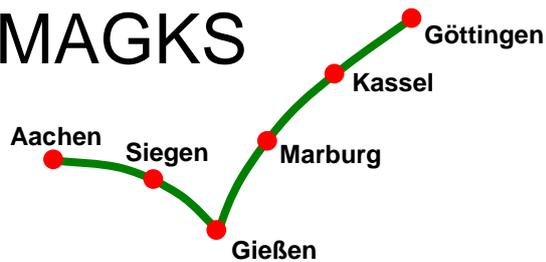


MAGKS



**Joint Discussion Paper
Series in Economics**

by the Universities of
Aachen · Gießen · Göttingen
Kassel · Marburg · Siegen

ISSN 1867-3678

No. 37-2011

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Commercial Passenger Rail Transport**

This paper can be downloaded from
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Customer Choice Patterns in Passenger Rail Competition

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Abstract

This study explores determinants of customer choice behaviour in passenger rail competition on two cross-border routes, Cologne-Brussels and Cologne-Amsterdam. It fills a gap in the literature on competition in commercial passenger rail by relying on newly collected stated preference data from about 700 on-train interviews. Our multinomial Logit regressions reveal two important effects that are closely connected to (psychological) switching costs. First, the customers on the route Cologne-Amsterdam, for whom competition is a purely hypothetical situation, value a competitive market structure lower than customers on the already competitive route Cologne-Brussels. Second, travellers show a status quo bias with a preference for the service provider on whose trains they were interviewed. This effect goes beyond the impact exercised by explanatory variables capturing the observable differences of the services and customers, including loyalty-enhancing effects like the possession of customer cards. Our results imply that entry into the commercial passenger rail market may be more difficult than often thought. Thus, the study contributes to explaining the low level of competition in these markets in Europe.

Keywords: Competition, Passenger, Rail, Transport, Discrete Choice, Multinomial Logit

JEL Codes: C25, D12, D40, L92

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1 Introduction

In the light of the ongoing liberalisation of the commercial passenger rail markets in Europe this study explores the determinants of customer choice behaviour in commercial passenger rail markets on two cross-border routes, Cologne-Brussels and Cologne-Amsterdam. Several national rail markets have been opened to on-track competition since the 1990ies including Germany, the UK, Austria, Italy and Sweden. In 2010 international services within Europe were also liberalised and the EU Commission has announced a proposal in 2012 for full market opening. Despite this *de facto* openness of a number of commercial passenger rail markets there has yet been only little entry.

Our research provides demand-induced reasons for the observed difficulties in establishing competition in these markets. Therefore, we add to the literature on entry and competition in commercial passenger rail markets (see for example Preston et al., 1999; Preston, 2009; Steer Davis Gleave, 2004; Ivaldi and Vibes, 2008; Friederiszick et al., 2009). These theoretical and empirical studies suggest that intramodal competition is feasible to a limited extent only. This is because some characteristics of the market complicate entry, for example strong economies of density, potential economies of scale, network effects and vehicle investments with a high risk of sunk costs.

The existing studies usually model demand for rail transportation as a function of major mode choice determinants such as price, travel time, frequency and certain quality indicators. Our study contributes to the literature on the demand for passenger rail services by empirically identifying switching costs (Klemperer 1995) and a status quo bias (Samuelson and Zeckhauser 1995) in passengers' choices among different intramodal service operators. Switching costs have, for example, been studied for airlines, credit cards, cigarettes, supermarkets, phone and electricity services (see Farrell and Klemperer 2007: 1981 for an overview) but have not been researched for the passenger rail market, yet. This was mainly due to a lack of empirical information on the choice determinants of rail customers.

Our analysis of customer preferences in intramodal competition is based on 700 interviews with passenger rail customers on two international routes. We choose Cologne-Brussels as the only route in Europe with significant and established on-track competition and Cologne-Amsterdam as a reference case with a cooperative service. In the main part of the interviews passengers on these routes were asked to state their preferences for three service alternatives by bringing these alternatives into a rank order. The alternatives comprise services offered by an entrant, an incumbent or a cooperation among the two firms. The latter represents the status quo of international rail services in Europe. The in total 21 scenarios differ in the prices of the three alternatives. In addition, we collected information on the socio-economic characteristics of the travellers and on the reasons and characteristics of their journeys.

We econometrically analyse and compare the preferences of travellers on the competitive route (Cologne-Brussels) and the cooperative route (Cologne-Amsterdam). This is done by estimating a multinomial Logit discrete choice model for both markets as it has become standard in transport modelling (see, for example, Louviere et al., 2000). In line with Oum (1990) we for example identify travel purpose, travel class and prices as main influencing factors for rail customers' choice between different rail services. With regard to switching costs, which we specifically aim to identify, we for example confirm strong influences of customer cards for the passenger rail market.

Based on these regressions we determine the mode choice probabilities of the respondents, i.e. their likeliness of choosing the service of the entrant, the incumbent, or a cooperation of the two. The estimated probabilities enable us to compare the preferences on the route with established competition to those on the route served in cooperation. Moreover, we compare customers' preferences for the hypothetical entrant RailX on the route Cologne-Amsterdam to those for the well-known entrant Deutsche Bahn on the route Cologne-Brussels. These comparisons suggest that travellers are subject to a status quo bias in favour of the better known company (see for example Hensher, 2009) and/or the better known market structure which goes beyond the impact exercised by the explanatory variables considered in the regressions. These include price, the possession of loyalty cards, being a frequent traveller or being offered a connection without the need to switch trains.

The dataset presented in this paper and the econometric analysis more than complement prior research. By highlighting the importance of switching costs and psychological factors of travel choice which can lead to a status quo bias we provide a novel view on competition in commercial passenger rail transport. These effects are likely to impact both the view on the market potential of entrants as well as the welfare consequences of competition in these markets.

These points are illustrated in greater detail below. Section 2 reviews the related literature. The survey design and the data collected are presented in section 3. In section 4, we specify a function for the utility that travellers receive from consuming rail transportation services and estimate the parameters of this function from the data collected. Based on the regression results, we calculate choice probabilities for the cooperation and the entrant and discuss the effects of switching costs in section 5. Section 6 concludes.

2 Related Literature

In this section, we show how our paper relates to existing literature on commercial passenger rail transport. Moreover, we give an overview on relevant (psychologically motivated) effects that arise when customers choose between competing products.

2.1 Competition in Commercial Passenger Rail Transport

A comprehensive study on passenger rail competition was carried out by Preston et al. (1999) who perform a simulation-analysis on the potential for on-track competition in the UK passenger rail industry and its welfare effects. They focus on the intramodal effects, but take intermodal shifts into account. On the demand side they use stated and revealed preference data obtained from a survey which looks at customer choices of preferred departure times, ticket types, class and mode of travel on a specific UK route. The analysed scenarios vary in the price levels of entrant and incumbent and in the interavailability of tickets. They find that a few entry scenarios could be attractive, e.g. cream-skimming and niche entry through product differentiation, but also conclude “that on-track competition can increase benefits to users but usually reduces welfare because of greater reductions in producer surpluses” (Preston et al., 1999: 92).

The same model is used for a simulation of competition in the Swedish market (see Preston, 2009), in which a major difference are the lower track access charges. For Sweden the model indicates that head-on competition could also be commercially feasible on the important intercity routes. Steer Davis Gleave (2004) use a similar approach to model the effects of intramodal competition on two international high-speed routes and to assess the overall impact of competition in European high speed rail. Based on the model results, on case studies and stakeholder views they see potential for competition in international passenger rail services with cabotage.

Ivaldi and Vibes (2008) use a game theoretic simulation model to analyse intramodal and intermodal (rail, road, and air) competition. On the demand side, this model is based on discrete choice theory. In section 4 below, we present a similar, non-nested (i.e. for intramodal competition only) demand model. On the supply-side, firms are assumed to compete in prices á la Bertrand. Due to the lack of sufficient data, Ivaldi and Vibes (2008) do not *estimate* their model but instead *calibrate* it to the link Cologne-Berlin in Germany. Based on this calibrated model they evaluate the effect of structural and regulatory changes. For intramodal competition they conclude that low-cost entry could be viable and beneficial to consumers.

Friederiszick et al. (2009), on the one hand, look at intermodal competition between air and rail travel. On the other hand, they analyse intramodal competition in a separate approach. In the latter analysis they explore the entry potential on 207 national and international routes starting or

ending in Germany. Based on a profitability analysis for the routes they conclude that entry could be attractive on intercity routes. However, they do not consider strategic interactions between entrant and incumbent and do not take intermodal shifts into account.

To the best of our knowledge, none of the studies on competition in passenger rail transport so far looked at the impact of switching costs or psychological effects on the choice between several rail service providers. This would partly be due to the lack of empirical data, as there are only few examples of on track passenger rail competition in Europe and information would usually be confidential.

2.2 Customer Choice Behaviour for Competing Products

The impact of switching costs on competition has largely been discussed for other industries, for example, by Farrell and Klemperer (2007) and by Klemperer (1995). Seabright et al. (2003: 60) point out for the passenger rail sector, that “switching costs (natural or strategic) should be a strong limitation to competition”. For industries with network effects and/or substantial economies of scale, which are both typical for the rail industry, Farrell and Shapiro (1988) and Farrell and Klemperer (2007) discuss, that incumbent firms may prevent entry into the market if switching costs exist.

