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Forecasting Demand for High Speed Rail

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Abstract

It is sometimes argued that standard state-of-practice logit based models cannot forecast the demand for substantially reduced travel times, for instance due to High Speed Rail (HSR). The present paper investigates this issue by reviewing travel time elasticities for long-distance rail travel in the literature and comparing these with elasticities observed when new HSR lines have opened. This paper also validates the Swedish official long-distance model and its forecasted demand for a proposed new HSR track, using aggregate data revealing how the air-rail modal split varies with the difference in generalized travel time between rail and air. The official linear-in-parameters long-distance model is also compared to a model applying Box-Cox transformations. The paper contributes to the empirical literature on long-distance travel, long-distance elasticities and HSR passenger demand forecasts. Results indicate that the Swedish state-of-practice model, and similar models, is indeed able to predict the demand for a HSR reasonably well. The non-linear model, however, has better model fit and slightly higher elasticities.

Keywords: High Speed Rail, Travel Demand, Forecasting, Air-rail Share, Cost-benefit Analysis

JEL Codes: D61, R41, R42, C25, J22

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Introduction

Long-distance travel stands for a disproportionately large share of traffic production compared to its share of trip making. Worldwide there are great hopes that High Speed Rail (HSR) may help to alleviate the heavy load of traffic in road and air corridors and improve interregional accessibility. There is a wide political backing for investments in HSR in many countries and the European Union is considering increasing the financial funding for HSR projects (European Commission, 2010). However, HSR requires substantial investments. The economic rationale for allocating public money to construction of new HSR tracks is highly dependent on the present volume of rail travel, generation of new rail trips, and the extent to which air and car trips would be diverted to rail.

A common argument is that state-of-practice forecast models tend to underpredict demand when travel times are substantially reduced for instance due to HSR, and specifically that such models predict too small a diversion of trips from air to rail. There have so far not been many studies trying to validate forecast models in this respect, which is the purpose of the present study. Flyvbjerg et al. (2005) analyze, however, statistically how accurate demand forecasts are, finding that these have systematically overestimated traffic volumes of rail investments. Moreover, Flyvbjerg et al. find that forecasts have not improved over time as estimation techniques have improved and that the demand for road investments is not overestimated as much as for rail investments, indicating that the overestimation of demand for rail investments is not primarily connected to the validity of forecast models, but to strong political pressure.

The purpose of this paper is to investigate whether state-of-practice forecasting models can predict the demand for HSR. First, model-based long-distance elasticities in the literature are compared with elasticities observed when new HSR lines have been introduced. Then the paper describes the official Swedish long-distance model briefly, studies its elasticities and demand forecast for a suggested HSR track, and validates the forecast against previous literature and aggregate Swedish data. The Swedish official long-distance model, within the modeling package Sampers (administered by the Swedish Transport Administration), has been in use for some ten years and is one of the most comprehensive state-of-practice long-distance models in the world presently in use for appraisal. The response of the linear-in-parameters official long-distance model is also compared to that of a model applying Box-Cox transformations on time and cost parameters. The paper contributes to the empirical literature on long-distance travel elasticities and HSR passenger demand forecasts.

There are reasons to believe that long-distance models are less reliable than models for regional travel. First, the vast majority of forecasting models deal with regional travel, although the interest in HSR has triggered the development of long-distance models in many countries (e.g. Ben-Akiva et al. (2010), de Bok et al. (2010), Outwater et al (2010) and Rohr el al. (2010)). When developing long-distance models the same modeling techniques are used as have traditionally been used for regional travel although long-distance travel seems to be more heterogeneous. Second, non-linearity in the sensitivity to travel time makes long-distance modeling complex. Gaudry (2008) demonstrates that mode choice logit models assuming linear sensitivity underestimate the cross-elasticity in HSR line forecasts. Daly (2010) reveals a large amount of evidence of non-linear time and cost sensitivity in previous research. Third, since long-distance travel is less frequent and less evenly distributed in the population, data collection is more difficult. For instance, long reporting periods used to increase the chance that the respondent can report at least one journey induces underreporting of trips due to forgetfulness (Armoogum & Madre, 1997; Axhausen et al., 1997).

Section 2 reviews evidence of elasticities for HSR investments in the literature. Evidence of cross-elasticities of long-distance travel is virtually non-existent, and this section therefore concentrates on direct elasticities. Besides, cross-elasticities are less meaningful to compare between situations since they tend to be highly dependent on specific market conditions. Section 3 describes the Swedish long-distance model, with focus on the relevance for its HSR demand forecasts. The section also reports the implied average elasticities and cross-elasticities, which are compared with the previous evidence.

The Swedish long-distance model has been used to forecast the demand for a proposed new HSR track of about 500 km, connecting the country's two largest cities: Stockholm and Gothenburg. In this corridor there is already an HSR line, called X2000, with a travel time of 3h and 5min operating on upgraded conventional tracks. With the new track the travel time is supposed to decrease to 2h and 14min[1]. Section 4 describes the forecasted demand response to the suggested HSR track and compares it with international evidence. Since cross-elasticities are rare in the literature and difficult to compare between different situations, section 5 validates the forecasted effect on rail-air mode split against aggregate traffic count data and corresponding generalized travel time difference between air and rail in different relations. Section 6 concludes.

Elasticities in the literature

The literature on rail travel time elasticities and cross-elasticities for long-distance travel is fairly limited. Long-distance models, which can produce elasticities, are few, but examples are Román et al. (2007), Atkins (2003), Cabanne (2003), de Bok et al. (2010) and Rohr et al. (2010). The elasticities implied by these studies, reported in Table 1, are in the range of -0.36 to -1.31. The former two papers report time and price elasticities on number of trips for a particular HSR line. The three latter report average trip distance elasticities, giving the approximate average percentage change in travel distance by rail, in response to a percentage change in the generalized cost of rail trips uniformly over all origin-destination pairs. Dargay (2010) reports average trip distance elasticities estimated on time series data, which have a tendency to be higher (in absolute terms) than those estimated on cross-section data, but it remains unclear why. Dargay also reports higher (absolute) elasticities for longer trips.

