Professorship of Mobility Policy
TUM School of Social Sciences and Technology
Technical University of Munich

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Allister Loder

Lekha Kosuri

Sebastian J. Goerg

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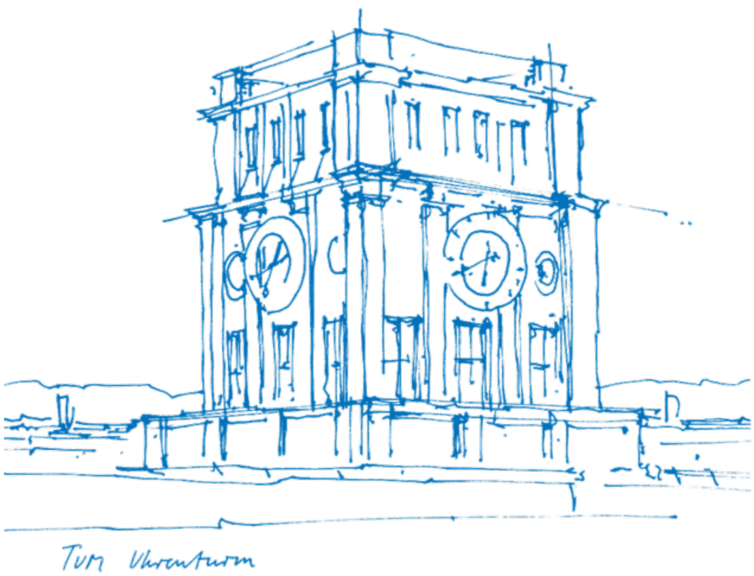

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Allister Loder
Professorship of Mobility Policy
Technical University of Munich
DE-80333 Munich
allister.loder@tum.de

Lekha Kosuri
Professorship of Mobility Policy
Technical University of Munich
DE-80333 Munich
lekha.kosuri@tum.de

Sebastian J. Goerg
Professorship of Economics
Technical University of Munich
DE-94315 Straubing
s.goerg@tum.de

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Abstract

The “Deutschlandticket” is Germany’s most recent public transport fare innovation. For a fixed price of 49 euros per month, it offers unlimited use of all local and regional public transport services, while only long-distance services like the ICE, TGV, or RailJet cannot be used. This ticket was introduced in May 2023, and initial predictions were up to 17 million owners in Germany, but current levels are around 11-12 million. In addition, a public debate about its price increases challenges these ownership levels further. Hence, the policy and research question is why this gap exists and how customers respond to price changes. In this paper, we use the data from “Mobilität.Leben”-study, comprising questionnaires and semi-passive travel diaries with waypoint tracking, to understand with discrete choice models the consumer behavior. Using stated intention and revealed ownership of the “Deutschlandticket” together with travel behavior before the introduction of the “Deutschlandticket” we find that intention among those without an existing season ticket and ownership among those who stated interest is primarily driven by place of residence, employment status, and travel behavior, where low pseudo R^2 values suggest a high impact of non-deterministic factors, e.g., individual reasons. Using stated choice data from a “Deutschlandticket” choice experiment, we find the demand elasticity to be -1.6, i.e., demand is rather elastic. The policy implications are that the elastic demand threatens the public transport agencies’ revenue streams, while the potential to systematically increase ownership seems limited.

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1 Introduction

Public transport fare policy innovations are gaining momentum, especially since the end of the pandemic, working from home is threatening revenue streams from ticket sales (Jenelius, 2022; Ziedan *et al.*, 2024). The most notable case of fare policy innovation is most likely fare-free public transport with its prime role model Tallinn, Estonia (Cats *et al.*, 2017), but which is considered to typically serve jointly economic, sustainability or social policy objectives, hence not being a transport policy alone (Keblowski, 2020). Next to these fare-free developments, there is also a trend to offer public transport season tickets for regional and nationwide travel at a substantial discount. Here, the likely most famous fare is Vienna's 365-Euro-Ticket, which offers unlimited travel in the city for 365 euros per year (Buehler *et al.*, 2016), an idea that has also been tested elsewhere (Hahn *et al.*, 2024). At the nationwide level, notable schemes are Switzerland's "Generalabonnement" since 1990 and Austria's "Klimaticket" since 2021, allowing unlimited travel on all public transport lines, except mainly tourist routes. Switzerland is further innovating its fare system by testing three-part fares (Sticher and Blättler, 2024; Weibel *et al.*, 2024). One of the latest fare innovations as of 2024 is the "Deutschlandticket", Germany's most recent public transport fare innovation. For a fixed price of 49 euros per month, it offers unlimited use of all local and regional public transport services, while only long-distance services like the ICE, TGV, or RailJet cannot be used.

Initially, Deutsche Bahn (DB) and the Association of German Transport Companies (VDV) expected up to 17 million subscribers to the "Deutschlandticket" (VDV, 2023). As of mid-2024, approximately 11.2 million individuals were reported to be actively using the "Deutschlandticket", with 20 million unique users since its introduction and around three-quarters of users aiming at owning the "Deutschlandticket" continuously (Deutsche Bahn AG and VDV, 2024). Half of these 11.2 million customers are new customers where most transferred from buying single tickets, while a fifth of these are entirely new customers to public transport (Ackermann, 2023). It is further reported that not every season ticket owner has already transferred to the "Deutschlandticket", citing reasons that the existing season ticket is cheaper or that it offers additional benefits the "Deutschlandticket" is not offering (Deutsche Bahn AG and VDV, 2024). A study from 2023 shows that up to ten percent of the population shows interest in subscribing to the "Deutschlandticket", where non-buying intention decreases with density, being lowest in rural areas with 80% of the relevant population. Here, the most frequently cited reasons for not buying the ticket are no need for it and it does not pay off, in low-density areas up to 20% also cite the lack of connectivity and services in their area as a key reasons (Ackermann, 2023). Perhaps interestingly, no income effect is reported (Deutsche Bahn AG and VDV, 2024; Loder *et al.*, 2024b). The current ownership levels lead to the situation that around 50% of all local public transport trips are made in 2024 with the "Deutschlandticket" (Deutsche Bahn AG and VDV, 2024). Nevertheless, the current ownership levels are still substantially less than predicted, leading to the first research question of whether systematic reasons exist that explain the difference between the intention volumes and the actual "Deutschlandticket" ownership. Additionally, since its inception, the "Deutschlandticket" has faced political discussion regarding its funding through subsidies and fare box revenues. Although research suggests that the "Deutschlandticket" has a net positive benefit of 3 billion euros per year for society (Krämer, 2024), the question of raising the costs of the "Deutschlandticket" in order to compensate the revenue losses is prevalent in some instances even challenging the existence of this fare innovation altogether. This discussion leads to the second research question of how consumers will respond to a price increase and what implications it has for the public transport system. To answer these two research questions, the application of discrete choice methods (Louviere *et al.*, 2000; Hensher *et al.*, 2015) is considered appropriate for understanding mobility tool ownership behavior (e.g., Scott and Axhausen, 2006; Loder and Axhausen, 2018) and demand elasticities (Ben-Akiva and Lerman, 1985) as this is one core research area of choice modeling (Haghani *et al.*, 2021).