Switching costs are defined by Klemperer (1995) as costs that a consumer incurs from switching to a competitor’s product even when the products of the two firms are functionally equal. He identifies several types of costs potentially involved with switching service providers, i.e. need for compatibility with existing equipment/services, transaction costs to switch suppliers, costs of learning to use new brands, uncertainty about the quality of untested brands, effects of discount coupons and similar devices and non-economic brand-loyalty. In the passenger transport sector, switching costs have mainly been analysed for airline competition. Studies usually include the impact of customer loyalty programmes and brand-loyalty (see for example Carlsson and Löfgren, 2006; Chen and Chang, 2008) and identify substantial impacts of switching costs.

Behavioural economics can give further explanations for customer preferences under competition. Samuelson and Zeckhauser (1988) propose that consumers are disproportionately likely to stick with the status quo. They explain the “status quo bias” with rational decision making in the presence of transaction cost and/or uncertainty, with cognitive misperceptions and psychological commitment. Samuelson and Zeckhauser (1988: 10) suggest that the “individual may retain the status quo out of convenience, habit or inertia, policy (company or government) or custom, because of fear or innate conservatism, or through simple rationalization.”

The status quo effect thus describes the general effect of preferring the actual/known product. It includes the above described effects of switching costs. Such an effect is well known to

stated preference analysis in the transport sector. It is often discussed as “inertia” effect and strongly explained by habitual behaviour (see e.g. Goodwin, 1977, for a discussion of habitual choice and Train, 2009).

In our stated preference experiment we expect that a status quo bias would lead to an especially high preference for the rail service operator chosen at the time of the interview as similarly proposed by Cantillo et al. (2007). They also point out that such behaviour could prevail after a change in circumstances, as a change might involve costs, both objective and psychological. Thus, we expect to find a status quo bias also on the route with established competition.

3 The Data

3.1 Study Design and Data

In this section, we provide information on the study design and the data collected. The data set consists of stated and revealed preference data as well as socio-demographic information of almost 700 passengers on trains of Deutsche Bahn and Thalys on the two international routes Cologne-Brussels and Cologne-Amsterdam. The passenger-interviews were conducted by students of the International School of Management in Frankfurt/Main during a two week period in May 2010.

The routes Cologne-Brussels and Cologne-Amsterdam were chosen because they share the characteristics of being international routes with a similar distance and a similar mix of customers, e.g. business and leisure travellers. The main difference of the two routes is the fact that rail customers on the Brussels-route already experience competition between Thalys and Deutsche Bahn. In contrast, on the Amsterdam-route passenger rail services are provided by Deutsche Bahn and Dutch Railways (NS) in cooperation. This allows us to study the effect of experience with competition on the preferences of the interviewees.

At the time of the interview, competition between Thalys and Deutsche Bahn takes the following form: Customers face two generally separate information and sales systems², independent pricing systems and different customer retention programs. In case of delay, customers cannot easily access a train of the other company. Coordination only occurs in some areas such as schedule planning.

The market survey consisted of two parts:

² Only the DB sales systems inform about Thalys trains and partly sell tickets, but not vice versa. Some information on DB trains can also be found on the distribution platforms of SNCF (www.tgv-europe) and SNCB (www.b-europe.com). However, this might only include a selection of destinations in Germany and does not cover discount tickets of DB.

- (1) We collected data on the socio-demographic characteristics of the customers as well as characteristics of their journey and ticket at the time of the interview.
- (2) We collected stated preference data on the preferences of the interviewees in 21 scenarios of intramodal competition between an entrant and an incumbent.

The socio-demographic and general travel characteristics of the customers include gender, age, and travel frequency on this route during the last 12 months as well as the possession of a discount/loyalty card. Other characteristics are related to the specific journey of the decision maker. These are the purpose of the journey, the class chosen, the distribution channel and the country where the ticket was bought. An overview on the definitions of these variables is provided in the Appendix.

In the second part of the interview, the rail passengers were asked to rank – i.e. to make a discrete choice – three types of train-service on the respective route for different combinations of prices (see Figure 1 for a sample-page from the questionnaire). The $J = 3$ alternatives in the choice set of traveller n are:

- (1) Service provided by an entrant in a situation with competition
- (2) Service provided by an incumbent in a situation with competition
- (3) Integrated service provided in cooperation by the two railways

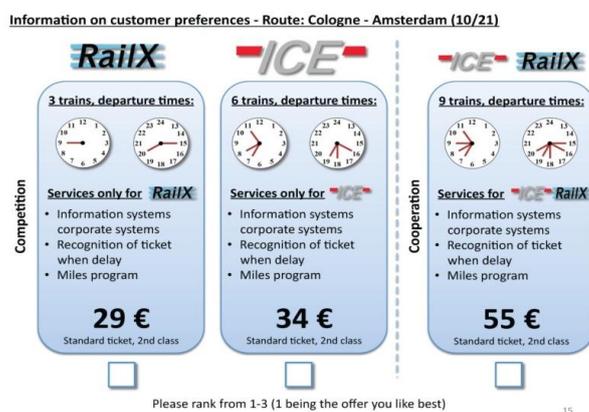


Figure 1: Example of stated choice scenarios

The interviewees on both routes were given the information that the difference between cooperative and competitive services lies in integrated or separate (i) information and sales systems, (ii) ticket acceptance in case of train disturbances, and (iii) bonus programs. On the Brussels-route, Thalys is the incumbent and DB the entrant. On the Amsterdam-route, DB is presented as the incumbent and a hypothetical firm RailX as the entrant. Hence, competition on the route Cologne-Amsterdam constitutes a hypothetical situation. On both routes the incumbent is assumed to provide a higher number of services than the entrant (6 vs. 3 train pairs per day). This depicts the

situation with Thalys and Deutsche Bahn on the Brussels-Cologne itinerary for the train schedule in 2010. The number of integrated services by the cooperation equals the sum of services of entrant and incumbent, i.e. there is no change in the total number of services between cooperation and competition.

The alternative “cooperation” in the SP experiment represents the way international services have been organised before market liberalisation. And it still is the predominant organisational form of cross-border services in Europe. The railways involved usually cooperate and provide a joint monopoly service. For the competitive alternatives we assume a specific situation with infrastructure bottlenecks impeding an increase in frequency. Entry would only be possible if the entrant replaces the services of the incumbent. This is a probable situation on many national and international connections in Europe due to infrastructure bottlenecks on links or in nodes. We also use the fixed total number of services to simplify identifying how customers value the potential drawbacks presented from competition (e.g. disintegration of services on the marketing and sales side) compared to cooperation. In many cases, however, on-track competition would lead to benefits with regard to higher frequency and other service improvements which we do not consider here.

In the stated preference scenarios, the price of the incumbent (p_i) and that of the entrant (p_e) takes one of six values in the interval between the regular price for a second class-trip on each route and the lowest price for special offers. On the Brussels route prices are chosen from {19, 24, 29, 34, 39, 45}. On the Amsterdam route prices are chosen from {19, 29, 34, 39, 45, 55}. The cooperative price (p_c) is kept constant at the value of the second class regular price charged at the time of the survey: 45 Euro for Cologne-Brussels and 55 Euro for Cologne-Amsterdam. The scenarios assume that the incumbent does not charge a price below that of the entrant, which defines 21 scenarios in total.

3.2 Data Quality

How well is real market behaviour captured by stated preference data? Bates (1998) and Wildert (1998) discuss some issues with regard to data quality of stated preference experiments that can be summarised by the following two questions: How well does the scenario setting relate to the interviewees’ actual decisions (design of the study)? How was the attitude towards answering the questionnaire (inclination to respond)? We analyse these two questions in turn.

Regarding the design of the questionnaires used in our study, we chose a form that closely resembles the concrete situation that customers face when making their travel decisions. After deciding to travel by rail, customers would search for train departure times and compare the prices of the (hypothetical) rail companies operating on the desired route either competitively or

cooperatively as is reflected in our questionnaires. We deliberately did not choose a two level approach in which the customers would, first, have been asked if they prefer competition or cooperation and, second, would have had to decide between entrant and incumbent in a competitive situation. We decided against this approach as the decision between cooperation and competition is quite abstract and, thus, might have lowered the quality of the answers and increased a hypothetical bias.

Concerning interviewees' inclination to respond, the number of 21 scenarios must not be considered too extensive for our stated preference analysis. Louviere and Hensher (2001: 129) point out: "There is little agreement on what "complicated" or "lengthy" means and little empirical evidence to support this conventional wisdom". We decided to use 21 scenarios because the complexity of our study is low, as only one attribute (price) changes. Additionally, pre-tests showed that the questionnaires could be answered in reasonable time. On average it took respondents 15 to 20 minutes to answer the questionnaire.

With idle time during their train journey, the travellers were positively inclined to answering the questions. Only in a very few cases, we observe effects such as weariness that might have affected their answers. As such effects are unsystematic they may be expected to only raise the variance of the error term in our regressions below. As a result, the economically plausible effects might not be found to be statistically significant. Since the number of observations in our regressions is large and the number of possibly impaired observations is small, we do not find any indication of an effect on statistical significance.

