterns, in which the decisions are likely to be conditional on previous decisions and other external factors as discussed in discriminate analysis. In other words, there is no strict evidence as to whether travellers choose pattern or if patterns emerge from outside factors.

As the fourth contribution, is the discovery in differences between motivations according to the stage of usage. In general, the initial HSR usage uptake was driven more by personality related factors, later gradual usage increases were more related to service quality, while in continue usage, a number of HSR traveller found it difficult to explain their adaptation with limited reasons, and finally, usage reductions were mainly linked to life course events as well as the expensive travel cost by HSR. This would be helpful for HSR operators on implanting policy to attract different target groups.

By doing the comparisons among regions, hopefully some important aspect that relate to perceptions to public transportation or infrastructure, can be transferable. Especially in developing countries the proposed survey methodology can also be used to tackle uncertain situations. Policy makers especially in these countries generally face a lack of long-term behavioural data for analysis, as panel data are often difficult to obtain.

Reference

Aarts, H., Verplanken, B., & van Knippenberg, A. (1998). Predicting Behavior From Actions in the Past: Repeated Decision Making or a Matter of Habit? *Applied Social Psychology, 28*(15), 1355-1374. doi:10.1111/j.1559-1816.1998.tb01681.x

Abou-Zeid, M., Schmöcker, J.-D., Belgiawan, P. F., & Fujii, S. (2013). Mass effects and mobility decisions . *Transportation Letters, 5*(3), 115–130. doi:10.1179/1942786713Z.00000000011

Abrate, G., Piacenza, M., & Vannoni, D. (2009). The impact of Integrated Tariff Systems on public transport demand: Evidence from Italy. *Regional Science and Urban Economics, 39*, 120-127. doi:10.1016/j.regsciurbeco.2008.05.014

Ahlfeldt, G., & Feddersen, A. (2010). *From periphery to core: economic adjustments to high speed rail.* London: London School of Economics & University of Hamburg.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl, & J. Beckmann (Eds.), *Action Control: From Cognition to Behavior* (pp. 11-39). Berlin: Springer Heidelberg. doi:10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. doi:10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1980). *Understanding Attitudes and Predicting Social Behavior*. Englewood Cliffs, NJ: Prentice-Hall.

Albalate, D., & Bel, G. (2013). *The Economics and Politics of High-Speed Rail: Lessons from Experiences Abroad.* Lexington Books.

Andersson, D. E., Shyr, O. F., & Fu, J. (2010). Does high-speed rail accessibility influence residential property prices? Hedonic estimates from southern Taiwan. *Journal of Transport Geography, 18*, 166-174. doi:10.1016/j.jtrangeo.2008.10.012

Andreoni, A., & Postorino, M. N. (2006). A multivariate ARIMA model to forecast air transport demand. *Association for Eruopean Transport*.

Ball, P. (2004). *Critical mass: How one thing leads to another*. New York: Farrar, Straus and Giroux.

Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science, 15*(5), 215-227. doi:10.1287/mnsc.15.5.215

Bass, P., Donoso, P., & Munizaga, M. (2011). A model to assess public transport demand stability. *Transportation Research Part A, 45*, 755-764. doi:doi:10.1016/j.tra.2011.06.003

Beck, M. J., Rose, J. M., & Hensher, D. A. (2013). Environmental attitudes and emissions charging: An example of policy implications for vehicle choice. *Transportation Research Part A, 50*, 171–182. doi:10.1016/j.tra.2013.01.015

Belgiawan, P., Schmöcker, J.-D., & Fujii, S. (2012). Explaining the desire to own a car among Indonesian students. *In Proceedings of the 32nd Japan Society of Traffic Engineers Conference* (pp. 259-266). Tokyo: Japan Society of Traffic Engineers.

Ben-Akiva, M., & Lerman, S. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand.* Cambridge, MA: MIT Press.

Ben-Akiva, M., de Palma, A., McFadden, D., Abou-Zeid, M., Chiappori, P.-A., de Lapparent, M., . . . Walker, J. (2012). Process and context in choice models. *Marketing Letters, 23*(2), 439-456. doi:10.1007/s11002-012-9180-7

Ben-Akiva, M., Mcfadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., . . . Munizaga, M. A. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters, 13*(3), 163-175. doi:10.1023/A:1020254301302

Bettman, J. R., & Park, C. W. (1980). Effects of Prior Knowledge and Experience and Phase of the Choice Process on Consumer Decision Processes: A Protocol

Analysis. *Journal of Consumer Research, 7*(3), 234-248. Retrieved from http://www.jstor.org/stable/2489009

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models. *STRC, 3rd Swiss Transport Research Conference.* Monte Verita, Ascona. Retrieved from http://www.strc.ch/conferences/2003/bierlaire.pdf

Bierlaire, M., & Fetiarison, M. (2009). Estimation of discrete choice models: extending BIOGEME. *Proceedings of the 9th Swiss Transport Research Conference (STRC).*

Börjesson, M. (2014). Forecasting demand for high speed rail. *Transportation Research Part A, 70*, 81-92. doi:10.1016/j.tra.2014.10.010

Bullock, R., Salzberg, A., & Jin, Y. (2012). *High-Speed Rail – The First Three Years: Taking the Pluse of China's Emerging Program.* World Bank Office. Beijing: China Transport Topics No. 04.

Burke, Ó. (2011). Identification and Estimation. In Ó. Burke, *Statistical Methods Autocorrelation.* Oxford, U.K.: University of Oxford.

Cao, J., Liu, X. C., Wang, Y., & Li, Q. (2013). Accessibility impacts of China's high-speed rail network. *Journal of Transport Geography, 28*, 12-21. doi:dx.doi.org/10.1016/j.jtrangeo.2012.10.008

Cascetta, E., & Coppola, P. (2014). High Speed Rail (HSR) induced demand models. *Proceida- Social and Behavioral Sciences, 111*, 147-156. doi:10.1016/j.sbspro.2014.01.047

Chao, C., Shyr, O. F., Chao, C., & Tsai, L. (2012). What drives college-age generation Y's perceived value on high speed rail. *African Journal of Business Management, 6*(43), 10786-10790. doi:DOI: 10.5897/AJBM11.2433

Chen, G., & Silva, J. d. (2013). Regional impacts of high-speed rail: a review of methods and models. *Transportation Letters, 5*(3), 131-143. doi:10.1179/1942786713Z.00000000018

Chen, L. (2013). Analysis the Corridor Traffic Choice Behavior Between Chengdu and Chongqing Based on Logit Model (Master thesis). Chengdu: Southwest Jiaotong University.