This paper contributes with an empirical analysis of the choice behavior of "Deutschlandticket" ownership with respect to stated intention and ownership. Using the panel aspect of our "Mobilität.Leben" study (Loder *et al.*, 2024c), we use the unique opportunity of having observations of actual travel behavior based on a semi-passive travel diary with waypoint tracking and stated intention before the introduction of the "Deutschlandticket", which serve among other socio-economic variables as explanatory variables in explaining the stated "Deutschlandticket" ownership after its introduction using discrete choice models. In addition, the study also includes a discrete choice experiment about "Deutschlandticket" ownership at different price levels that we use in a multinomial logit model to estimate the price elasticity of demand of the "Deutschlandticket". We find that intention among those without an existing season ticket and ownership among those who stated interest are primarily driven by place of residence, employment status, and travel behavior, where low pseudo R^2 values suggest that a large share of the variance stems from other factors, e.g., individual reasons, not captured by our models. Using stated choice data from a "Deutschlandticket" choice experiment, we find the demand elasticity to be -1.6, i.e., demand is rather elastic. Our investigation's implications are, hence, that the elastic demand threatens the public transport agencies' revenue streams, while the potential to systematically increase ownership seems limited.

This paper is organized as follows. Section 2 summarizes the state of the art on season ticket ownership. Then, Section 3 provides the data selected from the "Mobilität.Leben" study to answer the research questions as well as the selected research methods. Section 4 presents the results of this investigation before Sections 5 and 6 end this paper with a discussion and conclusions respecively.

2 Public transport season-ticket ownership

Public transport season tickets offer unlimited travel in a specified public transport network within a specified period of time, usually per week or month. In urban areas, these networks are typically defined by fare zones. Season tickets are typically available as a subscription or without a subscription, while in most cases, they are "pre-paid" tickets. The key advantage of season tickets is that they provide a fixed price for a specific period compared to pay-per-use rates. The economic and behavioral mechanisms have been explained, e.g., the insurance effect, which describes how customers prefer to avoid price fluctuations, making budget planning more manageable (Wallimann, 2024; Wirtz *et al.*, 2015); the convenience effect, which reduces the mental and financial burden of deciding if each trip is "worth it" for users (Wirtz *et al.*, 2015); and the appeal of zero marginal trip cost once a season ticket is purchased (FitzRoy and Smith, 1999; Wittmer and Riegler, 2014). At the same time, it is important to acknowledge that high perceived costs can deter passengers, particularly those with lower incomes, from purchasing these tickets due to the significant upfront expense (Graham and Mulley, 2012).

In literature, season ticket research focuses on assessing the impact of the introduction of such tickets on public transport demand. Here, the general trend is that public transport usage is usually increasing with the introduction as reported by many (e.g., FitzRoy and Smith, 1999; Abrate *et al.*, 2009; Hahn *et al.*, 2024). Nevertheless, the effects are, as expected, heterogeneous: the implementation of the "KlimaTicket", similar to the "Deutschlandticket" albeit priced annually at a higher price but also includes long-distance services, has led to a 3 to percentage point increase in public transport usage in Austria compared to what would have occurred without the ticket (Wallimann, 2024), while the introduction of a season ticket in the Stockholm-Mälardalen region has led to an increase of 24% in public transport patronage (Alhassan *et al.*, 2020). Another noteworthy initiative is Tallinn's fare-free public transport system, which can be considered a special case with a season ticket priced at zero. The introduction resulted in a 14% increase in public transport ridership within a year, even though the city previously had high public transport usage and low ticket costs (Cats *et al.*, 2017). It is essential here to consider that the impact of free tickets tends to be more significant than that of reduced flat fares, primarily due to the zero-price effect (Busch-Geertsema *et al.*, 2021). This was evident also with the German "9-Euro-Ticket", which boosted ridership substantially (Loder *et al.*, 2024a), and led to crowded train stations (Lu *et al.*, 2024). Generally, Hörcher and Graham (2020) demonstrated that season ticket holders tend to overuse public transport, as their marginal fare effectively becomes zero, potentially leading non-season-ticket holders to opt for driving instead. Hence, it can be relevant to consider the disutility of driving in the choices (Batarce *et al.*, 2016; Hörcher *et al.*, 2018). On the contrary, also a flat-rate bias is reported in literature for some public transport users where they would be better off financially if they would per-per-use instead of the season ticket (Wirtz *et al.*, 2015).

Regarding factors leading to season ticket ownership, as such a ticket is a private good, there is apparently negative price elasticity of demand for season tickets (Wallimann *et al.*, 2023; Kholodov *et al.*, 2021), implying that price is a key determinant. Another frequently reported key determinant depends on the average number of trips as this reduces the unit price of a trip substantially (Axhausen *et al.*, 1998; Vortisch *et al.*, 2014). Further investigations of socio-demographic and socio-economic factors revealed substantial differences in characteristics of age, income, travel attitude, gender, residential space, car ownership, and public service quality (e.g., Graham and Mulley, 2012; Vance and Peistrup, 2012; Ruiz, 2004; Loder and Axhausen, 2018; Vortisch *et al.*, 2014; Kholodov *et al.*, 2021), suggesting that context matters a lot. Here, it is particularly known that public transport use and, hence, season ticket ownership results from factors of the built environment (Ewing and Cervero, 2010).