All else equal, one expects that the trip elasticities for a *particular HSR line* is higher than *average trip* elasticities, predicting the change in number of trips in response to a uniform travel time change in all trip relations, because one of the responses to changes in travel times are destination choice: when travel time reduces, trips become on average longer. On the other hand, one expects that for a uniform change in travel times over all origin-destination pairs, *distance*

[1] The cost is assessed to €10-€15 billion.

elasticities are higher than the *trip* elasticities for the same reason. Hence, when comparing the elasticities of travel time on number of trips for a particular HSR line and on average trip distance over all origin-destination pairs, as in Table 1, there is no a prior expectation as to which ones that should be highest. And indeed, there is no clear pattern. Note also that one expects that models estimated on data with less accurate travel time information or with poor model specification tend to have lower elasticities.

Further down Table 1 also includes observed elasticities found after the opening of three HSR lines. When the TGV (Train à Grande Vitesse) was introduced, the rail travel time was first reduced by 30 percent, and the implied travel time elasticity was then about -1.6 (with respect to number of trips). When travel time was further reduced by 25 percent, the elasticity was lower, -1.1. The number of trip elasticities for the Madrid-Barcelona HSR line was -1.3 and for Madrid-Seville -1.2 (computed from volumes from Sánchez-Borràs (2010)). The observed elasticities seem thus in general to be larger than the model-based, indicating that at least some of the models may underpredict elasticities. The reason for the higher observed elasticities may, on the other hand, be that the train alternative has been very unattractive before the introduction of HSR, in particular in the Spanish cases.

Cross-elasticities of air demand on HSR travel time are difficult to estimate and rare in the literature (exceptions are Ben-Akiva et al., (2010) and Rohr et al. (2010)). Correlations in time and cost trends for different modes do not usually allow estimation of cross-elasticities in time series data, and in logit models cross-elasticities are very sensitive to different model specifications.

Table 1: Elasticity with respect to rail in-vehicle travel time in the literature.

Study	**Elasticity**	**Comment**
Román et al. (2010)	-0.4 (Madrid-Barcelona) -0.6 (Madrid-Zaragoza)	Cross-section RP/SP data. Spanish HSR corridors.
Atkins (2002)	-0.9/-1.3 (bsn); -0.8/-0.9 (priv)	Cross-section RP/SP data. UK HSR corridors.
Cabanne (2003)	0.3 / 0.45 -0.16 (Air cross-elasticity)	Time series data models. Elasticity of rail accessibility. French HSR corridor.
Bok et al. (2010)	-0.6 (bsn) -0.5 (commute) -0.3 (other)	Average distance elasticity. Portugal. Cross-section RP data.
Rohr et al. (2010)	-0.9 (bns) -0.4 (priv)	Average distance elasticity. UK. Cross-section RP data.
Dargay (2010)	-0.49 - -3.04	Aggregate time series. UK. Different purposes and trip length segments.
Paris-Lyon (Nash, 2010)	-1.6 (phase 1) -1.1 (phase 2)	HSR line 1981 – 1983.
Madrid-Barcelona	-1.3	HSR line 2008.
Madrid-Sevilla	-1.2	HSR line 1992.

The diversion of trips from other travel modes in different corridors demonstrates the variability in cross-elasticities. When the TGV between Paris-Lyon (HSR travel time 2h) was introduced 1981 roughly half the additional rail traffic consisted of newly generated trips (Vickerman, 1997), and there was almost no direct substitution of car trips (Nash, 2010). For the Madrid-Seville HSR line (2h 15m) opening in 1992, where the initial market share for rail was much lower, only 15 percent of the increase in rail trips was newly generated. Some of the increase in rail travel was due to substitution of car trips, but most of the additional rail trips were substituted air trips (COST318, 1998). In Germany, where the HSR uses existing networks, only 12 percent of the travelers on the HSR lines have shifted from other modes (Cheng, 2010). Cheng suggests that the high price of the train service explains the low shift, and another explanation is that HSR compete less with air travel because it is more focused on regional travel. Sánchez-Borràs et al. (2010) explore specifically how the demand and market share for rail depend on ticket prices.

The air-rail split in Paris-Lyon (2h) is 9-91 percent (COST318, 1998). The air-rail mode split in the Madrid-Seville corridor (2h 15m) is 20-80 percent, as is the air-rail split in the London–Paris corridor with the same HSR travel time (2h 15m) (Eurostar, 2011). The HSR line operating in the Madrid-Barcelona corridor (2h 38m), opened in 2007, has an air-rail mode split of 53-47 percent, but the HSR is more competitive on the shorter travel segment Madrid-Zaragoza (Sánchez Borràs et al, 2011).

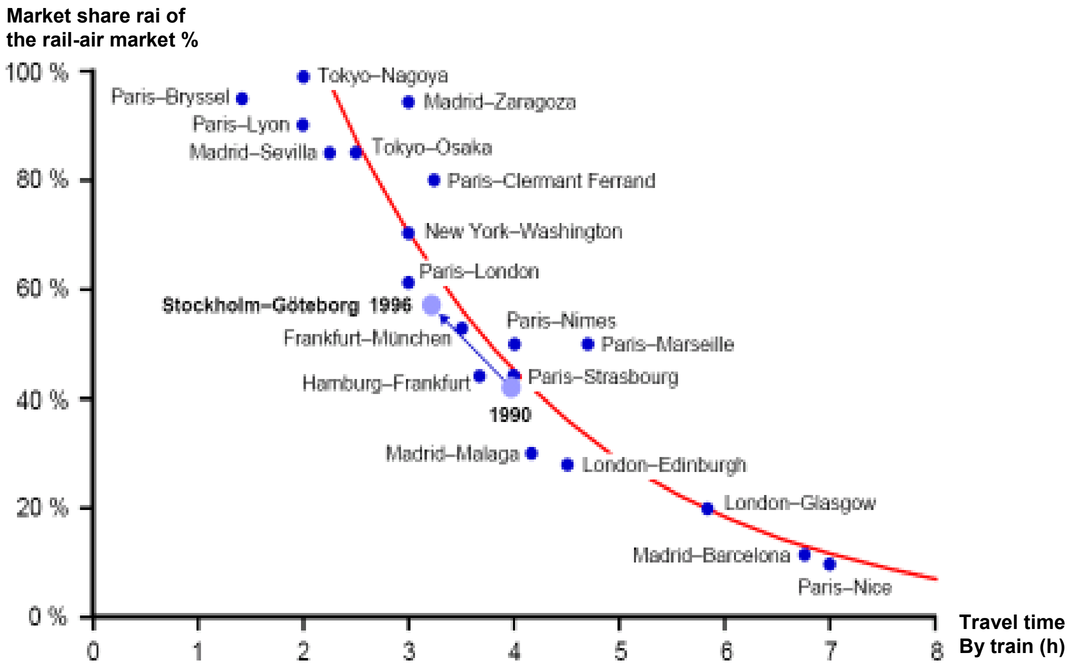

Figure 1: Estimated relationship between air-rail split and in-vehicle train travel time. Source Jansson and Nelldal (2010). The shares in this do not correspond exactly to those referred in this text, because the latter are more recent updates.