Cheng, H. (2007). Panel data analysis—advantages and challenges. *TEST, 16*(1), 1-22. doi:10.1007/s11749-007-0046-x

Cheng, Y.-H. (2010). High-speed rail in Taiwan: New experience and issues for future development. *TransportPolicy, 17*(2), 51-63. doi:10.1016/j.tranpol.2009.10.009

Clifton , K. J., & Handy , S. L. (2003). Qualitative Methods in Travel Behaviour Research. (P. R. P. Jones, Ed.) *Transport Survey Quality and Innovation*, 283-302. doi:10.1108/9781786359551-016

de Montjoye, Y.-A., Hidalgo, C. A., Verleysen, M., & Blondel, V. D. (2013). Unique in the Crowd: The privacy bounds of human mobility. *Scientific Reports, 3*. doi:10.1038/srep01376

DeMaio, P. (2009). Bike-sharing: History, Impacts, Models of Provision, and Future. *Journal of Public Transportation, 12*(4), 41-56.

Demizu, F., Li, Y.-T., Schmöcker, J.-D., Nakamura, T., & Uno, N. (2016). Time Series Analysis of Shinkansen (High Speed Rail) Construction Impact on Rail and Air Demand: Analysis with Tohoku Data. *TRB annual meeting.* Washington DC.

Demizu, F., Li, Y.-T., Schmoecker, J.-D., Nakamura, T., & Uno, N. (2015). Demand Impact of High Speed Rail Construction in North-East Japan. *The 20th International Conference of Hong Kong Society for Transportation Studies.* Hong Kong.

DiStefano , C., Zhu, M., & Mindrila, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. *Practical Assessment, Research & Evaluation, 14*(20). Retrieved from http://pareonline.net/getvn.asp?v=14&n=20

Dowling, R. G., & Colman, S. B. (1995). Effects of Increased Highway Capacity:

Results of Household Travel Behavior Survey. *Transportation Research Record*(1493), 143-149. Retrieved from http://onlinepubs.trb.org/Onlinepubs/trr/1995/1493/1493-017.pdf

Enders, W. (2010). *Applies Econometric Time Series* (3rd ed.). Alabama, U.S.A.: A Wiley-Interscience Publication. Retrieved from www.wiley.com/college/enders

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*(3), 272-299. doi:10.1037/1082-989X.4.3.272

Fishbein , M., & Ajzen, I. (2010). *Predicting and Changing Behavior: The Reasoned Action Approach* (1st ed.). New York: Tayor & Francis Group.

Fishman, E., Washington, S., & Haworth, N. (2013). Bike Share: A Synthesis of the Literature. *Transport Reviews: A Transnational Transdisciplinary Journal*. doi:10.1080/01441647.2013.775612

Fishman, E., Washington, S., & Haworth, N. (2014). Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia. *Transportation Research Part D, 31*, 13-20. doi:10.1016/j.trd.2014.05.013

FitzRoy, F., & Smith, I. (1998). Public transport demand in Freiburg: why did patronage double in a decade? *Transport Policy, 5*, 163-173.

Fu, C., Chen, Y.-J., & Chou, H.-Y. (2008). An influence study for intercity travel behaviors after operation of high speed rail: A case study for Tainan-Taipei route, (in Chinese). *13th Forum of Urban Planning, Taiwan.* Taipei.

Fu, X., Oum, T. H., & Yan, J. (2014). An Analysis of Travel Demand in Japan's Intercity Market. *Journal of Transport Economics and Policy, 48*(1), 97-113.

Garmendia, M., Ribalaygua, C., & Ureña, J. M. (2012). High speed rail: implication for cities. *Cities, 29*, S26-S31. doi:10.1016/j.cities.2012.06.005

Giles, J. (2012). Computational social science: Making the links. *Nature, 488*(7412), 448-450. doi:10.1038/488448a

Gong, Y., Liu, Y., Lin, Y., Yang, J., Duan, Z., & Li, G. (2012). Exploring spatiotemporal characteristics of intra-urban trips using metro. *Geoinformatics (GEOINFORMATICS), 20th International Conference*, (pp. 1-7). Hong Kong. doi:10.1109/Geoinformatics.2012.6270316

González, M. C., Hidalgo, C. A., & Barabási, A.-L. (2008). Understanding individual human mobility patterns. *Nature, 453*(7196), 779-782. doi:10.1038/nature06958

Goulias, K. G. (1999). Longitudinal analysis of activity and travel pattern dynamics using generalized mixed Markov latent class models. *Transportation Research Part B, 3*, 535-557.

Guo, F., & Feng, H. (2009). *Establishing Public Transport Service Network by taking THSR as Transfer Nodes, (in Chinese).* Council for Economic Planning & Development, Department of Urban and Housing Development. Taiwan: Taiwan Economic Forum, Executive Yuan (Taiwan).

Gwilliam, K. (2008). A review of issues in transit economics. *Research in Transportation Economics, 23*, 4-22. doi:doi:10.1016/j.retrec.2008.10.002

Hershberger, S. L. (2005). Factor score estimation. In B. S. Everitt, & D. C. Howell (Eds.), *Encyclopedia of statistics in behavioral science* (pp. 636-644). New York: John Wiley.