The relationship between stated interest or intention and actual behavior has been extensively studied, yielding contradictory results due to its complexity. The theory of planned behavior asserts that stated interest, as shown in surveys, can accurately predict actual behavior. These intentions are influenced by a person's attitudes toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991, 2011). This theory has been successfully applied to analyze the behavioral and attitudinal factors affecting the purchase of season tickets and the use of public transport (Wittmer and Riegler, 2014; Ambak *et al.*, 2016; Donald *et al.*, 2014; Ng and Phung, 2021), where, for example, environmental concern is cited as a factor to state the intention for public transport use (Ng and Phung, 2021). Research also suggests that factors leading to the intention of using public transport differ by trip purpose (Shaaban and Maher, 2020). Nevertheless, literature also suggests that strong and weak intentions in humans are reported (Bhattacherjee and Sanford, 2009), where it is unclear how this is the case for public transport use. Another frequently reported aspect of driving intention is habit, but more for car use than for public transport (Ng and Phung, 2021; Kholodov *et al.*, 2021).

The modeling of season ticket ownership (or mobility tool ownership) has a long tradition in transport planning and choice modeling (Jong *et al.*, 2004; Haghani *et al.*, 2021). As with presumably most discrete choice analyses, the logit model (e.g., Axhausen and Beige, 2008) and its derivates of multinomial logit (van den Berg *et al.*, 2008), nested logit (Püschel *et al.*, 2023), mixed logit (van den Berg *et al.*, 2008), and more advanced models of the generalized extreme Value (GEV) family (Habib and Sasic, 2014), are the most frequently used approaches. Nevertheless, the literature also presents a variety of probit approaches, particularly multivariate approaches, which aim to capture further correlation structures. For example, Scott and Axhausen (2006) used bivariate ordered probit models to model the number of cars and season tickets at the household level, where the correlation of the multivariate normal distribution suggests strong substitution patterns. Similarly, a multivariate probit model with sample selection was used not only to capture the substitution pattern between car and season ticket but also to model season ticket type (Becker *et al.*, 2017). Based on the generalized heterogeneous data model (GHDM) approach introduced by Bhat (2015), a probit-based model for jointly model car and season ticket ownership together with the mode use frequencies has been developed too (Loder and Axhausen, 2018). Here also, more traditional structural equation modeling (SEM) has been used too (e.g., Simma and Axhausen, 2001). Nevertheless, with deep learning approaches gaining momentum, choice analysis is building on these advances (e.g., Feng *et al.*, 2024; Püschel *et al.*, 2023).

3 Data and method

3.1 Data

This study uses data from the "Mobilität.Leben" study. It is a twenty-month panel study with a six-wave survey and semi-passive travel diaries with waypoint tracking using a smartphone app that was initiated to observe two natural travel behavior experiments in Germany in the years 2022 and 2023. The first experiment was the introduction of the "9-Euro-Ticket" (and fuel excise tax) for three months from June to August 2022 in response to the 2022 cost-of-living crisis by the German government. The second experiment was the permanent introduction of the successor to the "9-Euro-Ticket", the "Deutschlandticket", which is priced at 49 Euro per month. The overall study design and survey method are described in Loder *et al.* (2024c). Overall, "Mobilität.Leben" includes 2,624 individuals who were either self-recruited primarily in the Munich metropolitan area or externally recruited from all over Germany through a professional agency. In total, 1,140 individuals used the smartphone app and reported travel behavior with the smartphone app; not everybody participated in the smartphone app as not every self-recruited individual was able to install and activate the app on their smartphone as well, and we were not able to offer individuals recruited externally to participate in the app. Through the twenty months, 218 individuals completed the survey and reported travel behavior from before the introduction of the “9-Euro-Ticket” towards long after the introduction of the “Deutschlandticket”. Focusing only on the “Deutschlandticket,” more than 600 individuals recorded their travel behavior with the smartphone app before and after the introduction and completed a questionnaire before and after the ticket’s introduction.

The data collected in the “Mobilität.Leben” study provides rich information on relevant socio-economic attributes of individuals and their households, as well as several travel behavior measures based on questions taken from Germany household travel survey, “Mobilität-in-Deutschland” (Bundesministerium für Verkehr und digitale Infrastruktur, 2018); considering the two natural travel behavior experiments, several questions asked explicitly about changes in travel behavior, i.e., mode choice and activities, caused by these two interventions. The smartphone app for collecting the travel diaries works as follows: participants install it on their device and activate it using a dedicated code that establishes a link between their travel diaries and survey responses. The smartphone app collects waypoints using global navigation satellite system data once the smartphone detects movements; once a smartphone stops moving, these waypoints are linked to a trip, and the mode and activity are inferred using a computer algorithm. The results are presented to the app user, who can edit and validate entries. Overall, the travel diaries thus provide a detailed measurement of travel distance and travel time by mode as well as activity times of individuals over several weeks. The geospatial information further allows subsetting of the data, e.g., restricting an investigation to focus only on trips within Germany when needed.

In this analysis, we use two subsets of the “Mobilität.Leben” data. First, for the analysis of the revealed intention and ownership choices, i.e., revealed preference (RP) data, we utilize data from those study participants who used the smartphone travel diary, i.e., living primarily in the Munich metropolitan area, because the pre-“Deutschlandticket” travel behavior is expected to provide rich information regarding explaining intention and ownership. Section 3.1.1 details about the data for this analysis. Second, for the analysis of the stated preferences, i.e., stated preference (SP) data, we use data from those participants recruited externally from across Germany in order to obtain a sample as representative as possible because of the relevance to estimating the price elasticity of demand as unbiased as possible. Section 3.1.2 summarizes the data selected for this analysis. To better understand the differences across both selected samples, we compare the statistics on season ticket ownership in Table 1. It can be clearly seen that the two samples differ. The Munich-oriented RP sample has a much higher share of existing season ticket ownership, which is intuitive as in metropolitan areas, typically more people use public transport (Ewing and Cervero, 2010). This aspect is then further propagated

Table 1: Comparing season ticket ownership across the RP and SP sample considered for this analysis. Note that for the SP sample, only 405 individuals are considered instead of the 567 as not everybody completed the relevant questionnaires in 2023.

		"Deutschlandticket"	
	Existing owner	Intention	Ownership
RP sample	31.0 %	29.0 %	14.34%
SP sample	8.2%	13.8%	4.9%

in the intention and ownership levels. Consequently, using the RP sample for the SP analysis, i.e., elasticity estimation, the estimates will be clearly biased towards the metropolitan area.