4 Empirical Analysis

In the following, we present the design and the results of our empirical analysis of the above data. In particular, we analyse the process of decision making of the interviewed passengers by performing multinomial logit regressions for discrete choices. These are based on the assumption that the interviewed passengers ranked the three alternatives – i.e. *rival*, *Deutsche Bahn*, or *cooperation* – according to their utility function. The alternative that yields the interviewee the highest utility receives rank 1 and is assumed to be the respondent's observed choice in a real-world situation. In section 4.1, we present the utility function. Section 4.2 presents the regression results for this utility function and draws economic inferences from this regression.³

³ A more technical description of discrete choice models and the regression tables is presented in Appendix O

4.1 The Utility-Function

We assume that decision maker n obtains utility U_{nj} from alternative j . $j=1$ applies if the decision maker chooses the *rival* of Deutsche Bahn, i.e. Thalys on the Brussels-route and RailX on the Amsterdam-route. $j=2$ applies when choosing *Deutsche Bahn* service, and $j=3$ applies for the *cooperation* offer. Based on this *unobservable* utility function an interviewed passenger makes his/her *observable* ranking-decision and chooses alternative j if $U_{nj} > U_{ni} \forall j \neq i$.

The basic idea of discrete choice modelling is to infer information about the interviewees' unobservable decision making process by analysing their observable choices. This is done by specifying utility U_{nj} as a function that relates the three above alternatives to observable attributes of the alternatives and of the decision maker. The economic reasoning for including certain attributes, labelled $x_{nj} \forall j$, is explained further below. They enter utility function (0) in form of the column-vector \mathbf{x}_{nj} .

$$U_{nj} = \boldsymbol{\beta}_j' \mathbf{x}_{nj} + \varepsilon_{nj} \quad (0)$$

Given the assumption that the error term ε_{nj} is independently, identically distributed extreme value one can calculate the probability of a particular decision maker to prefer either of the alternatives j to the others. The column-vector of coefficients $\boldsymbol{\beta}_j$ is estimated as the set of parameters that maximises the likelihood to observe the decision makers' choices as stated in the interviews. We assume a utility function that applies to all customer groups. Therefore, $\boldsymbol{\beta}_j$ is not indexed by n . Note that econometrically estimating this utility function does not mean to cardinally measure utility, which would be at odds with utility theory. Rather, the estimated function is a means of predicting the probability that a certain type of customer would choose one of the alternatives j . The specification of the utility-function in non-matrix form looks as follows.

$$\begin{aligned}
 U_{nj} = & \beta_{j,1} & + \beta_{j,2} \cdot D_{\text{class}=1} & + \beta_{j,3} \cdot D_{\text{business}} & + \beta_{j,4} \cdot D_{25} \\
 & & + \beta_{j,5} \cdot D_{6+} & + \beta_{j,6} \cdot D_{\text{DB}} & + \beta_{j,7} \cdot D_{\text{discount}_r} \\
 & & + \beta_{j,8} \cdot D_{\text{direct}} & & \\
 + (p_r/p_c) \cdot & \left[\beta_{j,9} & + \beta_{j,10} \cdot D_{\text{discount}_r} & + \beta_{j,11} \cdot D_{\text{business}} \right. \\
 & + \beta_{j,12} \cdot D_{\text{internet}} & + \beta_{j,13} \cdot D_{\text{direct}} & \left. \right] \\
 + (p_{\text{DB}}/p_c) \cdot & \left[\beta_{j,14} & + \beta_{j,15} \cdot D_{\text{DB}25} & + \beta_{j,16} \cdot D_{\text{DB}50} \right. \\
 & + \beta_{j,17} \cdot D_{\text{DB}100} & + \beta_{j,18} \cdot D_{\text{business}} & + \beta_{j,19} \cdot D_{\text{internet}} \\
 & + \beta_{j,20} \cdot D_{\text{direct}} & & \left. \right] \\
 & + \varepsilon_{nj}
 \end{aligned} \quad (0)$$

We include a constant associated with coefficient $\beta_{j,1}$. This constant ensures that the unobserved part of utility ε_{nj} has zero mean by construction. $\beta_{j,1}$ measures the overall likeliness of a group of passengers of preferring the *rival* ($\beta_{1,1}>0$) or *Deutsche Bahn* ($\beta_{2,1}>0$) to the cooperative offer. Moreover, we include a set of dummy variables to control for the possibility that different groups of passengers differ in their non-price related inclination to choose either of the alternatives. Dummies⁴ are included for the following groups of customers, which sometimes overlap:

- (1) First-class passengers ($D_{\text{class}=1}$)
- (2) Business travellers (D_{business})
- (3) Frequent travellers (D_{25} and D_{6+} , i.e. an interviewee has travelled 2-5 times or at least 6 times on this route over the 12 months prior to the interview)
- (4) Holders of a discount card of Deutsche Bahn (D_{DB}) or its rival (D_{discount_r})
- (5) Travellers who (at the time of the interview) only travel between places on the routes Cologne-Amsterdam or Cologne-Brussels without the need to switch trains (D_{direct})

In section 4.2, we present our hypotheses concerning the signs of the coefficients β and the results of our regressions.

4.2 The Results of the Regression

We estimate the above model by means of multinomial logit-regressions. We only include business and leisure travellers in the regressions, because we expect commuters to have a different utility function in comparison to passengers who only travel occasionally on this route. In our regressions we find some evidence for this effect that is likely to distort our estimates. Therefore, the below results apply to non-commuters only, who account for the vast majority of respondents in our samples (94% on average). The tables of the estimated regressions are provided in Table 1.⁵

Concerning the signs of the coefficients β we present our expectations and the results obtained from the regressions in turn. Our expectations are formulated as either crosschecks or hypotheses. The earlier should be satisfied in order to show the general plausibility of our calculations. The latter are at the focus of our research. Accepting or rejecting these hypotheses helps to better understand the demand characteristics of commercial passenger rail transport.

Hypothesis 1: We expect the coefficient of the dummy variable for first-class passengers ($D_{\text{class}=1}$) to be negative ($\beta_{j,2}<0$). This is because first-class passengers are expected to have a high

⁴ As is standard, a dummy variable takes a value of 1 if interviewee j belongs to a certain group of customers and 0 otherwise. An overview on the definition of variables is provided in the Appendix.

⁵ Note that the absolute values of the coefficients in these regressions cannot be compared because the coefficients are scaled by the standard error of the unobserved factors. Coefficients and standard errors are not separately identified and the standard errors differ for each two regressions (Train 2009: 41).

preference for comfort as has been shown, e.g., by Oum et al. (1986) for the demand of air travel. One aspect of comfort is the convenience of having a high number of connections on a route. The number of connections per day is highest for the cooperative offer.

In our regressions, first-class passengers are found to prefer cooperation to either of the competitive offers. However, this effect is not always statistically significant.

Hypothesis 2: Business travellers (D_{business}) are expected to have an above-average preference for frequent connections ($\beta_{j,3} < 0$). This is because it is more important for business travellers to keep their appointments than for leisure travellers. Whitaker et al. (2005) show for the airline sector that business travellers are much less flexible on departure/arrival times and value a preferred schedule four to five times higher than leisure travellers.

In all regressions, business travellers show a significant preference for cooperation.

Hypothesis 3: Customers who possess a customer card are to some extent locked in to the issuer of the card. BahnCard-holders (D_{DB}) are expected to have a reduced preference for the *rival* of *Deutsche Bahn* ($\beta_{1,6} < 0$). Customers who hold a discount-card of the *rival* (D_{discount_r}) are expected to have a reduced preference for *Deutsche Bahn* ($\beta_{2,7} < 0$).

This expectation of a positive relationship between customer loyalty programmes and the market share of the respective company is in line with, e.g., Bolton et al. (2000), Rust et al. (2000) and Verhoef (2003). They show that customer loyalty programmes have a significant positive effect on customer retention. For the airline sector, empirical studies (e.g. Carlsson and Löfgren, 2006) conclude that members of loyalty programmes have higher switching costs.

Hypothesis 4: We expect customers with a discount-card to have a higher preference for the cooperative offer as compared to an isolated offer by the issuer of the card, i.e. *Deutsche Bahn* ($\beta_{2,6} < 0$) or its rival ($\beta_{1,7} < 0$). This is because in case there is cooperation a discount card can be used on the trains of both competitors. Thus, in the cooperative case a discount card would be of greater value to customers.

Concerning the effect of customer loyalty cards as proposed in hypotheses 3 and 4, we find that holding a BahnCard or a Thalys-card significantly affects customers' choices. The stated preference analysis of travellers who were interviewed on DB-trains supports the propositions that holding a BahnCard (i) reduces the probability to choose the *rival* and (ii) increases the interviewees' preference for *cooperation* ($\beta_{1,6} < \beta_{2,6} < 0$). The holders of the Thalys loyalty card show an even stronger preference for cooperation. They represent a small group

of interviewed customers (max. 5%) who go by train on the route relatively frequently. Please note that the aggregate effect of holding a customer card cannot be determined solely with regard to these fixed effects but requires taking into account the effect of the discount cards on price-sensitivity.

Hypothesis 5: Passengers who (at the time of the interview) travel on a direct train on one of the two routes (D_{direct}) are expected to have a higher preference for competition ($\beta_{j,8} > 0$) than customers on itineraries beyond Brussels, Cologne and Amsterdam that involve changing trains. We expect that travellers on direct trains have lower transaction costs and could more easily switch between the offers of the competitors. In contrast, travellers who need to switch trains may have an additional preference to buy a single ticket for their entire trip. Their preference for competition might possibly be lower because of an additional preference to exploit network effects.⁶

The evidence is inconclusive regarding this hypothesized effect.