Hills, P. J. (1996). What is induced traffic? *Transportation, 23*(1), 5–16. doi:10.1007/BF00166216

Hsiao, C.-H., & Yang, C. (2010). Predicting the travel intention to take High Speed Rail among college students. *Transportation Research Part F, 13*, 277-287. doi:10.1016/j.trf.2010.04.011

Hurt, T. H., Joseph, K., & Cook, C. D. (1977). Scales for the Measurement of Innovativeness. *Human Communication Research, 4*(1), 58-65. doi:10.1111/j.1468-2958.1977.tb00597.x

Iacono, M., & Levinson, D. (2015). Methods for estimating the economic impact of

transportation improvements: an interpretive review. In R. Hickman, M. Givoni, D. Bonilla, & D. Banister, *Handbook on Transport and Development* (pp. 243-258). Northampton, Massachusetts: Edward Elgar. doi:10.4337/9780857937261.00023

Iacono, M., & Levinson, D. M. (2008). Review of Methods for Estimating the Economic Impact of Transportation Improvements. *Social Science Research Network*. doi:dx.doi.org/10.2139/ssrn.1736116

IMF. (2013). *World Economic Outlook Database October 2013 Edition.* International Monetary Fund. Retrieved November 12, 2013, from http://www.imf.org/external/pubs/ft/weo/2013/02/weodata/index.aspx

Ito, H., & Lee, D. (2005). Assessing the impact of the September 11 terrorist attacks on U.S. airline demand. *Journal of Economics and Business, 57*, 75-95. doi:doi:10.1016/j.jeconbus.2004.06.003

Jones, P., Koppelmann, F., & Orfeuil, J. (1990). Activity analysis: State-of-the-art and future. In P. Jones, *Developments in Dynamic and Activity-Based Approaches to Travel Analysis (Oxford Studies in Transport)* (pp. 34-55). Aldershot: Gower.

Kitamura, R. (1990). *Panel Anlysis in Transoprt Planning: An Overview.* Universityo f California Berkeley, CA 94720: The University of California Transportation Center.

KMLIT. (2009). *Report onAREX Service Demand (In Korean).* Korean Ministry of Land, Infrastructure and Transport. Public Policy Institule for People. Retrieved 2013, from http://www.ppip.or.kr/

Korea JoongAng Daily. (2013, September 13). *Seoul Station is a hit for air travel*. Retrieved April 5, 2016, from Korea JoongAng Daily: http://mengnews.joins.com/view.aspx?gCat=050&aId=2977527

Kuo, C.-W., & Tang, M.-L. (2013). Relationships among servic e quality, corporate image, customersatisfac tion, and behavioral intention for the elderly in high speedrail services. *Journal of Advanced Transportation, 47*, 512-525. doi:10.1002/atr.179

Kyte, M., Stoner, J., & Cryer, J. (1988). A Time-series Analysis of Public Transit Ridership in Portland, Oregon, 1971-1982. *Transportation Research-A, 22A*(5), 345-359.

Lane, B. W. (2012). A time-series analysis of gasoline prices and public transportation in US metropolitan areas. *Journal of Transport Geography, 22*, 221-235. doi:doi:10.1016/j.jtrangeo.2011.10.006

Lee, S. S., & Senior, M. L. (2013). Do light rail services discourage car ownership and use? Evidence from Census data for four English cities. *Journal of Transport Geography, 29*, 11-23. doi:http://dx.doi.org/10.1016/j.jtrangeo.2012.12.002

Li, Y.-T., & Schmöcker, J.-D. (2014). Demand Impact of Access Links to Taiwan High Speed Rail. *Presented at 19th International Conference of Hong Kong Society for Transportation Studies (HKSTS)*, (pp. 103-110). Hong Kong.

Li, Y.-T., & Schmöcker, J.-D. (2016). Adaptation patterns to high speed rail usage in Taiwan and China. *Transportation*, 1-24. doi:10.1007/s11116-016-9679-5

Li, Y.-T., & Schmöcker, J.-D. (2016). Public Transport Accessibility Impact on Demand for Taiwan's High Speed Rail Stations. *Transportation Letters (under review).*

Li, Y.-T., Schmöcker, J.-D., & Fujii, S. (2015). Demand adaptation towards new transport modes: the case of high-speed rail in Taiwan. *Transportmetrica B: Transport Dynamics, 3*(1), 27-43. doi:10.1080/21680566.2014.946456

Li, Y.-T., Schmöcker, J.-D., & Zhang, D. (2016). The impact of attitudes and perceptions on high speed rail usage uptake in Taiwan and the Shanghai area (forthcoming). *14th World Conference on Tansport Research.* Shanghai: Transportation Research Procedia.

Lieven, T., Mühlmeier, S., Henkel, S., & Waller, J. F. (2011). Who will buy electric cars? An empirical study in Germany. *Transportation Research Part D, 16*,

236-243. doi:10.1016/j.trd.2010.12.001
Link, C., Raich, U., Sammer, G., & Stark, J. (2012). Modeling Demand for Electric Cars - A Methodical Approach. *Social and Behavioural Sciences, 48*, 1958-1970. doi:10.1016/j.sbspro.2012.06.1169
Liu, J., & Zhang, N. (2012). Intercity Travel Behaviors with the Introduction of High-Speed Rail. *CICTP 2012*, (pp. 1793-1801). Beijing. doi:10.1061/9780784412442.182
Mahajan, V., Muller, E., & Bass, F. M. (1990). New product diffusion models in marketing: A review and directions for research. *Journal of Marketing, 54*(1), 1-26. Retrieved from http://www.jstor.org/stable/1252170
Mahajan, V., Muller, E., & Bass, F. M. (1995). Diffusion of new products: Empirical generalizations and managerial uses . *Marketing Science, 14*(3), G79 - G88 . doi:10.1287/mksc.14.3.G79
McNally, M. G. (2008). The four-step model. In D. A. Hensher, & K. J. Button, *Handbook of Transport Modelling* (2nd ed., pp. 35-53). Amsterdam: Elsevier.
McNally, M. G., & Rindt, C. R. (2008). The Activity-Based Approach. In D. A. Hensher, & K. J. Button, *Handbook of Transport Modelling* (2nd ed., pp. 55-73). Amsterdam: Elsevier.
Mohring, H. (1972). Optimization and Scale Economies in Urban Bus Transportation. *The American Economic Review, 62*(4), 591-604.
MOTC, Taiwan. (2015). *National Household Travel Survey Summary Analysis (in Chinese).* MOTC, Taiwan.
Nash, C. (1991). *The Case for High Speed Rail.* Institute of Transport Studies, University of Leeds. Leeds: White Rose University Consortium. Retrieved from http://eprints.whiterose.ac.uk/2236/
National Unemployment Statistics. (2013). Retrieved July 15, 2013, from Republic of China (Taiwan) National Statistics: http://ebas1.ebas.gov.tw/pxweb/Dialog/NI.asp
Norton, J. A., & Bass, F. M. (1987). A diffusion theory model of adoption and substitution for successive generations of high-technology products. *Management Science, 33*(9), 1069 - 1086 . doi:10.1287/mnsc.33.9.1069
Ollivier, G., Sondhi, J., & Zhou, N. (2014). *High-Speed Railways in China: A Look at Construction Costs.* World Bank Group. Washington, DC: The World Bank. Retrieved from http://documents.worldbank.org/curated/en/2014/07/19761655/high-speed-railways-china-look-construction-costs
Owen, A. D., & Phillips, G. A. (1987). The Characteristics of Railway Passenger Demand. *Journal of Transport Economics and Policy, 21*(3), 231-253.
Pallister, J. G., & Foxall, G. R. (1988). Psychometric properties of the Hurt–Joseph–Cook scales for the measurement of innovativeness. *Technovation, 18*(11), 663-675.
Peña, D., Taio, G. C., & Tsay, R. S. (2001). *A course in Time Seriese Analysis*. New York, Chichester, Weinheim, Brisbane, Singapore, Toronto, Canada: A Wiley-Interscience Publication.
Pendyala, R. M., & Pas, E. I. (2000). Mutli-Day and Multi-Period data for Travel Demand Analysis and Modeling. *TRB Transportation Research Circular E-C008: Transportation Surveys: Raising the Standard*. Retrieved 2015, from http://onlinepubs.trb.org/onlinepubs/circulars/ec008/workshop_b.pdf
Pinjari, A. R., & Bhat, C. R. (2011). Acitivity based travel demand analysis. In A. de Palma, R. Lindsey, E. Quinet, & R. Vickerman (Eds.), *A Handbook of Transport Economics* (pp. 213-248). Cheltenham, UK: Edward Elgar Publishing.
Quddus, M. A., Bell, M. G., Schmöcker, J.-D., & Fonzone, A. (2007). The impact of the congestion charge on the retail business in London: An econometric analysis. *Transport Policy, 14*, 433-444. doi:10.1016/j.tranpol.2007.04.008