Jansson and Nelldal (2010) have estimated and plotted the relationship between rail travel time and the air-rail modal split on an aggregate level depicted in Figure 1. This relationship suggests that rail travel time is the only important determinant for the resulting air-rail market-share and Jansson & Nelldal suggest that it could be used to validate passenger forecasts. However, this type of relationship ignores the strong evidence found in the modeling studies referred above that the market share for rail is context-specific, depending on demographics, accessibility to airports and train stations, relative differences in air and rail ticket fares (determined partly by competition between travel modes), frequencies and the share of business travel. If these factors changes over time this relationship would not be valid for forecasting. This type of relationship is also sensitive to selection effects, i.e. to which origin-destination pairs that are included.

The forecast model

The Swedish national forecasting model, called Sampers, is administered by the Swedish Transport Administration. Different versions of Sampers have been used by the Transport Administration for evaluations for approximately 10 years. The model includes five regional models and one model for national long-distance trips. All sub-models are nested logit models including frequency, destination and mode choice interacting with the Emme/2 network assignment software. The long-distance sub-model includes car, coach, rail and air. The destination choice includes 700 zones on the national level. Different sub-models are estimated for business trips and private trips. A more detailed description of the estimation of an early version of this model can be found in Beser & Algers (2002). For a more detailed description of the estimation and calibration of the model, see the Technical report (Transek AB, 2004).

Estimation Data and Underreporting in Long-Distance Travel Surveys

All sub-models have been estimated on the national travel survey, collected in 1994–2000. The survey consists of a one-day travel diary including all trips and a long-distance travel diary including trips taking place in the period starting one day before the survey day and extending 30 days back in time for trips at least 100 km, and 90 days back for trips at least 300 km. The long-distance model is estimated based on 65015 observed trips.

Calibration of the model against the long-distance travel survey and traffic counts for rail and air indicated considerable underreporting in the survey for these modes (about 30 percent for train and 15 percent for air). Comparisons between the long-distance and the one-day survey indicated also that car trips below 400 km are underreported in the long-distance travel survey (but no underreporting is indicated for longer car trips). The underreporting could be due to forgetfulness or fatigue effects, in particular for individuals making many long-distance trips. The problem of underreporting and possible bias in long-distance surveys extending over a longer period has been acknowledged in other countries and should be subject to further research.

Supply data, including various travel time and distance components for each travel mode, were fetched from the Emme/2 system. Car travel times were calculated using the assumption that a half-hour break is taken every two hours[2]. Fare matrices were used for scheduled travel modes. Car travel costs were assumed to be proportional to the trip distance.

Implicit Values of Time

The cost parameter is generic across modes and deflated in the forecast, with an income elasticity of -0.5 in real terms. Hence, if average incomes increase 10% over time, the cost parameters decrease 5%. The in-vehicle travel time parameter is segmented with respect to length of stay for private trips; it is higher for one-day trips than for overnight stays, presumably because there are more time constraints applying for one-day trips. For private trips, but not for

[2] This assumption was deduced from comparing reported travel times (including stops) with travel times imputed from the Emme/2 system.

business trips, the in-vehicle time parameter is significantly higher for car than for other modes. Many modeling studies (Börjesson, 2010; Wardman, 2004) have found that the marginal valuation of first wait time declines with increasing headway. Since this proved to be difficult to model directly, a piecewise linear function transforming headway into disutility of wait time was applied[3].

Table 2 reports the values of time of the business and private trips model. The values of time for private trips can be compared with the recently estimated Swedish national value of times (Börjesson & Eliasson, 2011) based on Stated Choice data: Car €12/h, rail €10/h and coach €6.5/h in price level 2008. The value of time for one-night car trips is relatively high in the demand model, but apart from that the figures are similar.

Table 2: Values of time derived from model estimation. Unit €/h; price level 2008. Different values of time are reported for business trips because the cost parameter are segmented with respect to high and low income for those trips.

	Business high income	**Business low income**	**Private trips 1-5 days**
In-vehicle time all models; One-day trips	115.6	64.9	
In-vehicle time all models; Overnight stay	58.9	33.1	
Wait time One-day trips	227.0	127.5	
Wait time Overnight stays	92.7	52.1	
Value of one transfer One-day trips	61.6	34.6	
Value of one transfer Overnight stays	45.8	25.7	
In-vehicle time car One-day trips			17.9
In-vehicle time car Overnight stays			11.0
In-vehicle time other modes; One-day trips			7.7
In-vehicle time other modes; Overnight stays			5.5
Wait time (see eqn. 1) One-day/Overnight			20.8
Value of one transfer			11.1

How should a new technology be included in the model?

As stated in the introduction, a common argument is that state-of-practice forecast models tend to underpredict demand when travel times are substantially reduced for instance due to HSR. The first thing to note is that the cross-sectional data that the present model, and presumably most other models, is estimated in includes a larger variability in travel times than the time shift due to HSR. To forecast the effect of the HSR should therefore not be impossible.

Another possible difficulty of forecasting demand for HSR could arise because travelers view HSR as another mode than conventional rail in some way. Using SP data, Burge et al. investigate whether travelers place a value on HSR compared conventional rail, over and above the value due to differences in level of service attributes, by estimating a mode-specific constant for HSR. They do find a positive HSR constant for car and air travelers but not for rail travelers. Since the stated preferences of the latter are assumed more creditable, the conclusion is that this constant should not be used for forecasting. A similar Swedish study (WSP Analysis & Strategy, 2012), also based in stated preferences,

[3] From Swedish the value of time study 1994 (Dillén & Algers, 1998): $Wait = 0.5\cdot(min(Headway,60)+0.5\cdot(min(Headway,120)60)(Headway>60)+0.2\cdot(Headway-120)\cdot(Headway>120))$.

gives the same results. Burge et al. and WSP (2012) also investigate how to include HSR and convectional rail in the nested model structure, which depend on the substitution patterns between HSR, conventional rail the travel modes. The studies give some support for including HSR and conventional rail as different modes in the nesting structure, but this is still uncertain given the lack of revealed preference data in these studies.