⁶ On the route Cologne-Brussels there are two further relevant groups of customers. First, passengers who travel from Cologne to Paris. This route is served as a direct train by Thalys. Second, passengers who travel from Frankfurt to Brussels. This route is served as a direct train by Deutsche Bahn. Our empirical results show that these two groups answered the questionnaire no different than passengers whose journey goes beyond Cologne/Brussels and who, thus, have to switch trains in between. Therefore, we do not further distinguish between customer-groups according to their destinations.

			Cologne to Amsterdam				Cologne to Brussels (DB trains)				Cologne to Brussels (Thalys trains)			
		E(sign)	observed utility (rival, j=1)		observed utility (DB, j=2)		observed utility (Thalys, j=1)		observed utility (DB, j=2)		observed utility (Thalys, j=1)		observed utility (DB, j=2)	
			coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
$\beta_{j,1}$	constant	(±)	8.8428	0.6615 ***	11.3020	0.6227 ***	7.7507	0.4338 ***	5.3160	0.4015 ***	10.1105	0.5142 ***	6.9851	0.5043 ***
$\beta_{j,2}$	$D_{class=1}$	(-)	-1.5973	0.2142 ***	-1.2394	0.1678 ***	-0.0659	0.1375	-0.7687	0.1167 ***	-0.3372	0.1674 **	-0.9523	0.1847 ***
$\beta_{j,3}$	$D_{business}$	(-)	-6.6087	0.8142 ***	-4.4295	0.6418 ***	-1.9052	0.5157 ***	-1.6665	0.4731 ***	-3.2024	0.6610 ***	-2.5943	0.7191 ***
$\beta_{j,4}$	D_{25}	(±)	-1.5013	0.1425 ***	-0.4107	0.1311 ***	0.0984	0.1056	0.2037	0.0880 **	-0.4852	0.1159 ***	0.1488	0.1095
$\beta_{j,5}$	D_{6+}	(±)	-0.8763	0.2241 ***	-0.2205	0.1721	-0.3084	0.1441 **	0.6880	0.1072 ***	0.6249	0.1635 ***	0.6741	0.1706 ***
$\beta_{j,6}$	D_{DB}	(-)	-2.3220	0.7484 ***	-1.4570	0.5719 **	-1.6957	0.3241 ***	-0.6507	0.2514 ***	-0.0165	0.3279	0.2753	0.3199
$\beta_{j,7}$	$D_{discount_r}$	(-)	-0.3287	0.7499	0.6876	0.6981	-4.9809	2.1133 **	-5.0551	2.3651 **	-4.3963	1.0012 ***	-3.9530	1.5692 **
$\beta_{j,8}$	D_{direct}	(+)	0.5470	0.6754	0.5483	0.5784	1.9485	0.9875 **	2.7787	0.9317 ***	-1.2577	0.7101 *	-0.8455	0.7507
$\beta_{j,9}$	ρ_r/ρ_c	(-) (±)	-9.0442	0.7223 ***	-1.5133	0.6677 **	-11.5444	0.7463 ***	0.2248	0.5040	-12.8689	0.7455 ***	-1.5754	0.6148 ***
$\beta_{j,10}$	$(\rho_r/\rho_c) \cdot D_{discount_r}$	(+) (±)	0.7858	1.1917	-0.4154	1.0339	6.5467	2.6505 **	5.8805	2.8543 **	4.6170	1.2136 ***	2.2332	1.8458
$\beta_{j,11}$	$(\rho_r/\rho_c) \cdot D_{business}$	(+) (±)	3.4270	0.8851 ***	1.1820	0.6952 *	3.7570	0.8894 ***	-0.7248	0.6083	5.0164	0.9204 ***	0.9093	0.8432
$\beta_{j,12}$	$(\rho_r/\rho_c) \cdot D_{internet}$	(-) (±)	-1.3391	0.8091 *	0.8478	0.6977	-1.3030	0.8346	1.5066	0.4674 ***	-1.2294	0.7152 *	-0.5592	0.5636
$\beta_{j,13}$	$(\rho_r/\rho_c) \cdot D_{direct}$	(-) (±)	-1.3391	0.8091 *	0.8478	0.6977	-2.9912	1.6258 *	-1.1561	1.1760	2.0179	1.0090 **	1.3303	0.9196
$\beta_{j,14}$	ρ_{DB}/ρ_c	(±) (-)	-1.7327	0.7568 **	-11.1562	0.7875 ***	2.5280	0.7021 ***	-7.2831	0.4856 ***	1.7635	0.6218 ***	-7.3740	0.5255 ***
$\beta_{j,15}$	$(\rho_{DB}/\rho_c) \cdot D_{DB25}$	(±) (+)	1.3230	0.8935	1.8962	0.7161 ***	1.8392	0.4903 ***	1.6117	0.3851 ***	-1.4504	0.5604 ***	-0.8157	0.5509
$\beta_{j,16}$	$(\rho_{DB}/\rho_c) \cdot D_{DB50}$	(±) (+)	0.8445	0.8894	1.6879	0.7153 **	1.2034	0.4974 **	1.1124	0.3852 ***	-0.5215	0.5153	0.1299	0.5072
$\beta_{j,17}$	$(\rho_{DB}/\rho_c) \cdot D_{DB100}$	(±) (+)	0.2290	0.9392	0.7006	0.7612	-0.5387	0.9140	2.5271	0.4842 ***				
$\beta_{j,18}$	$(\rho_{DB}/\rho_c) \cdot D_{business}$	(±) (+)	2.5872	0.9359 ***	3.0619	0.8540 ***	-2.4289	0.8236 ***	2.0086	0.5479 ***	-1.9451	0.7704 **	0.7768	0.7774
$\beta_{j,19}$	$(\rho_{DB}/\rho_c) \cdot D_{internet}$	(±) (-)	1.4461	0.5652 **	-0.5377	0.5587	1.5008	0.9458	-1.6874	0.5927 ***	1.4431	0.8541 *	0.5984	0.7525
$\beta_{j,20}$	$(\rho_{DB}/\rho_c) \cdot D_{direct}$	(±) (-)	0.3184	0.8189	-1.8876	0.8262 **	1.4276	1.4075	-1.3137	0.9534	-0.5052	0.8610	-0.4187	0.8297
Mc-Fadden R ²			36.54%				23.92%				27.11%			
number of observations			3,780				5,116				3,675			

Table 1: Multinomial logit regressions⁷

⁷ The column E(sign) shows the expected sign of the estimated coefficients according to our hypotheses and crosschecks. For example, (-) | (+) means that the coefficient associated with the rival is expected to be negative, while that associated with Deutsche Bahn is expected to be positive. (-) means that both coefficients are expected to be negative. (±) means that we do not have particular expectations regarding the sign of the respective coefficient. *, **, or *** denote the 10%, 5%, or 1% level of significance. The variables are defined in Table 4 in the Appendix.

The variables D_{25} and D_{6+} indicate travellers (D_{25}) who have travelled on the respective route 2-5 times over the 12 months prior to the interview and those (D_{6+}) who have travelled on this route at least six times. Frequent travellers might (i) show an especially high habitual behaviour, (ii) reveal a high experience with either competitive or cooperative market situations or (iii) have a preference for high service frequencies. In this context Seabright et al. (2003) assume that frequent travellers may have high switching costs, while occasional travellers are unlikely to have switching costs. Because of this multitude of effects we do not have specific expectations concerning the signs of the coefficients $\beta_{j,4}$ and $\beta_{j,5}$ that are associated with these frequent traveller variables but include D_{25} and D_{6+} in order to prevent an omitted variables bias. Indeed, the estimated coefficients for frequent travellers do not show a clear pattern. However, we can neither reject the presumption that frequent travellers show habitual travel choice behaviour.

In addition to these fixed effects, the utility depends on the price of the *rival* (p_r) and the price of *Deutsche Bahn* (p_{DB}). Therefore, we include these variables in the specification of utility function (1). Note that prices are not included in levels but relative to the cooperative price (p_c), i.e. we include p_{DB}/p_c and p_r/p_c . This scaling does not affect the interpretation of the estimates because the cooperative price is constant across all 21 scenarios. However, the scaling facilitates the comparison of the regression-results for the route Cologne-Amsterdam (with $p_c=55$) and the route Cologne-Brussels (with $p_c=45$). Regarding the coefficients associated with these variables we formulate hypothesis 6.

Hypothesis 6: The own-price elasticity of rail-travel is negative. The utility of choosing either alternative depends negatively on its own price ($\beta_{1,9}<0$ and $\beta_{2,14}<0$). The related price effect of competition may be considered particularly important in book-ahead markets such as long distance rail services (Preston, 2009: 4) as analysed in this paper. Empirical studies on price elasticities are summarised for example by Oum et al. (1990).

The own-price effects are negative and statistically significant at the 1%-level in all regressions. In the Brussels case the own price effect is considerably higher for the incumbent which could be explained by its higher service frequency, i.e. a price decrease would be likely to attract a large proportion of additional customers.

Prior research as well as pre-tests with our dataset suggest that interviewees' sensitivity towards price changes varies across different groups of customers. Therefore, we control for these effects by including interaction terms where relative prices are multiplied with dummy variables that

indicate the respective groups of customers.⁸ Regarding the related coefficients we have the following expectations.