Roger, E. M., & Schoemaker, F. F. (1971). *Communication of Innovations: A Cross-cultural Approach.* New York: Free Press.

Sasaki, K., Ohashi, T., & Ando, A. (1997). High-speed rail transit impact on regional systems: does the Shinkansen contribute to dispersion? *The Annals of Regional Science, 31*(1), 77-98. doi:10.1007/s001680050040

Schmöcker, J.-D., Hatori, T., & Watling, D. (2014). Dynamic process model of mass effects on travel demand. *Transportation, 41*(2), 279-304. doi:10.1007/s11116-013-9460-y

Shaheen, S. A., Zhang, H., Martin, E., & Guzman, S. (2011). China's Hangzhou Public Bicyle: Understanding Early Adoption and Behavioral Response to Bikesharing. *Transportation Research Record, 2247*, 33-41. doi:10.3141/2247-05

Sharmeen, F., Arentze, T., & Timmermans, H. (2010). Modelling the dynamics between social networks and activity-travel behavior: Literature review and research agenda. *Presented at the 12th world conference on transport research* (pp. 1-10). Lisbon, Portugal: Instituto Superior Técnico.

Su, C.-W., Chang, C.-W., Lu, Y.-C., & Liu, J.-R. (2012). *A Study on Selecting a Feasible Mode for Seamlessly Transferring between HSR and TR Stations , (in Chinese).* Ministry of Transportation and Communications (Taiwan). Taipei: MOTC.

Teo, J. S., Schmöcker, J.-D., Leon, F., Li, Y.-T. J., Ji, J., Atanasiu, G., & Taniguchi, E. (2015). Agent-Based Evacuation Model Considering Field Effects and Government Advice. *Transportation Reaserch Record*(2532), 129-140. doi:10.3141/2532-15

The Korea Times. (2009, September 10). *Waste of Taxpayer Money*. Retrieved April 5, 2016, from The Korea Times - Opinon: http://www.koreatimes.co.kr/www/news/opinon/2009/09/137_51601.html

THSR. (2014). *Annual Report homepage*. Retrieved July 6, 2013, from Taiwan High Speed Rail (THSR): http://www.thsrc.com.tw/en/about/ab_stock.asp#AnnualReport

Train, K. (2009). *Discrete Choice Methods with Simulation* (2nd ed.). Berkeley, California: Cambridge University Press. Retrieved from http://eml.berkeley.edu/books/train1201.pdf

Triandis, H. C. (1977). *Interpersonal behavior.* Monterey: Brooks/Cole.

Turner, J. C. (1991). *Social Influence* (1st ed.). Blemont, CA, USA: Wadsworth Publishing.

Urban Construction and Communications Commission. (2010). *Report of 4th Comprehensive Transportation Survey of Shanghai.* Shanghai: Urban Construction and Communications Commission.

Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences, 43*(3), 303–343. doi:10.1016/S0165-4896(02)00023-9

Wang, L., Lo, Y., Fan, S., & Chao, W. (2009). *Analysis of Population Projections for Taiwan Area: 2008 to 2056, (in Chinese).* Council for Economic Planning & Development, Department of Manpower Planning. Taipei: Taiwan Economic Forum, Executive Yuan (Taiwan).

World Bank. (2014). *Purchashing power parity (PPP) conversion factor*. Retrieved October 10, 2014, from World development indicators: Exchange rates and prices: http://wdi.worldbank.org/table/4.16

Ye, Y.-l., & Wang, Y.-s. (2010). Research on Travel Mode Choice Behavior in Shanghai-Hangzhou Transport Corridor. *Jouranl of the China Railway Society, 32*(4), 13-17. doi:10.3969/j.issn.1001-8360.2010.04.003

Yee, J. L., & Niemeier, D. (1996). Advantages and Disadvantages: Longitudinal vs. Repeated Cross-Section Surveys. *Project Battelle 94-16.*

Yu, K.-h. P., & Johannesson, J. (2010). Near-bankruptcy of the Taiwan High Speed Rail Corporation: What Went Wrong? *International Journal of Business and*

Management, 5(22), 14-22.