In the late 1990's HSR running on upgraded conventional tracks was introduced in Sweden, called X2000. Different nesting structures including X2000 and conventional trains as one single and as two separate modes were explored (Beser Hugosson, 2003), giving some support for including the two train types as separate modes at the same level as other travel modes in the nesting structure. This means that if a new X2000 line was introduced with the same level of service as the conventional train, the market share for rail would instantly be twice as high. However, X2000 is different from conventional trains in the sense that these trains operate primarily between the largest cities at attractive departure times and with higher fares. The differences between the train types captured by the demand model could arise because of these differences, since they are not sufficiently captured by the models. For instance, the modeled impact of train fare is unreliable because of uncertain fare information and departure time is not accounted for. Since it is uncertain what the mode difference found in the estimation represents all train types, including the proposed HSR type evaluated in the present paper, are modeled as a single train mode in the later versions of Sampers.

Elasticities

The calibrated model implies certain elasticities, shown in Table 3, which can be interpreted as the percentage change in travel demand D per percentage change in a given attribute, x. These elasticities have been calculated by applying the model to a base scenario and to a scenario where the given attribute has been increased ten percent uniformly over all trip relations. The own elasticity, ε, is then computed as

$$\varepsilon = \frac{\ln(D_{m1}/D_{m2})}{\ln(x_{m1}/x_{m2})}, \qquad (1)$$

where x_{m1} and x_{m2} are the attributes referring to mode m (e.g. in-vehicle time and fare), in the base and change scenario, respectively. D_{m1} and D_{m2} indicate total demand, which can be measured as total travel distance per day, or as number of trips per day, with mode m. In Table 3 only elasticities with respect to total travel distance per day are reported. The elasticities for travel distance per day are larger (in absolute terms) than elasticities for number of trips per day, because responses to increased generalized travel costs include not only fewer trips but also shorter trips. The table also reports cross-elasticities, referring to the change in travel distance per day with mode m in response to a change in an attribute associated with another mode n:

$$\epsilon = \frac{\ln(D_{m1}/D_{m2})}{\ln(x_{n1}/x_{n2})}. \qquad (2)$$

All the elasticities have the expected sign. As travel time or travel cost increases for one travel mode, the demand for that mode falls, while the demand for travel with other modes increases.

The rail fare elasticity is -0.72 for business trips and -0.59 for private trips. These numbers are similar to those reported by Rohr et al. (2010), who find the corresponding elasticities to be -0.5 (business), -0.9 (commuting trips) and -0.6 (other private trips), computed using the same method. However, these elasticities are lower than -1 as reported by Dargay (2010) who uses time series data. The elasticity for rail in-vehicle travel time is -1.50 for business trips and -1.01 for private trips. These figures are slightly higher (absolute value) than what is reported by Rohr et al. (2010) and Román et al. (2007).

Table 3: Arc elasticities for travel distance, derived from a ten percent increase in each attribute

		Car	Coach	Air	Rail	Total
Car in-vehicle time	Business	-0.87	0.60	0.55	0.66	-0.11
	Private	-0.53	0.57	0.60	0.54	-0.19
	Total	-0.58	0.58	0.57	0.57	-0.17
Fuel Price	Business	-0.14	0.11	0.09	0.10	-0.03
	Private	-0.15	0.16	0.17	0.15	-0.04
	Total	-0.14	0.16	0.12	0.14	-0.04
Rail in-vehicle time	Business	0.16	0.14	0.16	-1.50	-0.07
	Private	0.06	0.09	0.20	-1.01	-0.08
	Total	0.08	0.10	0.18	-1.12	-0.08
Rail Fare	Business	0.07	0.07	0.07	-0.72	-0.04
	Private	0.04	0.07	0.06	-0.59	-0.05
	Total	0.05	0.07	0.06	-0.61	-0.05
Income	Business	-0.59	-1.57	6.48	1.50	2.15
	Private	0.25	0.34	0.42	0.35	0.29
	Total	0.11	0.13	3.85	0.60	0.72

The fuel price elasticity on car travel is low, around -0.14, and very similar to what is reported by Rohr et al. For all car trips, of which the vast majority is regional trips, many studies have found a long-run fuel price elasticity of around -0.3 (Goodwin et al., 2004; Graham & Glaister, 2004; Dargay, 2010). This is also what is found in Sampers' regional models. Dargay (2010) also finds a lower elasticity for long-distance trips than for regional trips (about -0.2). In summary, the direct elasticities reported in Table 3 are well in line with other studies using cross sectional data.

Cross-elasticities for travel time are consistently higher for car than for rail. This is because a general property of nested logit models is that an improvement of an alternative in a nest will have the same proportional impact on the probability of all other alternatives in the nest, and this impact is proportional to the market share of the improved alternative. Nesting structures with air, rail and coach in the same nest, which would imply higher cross-elasticities between these modes, have been explored but were not supported by the data (Beser Hugosson, 2003).

The income elasticities on car and coach trips are considerably lower than what is typically reported for trip generation Dargay (2010), which can be explained by the fact that these elasticities take into account the possibility to adapt not only by changing trip frequency but also by changing mode or destination. For business trips, coach and car income elasticities are even negative, because at higher income car and coach trips are substituted by air or rail. Interestingly, Dargay (2010) found a similar pattern as found here: lower income elasticity for car and coach than for air and rail.

High Speed Rail Forecast

The Swedish Transport Administration has used the official Sampers long-distance model (referred to as Sampers in the rest of this paper) to forecast the effects of a proposed HSR rail track in the Stockholm-Gothenburg corridor. The thick line on the map in Figure 2 marks HSR track under evaluation (the conventional rail network is depicted with thinner lines). The travel demand has been forecasted in a HSR scenario and in a baseline scenario, the former with the new HSR investment and the latter without. Both scenarios refer to year 2020.

In the baseline scenario the travel time of the X2000 trains is on average 3h 5m and there are 18 return trips a day. In the HSR scenario it is assumed that the travel time decreases to 2h 14m and the frequency increases to 24 double tours a day. The fare is assumed to be equal in both scenarios. There are also some slower conventional trains taking other routes in both scenarios not further discussed here. All trains stop at some intermediate stations, but since the number of people living in these towns is relatively small, we neglect these in this analysis.