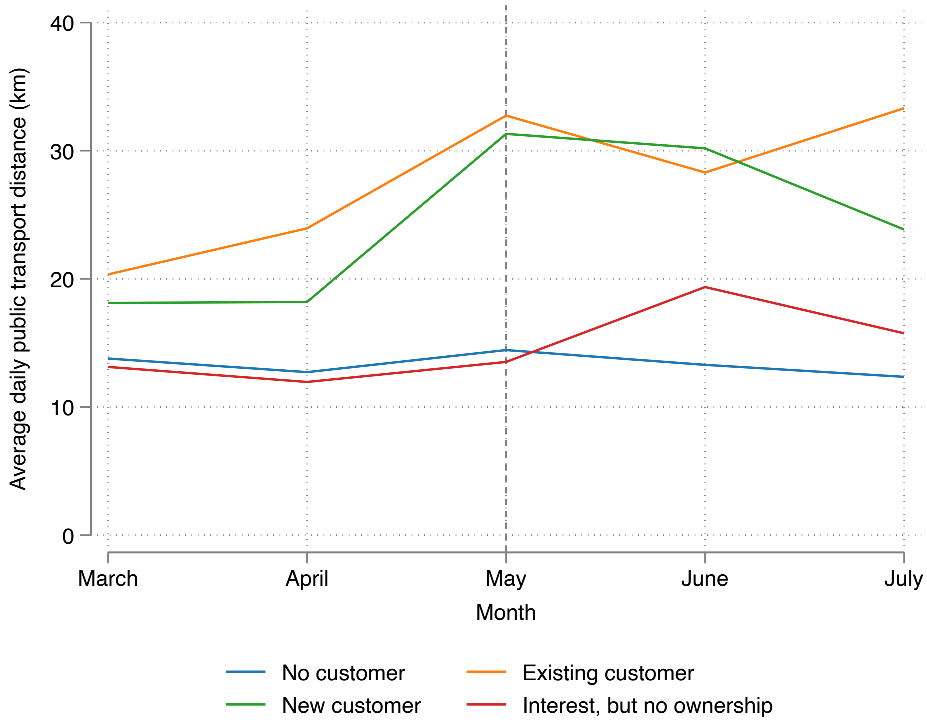
3.1.1 Revealed intention and ownership data

For this investigation, we focus, as aforementioned, on study participants who collected travel diary entries with their smartphones because we expect that their pre-"Deutschlandticket" travel behavior is informative. This group of participants is further categorized into four groups: (i) existing season ticket customers before the "Deutschlandticket" introduction, (ii) respondents who mentioned interest in subscribing to the "Deutschlandticket" but did not obtain in, (iii) respondents who are new season ticket customers with the "Deutschlandticket" (iv) respondents who neither had a season ticket before the "Deutschlandticket" and stated interest in it. Figure 1 shows the average travel distance when mobile of these four groups throughout the period of the introduction of the "Deutschlandticket" from March to July 2023.

It is apparent from Figure 1 that these four groups differ in their travel behavior. It is particularly interesting to see first that daily travel distances for all "Deutschlandticket" owners increased by around 50% with its introduction. Second, when comparing those who stated interest in the ticket, those who eventually got it had a public transport use before the "Deutschlandticket" similar to the behavior of existing season ticket owners, while those who eventually did not get it had a travel behavior similar to those not at all interested in the "Deutschlandticket". Hence, as expected, the pre-"Deutschlandticket" travel behavior influences interest in and ownership of the "Deutschlandticket".

For the analysis of revealed intention and ownership choices, we select all variables from

Figure 1: Public transport travel behavior of “Deutschlandticket” customer groups from March to July 2023. The “Deutschlandticket” was introduced on May 1st, 2023.



the data listed in Table 2. Next to the two dependent variables y_{int} for the intention and y_{own} for the ownership, we select the following variables based on the following hypotheses or expectations based on media reports or travel behavior research. With season tickets typically used for commuting, employment status x_{emp} is expected to increase interest and ownership. Being retired x_{ret} is also expected to increase interest and ownership of the “Deutschlandticket” as this new ticket offers the elderly unprecedented options to travel across the nation for a limited budget. Using public transport more x_{ptdist} (and the car more $x_{cardist}$) before the “Deutschlandtickiet” introduction is expected to increase (decrease) the probability of interest in and ownership of the “Deutschlandticket”. Considering the impact of the built environment on travel behavior (Ewing and Cervero, 2010), it can be expected that respondents having good public transport access at their household location x_{ga} as well as living in urbanized areas outside the metropolitan centers, e.g., in mid-sized cities in an urban $x_{sp,medcity-urban}$ or rural $x_{sp,medcity-rural}$ area have a higher probability of interest in and ownership of the “Deutschlandticket”; living in the latter areas is expected to increase interest and ownership in particular because of the substantial price cut of the “Deutschlandticket” compared to the season tickets offered before. Further included control variables are the respondent considering himself male x_{male}, living in a car-free household $x_{carfree}$, and having had a season ticket

Table 2: Variables for the revealed choice analysis.

Symbol	Description
y_{int}	Intention for the Deutschlandticket
y_{own}	Has the Deutschlandticket
x_{emp}	Respondent is employed.
x_{ret}	Respondent is retired.
x_{ptdist}	Average daily public transport travel distance (km)
$x_{cardist}$	Average daily car travel distance (km)
x_{male}	Respondent considers himself male.
x_{ga}	Household has good access to public transport, i.e., a railway or subway station is within a 5-minute walk accessible.
x_{abo19}	Had a season ticket before the pandemic
$x_{carfree}$	Lives in a car-free household
Net household income	
base	1499€ or less
$x_{1500-2499}$	1500€-2499€
$x_{2500-3999}$	2500€-3999€
$x_{4000more}$	4000€ or more
Spatial typology	
base	Metropolis
$x_{sp,medcity-urban}$	Medium-sized city in urban area
$x_{sp,medcity-rural}$	Medium-sized city in rural area
$x_{sp,other}$	Other

before the pandemic x_{abo19}. Note that we excluded all respondents from the analysis who had a season ticket directly before introducing the “Deutschlandticket”. Last, we include net household income on a four-level scale to verify the reported income-insensitivity of “Deutschlandticket” ownership.