Crosscheck 1: We expect business travellers (D_{business}) to be less price sensitive than leisure customers because they often do not pay for the trip themselves ($\beta_{1,11}>0$ and $\beta_{2,18}>0$). This expectation is confirmed by a large number of studies (see Oum et al., 1990, for an overview).

Except for one case,⁹ we find that business customers react less sensitively to price changes than leisure travellers.

Hypothesis 7: We expect that passengers who have bought their ticket on the internet (D_{internet}) react more sensitively to changes in the ticket price ($\beta_{1,12}<0$ and $\beta_{2,19}<0$). This hypothesis is based on the assumption that internet users are inclined to search for the best prices and are used to check with a number of service providers. They can be expected to have lower transaction costs.

We find the own-price effect that is associated with internet-users to be either negative or statistically insignificant. This provides some faint evidence that internet-users are more price-sensitive than travellers who buy their tickets offline.

Crosscheck 2: We expect that travellers who possess a loyalty card are less sensitive to changes in the price of the service of the card's issuer ($\beta_{2,15}>0$, $\beta_{2,16}>0$, $\beta_{2,17}>0$, and $\beta_{1,10}>0$). The loyalty cards included in the study provide benefits/rewards to frequent travellers (Thalys The Card) and discounts (DB BahnCards, NS RailPlus).

BahnCard-holders tend to react less sensitive to changes in DB's price than customers without a BahnCard. The same effect is found for owners of Thalys The Card with respect to Thalys. However, these effects are not always statistically significant.

⁸ For example, the coefficient $\beta_{1,9}$ measures the sensitivity of a customer's decision to choose *rival* when the price of the rival is varied and when the customer is of the following type: He/she does not possess a discount card of the rival ($D_{\text{discount}_r}=0$), is a private traveler ($D_{\text{business}}=0$), did not buy the ticket over the internet ($D_{\text{internet}}=0$), and considers the route Cologne-Amsterdam or Cologne-Brussels only part of his/her current journey ($D_{\text{direct}}=0$).

The price sensitivity of an otherwise identical business traveler is measured by the sum of the coefficients $\beta_{1,9}$ and $\beta_{1,11}$.

⁹ See $\beta_{2,18}$ in the regression for the route Cologne-Brussels with the data of Thalys-customers, which is statistically insignificant.

Crosscheck 3: The higher the discount of the card the lower the price-sensitivity should be ($\beta_{2,15} < \beta_{2,16} < \beta_{2,17}$). The DB BahnCard can be bought with a 25%, 50% or 100% discount. We assume that the level of discount influences the price sensitivity of the respondents.

We do not find price-sensitivity to decrease with the size of the discount granted. This indicates that some BahnCard-holders either do not consider the possession of the discount card in their answers or they are unsure whether they would buy a BahnCard if the examined hypothetical situations became true. An NS discount card (on the route Cologne-Amsterdam) has no effect on customers' price-sensitivity as it has no connection to any of the presented operators in the scenarios.

Crosscheck 4: In accordance with Hypothesis 5, we expect that passengers who travel on a direct train between Cologne and Brussels (or Amsterdam) react more sensitively to price-changes than customers who have to switch trains ($\beta_{1,13} < 0$ and $\beta_{2,20} < 0$).

Again, the evidence is inconclusive regarding these customer groups.

Although the services by Deutsche Bahn and its rival are expected to be substitutes, which implies positive cross-price elasticities, the coefficients $\beta_{2,9}$ and $\beta_{1,14}$ need not necessarily take positive signs. This is because, e.g., an increase in the price of the Deutsche Bahn ticket makes customers switch to the rival and to the alternative cooperation. Finding $\beta_{1,14} > 0$ would indicate that a greater portion of passengers switches to the entrant than to the cooperation. We do not have any expectations concerning this switching behaviour.

These results prove fairly robust to changes in the specification of the regression and are not indicative of difficulties like a bias caused by the endogeneity of regressors. In this context, one might argue that certain types of travellers (for example, frequent travellers) are more likely to hold a customer card than others. This would cause some of the dependent variables included in our regressions to be in an endogenous causal relationship. We examine this hypothesis and find only weak evidence which would support this objection (see the Appendix). Therefore, we also examine whether this endogeneity impacts the coefficients estimated in our multinomial Logit-regressions. We do not find any evidence that the estimated coefficients are subject to a bias caused by the endogeneity of regressors.

Summary of our findings: Our analysis supports hypotheses 1, 2, 3, 4, 6 and 7. We cannot substantiate hypothesis 5. The results of the crosschecks imply that the regression-results are economically plausible.

5 Deriving Choice Probabilities

In this section, we use the above regression to forecast and interpret the choice probabilities of the cooperative and competitive offers for several scenarios. In subsection 5.1 we provide analyses of interviewees' preferences for cooperation versus competition. In subsection 5.2 we analyse interviewees' preferences for the competitors.

5.1 Analysing Interviewees' Choice Probability of Cooperation

The above interpretation of coefficients' signs and significance-levels does not allow for comparisons across the three regressions. This is because the estimated coefficients constitute ratios of the underlying coefficients and the standard deviation of the error term, which differs across the regressions. Therefore, in this section we calculate and compare the probabilities $P_{n,j}$ (see equation (8) in the Appendix) that some homogeneous group of customers n chooses the alternative *rival* ($j=1$), *Deutsche Bahn* ($j=2$), or *cooperation* ($j=3$).

We obtain the aggregate probabilities from these group-specific probabilities by means of aggregation using the classification-method (Ben-Akiva and Lerman, 1985: 138). Hence, we approximate the aggregate probability by the sum of group-specific probabilities weighted by the share ϕ_n of group n in the population all customers.

$$P_j = \sum_n \phi_n \cdot P_{n,j} \quad (0)$$

In case of the above regressions we consider 512 customer groups, because every of the eight variables $D_{class=1}$, $D_{business}$, D_{25} , D_{6+} , D_{DB} , $D_{discount_r}$, $D_{foreign}$, and $D_{internet}$ can take a value of 1 or 0. Moreover, BahnCard-customers ($D_{DB}=1$) may possess one of three types of BahnCard.¹⁰ The shares ϕ_n are calculated based on the occurrence probabilities for each of these features in the sample. In case of first-class and business travellers we do not use the sample shares but the ones provided by Deutsche Bahn and Thalys which were obtained from surveys larger than our sample. The latter choice affects the calculated values only to a small extent, though, and does not change our qualitative conclusions at all.

The travellers' probability of choosing the alternative *cooperation* is shown for our three samples on the ordinate in the graphs below. On the abscissa we map the price of the entrant relative to the cooperative price (p_e/p_c). We show two alternative pricing scenarios. First, entrant and incumbent lower their prices by the same amount (see Figure 2). Second, the entrant varies its price

¹⁰ There are 2^7 combinations of the 7 dummy variables excluding D_{DB} . A traveler may either possess no or one of three types of BahnCard. Therefore, the total number of combinations is $4 \cdot 2^7 = 512$. In the Thalys-sample we do not observe travelers possessing a BahnCard100. In this sample, the total number of combinations is $3 \cdot 2^7 = 384$.

while the incumbent leaves its price at the cooperative price (see Figure 3). The alternative *cooperation* is found to be rather meaningless when both firms set individual prices at a level below 60% of the cooperative price. Therefore, we only show the curves for relative prices above that level.

We would have expected the alternative *cooperation* to Pareto-dominate the other alternatives if the same price is charged for all of them. This is because the alternative *cooperation* was presented both with the highest frequency and with integrated marketing services. However, the raw data reveals that even at identical prices some customers prefer separate offers to the cooperative offer. This answering behaviour is not specific to any particular group of customers and is mirrored in our empirical choice probabilities. Some hypothetical explanations for this behaviour might be the prevalence of a status quo bias or a generally positive attitude of some respondents towards competition and other expected benefits which were not presented in the scenario. In this context, Cantillo et al. (2007: 197) point out that “some individuals may be endowed with a high disposition to change (negative inertia)”.

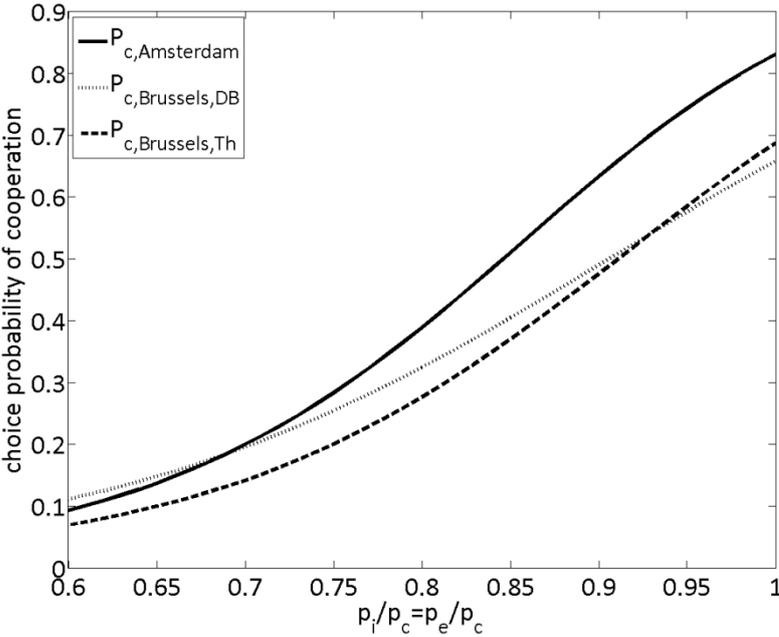


Figure 2: Probability that cooperation is the first choice if entrant and incumbent both lower their price