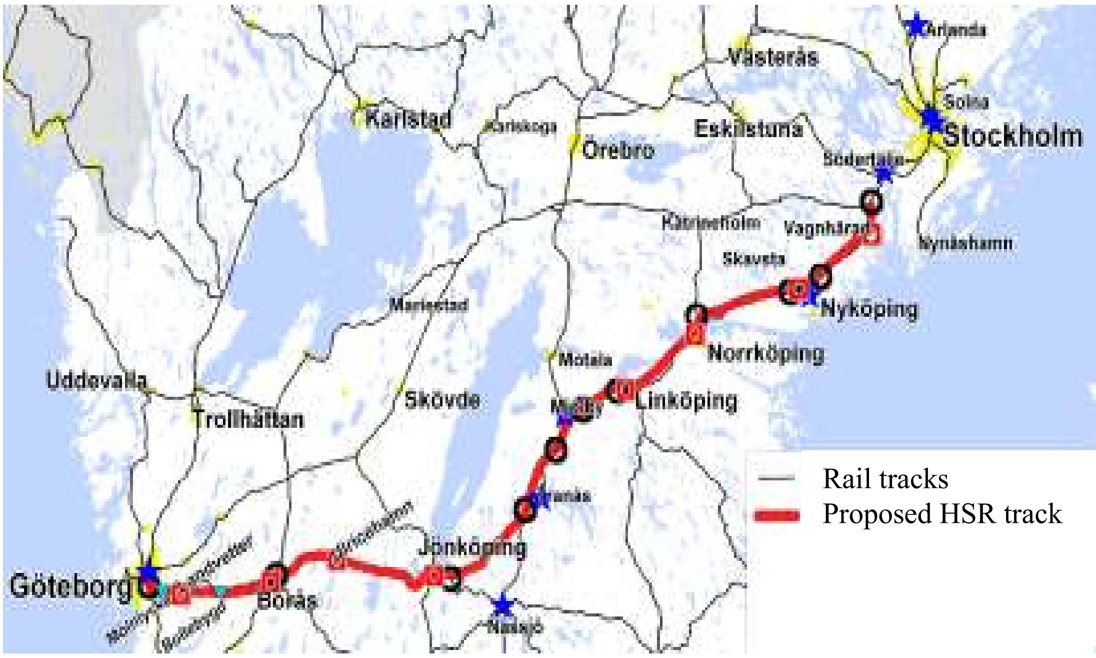

Figure 2: The evaluated HSR rail track in the Stockholm-Gothenburg corridor

Since there are already a type of HSR in the corridor, the travel time gain from a new HSR track is relatively small, 28 percent. Table 4 summarizes the forecasted travel demand and market share in the 2020 baseline scenario and HSR scenario. According to the forecast the number of rail trips would increase by 40 percent or 0.63 million trips per year when the HSR track is introduced, of which 75 percent are newly generated, 16 percent are diverted from air, and 9 percent are diverted from car and almost nothing from coach.

The predicted market share for rail in the HSR scenario is 49 percent for all trips, which is close to the observed market share for rail in the Madrid-Seville corridors (COST318, 1998). Concentrating on the air-rail mode split only, the share of rail trips increases from 65 percent to 75 percent for all trips. For Madrid-Seville and London-Paris (where the HSR travel time is the same and in the Stockholm-Gothenburg case), the market share for rail is higher, about 80 percent.

Table 4: Base line and forecast scenario 2020

	RAIL			**AIR**			**CAR**			**COACH**		
	Priv	Bsn	Tot	Priv	Bsn	Tot	Priv	Bsn	Tot	Priv	Bsn	Tot
Million trips per year												
Baseline	1.13	0.47	1.60	0.33	0.52	0.85	1.30	0.21	1.52	0.10	0.00	0.10
HSR	1.45	0.78	2.23	0.31	0.44	0.75	1.27	0.19	1.46	0.19	0.00	0.19
% change	29	67	40	-4	-16	-12	-3	-10	-4	-3	-11	-3
Market share												
Baseline	0.40	0.39	0.39	0.11	0.43	0.21	0.45	0.18	0.37	0.03	0.00	0.02
HSR	0.46	0.55	0.49	0.10	0.40	0.17	0.40	0.18	0.32	0.03	0.00	0.02

From the numbers in Table 4 we may compute the demand elasticities for the HSR line using the formula (1), where demand D_{m1} and D_{m2} now are taken to be number of rail trips and x_{m1} and x_{m2} are taken to be the rail travel time in the baseline and the HSR scenario. The direct elasticity on number of rail trips is -1.6 for business trips, -0.78 for private trips and -1.0 for all trips. This is similar to the second phase of the opening of the Paris-Lyon HSR line (Nash, 2010), but lower than observed for the first phase of the opening of the Paris-Lyon line, the Madrid-Barcelona HSR line and the Madrid-Seville HSR line. The higher elasticities in the latter cases is likely due to the fact that the share of rail trips was initially much lower than in the Stockholm-Gothenburg case. The corresponding cross-elasticities with respect to air, computed by (2), are 0.14 for private trips, 0.54 for business trips and 0.38 for all trips.

Recently a new long-distance model has been estimated based on the same data and basic model specification as the official Sampers model but applying Box-Cox transformations to the travel time and cost variables (see WSP Analysis & Strategy (2012)) for a detailed description of the estimation). This model is referred to as 'the non-linear model' in the following. The estimation showed clear evidence for non-linearity with Box-Cox parameters less than unity. The non-linear model has also been used to forecast the effects of the Stockholm-Gothenburg HSR track. Surprisingly, the total elasticity resulting from this forecast is only slightly higher than that resulting from the corresponding Sampers forecast: -1.15 (for all trips). The direct elasticity on number of rail trips is -2.1 for business trips, -0.77 for private trips and[4]. Moreover, the average elasticities computed in section 3.4 are similar between the models.

Validation of the forecasts

In this section, the air-rail mode split predicted by the Sampers model and the non-linear model, in response to the introduction of the HSR line, is validated against aggregate data. Specifically a relationship between the difference in generalized travel time between air and rail and the air-rail mode split found in aggregate traffic count data is estimated. The estimated relationship is then compared to the demand model of Sampers and the non-linear model using incremental logit. In the aggregate data all relations connecting Stockholm to another domestic airport are included.

[4] The corresponding cross-elasticities with respect to air are 0.15 for private trips, 0.71 for business trips and 0.34 for all trips.