In the following, we exclude all respondents who had a season ticket before the introduction of the “Deutschlandticket” as those either get the “Deutschlandticket” automatically or, as reported in the introduction, did not pick the ticket as their current one is cheaper and/or gives them additional benefits. In other words, including them in the analysis of intention and ownership is meaningless. Further removing all study participants who did not provide travel diary data before and after the “Deutschlandticket” introduction or completing the relevant questionnaires leaves us with 400 complete responses for this investigation. Table 3 summarizes the statistics of our sample. It can be seen that 42% stated interest in the “Deutschlandticket”, but only half of those, i.e., 21%, eventually went into the “Deutschlandticket” subscription. Further, recruiting in the Munich area is also reflected in the income distribution, which is skewed towards higher

Table 3: Sample descriptive statistics for the revealed preference analysis.

Continuous variables	Mean	SD	Min	Max	N
Intention for the Deutschlandticket	0.42	0.49	0.00	1.00	400.00
Has the Deutschlandticket	0.21	0.41	0.00	1.00	400.00
Male	0.55	0.50	0.00	1.00	400.00
Had a season ticket before the pandemic	0.29	0.45	0.00	1.00	400.00
Lives in a car-free household	0.29	0.45	0.00	1.00	400.00
Has good public transport access	0.34	0.48	0.00	1.00	400.00
Is employed	0.57	0.49	0.00	1.00	400.00
Is retired	0.14	0.34	0.00	1.00	400.00
Average daily public transport travel distance (km)	15.80	20.93	0.00	123.20	400.00
Average daily car travel distance (km)	22.51	22.25	0.00	163.25	400.00
Categorical variables	Level		N	(%)	
Net household income	1499€ or less		29	7.51	
	1500€-2499€		55	14.25	
	2500€-3999€		119	30.83	
	4000€ or more		183	47.41	
Spatial typology	Metropolis		225	56.25	
	Medium-sized city in urban area		69	17.25	
	Medium-sized city in rural area		25	6.25	
	Other		81	20.25	

incomes than the German average. Note that fourteen individuals decided not to report their household income.

3.1.2 Stated choice data

The analysis of stated choice data regarding ‘Deutschlandticket’ ownership utilizes a separate segment of the ‘Mobilität.Leben’ dataset. To accurately assess how individuals will respond to price changes, i.e., the price elasticity of demand, our rationale is to estimate this parameter as unbiased, i.e., representative, as possible. Therefore, we utilize the responses from participants in the nationally representative survey conducted by a professional agency.

The actual stated choice data was collected in September 2022, i.e., after the “9-Euro-Ticket”, where the discussion on a successor to this ticket and its pricing was in full swing. Thus, to understand and predict the purchasing decisions of consumers for a successor ticket to the “9-Euro-Ticket”, we designed a discrete choice experiment. In this experiment, we defined the following alternatives and the price attribute levels based on public debate and other real-world examples.

None No season ticket

LT A local season ticket covering the area of existing transit districts that is priced at 19 or 29 Euro per month, following the idea of providing mobility for 1 Euro/day.

DT The "Deutschlandticket", the successor to the "9-Euro-Ticket", is priced at 49, 59, 69 or 99 Euro per month, following the currently discussed price points for that ticket.

LD A season ticket that is similar to the Austrian Klimaticket and the Swiss Generalabonnement that combines the "Deutschlandticket" with the BahnCard 100, a season ticket allowing for unlimited travel on all long-distance train services, e.g., ICE, IC, EC, RailJet, TGV, in Germany that are not included in the "Deutschlandticket". The defined price levels are 249 and 349 Euro per month.

KM A distance-based fare system, i.e., based on the traveled kilometers, with a price cap at a price for the Deutschlandabo, including long-distance services. The distance fares are 10 or 20 EUR per 100 km and are aligned with prices typically obtained from using the half-fare card BahnCard 50.

We employed a full-factorial design, a total of 32 choice sets, and grouped them into four blocks, i.e., each respondent is tasked with a total of eight decision scenarios, where only price attributes vary.

For this analysis, we focus on 567 respondents recruited nationwide through an external agency that completed the relevant questionnaire, i.e., the third wave of the survey. We further excluded speeders from the sample. For these respondents, Figure 2 shows the choices across all choice tasks, i.e., price levels of the alternatives. It can be seen that more than 50% of choice tasks report a choice for no ticket at all, with the local ticket and "Deutschlandticket" coming second and third. Figure 3 shows the share of choices for the "Deutschlandticket" separated by the ticket's price levels. Here, it can be seen that at 49 Euro per month, around 20% of the sample would buy the ticket, while for 99 Euro per month, only slightly more than five percent of the sample would do.

For the analysis of this choice behavior, we select the variables listed in Table 4 following an iterative model-building process. The price variables p_{LT}, p_{DT}, p_{LD}, and p_{KM} correspond to the price attribute levels from the discrete choice experiment. The further selected explanatory variables are a household location with good access to public transport x_{ga}, the respondent having any public transport season ticket at the time of completing the questionnaire x_{abo}, the respondent considering himself male x_{male}, and the linearized household income x_{inc}. Table 5 lists the summary statistics for the selected sample.

Figure 2: Observed sample shares of choices in the discrete choice experiment on the "Deutschlandticket" and related public transport tickets.

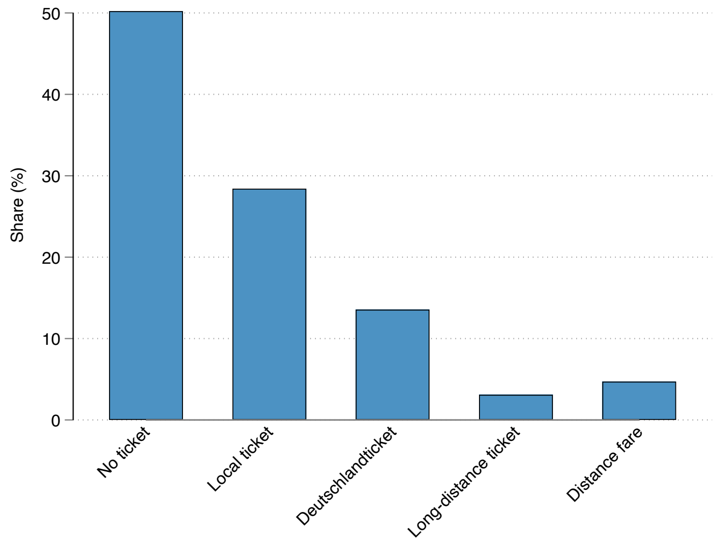


Figure 3: Changes in the shares of respondents choosing the "Deutschlandticket" as a function of the ticket's price.