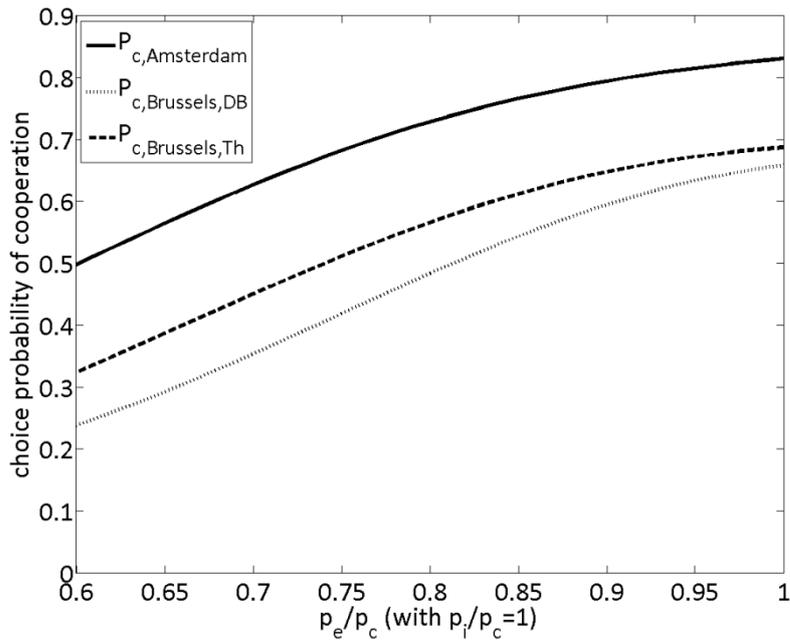


Figure 3: Probability that cooperation is the first choice if only entrant lowers its price

	A'dam	Brussels	
		Thalys	DB
p_i/p_c	0.17	0.10	0.10
p_e/p_c	0.40	0.26	0.19

Table 2: Minimum unilateral price discount such that the share of cooperation drops below 50%

Analysing the above curves and Table 2 yields the following conclusions.

1. Most interviewees see benefits in cooperative offers but lower prices of the competitive offers can offset these benefits. When the competitors charge identical prices at the level of the cooperative price 66% (Brussels, DB), 69% (Brussels, Thalys), or 83% (Amsterdam) of the interviewed travellers prefer cooperation to one of the competitive offers. When the competitors charge identical prices at a level of 80% of the cooperative price the share of customers that would choose the cooperative offer reduces to 28% (Brussels, Thalys), 32% (Brussels, DB), or 39% (Amsterdam).
2. On the route to Amsterdam we generally find a stronger preference for *cooperation* than on the route to Brussels. The price discount that would lead to a drop of the cooperation's share below 50% is about twice as high on the Amsterdam route (see Table 2). First, this finding may indicate that travellers on this route are unfamiliar with competition which is a new, unknown market structure for them. Second, this finding may also reflect that the entrant

(RailX) is a hypothetical company so that interviewees' uncertainty about this unknown brand is high. This also results in low choice probabilities for the entrant on the Amsterdam-route (also see chapter 5.2).

3. On the route to Brussels we find a relatively higher preference for one of the competitive offers. This might indicate that the travellers on this route are already used to competition and have experienced that the service offered by competitors needs not imply a lower utility than that of an integrated cooperation.
4. Table 2 shows that the incumbent must generally lower its price by less (i.e. by 10%; Brussels, Thalys) than the entrant (i.e. by 26%; Brussels, Thalys) to attract additional customers from the cooperation. The costs related to switching to the entrant or to the incumbent indicate the importance of frequencies. It is less costly for rail customers to change from the cooperation with nine daily train pairs to the incumbent's offer with six daily train pairs than to the entrant's offer with only three train pairs per day.

From the second and the third observation we conclude that the customers have a preference for the market structure and the firms that they know and whose service-quality they can appraise. We thus identify status quo biases in the choice probabilities. The first observation shows that a majority of the interviewees prefers the cooperative offer to competitive services unless these grant a price discount that is sufficiently high. Our scenario setting implies disadvantages from competition for them, as for example a split of frequencies and a disintegration of marketing and sales services. Customers might incur costs from using or learning to use new competitive services. The existence of these costs implies that liberalisation and the introduction of competition do not automatically benefit rail passengers. They rather have to be offset by a sufficient decrease in price and/or an increase in service quality and frequency.

5.2 Analysing Interviewees' Choice Probabilities for the Entrant

We turn to an analysis of the interviewed passengers' responses when faced with the decision for one of the two competitors only. Below, we provide the choice probabilities for the entrant on the two routes for different combinations of relative prices. These choice probabilities can be derived from our regressions in the following way. In equations (6) and (7) we define the probability $P_{n,j}$ that some homogeneous group of customers n chooses alternative j . Therefore, the conditional probability of choosing firm j ($\rho_{n,j}$) given that the cooperative offer is not chosen, which occurs with probability $1-P_{n,c}$, is defined as follows.

$$\rho_{n,j} = P_{n,j} / (1 - P_{n,c}) \quad (0)$$

We obtain the aggregate choice probabilities (ρ_i) from the group-specific values by means of aggregation using the classification-method (Ben-Akiva and Lerman, 1985: 138) as described in chapter 5.1 above.

In the graphs below, we show the choice probabilities ρ_e of the entrant (i.e. RailX on the Amsterdam-route and DB on the Brussels-route) for varying prices of the entrant. By mapping choice probabilities on the abscissa and prices on the ordinate, these graphs are designed to resemble (residual) demand curves and, thus, show the own-price effects of varying the entrant’s price.¹¹ To get an impression of the effects of changes in the incumbent’s price we show the choice probability curves for p_i/p_c equalling 1.0, 0.9, or 0.8. Please note that the curves show the complete pricing range, although very low price ratios and prices of the incumbent below the entrant’s prices have not been covered by the scenarios.

The horizontal and vertical dotted lines mark the price that the entrant must charge for an average consumer to be indifferent between choosing the entrant or the incumbent, i.e. both companies are chosen with a probability of 50%. These prices are also shown in Table 3. As an example for the interpretation of the curves, consider a situation where the incumbent on the Amsterdam route sets its price at the current level ($p_i/p_c=1.0$). In order to make the average consumer indifferent between choosing the incumbent or the entrant the entrant must lower its price to a level of 80% of the current price. Hence, for $p_i/p_c=1.0$ a traveller’s average costs of switching from the incumbent to the entrant amount to 20% of the current price.

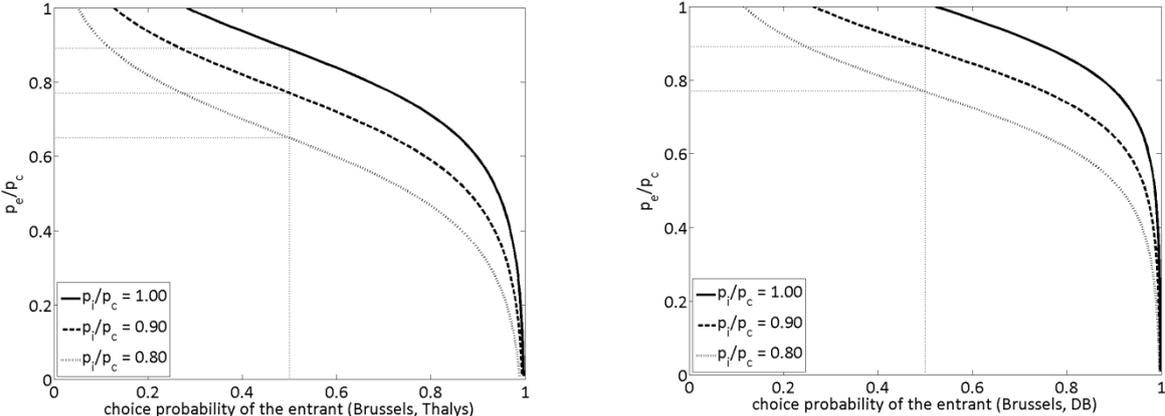


Figure 4: Choice probabilities of the entrant on the route Cologne-Brussels

¹¹ The choice probability of the incumbent $\rho_i=1-\rho_e$ can be inferred from these graphs as the horizontal distance between the curves and the vertical axis at the right side.

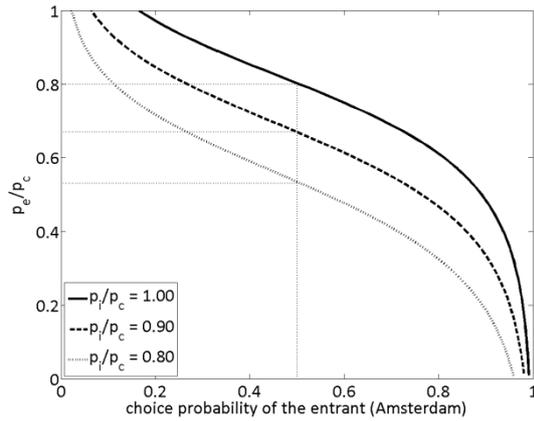


Figure 5: Choice probabilities of the entrant on the route Cologne-Amsterdam

	A'dam	Brussels	
		Thalys	DB
	p_e/p_c	p_e/p_c	p_e/p_c
$p_i/p_c = 1.0$	0.80	0.88	≈ 1.0
$p_i/p_c = 0.9$	0.67	0.77	0.88
$p_i/p_c = 0.8$	0.53	0.65	0.76

Table 3: Price decrease required for 50% choice probability

Analysing the curves reveals the following choice patterns.