Aggregate data

The function describing the generalized travel time differences between air and rail in the aggregate data is denoted ΔGTT. This ΔGTT includes the components in-vehicle travel time, access/egress time including an estimate of check-in, security, service, baggage delivery at the airports, first wait time and number of transfers. All travel time components are translated to the equivalent in-vehicle time using the relative weights of the national guidelines for cost-benefit valuations[5]. The difference in fare is not included explicitly in this function, but picked up by the constant, because the difference in average air and rail fare is relatively constant across trip relations[6]. Rail is, however, on average cheaper but slower than air, implying that the market share for air is higher for business trips than for the more price-sensitive private trips. For this reason, business trips and private trips are analyzed separately. Aggregate traffic volumes for 2007 were obtained from the rail operators and Swedavia Swedish Airports.

Estimation result

A relationship between ΔGTT and air-rail mode split was estimated on the aggregated data by applying exponential regression. The reason for choosing an exponential function (truncated at 100 percent), as opposed to a logit model, is that it reaches 100 percent and can therefore pick up the effect that air service reduces or vanishes in travel relations where rail becomes very competitive. The estimated exponential functions for private and business trips are plotted as continuous lines in Figure 3 and Figure 4 ('Exponential model' in the figures). The parameters of the exponential function are shown in Table 5. The aggregated trip volumes used in the estimation of the exponential function are marked by dots in the same figures[7].

Table 5: Exponential models explaining how air-rail mode split depends on difference in generalized travel time.

	Business trips			Private trips		
Nr. Obs.		23			23	
R-squared:		0.849			0.877	
	Estimate	Std. Error	T-value	Estimate	Std. Error	T-value
Intercept	-0.129	0.034679	-3.732	-0.6837	0.0572	-11.96
ΔGK	-0.003	0.000255	-10.884	-0.0069	0.00056	-12.33

The figures also include the Sampers demand functions applied as an incremental logit model ('Incremental logit Sampers' in the figures). The incremental model is calibrated based on the present rail-air split in the Stockholm-Gothenburg corridor and the corresponding difference in generalized travel time ΔGTT_{SG} (given in minutes of rail in-vehicle time). The share of rail trips is denoted R_{SG}, and equals 0.29 for business trips and 0.73 for private trips ('Stockholm-Gothenburg Base scenario' in the figures) according to the aggregate trips volumes[8]. ΔGTT_{SG} is 47 minutes for business trips and 48 minutes for

[5] A detailed description of the computation of ΔGTT is available on request from the author.

[6] Average domestic flight ticket price is almost independent of the trip distance. Average rail fares are more strongly related to the trip distance but the impact is limited. For instance, the price of a normal ticket Stockholm - Malmo is less than twice the price Stockholm - Linkoping, although the distance is three times as long.

[7] Traffic counts are available on request from the author.

[8] Note that this air-rail split does not correspond exactly to the Sampers forecast in Table 4, partly because Sampers is not calibrated perfectly and because Table 4 refers to a forecast for 2020.

private trips. The share of rail trips (of the total number of air and rail trips) in a relation is then predicted by the incremental logit function:

$$R(\Delta GTT) = \frac{P_{rail}}{P_{rail}+P_{air}} = \frac{R_{SG}exp(\beta(\Delta GTT-\Delta GTT_{SG}))}{(1-R_{SG})+R_{SG}exp(\beta(\Delta GTT-\Delta GTT_{SG}))},$$

where P_{rail} and P_{air} are the market share for rail and air and β is the parameter corresponding to in-vehicle time for one-day trips in Sampers. The incremental non-linear models are plotted in the same figures ('Incremental non-linear model'). Note, however, that for private trips the Sampers and the non-linear model do not include identical trips (the latter includes commuting trips in a separate model), so the non-linear model just serves as an illustration in this case. The figures also depict the air-rail mode split of the linear Sampers forecast ('HRS scenario'), assuming that the rail travel time decreases by 51 minutes (in-vehicle travel time decreases from 3h 5m to 2h 14m). This would imply that ΔGTT_{SG} become -4 minutes for business trips and -3 minutes for private trips.

Figure 3 suggests that the Sampers model for business trips has a rather good model fit, as long as the share of rail trips is less than 60 percent. Above this point the curve fit is rather poor. As pointed out by Gaudry (2008), this is a typical problem with the linear-in parameters logit model because the response curve is forced to be symmetric around the inflexion point at 0.5. The curve fit, compared to the 'Exponential model', for the non-linear model is better. For the part of the response curve relevant for this particular forecast, however, the slope of the Sampers and the non-linear response curves is similar, explaining why the forecasts with these models are similar (see section 4).

Figure 4 shows that for private trips the fit of Sampers' response curve, compared to the 'Exponential model', is not as good as for the business model, in particular for high market shares. Again, the non-linear model does considerable better, in particular for high market shares for rail. This curve should, however, not be compared to the Sampers curve in detail since the models do not include identical trips. The forecasts of the two models are similar also for private trips (see section 4).

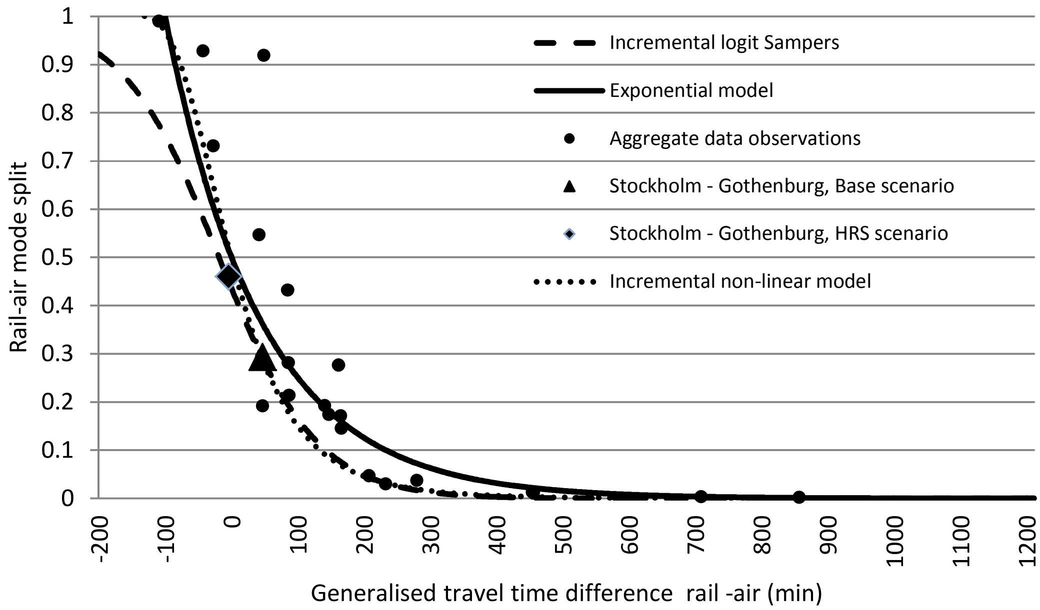

Figure 3: Share for rail travel, R, as function of generalized travel time difference between air and rail, ΔGTT, business trips.