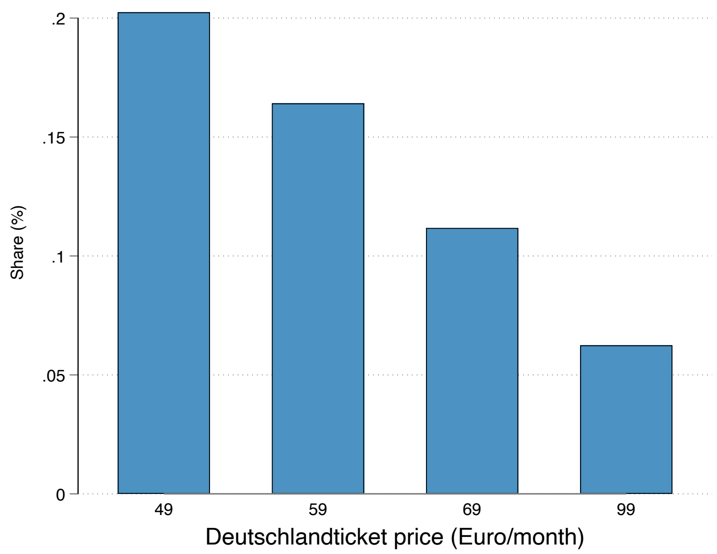


Table 4: Variables for the stated choice analysis.

Symbol	Description
p_{LT}	Price attribute for the local ticket from the discrete choice experiment.
p_{DT}	Price attribute for the "Deutschlandticket" from the discrete choice experiment.
p_{LD}	Price attribute for the long-distance season ticket from the discrete choice experiment.
p_{KM}	Price attribute for the distance-based fare from the discrete choice experiment.
x_{ga}	Household has good access to public transport, i.e., a railway or subway station is within a 5-minute walk accessible.
x_{abo}	Respondent has any public transport season ticket in late 2022, i.e., before the introduction of the "Deutschlandticket"
x_{male}	Respondent considers himself male.
x_{inc}	Monthly net household income linearized from the four-level scale using the midpoint values.

Table 5: Sample descriptive statistics for the stated choice analysis.

Continuous variables	Mean	SD	Min	Max	N
Price for the local ticket (LT)	24.98	5.00	20.00	30.00	4522.00
Price for the "Deutschlandticket" (DT)	68.89	18.69	49.00	99.00	4522.00
Price for the long-distance "Deutschlandticket" (LD)	298.98	50.01	249.00	349.00	4522.00
Price for the distance-based fare (KM)	15.00	5.00	10.00	20.00	4522.00
Has good public transport access	0.19	0.40	0.00	1.00	4522.00
Has a public transport season ticket at time of questionnaire	0.20	0.40	0.00	1.00	4522.00
Respondent considering himself male	0.60	0.49	0.00	1.00	4522.00
Linearized net monthly household income	3146.84	1413.53	1000.00	5000.00	4522.00

3.2 Methods

3.2.1 Revealed choices

For the analysis of revealed intention and ownership, we use for each a binary logit model with all the underlying assumptions about the error term distribution (McFadden, 1973; Ben-Akiva and Lerman, 1985), where the dependent variables of each model are "Deutschlandticket" intention, y_{int}, and "Deutschlandticket" ownership, y_{own}. Here, we specify a utility function for each decision maker n with additive errors

$$U_n = V_n + \varepsilon_n.$$

where U_n is the random utility, V_n the deterministic part of the utility and ε_n the random error term. The relationship between the deterministic part of the utility function, V_n, and choice probabilities P_n is established by the following equation

$$P_n\left(\boldsymbol{\beta}\right) = \frac{1}{1 - e^{-V_n}}.$$

After iterative model development, we use the same utility function for understanding the choice behavior for intention as well as ownership, where the utility function is linear in parameters and reads as follows

$$\begin{aligned}
U = \alpha &+ \beta_{emp} x_{emp} + \beta_{ret} x_{ret} + \beta_{ptdist} x_{ptdist} + \beta_{cardist} x_{cardist} \\
&+ \beta_{sp,medcity-urban} x_{sp,medcity-urban} + \beta_{sp,medcity-rural} x_{sp,medcity-rural} \\
&+ \beta_{sp,other} x_{sp,other} + \beta_{ga} x_{ga} + \beta_{male} x_{male} \\
&+ \beta_{inc,1500-2499} x_{inc,1500-2499} + \beta_{inc,2500-3999} x_{inc,2500-3999} + \beta_{inc,4000more} x_{4000more} \\
&+ \beta_{abo19} x_{abo19} + \beta_{carfree} x_{carfree} + \varepsilon. \qquad (1)
\end{aligned}$$

For the reader's convenience, we dropped the subscript for intention and ownership. Here, α corresponds to the constant of each model, while the βs are the parameters to be estimated for all variables selected for this investigation and listed in Table 2. In the investigation, we estimate the model parameters $\boldsymbol{\beta}$ for in total three models:

- M1 Intention for the "Deutschlandticket" (y_{int}) among all respondents not already having a season ticket before the introduction of the "Deutschlandticket"
- M2 Ownership of the "Deutschlandticket" (y_{own}) among all respondents not already having a season ticket before the introduction of the "Deutschlandticket"
- M3 Ownership of the "Deutschlandticket" (y_{own}) among all respondents stating interest in the "Deutschlandticket", i.e., $y_{int} = 1$.

The parameters are estimated with maximum likelihood and robust standard errors.