Yue, Y., Lan, T., Yeh, A. G., & Li, Q.-Q. (2014). Zooming into individuals to understand the collective: A review of trajectory-based travel behaviour studies. *Travel Behaviour and Society, 1*(2), 69-78. doi:doi: 10.1016/j.tbs.2013.12.002

Zhong, C., Bel, G., & Warner, M. E. (2014). High-speed rail accessibility: a comparative analysis of urban access in Los Angeles, San Francisco, Madrid, and Barcelona. *European Journal of Transport and Infrastructure Research, 4*(14), 468-488. Retrieved from http://hdl.handle.net/2445/68516

Appendix A

Questionnaires of Long-term usage survey (for Chapter 5)

The survey was coded via an online questionnaire website and responses collected from September to October 2014. In order to reach a wide population range, it was conducted in both traditional Chinese (Taiwan version) and simplified Chinese (Shanghai version). In Taiwan, the recruitment was via an announcement in a popular Bulletin Board System (Ptt.cc). Similarly, in China, the recruitment was via two online communities (bbs.tianya.com and kdslife.com) as well as the popular instant message service by Tencent.

For better understanding, the questionnaire was translate into English with shorten version of the survey. The overlaps of Section A to D was omitted and this dissertation took pattern 7 as the example of the entire survey (as pattern 7 contains all the section from A to D).

User Adaptation towards HSR (English)

HIGH SPEED RAIL USAGE AND ADAPTATION SUVERY

Information about this survey

This survey is intended for persons who have used high speed rail for a few times. The study is being conducted by researchers at Kyoto University (京都大學) and Tongji University (同濟大學), to understand high speed rail users travel behavior across the strait. Since this study is conducted in several places, certain questions or terminology may be inapplicable for your context. The information we collect from you will help us suggest ways and policies to improve public transportation in the future.

The survey is expected to take about 10 to 15 minutes to complete. Your participation in this study is completely voluntary, and the survey is anonymous, which means the data collected will be kept strictly confidential. Your answers are used for academic research only, not for any commercial reasons.

As a thank you for your time we will provide you with a mobile phone voucher worth RMB10 upon

completion of this survey. Contact info in case of questions:

PhD student Joe Yeun-Touh Li 李元拓

Professor Jan-Dirk Schmöcker

ITS Laboratory, Dept. of Urban Management, Graduate School of Engineering, Kyoto University, Japan

Your experience is important to us! If you are willing to fill out this survey, please click on the "Next" button below. Thank you for your participation and we will appreciate your help with this questionnaire.

User Adaptation towards HSR (English)

A first evaluation of yourself and your perception to innovativeness

Before beginning the first section, we would like to understand how you look to yourself as what kind of person in innovativeness. During these questions, you are encouraged to answer in a slightly faster pace due to your first coming up answer.

* 1. Please rate your level of agreement with the following statements...

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
My peers often ask me for advice or information	○	○	○	○	○
I enjoy trying out new ideas	○	○	○	○	○
I seek out new ways to do things	○	○	○	○	○
I am generally cautious about accepting new ideas	○	○	○	○	○
I frequently improvise methods for solving a problem when an answer is not apparent	○	○	○	○	○
I am suspicious of new inventions and new ways of thinking	○	○	○	○	○
I rarely trust new ideas until I can see whether the vast majority of people around me accept them	○	○	○	○	○
I feel that I am an influential member of my peer group	○	○	○	○	○
I consider myself to be creative and original in my thinking and behavior	○	○	○	○	○
I am aware that I am usually one of the last people in my group to accept something new	○	○	○	○	○
I am an inventive kind of person	○	○	○	○	○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I enjoy taking part in the leadership responsibilities of the groups I belong to	○	○	○	○	○
I am reluctant about adopting new ways of doing things until I see them working for people around me	○	○	○	○	○
I find it stimulating to be original in my thinking and behavior	○	○	○	○	○
I tend to feel that the old way of living and doing things is the best way	○	○	○	○	○
I am challenged by ambiguities and unsolved problems	○	○	○	○	○
I must see other people using new innovations before I will consider them	○	○	○	○	○
I am receptive to new ideas	○	○	○	○	○
I am challenged by unanswered questions	○	○	○	○	○
I often find myself skeptical of new ideas	○	○	○	○	○

User Adaptation towards HSR (English)

* 2. Have you ever use HSR before?

- ◯ Yes
- ◯ No

User Adaptation towards HSR (English)

SECTION A – YOUR EXPERIENCE AND TRAVEL PATTERN OF USING HIGH SPEED RAIL

In this section, we would like to ask a few question on how often you use HSR and trip purpose. Note that the ROUND TRIP counts INDEPENDENTLY.

* 3. How often do you use HSR this year (2014)?

- ◯ Never
- ◯ One single trip / Round trip
- ◯ A few times
- ◯ Monthly / or Almost monthly
- ◯ Weekly / or Almost weekly
- ◯ Daily / or Almost daily

* 4. In this year (2014), your trip purpose were mainly for?

- ◯ Commuting
- ◯ Business
- ◯ Returning-home
- ◯ Leisure

其他 (請註明)

User Adaptation towards HSR (English)

SECTION A – YOUR EXPERIENCE AND TRAVEL PATTERN OF USING HIGH SPEED RAIL

* 5. When did you start using HSR?

- ◯ 2007~2008
- ◯ 2009~2011
- ◯ 2012~2013
- ◯ 2014
- ◯ Can't remember

User Adaptation towards HSR (English)

SECTION A – YOUR EXPERIENCE AND TRAVEL PATTERN OF USING HIGH SPEED RAIL

* 6. How often do you use HSR in 2007 and 2008?

- ◯ One single trip / Round trip
- ◯ A few times
- ◯ Monthly / or Almost monthly
- ◯ Weekly / or Almost weekly
- ◯ Daily / or Almost daily
- ◯ Can't remember

其他 (請註明)

* 7. Your trip purpose in 2007 and 2008 mainly were?

- ◯ Commuting
- ◯ Business
- ◯ Returning-home
- ◯ Leisure

其他 (請註明)

User Adaptation towards HSR (English)

SECTION A – YOUR EXPERIENCE AND TRAVEL PATTERN OF USING HIGH SPEED RAIL

* 8. How often do you use HSR in 2009, 2010 and 2011?