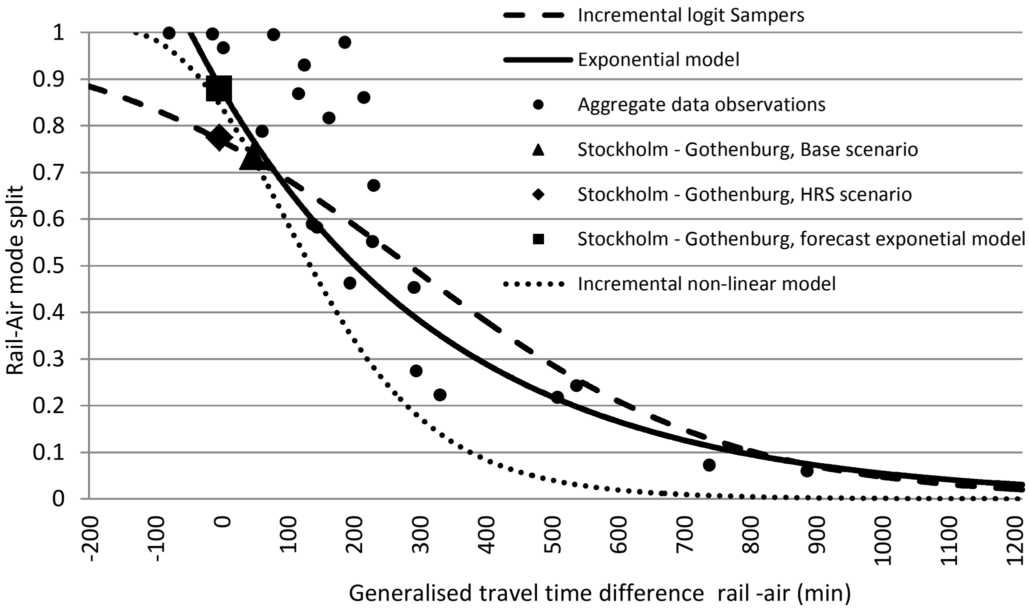

Figure 4: Share for rail travel, R, as function of generalized travel time difference between air and rail, ΔGTT, private trips.

According to this forecast the market share for rail increases from 29 percent to 46 percent for business trips and from 73 percent to 78 percent for private trips when the HRS line is introduced[9]. According to the exponential model, the market share for rail would be similar for business trips by higher, 88 percent, for private trips. Assuming that the direct elasticity is about right in Sampers this implies that the linear forecast model underpredict the reduction of air travel by 176 000 air trips per year (which is about 16 percent of the total current number of air trips). An important point to make here is that the incremental logit does not take into account the effect that the frequency of air service decreases when rail becomes more competitive. Taking this into account in a second step is, however, not the main reason for the underprediction.

Using the relative number of business and private trips for Stockholm-Gothenburg, the effect on the total air-rail splits can be computed[10]. According to the exponential model, the rail share increases from 55 to 71 percent and according to the linear incremental Sampers model the rail share increases from 55 to 67 percent. Hence, the exponential curve suggests that the total air-rail split is underestimated by four percentage points in the forecast. Even a 71 percent market share for rail is lower than for Madrid-Seville and London-Paris, with about the same rail travel time. The higher share for air could be due to the fact that the small airport located within the City of Stockholm is very

[9] This corresponds well to the increase from 78 percent to 82 percent for private trips and from 47 percent to 64 percent for business trips, as predicted by the forecast carried out with the differently calibrated Sampers model for 2020, described in Section four. The modal splits presented in this section are consistent with, and could have been derived from the elasticities and cross-elasticities computed from the full but differently calibrated Sampers forecasts in Section four.

[10] Business rail 304.039 trips; Business air 733.622 trips; Private rail 1.078.653; Private air 389.750 trips.

competitive, with high accessibility and fast check-in, security, service and baggage delivery[11].

Conclusion

It is often questioned whether state-of-practice forecasting models can predict the demand for HSR. The purpose of the present paper is to investigate this issue by reviewing elasticities from long-distance models in the literature and compare these with elasticities observed when new HSR lines have opened. This paper also validates the official Swedish state-of practice model (Sampers) and a new non-linear long-distance model applying box-cox transformations with aggregate Swedish data on air-rail mode split in different relations.

The elasticities of long-distance models estimated on cross-sectional data in the literature tend to be lower than the elasticities observed when the HSR lines in Madrid-Barcelona, Madrid-Seville and the first phase of the Paris-Lyon HSR line were opened. The high observed elasticities are, however, likely a result of very long initial rail travel times, in particular in the Spanish corridors.

The direct travel time elasticities implied by Sampers are well in line with or above those reported from other studies based on cross-sectional data. A similar UK model produces average elasticities in the same range. The non-linear model produces, as expected, even slightly higher elasticities than linear-in-parameters Sampers. The direct elasticity of in-vehicle travel time on travel demand in response to a proposed HSR line in the Stockholm–Gothenburg corridor is -1.0 in the Sampers model and -1.15 with the non-linear model, which is similar to the second phase of the opening of the Paris-Lyon HSR line (Nash, 2010). This is a relevant comparison, since the rail alternative is rather good also without a new HSR investment in this corridor, which indicates that at least the Swedish models predict credible elasticities.

The air-rail split of the HSR corridor Stockholm-Gothenburg predicted by Sampers and the non-linear model is relatively consistent with the aggregate data for business trips. The model fit in comparison to aggregate data is in general slightly better for the non-linear model than for the Sampers model, in particular for relations with high share of rail trips. Still, the demand forecasts for the proposed HSR line in the Stockholm–Gothenburg corridor are similar for Sampers and the non-linear model.

The Sampers model seems to underpredict the elasticities for private trips, in particular for high market shares. This is likely an effect of too low cross-elasticity of air demand to rail travel time, since the direct elasticities are consistent with earlier experiences and since cross-elasticities are more difficult to model. The model fit in comparison to aggregate data is seems, however, to be better for the non-linear model also for private trips, in particular for relations with high share of rail trips.