3.2.2 Stated choices

For the analysis of the stated choice behavior about "Deutschlandticket" ownership, we use the multinomial logit model (MNL) with five alternatives that require us to specify the respective utility function U_{int} for each alternative i, decision maker n and choice task t (McFadden, 1973). Here, we follow the approach of having an additive error term ε_{int} to the deterministic part of the utility V_{int}

$$U_{int} = V_{int} + \varepsilon_{int}.$$

The relationship between the deterministic part of the utility function and choice probabilities P_{int} is established in the usual MNL formula

$$P_{int}\left(\boldsymbol{\beta}\right) = \frac{e^{V_{int}}}{\sum_{j=1}^{J} e^{V_{jnt}}}.$$

As mentioned in Section 3.1.2, only the price attributes of each of the four tickets on offer are altered, which leads to the fact that only the price attribute from the experimental design enters each utility function as a variable. i.e., p_{LP} as the price for the Local ticket, p_{DT} as the price for the "Deutschlandticket", p_{LD} as the price for the long-distance season ticket, and p_{KM} as the price for the distance-based charge. Considering that all individual-specific effects are constant across all alternatives, we consequently enter them as shifts to the generic cost parameter of each ticket. We denote the generic cost parameter of each alternative by subscript "0", i.e., $\beta_{LT,0}$ for the local ticket, $\beta_{DT,0}$ for the "Deutschlandticket", $\beta_{LD,0}$ long-distance season ticket, and $\beta_{KM,0}$ for the distance-based fare. After our iterative model building, we specify the utility functions as follows.

First, considering the observed shares in Figure 2, we set the alternative, choosing no ticket as the base alternative, as only differences in utility matter. This leads to the following utility function for this alternative

$$U_{None} = 0. \tag{2}$$

Second, the utility function for the local ticket alternative is specific as follows

$$U_{LT} = \alpha_{LT} + \left(\beta_{LT,0} + \beta_{LT,ga} x_{ga} + \beta_{LT,abo} x_{abo}\right) p_{LT} + \varepsilon_{LT} \tag{3}$$

and comprises the alternative's specific constant α_{LT}, then shifts to the generic cost parameter $\beta_{LT,0}$ for having good access to public transport at the household location $\beta_{LT,ga}$ as well as having any season ticket at the time of the survey, i.e., before the introduction of the "Deutschlandticket" $\beta_{LT,abo}$, and the error term ε_{LT} capturing all unobserved effects. Third, the utility function for the "Deutschlandticket", U_{DT} is similar to the utility function of the local ticket, U_{LT} except for the fact that we introduce an income effect to investigate the income-independence of the "Deutschlandticket" using the income elasticity λ following Mackie *et al.* (2003); Axhausen *et al.* (2008). This leads to the following utility function

$$U_{DT} = \alpha_{DT} + \left(\beta_{DT,0} + \beta_{DT,ga} x_{ga} + \beta_{DT,abo} x_{abo}\right) \left(\frac{x_{inc}}{\bar{x}_{inc}}\right)^{\lambda} p_{DT} + \varepsilon_{DT}. \tag{4}$$

Fourth, the utility function for the long-distance ticket, U_{LD} follows the same pattern as the utility function for the local ticket, U_{LT} and is as follows

$$U_{LD} = \alpha_{LD} + \left(\beta_{LD,0} + \beta_{LD,ga} x_{ga} + \beta_{LD,abo} x_{abo}\right) p_{LD} + \varepsilon_{LD}. \tag{5}$$

Last, the utility function for the distance-based fare, U_{KM}, again follows a similar pattern as the functions before, with the exception that no shift for good access to public transport is included, but a shift for being male $\beta_{KM,male}$. This leads to the following utility function

$$U_{KM} = \alpha_{KM} + (\beta_{KM,0} + \beta_{KM,abo} x_{abo} + \beta_{KM,male} x_{male})\, p_{KM} + \varepsilon_{KM}. \quad (6)$$

Consequently, the parameters of the choice model are

$$\begin{aligned}\boldsymbol{\beta} =& (\alpha_{LT}; \alpha_{DT}; \alpha_{LD}; \alpha_{KM}; \beta_{LT,0}; \beta_{DT,0}; \beta_{LD,0}; \beta_{KM,0};\\ &\beta_{LT,ga}; \beta_{DT,ga}; \beta_{LD,ga}; \beta_{LT,abo}; \beta_{DT,abo}; \beta_{LD,abo}; \beta_{KM,abo}; \beta_{KM,male}; \lambda).\end{aligned}$$

We estimate the parameters with the Apollo Software in R (Hess and Palma, 2019) using maximum likelihood.

4 Results

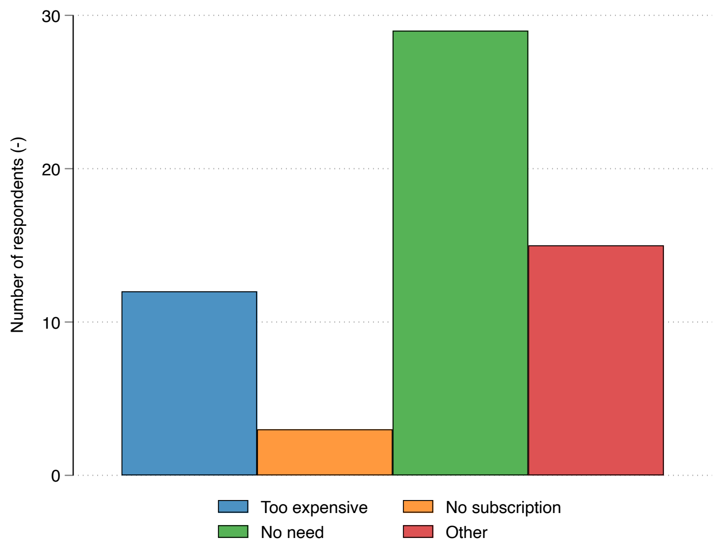
In this section, we present the results of the "Deutschlandticket" choice behavior. Section 4.1 presents the investigation based on revealed choice data and Section 4.2 the findings from the stated choice data.

4.1 Revealed preference

In total, we estimate three logit models to understand the "Deutschlandticket" choice behavior. As described in Section 3.1.1, this investigation uses the "Mobilität.Leben" data of those individuals who participated in the semi-passive travel diaries with waypoint tracking and are recruited in a convenience sample. All individuals who had a public transport season ticket before the introduction of the "Deutschlandticket" are excluded as they either got the ticket automatically or stayed with their old ticket, i.e., they are not relevant to understand the adoption behavior. The three models are

M1: Intention to buy the "Deutschlandticket" among all considered individuals.
M2: Ownership of the "Deutschlandticket" among all considered individuals.

Figure 4: Distribution of non-purchase reasons cited by respondents who revealed interest in the “Deutschlandticket” but did not get it in the end.



M3: Ownership of the “Deutschlandticket” among all individuals who were interested in the “Deutschlandticket”.