- ◯ Never
- ◯ One single trip / Return trip
- ◯ A few times
- ◯ Monthly / or Almost monthly
- ◯ Weekly / or Almost weekly
- ◯ Daily / or Almost daily
- ◯ Can't remember

其他 (請註明)

* 9. Your trips purpose in 2009, 2010 and 2011 mainly were?

- ◯ Commuting
- ◯ Business
- ◯ Returning-home
- ◯ Leisure

其他 (請註明)

User Adaptation towards HSR (English)

SECTION A – YOUR EXPERIENCE AND TRAVEL PATTERN OF USING HIGH SPEED RAIL

* 10. How often do you use HSR in 2012 and 2013?

- ◯ Never
- ◯ One single trip / Round trip
- ◯ A few times
- ◯ Monthly / or Almost monthly
- ◯ Weekly / or Almost weekly
- ◯ Daily / or Almost daily
- ◯ Can't remember

其他 (請註明)

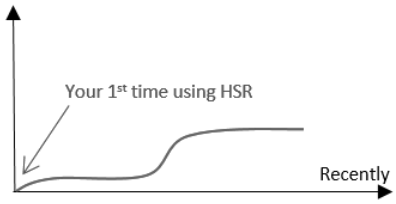
* 11. Your trips purpose in 2012 and 2013 mainly were?

- ◯ Commuting
- ◯ Business
- ◯ Returning-home
- ◯ Leisure

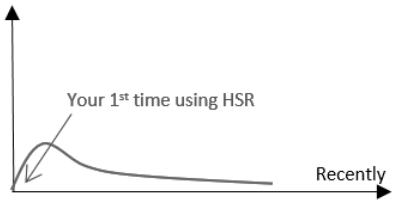
其他 (請註明)

SECTION B – YOUR TRAVEL PATTERN OF USING HIGH SPEED RAIL

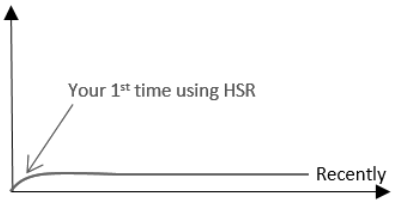
Considering your answers in the previous questions, which of these graphs below, is the most closely to your number of trips with HSR SINCE you started using HSR (y: frequency; x: time, NOTE that x0 is your starting time when you use HSR)



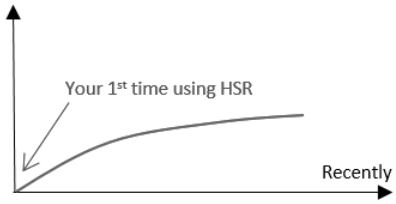
1. I seldom used HSR at the beginning, but increased significantly after some time, now I constantly using HSR for my travel.



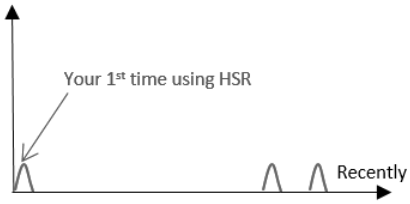
2. I used HSR more often at the beginning than nowadays...



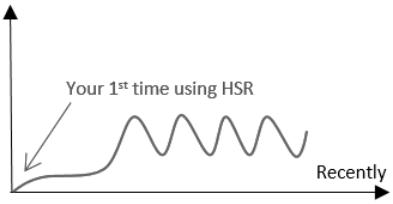
3. It didn't change much since I used HSR for the first time...



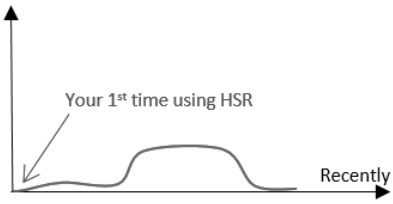
4. I keep increasing my HSR usage slowly since I started to use it.



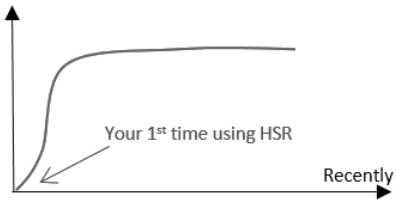
5. I would never use HSR unless due to unavoidable reasons.



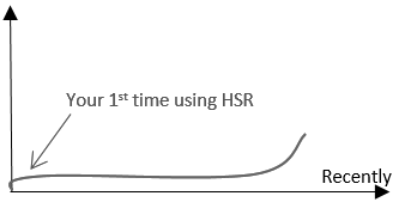
6. I seldom used HSR in the beginning, but now increased and have some (roughly) regular pattern depends on certain reasons.



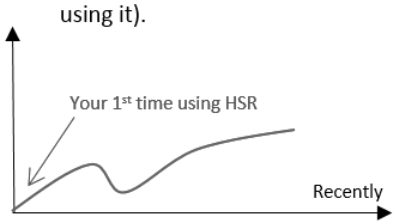
7. There is a certain period I used HSR more than usual, but due to some reason I decreased the frequency (or stop to using it).



8. Basically I prefer HSR for my inter-city travel since I started using it.



9. Not very much at the beginning, but recently increased a lot.

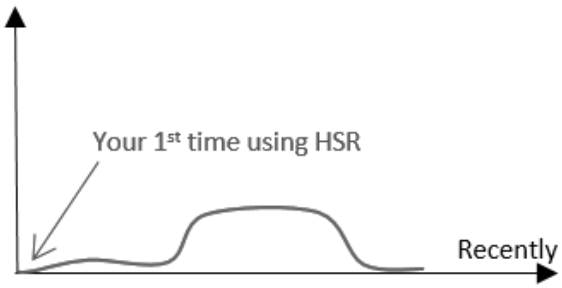


10. I increased at beginning, and then decreased sometimes, after that I increased again.

* 12. Which of the pattern above is the closest to your HSR travel pattern?

- 1. I seldom used HSR at the beginning, but increased significantly after some time, now I constantly using HSR for my travel.
- 2. I used HSR more often at the beginning than nowadays…
- 3. It didn't change much since I used HSR for the first time…
- 4. I keep increasing my HSR usage slowly since I started to use it.
- 5. I would never use HSR unless due to unavoidable reasons.
- 6. I seldom used HSR in the beginning, but now increased and have some (roughly) regular pattern depends on certain reasons.
- 7. There is a certain period I used HSR more than usual, but due to some reason I decreased the frequency (or stop to using it).
- 8. Basically I prefer HSR for my inter-city travel since I started using it.
- 9. Not very much at the beginning, but recently increased a lot.
- 10. I increased at beginning, and then decreased sometimes, after that I increased again.
- None of above is closely to my travel pattern.