In general the problems of forecasting such shifts in technology that HSR represents do not seem to be large, because the variability of travel time in the

[11] Another reason may be that many travelers feel see-sick on rail. In an interview among domestic air passengers 45 percent state that they at least sometimes feel sick on X2000 and 11 percent state that this affect their mode choices (WSP Analysis & Strategy, 2012).

cross-sectional data is much larger than the shift due to HSR. If travelers view HSR as a completely new travel mode, and not just as a fast train, the demand effect is more unpredictable. There are, however, not any evidences suggesting that this is the case. It would be interesting to apply these models to a recently opened HSR line elsewhere to verify this.

References

Armoogum, J., & Madre, J. (1997). *Accuracy of data and memory effects in home based surveys oftravel behaviour*. 76th Annual Meeting of the Transportation Research Board, Washington, D.C.

Atkins. (2003). *Stated preference and revealed preference surveys, Milestone 6 of High Speed Line Study for Strategic Rail Authority* (Unpublished).

Axhausen, K., Köll, H., Bader, M., & Herry, M. (1997). Workload, response rate and data yield: experiments with long-distance diaries. *Transportation Research Record: Journal of the Transportation Research Board*, (1593), 29-40.

Ben-Akiva, M., Cascetta, E., Coppola, P., Papola, A., & Velardi, V. (2010). High speed rail demand forecasting n a cometetive market: the Italian case study. *Unpublished*.

Beser Hugosson, M. (2003). *Issues in Estimation and Application of Long Distance Travel Demand Models*. Stockholm: Division for Transport and location analysis, Royal institute for Technology. Retrieved from http://kth.diva-portal.org/smash/record.jsf?searchId=1&pid=diva2:9360

Beser, M., & Algers, S. (2002). SAMPERS - The New Swedish National Travel Demand Forecasting Tool. *In: Lundqvist, L., Mattsson, L.-G. (Eds.), National transport models: recent developments and prospects*. Springer.

Biogeme. (n.d.). Retrieved June 15, 2011, from http://biogeme.epfl.ch/

Börjesson, M. (2010). Valuating perceived insecurity associated with use of and access to public transport. *Proceeding from the European Transport Conference, Glasgow*.

Börjesson, M., & Eliasson, J. (2011). *Experiences from the Swedish Value of Time study*. CTS Working Paper. Centre for Transport Studies, Royal Institute of Technology.

Cabanne, I. (2003). A long term model for long distance travel in France. *Proceeding from the European Transport Conference, Strasbourg*.

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

COST318. (1998). Interaction between High Speed Rail and Air Passenger Transport. *European Commission: Directorate General of Transport*.

Dargay, J. (2010). *The prospects for longer distance domestic coach, rail, air and car travel in Britain* (Unpublished). Report to the independent transport commission.: Institute for Transport Studies. Faculty of Environment Study for Strategic Rail Authority.

de Bok, M., Costa, Á., Melo, S., Palma, V., & Frias, R. D. . (2010). Estimation of a mode choice model for long distance travel in Portugal. *Proceedings from Word Conference of Transport Research, Lisbon*.

Dillén, J., & Algers, S. (1998). Further research on the national Swedish value of time study. *Selected Proceedings of the 8th World Conference on Transport Research*, *3*, 135–148.

European Commission. (2010). *White paper – "European transport policy for 2010: time to decide"* (White Paper). Brussels.

Eurostar. (2011). Eurostar contributes to rail renaissance as UK domestic passenger numbers hit highest level since 1920s. Retrieved December 1, 2011, from http://www.eurostar.com/UK/uk/leisure/about_eurostar/press_release/20110131_eurostar_contributes_to_rail_renaissance.jsp

Flyvbjerg, B., Holm, M. K. ., & Buhl, S. L. (2005). How (in) accurate are demand forecasts in public works projects? *Journal of the American Planning Association*, *71*(2), 131–146.

Gaudry, M. (2008). Non linear logit modelling developments and high speed rail profitability. *Agora Jules Dupuit, Publication AJD-127, www. e-ajd. org*.

Goodwin, P., Dargay, J., & Hanly, M. (2004). Elasticities of road traffic and fuel consumption with respect to price and income: a review. *Transport Reviews*, *24*(3), 275–292.

Graham, D., & Glaister, S. (2004). Road traffic demand elasticity estimates: a review. *Transport Reviews*, *24*(3), 261–274.

Jansson, K., & Nelldal, B. . (2010). High-speed trains in Sweden – a good idea? *Proceedings of the 12th World Conference on Transport Research Society, ID 02762*.

Nash, C. (2010). When to Invest in High-Speed Rail Links and Networks? *The Future for Interurban Passenger Transport: Bringing Citizens Closer Together*, 125.

Outwater, M. L., Tierney, K., Bradley, M., Sall, E., Kuppam, A., & Modugula, V. (2010). California Statewide Model for High-Speed Rail. *Journal of Choice Modelling*, *3*(1), 58–83.

Rohr, C., Fox, J., Daly, A, Patruni, B, Patil, S, & Tsang, F. (2010). Modelling long-distance travel in the UK. *Proceeding from the European Transport Conference, Glasgow*.

Román, C., Espino, R., & Martín, J. C. (2007). Competition of high-speed train with air transport: The case of Madrid-Barcelona. *Journal of Air Transport Management*, *13*(5), 277-284. doi:16/j.jairtraman.2007.04.009

Sánchez-Borràs, M. (2010). *High-speed rail in Spain*. Presented at the 1st TEMPO Conference on Sustainable Transport,, Oslo, Norway, 18-19 May 2010.

Sánchez-Borràs, M., Nash, C., Abrantes, P., & López-Pita, A. (2010). Rail access charges and the competitiveness of high speed trains. *Transport Policy*, *17*(2), 102-109. doi:10.1016/j.tranpol.2009.12.001

Transek AB. (2004). *Technical report of Sampers*.

Wardman, M. (2004). Public transport values of time. *Transport Policy*, *11*(4), 363-377. doi:10.1016/j.tranpol.2004.05.001

Vickerman, R. (1997). High-speed rail in Europe: experience and issues for future development. *The Annals of Regional Science*, *31*(1), 21-38. doi:10.1007/s001680050037

WSP Analysis & Strategy. (2012). *Höghastighetståg Del 2 – modellutveckling och känslighetsanalyser*.