1. The interviewees show a preference for the company on whose trains they were interviewed. This can be seen particularly well for the two Brussels-samples. The travellers who were interviewed on the DB-trains are rather indifferent between DB and Thalys as long as both companies set about the same prices. However, the travellers who were interviewed on Thalys-trains are less inclined to choose the entrant DB. In order to make travellers indifferent between Thalys and DB, the entrant DB must choose lower prices than the incumbent Thalys.
2. Interviewees on the Amsterdam route are reluctant to choose the hypothetical entrant RailX. To make travellers indifferent between choosing the entrant or the incumbent, the entrant must grant a more pronounced price-advantage as in the Brussels case. When the incumbent sets a price at the level of 100% (90%, 80%) of the current price the entrant would have to choose a price at the level of 80% (67%, 53%) of the current price.

The above choice probabilities are aggregated over different groups of customers. This aggregation hides the effect of possessing a customer card (loyalty or discount card) on a firm's market share. Therefore, we calculate the change in the probability of choosing either firm when a

traveller owns a customer card or not.¹² Regarding the discount and loyalty cards of Deutsche Bahn and Thalys, we find that holding a card raises the probability of choosing the respective company by 22 to 28 percentage points in the three data samples. We do not find a systematic difference between owners of Deutsche Bahn or Thalys cards.

Our results for Cologne-Amsterdam mirror the risk of a hypothetical bias and its implications for the interpretation of results. The above choice probabilities could be used to calculate the market share of an entrant in case of competition. It has to be noted, though, that some important impacts are missing here, as for example the choice behaviour of commuters and the effects of an intermodal shift are not included. Our findings imply that an unknown entrant – as on the route Cologne-Amsterdam – should only expect a low market share. The comparison with the route Cologne-Brussels indicates that this might only be a temporary phenomenon as customers would get familiar with the new market player which would result in an increase in market share. Therefore, the results for the route Cologne-Amsterdam should not be used to calculate long-term market shares of the entrant.

A study for the high speed rail connection Madrid-Barcelona (Román et al., 2007) shows how difficult market share forecasts are. On the basis of stated and revealed preference data the authors had suggested that even under the least favourable conditions for airlines the rail market share would not exceed 35% and had questioned the necessity of high speed rail investments between Madrid and Barcelona. However after two years of operation, in 2010 high-speed rail accounted for more than 50% of the market share¹³ (rail vs. air).

6 Conclusion

In this paper we present a new dataset for the analysis of travellers' preferences for long distance passenger rail transport. This dataset was collected by performing almost 700 interviews on-board trains on the two cross-border routes Cologne-Brussels and Cologne-Amsterdam. It contains socio-demographic data of the interviewed travellers, information regarding their trip at the time of the interview and stated-preference data for alternative service scenarios on these routes.

We use this dataset to explore the preferences of the interviewees for different long distance transport services. This analysis is performed by estimating a multinomial Logit, discrete choice

¹² This change is computed relative to a reference group when both rail-companies charge the high cooperative price that is the highest price presented in the scenarios. The reference group consists of second-class leisure travellers, who (i) travelled on this route only once over the last twelve month, (ii) do not possess a company card, and (iii) did not buy their current ticket on the internet.

¹³ „High-Speed Rail Gains Traction in Spain.” New York Times, March 15 2010.
<http://www.nytimes.com/2010/03/16/science/earth/16train.html>

model of demand. We draw conclusions both from the regression results and from the comparison of choice probabilities. As general effects we find that customers with a supposed preference for frequent connections/day (i.e. business- and first class-travellers) have a preference for cooperation among the two competitors, which would allow the travellers to easily use the trains of both firms. Additionally, the regressions support the hypothesis that business travellers react less sensitive to changes in ticket-prices. We also find a strong loyalty-enhancing effect of discount and loyalty cards on the choice of passenger rail service providers and some indication that travellers who buy their ticket online react more sensitive to ticket prices, thus indicating lower search costs.

In general, the interviewees tend to prefer the market structure and service providers they are using for their current trip which suggests the existence of a status quo bias. Customers who were interviewed on DB-trains have a particularly strong preference for Deutsche Bahn, and customers who were interviewed on Thalys-trains have a relatively stronger preference for Thalys. The unknown entrant RailX on the Amsterdam route faces a high percentage of reluctant customers that rather prefer the known incumbent operator or the known cooperative situation. It should only be a question of time, though, before customers get familiar with an entrant's services. Our results also imply that customers need not automatically benefit from the introduction of competition as they could have costs due to the disintegration of services. These costs seem to be especially high on the Amsterdam-route where rail services are currently provided in cooperation and customers have no direct experience with competition on the route. On the Brussels-route we identify a higher preference for the well-known competitive situation.

The status quo biases can be explained by the existence of switching costs and/or psychological persistence effects. As specific elements of switching costs we identify costs due to loyalty/company cards or the costs due to the unknown quality of untested brands. Thus we point out several effects which would work in favour of an incumbent in intramodal choice decisions. Entrants may gain most passengers if they have a well-known brand name and enter on routes with a high share of second class leisure travellers that do not possess a customer loyalty card and use the internet for purchasing tickets.

With our stated preference study we analyse demand effects that affect intramodal competition. We look at customer choice behaviour between two rail companies in a simple setting and specifically identify switching costs and psychological persistence behaviour. Our results complement the findings of prior research on competition in passenger rail markets. In particular, we suggest that the existence of a status quo bias in intramodal competition makes entry into commercial passenger rail even more challenging than often thought.

Acknowledgements

We gratefully acknowledge the cooperation of Deutsche Bahn, Thalys, SNCF and SNCB who permitted and supported the on-train surveys. We would like to thank the students of International School of Management (Frankfurt/Main) for carrying out the passenger-interviews.

Valuable comments on this paper were provided by Georg Götz, our colleagues at Justus-Liebig-University Giessen, Chris Nash and the referees for the TRB conference 2012. We would also like to thank the discussants and audiences at workshops in Münster and Giessen, Khumo Nectar Conference 2011, EARIE 2011, Infraday 2011 and TRB 2012.

Role of the funding source

The on-train interviews that form the basis of this econometric study have been carried out with support of the involved railway companies: DB, Thalys, SNCB and SNCF granted their permission for the interviews. DB and Thalys supplied the researchers with the tickets necessary to travel on the trains in order to conduct the interviews. DB supported the printing of the questionnaires.

Neither of the railway companies provided support beyond the stage of data collection. The companies were not involved in the interpretation of the data or the presentation of results and made no attempt to interfere in these stages.

Disclosure Statement

Christiane Warnecke worked for Deutsche Bahn (DB), passenger division, from 1999 to 2009. In 2009 she left DB to write her doctoral thesis at Justus Liebig University (JLU) in Giessen, Germany. Since then she has been working as a transport consultant and as a lecturer at International School of Management (ISM) in Frankfurt, Germany. From April 2011 to November 2011 she received a 50% research grant at JLU which was provided by DB. The research grant was part of a three year research funding agreement based on the principle of academic freedom.

Dirk Rompf has been working part time at the DB Holding as head of infrastructure strategy since January 2011. In parallel, he works as a professor and head of a master on mobility and logistics at the private business school ISM.

Johannes Paha is a post-doc researcher at JLU. He does not have a personal or business relationship to any of the companies.

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Appendix

In this appendix, we present a brief review of discrete choice modelling and regression approach. We also present the results of some tests which indicate that the coefficients calculated by means of these regressions are unlikely to suffer from an endogeneity bias. Furthermore, we do not find evidence that a possible correlation of an interviewee's answers across the 21 scenarios biases our results.

As presented in section 4, we assume that some decision maker n obtains utility U_{nj} from alternative j with $j=1$ denoting the *rival* of Deutsche Bahn, $j=2$ denoting *Deutsche Bahn*, and $j=3$ applying for the *cooperation* offer. This utility is unobservable. However, in our dataset we observe the ranking order of the three alternatives as chosen by the interviewees. A rational decision maker prefers alternative i to alternative j if and only if $U_{ni} > U_{nj} \forall j \neq i$. The basic idea of discrete choice modelling is to infer information about the interviewees' unobservable decision making process by analysing their observable choices.

We do this by econometrically relating interviewees' choices to observable attributes of (i) the three above alternatives j and of (ii) the decision maker. These attributes, labelled $x_{nj} \forall j$, are described in section 3 and summarised in Table 4. We specify a representative utility function that relates these observed factors to the decision maker's observed utility

$$V_{nj} = \beta_j' x_{nj} \forall j, \quad (0)$$

where x_{nj} is a vector of variables that relate to alternative j as faced by decision maker n . β_j denotes the coefficients of these variables. The specific functional form for the observed part of utility of this problem is described by equation (0). Since there are aspects of utility that the researcher does not or cannot observe, the observed part of utility V_{nj} does not perfectly equal the true utility U_{nj} . Utility is decomposed as

$$U_{nj} = V_{nj} + \varepsilon_{nj}, \quad (0)$$

where ε_{nj} captures the factors that affect utility but are not included in V_{nj} . The researcher does not know $\varepsilon_{nj} \forall j$ and therefore treats these terms as random.