SECTION B (1) – YOUR TRAVEL PATTERN OF USING HIGH SPEED RAIL



7. There is a certain period I used HSR more than usual, but due to some reason I decreased the frequency (or stop to using it).

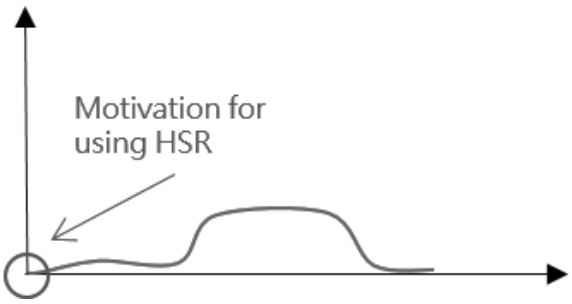
13. According to the pattern you chosen above, could you please ROUGHLY describe in numbers of how many SINGLE TRIPS or in text of your changes of using HSR per year? (Not mandatory)

2007	
2008	
2009	
2010	
2011	
2012	
2013	
2014	

User Adaptation towards HSR (English)

SECTION C – REASONS & PURPOSES OF SPECIFIC PATTERN PERIODS(1)

In this section, we would like to further understand your reasons and purpose according to the pattern you had chosen from our previous question. Please rate your level of agreement with the following statements.



* 14. As the pattern you had chosen above, the motivation or reason for you to start using HSR is because...

	Absolutely not the reason	Unimportant reason	Moderately important reason	Important reason	The most important reason
I was curious about HSR	○	○	○	○	○
It sounds exciting and cool	○	○	○	○	○
I expected it should be more comfortable than other modes	○	○	○	○	○
I thought it should be more reliable than other modes	○	○	○	○	○
I was often stuck in the traffic	○	○	○	○	○
I just didn't like other travel options	○	○	○	○	○
I expected it is safe for my travel	○	○	○	○	○
I expected HSR speedy, saving my time	○	○	○	○	○
I was encouraged by my friends' experience	○	○	○	○	○
I was encouraged by my family's experience	○	○	○	○	○

	Absolutely not the reason	Unimportant reason	Moderately important reason	Important reason	The most important reason
A lot of positive feedbacks coming from media / internet discussion encouraged me	○	○	○	○	○
My company / organization sent me on a business trip	○	○	○	○	○
I have to go somewhere immediately (or emergency events)	○	○	○	○	○
HSR had the sale campaign and the price seems so attractive	○	○	○	○	○
I expected HSR could help me to manage / increase my business activities	○	○	○	○	○
I expected to do my work while travel	○	○	○	○	○
Accessing to HSR station became easier	○	○	○	○	○
The frequency became convenient for my purpose	○	○	○	○	○
The other modes / options became worse (e.g. flights)	○	○	○	○	○

其他 (請註明)

User Adaptation towards HSR (English)

SECTION C – REASONS & PURPOSES OF SPECIFIC PATTERN PERIODS(1)

In this section, we would like to further understand your reasons and purpose according to the pattern you had chosen from our previous question. Please rate your level of agreement with the following statements.

* 15. The reasons of increasing your frequency of using HSR is because...

	Absolutely not the reason	Unimportant reason	Moderately important reason	Important reason	The most important reason
My company / organization sent me more business trips	○	○	○	○	○
I increase the frequency of HSR because I moved to other places.	○	○	○	○	○
I have changed / got my job (including getting your 1st job)	○	○	○	○	○
I got promoted in my career, which generates more business trips	○	○	○	○	○
I am satisfied with my previous HSR experience	○	○	○	○	○
I realized it's reliable	○	○	○	○	○
I felt more comfortable while travel compare to other mode	○	○	○	○	○
The traffic condition became worse	○	○	○	○	○
I felt safe for my travel	○	○	○	○	○
I realized it's speedy, saving my time	○	○	○	○	○
I was encouraged by my friends' experience	○	○	○	○	○

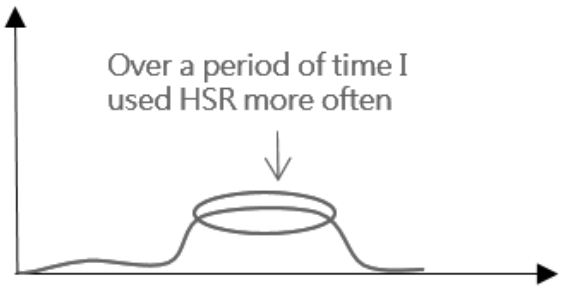
	Absolutely not the reason	Unimportant reason	Moderately important reason	Important reason	The most important reason
I was encouraged by my family's experience	○	○	○	○	○
A lot of positive feedbacks coming from media / internet discussion encouraged me	○	○	○	○	○
I realized HSR has sale campaign and the price is so attractive	○	○	○	○	○
I realized that HSR was good for my business	○	○	○	○	○
I realized that I could do my work while travel	○	○	○	○	○
The frequency improved, make it feasible for me to depart at anytime	○	○	○	○	○
HSR had improved its access to station, I felt now it has better connection	○	○	○	○	○
The other modes / options became worse (e.g. flights)	○	○	○	○	○

其他 (請註明)

User Adaptation towards HSR (English)

SECTION C – REASONS & PURPOSES OF SPECIFIC PATTERN PERIODS(1)

In this section, we would like to further understand your reasons and purpose according to the pattern you had chosen from our previous question. Please rate your level of agreement with the following statements.



* 16. The reasons of constantly using HSR is because...

	Absolutely not the reason	Unimportant reason	Moderately important reason	Important reason	The most important reason
I use HSR for regular commuting trips	○	○	○	○	○
I use HSR for a number of business trips	○	○	○	○	○
I often use HSR for returning-home trips	○	○	○	○	○
I often use HSR for leisure trips	○	○	○	○	○
I realized HSR was good for my business	○	○	○	○	○
I am satisfied with my previous HSR experience	○	○	○	○	○
It's reliable	○	○	○	○	○
I felt comfortable while travel compare to other mode	○	○	○	○	○
I don't want to stuck in the traffic	○	○	○	○	○
I now prefer HSR rather than driving cars	○	○	○	○	○
It's safe for my travel	○	○	○	○	○
I just got used to HSR	○	○	○	○	○
It's speedy, it has proven to save my time	○	○	○	○	○

	Absolutely not the reason	Unimportant reason	Moderately important reason	Important reason	The most important reason
I would not choose HSR for my own trips, but I chose it with others	○	○	○	○	○
I simply had to though I don't like it	○	○	○	○	○
I kept using because I was being encouraged to use HSR	○	○	○	○	○
I regularly booked discount ticket	○	○	○	○	○
My business now strongly depending on HSR	○	○	○	○	○
The frequency improved, make it feasible for me to depart at anytime	○	○	○	○	○
I am satisfied with HSR's access improvement	○	○	○	○	○
The other modes / options became worse	○	○	○	○	○

其他 (請註明)

User Adaptation towards HSR (English)

SECTION C – REASONS & PURPOSES OF SPECIFIC PATTERN PERIODS(1)

In this section, we would like to further understand your reasons and purpose according to the pattern you had chosen from our previous question. Please rate your level of agreement with the following statements.

* 17. The reasons of reducing frequency or stop using HSR is because...

	Absolutely not the reason	Unimportant reason	Moderately important reason	Important reason	The most important reason
My commuting trips pattern changed	○	○	○	○	○
My business trips pattern changed	○	○	○	○	○
My returning-home trips pattern changed	○	○	○	○	○
My leisure trips pattern changed	○	○	○	○	○
I have had a particular terrible experience	○	○	○	○	○
In general, I am NOT satisfied with my previous HSR experience	○	○	○	○	○
It became unreliable	○	○	○	○	○
I felt HSR wasn't safe	○	○	○	○	○
The service quality decreased (crowding, cleanness, and etc.)	○	○	○	○	○
HSR didn't help my business anymore	○	○	○	○	○
I now prefer other public transportation	○	○	○	○	○
I now prefer to drive	○	○	○	○	○

	Absolutely not the reason	Unimportant reason	Moderately important reason	Important reason	The most important reason
My friend had some terrible experience on taking HSR	○	○	○	○	○
My family had some terrible experience on taking HSR	○	○	○	○	○
I heard a lot of negative feedbacks from media / internet discussion	○	○	○	○	○
I am assigned on less business trips by my company / organization	○	○	○	○	○
I don't use HSR more often since I moved to other places	○	○	○	○	○
I have changed / got my job	○	○	○	○	○
My job task changed	○	○	○	○	○
The fare price is too expensive	○	○	○	○	○
HSR raised the price too much	○	○	○	○	○
I only use HSR when there's a discount, otherwise HSR wouldn't be my options	○	○	○	○	○
The frequency was not convenient	○	○	○	○	○
It took too much time to access to HSR station	○	○	○	○	○
I switched to other modes / options due to their improvement on its service	○	○	○	○	○

其他 (請註明)

User Adaptation towards HSR (English)

SECTION D – GENERAL PERCEPTION

* 18. Recently, what's your most frequently HSR OD pair?

	Taipei	Banchioa	Taoyuan	Hsinchu	Taichung	Chiayi	Tainan	Zouying
Original	◯	◯	◯	◯	◯	◯	◯	◯
Destination	◯	◯	◯	◯	◯	◯	◯	◯

* 19. According to your most frequently OD, what's your most likely alternative mode if HSR were temporally out of service?

- ◯ Car
- ◯ Bus
- ◯ Taxi
- ◯ Conventional Rail
- ◯ Airline
- ◯ I would give up that trip

其他 (請註明)

User Adaptation towards HSR (English)

SECTION E – INFORMATION ABOUT YOU (FINAL SECTION)

The following questions are to ensure that we have a representative sample of HSR users in each place of our study

* 20. What is your gender?

- ◯ Male
- ◯ Female

* 21. Marital status

- ◯ Single
- ◯ Married or Cohabiting (living together)
- ◯ Married but separated
- ◯ Divorced
- ◯ Other

* 22. Please state your age.

SECTION E – INFORMATION ABOUT YOU (FINAL SECTION)

* 23. What is your own personal monthly budget?

If in other currency, please provide estimate:

* 24. What is approximately your total monthly family income? (rough estimation of your income plus that of parents or spouse)

If in other currency, please provide estimate:

User Adaptation towards HSR (English)

SECTION E – INFORMATION ABOUT YOU (FINAL SECTION)

* 25. What's your highest degree of education?

- ◯ Elementary
- ◯ Junior High
- ◯ Senior High
- ◯ Collage / Bachelor
- ◯ Graduated / Master
- ◯ PhD

* 26. Do you have a license?

	Yes	No
Cars	◯	◯
Scooters	◯	◯
Heavy Bike	◯	◯

* 27. What is your Occupation?

其他 (請註明)

User Adaptation towards HSR (English)

SECTION E – INFORMATION ABOUT YOU (FINAL SECTION)

* 28. What is your employee grade level?

- ◯ Individual Contributor (基層員工、行政支援、助理)
- ◯ Professionals / Engineer (專案、工程師)
- ◯ Managers and Senior Technical Professionals (經理、副理等中階主管)
- ◯ Directors / Vice President (高階主管、顧問)
- ◯ Company owner (老闆)

其他 (請註明)

User Adaptation towards HSR (English)

SECTION E – INFORMATION ABOUT YOU (FINAL SECTION)

* 29. The city / county of your residence?

30. The city / county which your company / organization located in?

縣市:

郵遞區號:

User Adaptation towards HSR (English)

INFORMATION FOR RECEIVING INCENTIVES

We greatly appreciate your participation in this survey. In order to receive our incentives, please fill out the following questions, thank you!

31. Your personal PTT ID

32. Which PTT Board you access into our survey?

33. Please feel free for any comments about HSR user adaptation, your experience or this questionnaire in general, please use the box below.

User Adaptation towards HSR (English)

END OF THE SURVEY

Once again thank you for participating in this survey!
If you have any further question or comment related to the survey, please feel free to contact:

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