	0	1
$D_{\text{class}=1}$	2nd class	1st class
D_{business}	private	business travel
D_{25}	otherwise	2-5 rail travels on this route/year
D_{6+}	otherwise	6 or more rail travels on this route/year
D_{DB}	otherwise	possession of a BahnCard
D_{DB25}	otherwise	possession of a BahnCard 25
D_{DB50}	otherwise	possession of a BahnCard 50
D_{DB100}	otherwise	possession of a BahnCard 100
D_{discount_r}	otherwise	possession of a RailPlus Card (NS) or: possession of Thalys The Card
D_{internet}	otherwise	ticket was bought online
D_{direct}	otherwise	start/end of current trip is no further than Cologne/Amsterdam or: Cologne/Brussels

Table 4: Variable definitions

The joint density of the random vector $\varepsilon'_n = \langle \varepsilon_{n1}, \dots, \varepsilon_{nj} \rangle$ is denoted $f(\varepsilon_n)$. With this density, the researcher can make probabilistic statements about the decision maker's choice. The probability that decision maker n chooses alternative i is

$$\begin{aligned}
P_{ni} &= \text{Prob}(U_{ni} > U_{nj} \forall j \neq i) \\
&= \text{Prob}(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \forall j \neq i) \\
&= \int_{\varepsilon} I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \forall j \neq i) f(\varepsilon_n) d\varepsilon_n
\end{aligned} \tag{0}$$

where $I(\cdot)$ is the indicator function, equalling 1 when the expression in parentheses is true and 0 otherwise (Train, 2009: 15). The density $f(\varepsilon_n)$ is the distribution of the unobserved portion of utility within the population of people who face the same observed portion of utility (see our analysis in section 5). Given the assumption that each ε_{nj} is independently, identically distributed extreme value we can estimate V_{nj} by means of a multinomial logit model and compute the choice probability P_{ni} of alternative i by decision maker n as

$$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \tag{0}$$

Based on this theoretical groundwork of our empirical analysis we specify the interviewees' utility function as described in section 4.1. Concerning the interpretation of the below regression tables note that the same variables enter the utility-function of all alternatives. Therefore, any model with the same difference in corresponding coefficients is equivalent (Train, 2009: 20) so that the utility and the coefficients of the alternative *cooperation* are normalized to zero. As a consequence the estimated coefficients for the alternatives *rival* and *Deutsche Bahn* must be interpreted relative to the alternative *cooperation*. The regression tables are presented in section 4.2.

The multinomial Logit-regressions include variables that may be subject to endogeneity issues. In particular, the choice of buying a BahnCard or the loyalty card of another operator might depend on the number of trips made on this route during the last year (f), the state of being a business traveller ($D_{\text{business}}=1$), and being a traveller who buys his/her tickets over the internet ($D_{\text{internet}}=1$). These relationships are shown in Table 5 where we present the results of multinomial Logit-regressions for choosing one of the three types of the BahnCard and a binary Logit-regression for choosing the loyalty card of another rail-company. In the dataset collected from Thalys-customers at the Brussels-route, the multinomial Logit-regression does not include the BahnCard100-alternative as customers with such a loyalty card are not observed in this sample.

These regressions show that there are only weak relationships between the regressors included in our main multinomial Logit-regressions. We do not find any indication that these effects cause a bias in the coefficients estimated by these regressions. If the endogeneity between the loyalty card-variables and the other regressors had a biasing impact on the estimated coefficients we would expect to see a perceptible change in the estimated coefficients when excluding either of these two sets of independent variables. Hence, we exclude the loyalty card-variables and re-run the regressions for the choice of either rail-service provider. In all of the three regressions, all the remaining coefficients remain at vastly the same values as in the previous case. Similarly, the values of the Pseudo- R^2 drop only slightly from 27.11% to 26.18% (Brussels, Thalys), 23.92% to 21.92% (Brussels, DB), and 36.54% to 34.42% (Amsterdam). Therefore, we do not find any indication that the endogeneity of regressors would have caused a bias in the estimated coefficients.

		Multinomial Logit						Binary Logit			
		BahnCard 25 (k=1)		BahnCard 50 (k=2)		BahnCard 100 (k=3)		Loyalty Card Rival (l=1)			
		coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error		
Amsterdam	frequency (f)	$\gamma_{k,1}$	-0.9778	1.0641	-1.1823	0.9587	-2.7226	1.2683 **	$\delta_{l,1}$	2.3439	1.1981 **
	f^2	$\gamma_{k,2}$	0.2757	0.1926	0.3715	0.1705 **	0.5945	0.2203 ***	$\delta_{l,2}$	-0.3033	0.1982
	$D_{business}$	$\gamma_{k,3}$	1.1068	0.5717 *	0.7014	0.5041	0.5993	0.7448	$\delta_{l,3}$	-1.6722	0.6661 **
	$D_{internet}$	$\gamma_{k,4}$	1.6817	0.5503 ***	1.2270	0.4918 **	0.9030	0.7142	$\delta_{l,4}$	-0.9709	0.6742
	constant	$\gamma_{k,5}$	-2.5763	1.3269 *	-2.0118	1.2158 *	-0.7102	1.4898	$\delta_{l,5}$	-4.9682	1.6468 ***
			Mc-Fadden R ²	15.86%					Mc-Fadden R ²	12.31%	
		no. of obs.	180					no. of obs.	180		
Brussels (DB)	frequency (f)	$\gamma_{k,1}$	-0.2509	0.5954	0.6101	0.5718	1.2431	1.3871	$\delta_{l,1}$	-2.917935	2.641759
	f^2	$\gamma_{k,2}$	0.0952	0.1046	-0.0249	0.0986	-0.1509	0.2343	$\delta_{l,2}$	0.5597532	0.4557545
	$D_{business}$	$\gamma_{k,3}$	-0.0016	0.3420	0.4064	0.3306	0.3943	0.8080	$\delta_{l,3}$	-0.243706	1.466779
	$D_{internet}$	$\gamma_{k,4}$	0.4062	0.3573	0.1926	0.3571	-14.2236	756.7928	$\delta_{l,4}$	0.9848289	1.443586
	constant	$\gamma_{k,5}$	-1.1614	0.6579 *	-2.2529	0.6815 ***	-4.5257	1.7126 ***	$\delta_{l,5}$	-3.041708	2.621983
			Mc-Fadden R ²	5.39%					Mc-Fadden R ²	11.25%	
		no. of obs.	248					no. of obs.	248		
Brussels (Thalys)	frequency (f)	$\gamma_{k,1}$	0.3853	0.2138	-0.0843	0.2412	not applicable		$\delta_{l,1}$	0.8305	0.3271 **
	f^2	$\gamma_{k,2}$	-2.1341	1.0656	0.1897	0.5216			$\delta_{l,2}$	0.2118	0.8364
	$D_{business}$	$\gamma_{k,3}$	-0.8164	0.7804	0.3735	0.5358			$\delta_{l,3}$	0.2208	0.7874
	$D_{internet}$	$\gamma_{k,4}$	-0.1891	0.7139	-0.4138	0.5941			$\delta_{l,4}$	1.3657	0.7793 *
	constant	$\gamma_{k,5}$	-2.6362	0.5957 ***	-2.0153	0.5267 ***			$\delta_{l,5}$	-5.9182	1.3393 ***
			Mc-Fadden R ²	4.91%					Mc-Fadden R ²	16.72%	
		no. of obs.	183			no. of obs.	183				
Definition	f =	1	= 1								
		2	= 2-3								
		3	= 4-5								
		4	= 6-12								
		5	> 12 journeys on this route during the last 12 months								

Table 5: Determinants of choosing a loyalty card

Besides the issue of endogeneity, the results of our above regression may also be affected by heterogeneity across the answers of respondents in each group of customers. This may also pose difficulties because in our stated preference data with 21 scenarios each respondent accounts for 21 observations that may potentially be correlated. Therefore, we estimate a mixed logit model with random coefficients for the dummy variables ($\beta_{j,2}$ to $\beta_{j,7}$ and $\beta_{j,21}$) and the own-price effects ($\beta_{1,9}$ and $\beta_{2,14}$). Based on a likelihood ratio test we reject the hypothesis that a model with fixed coefficients as used in the main part of this paper describes the data as well as a mixed logit model with random coefficients. Nonetheless, for the following reasons we decide to use the model with fixed coefficients rather than the one with random coefficients.

First, we do not find evidence that our qualitative results (see section 4.2) differ across these models. Second, we find that the in-sample choice probabilities (see section 5.1) predicted by the two models are the same in expectation. We plot a histogram for each alternative j of the difference between the choice probabilities calculated from the two models for each observed individual and scenario. These differences follow bell-shaped distribution functions with mean zero. Third, we consider the results of the above multinomial logit regressions with fixed coefficients more reliable

than those obtained with random coefficients. This is because the *mlogit*-algorithm, which we use in Stata to obtain the multinomial logit results, returns very reliably to the presented results when we run the algorithm multiple times and requires a runtime of only few seconds. The *mixlogit*-algorithm, which we use, requires about 1.5 hours on a desktop computer to perform the random coefficient regression at default precision and returns different results when we repeat the calculation several times. Given that our datasets are large and we consider many explanatory variables this problem is only somewhat ameliorated when we raise the precision of the calculation.