Table 6 shows the resulting model estimates. First, across all models, it is observed that the pseudo R^2 is relatively low, with values around 0.10. This suggests that the random utility component plays a significant role in the choices, indicating a relatively smaller influence of the deterministic utility. In the context of this research, this implies that our available data explains only a small share of choices. Thus, the decision to purchase might depend on various reasons, e.g., individual aspects related to the job or other life circumstances.

In the “Mobilität.Leben” study, we asked for non-purchase reasons, as reported in Figure 4, many cited that ultimately they realized that they do not need the ticket as well they cited “other”, implying highly personal reasons. Across all three models, we observe that typical socio-demographic variables, particularly income, do not matter in the choice process (they are located in the lower part of Table 6).

Regarding the relevant influences, model M1 finds that a.) being employed, b.) using public transport before the new ticket’s introduction, and c.) not using the car increases the likelihood of interest in the ticket. Interestingly, the spatial typology matters as not living in a metropolis result in a higher probability of interest for the “Deutschlandticket”. This can be explained by

Table 6: Model estimates of the three models estimated based on the revealed interest and ownership choice data.

	M1: Intention (all)		M2: Ownership (all)		M3: Ownership (interested)	
	β	Rob. t	β	Rob. t	β	Rob. t
Relevant effects						
Constant	−1.072	(−2.00)	−2.805	(−4.03)	−1.250	(−1.56)
Is employed	0.904	(3.38)	1.725	(4.31)	1.555	(2.98)
Is retired	0.644	(1.77)	1.279	(2.64)	1.175	(1.78)
Average daily public transport travel distance (km)	0.009	(1.74)	0.021	(3.54)	0.023	(2.11)
Average daily car travel distance (km)	−0.013	(−2.23)	−0.019	(−2.32)	−0.014	(−1.22)
Spatial typology: Metropolis (base)						
Medium-sized city in urban area	0.869	(2.68)	1.075	(2.67)	0.640	(1.20)
Medium-sized city in rural area	0.826	(1.61)	1.900	(3.17)	2.460	(1.99)
Other	0.678	(2.06)	0.408	(0.96)	0.122	(0.22)
Has good public transport access	0.653	(2.59)	0.446	(1.44)	0.008	(0.02)
Insignificant control variables						
Male	−0.030	(−0.13)	0.233	(0.81)	0.165	(0.44)
Household income: less than 1500€ (base)						
1500€-2499€	0.037	(0.07)	0.230	(0.41)	0.239	(0.33)
2500€-3999€	−0.526	(−1.16)	−0.859	(−1.62)	−0.705	(−1.02)
4000€ or more	−0.422	(−0.94)	−0.718	(−1.37)	−0.562	(−0.82)
Had a season ticket before the pandemic	0.084	(0.35)	−0.153	(−0.47)	−0.302	(−0.75)
Lives in a car-free household	0.078	(0.26)	−0.021	(−0.05)	−0.018	(−0.04)
Observations	386		386		161	
Pseudo R^2	0.066		0.134		0.131	
ll	−245.033		−168.191		−96.863	

a higher share of people living in a metropolis already having a season ticket, while outside the metropolis, previous existing tickets were too expensive or did not offer required features. Regarding actual ownership, model M2 demonstrates a similar pattern for ownership as for interest. Considering the small sample size, the changes in statistical significance of being retired and good public transport access at the household location between M1 and M2 should be considered with care. Perhaps only the effect of "Spatial typology - Other" becoming insignificant could be considered meaningful: while for those living neither in a metropolis nor in medium-sized cities, i.e., in rural and rural suburban areas, the “Deutschlandticket” at first may look like an interesting alternative, the reduced supply in the form of less frequent access to public transport may reduce the likelihood of subscribing to the ticket in the end.

When comparing the marginal effects, especially for being retired, the probability for ownership increases by five percentage points more than in the case of being interested, suggesting that those may have become more aware of the benefits the ticket provides. Last, model M3 only considers actual ownership among those who stated interest, while model M2 models ownership among all eligible for the “Deutschlandticket” ownership. The model estimates suggest that neither having good access to public transport at the household location nor previous car use, but primarily previous public transport use and being employed matters for adopting the “Deutschlandticket”.

To better understand the extent of these effects, we use the model M3 estimates from Table 6 to predict the probability of ownership as a function of the two mentioned presumably key variables: previous public transport use and employment status. Figure 5 shows the results. Here, it can be seen that being employed increases the probability of ownership among all interested by around 15 percentage points, while typical commuting distances of 0 to 30 kilometers a day explain a range of about ten percentage points in the probability of “Deutschlandticket” ownership.

4.2 Stated choice

The discrete choice behavior of “Deutschlandticket” is, as explained in Section 3.1.2, based on the part of the “Mobilität.Leben” sample that has been recruited externally to obtain a representative nationwide sample. We selected this sample to estimate the cost sensitivity for the “Deutschlandticket” as unbiased as possible.

Figure 5: Predictions for the ownership model based on all interested individuals (the third model in Table 6

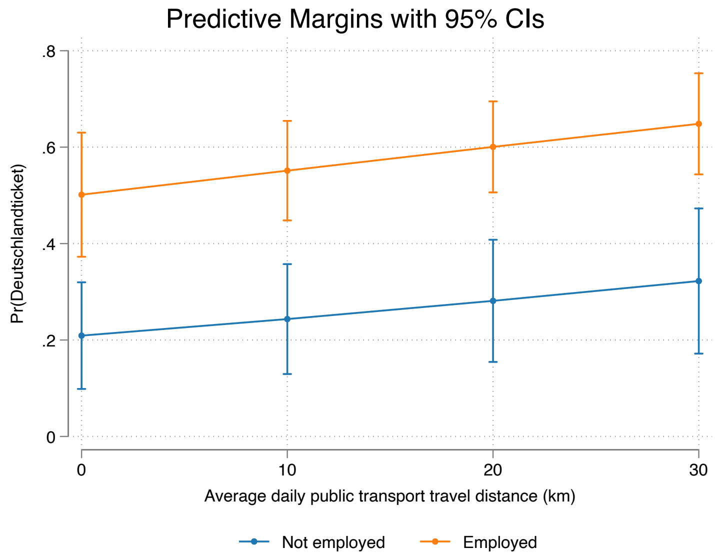


Table 7 summarizes the estimates from the multinomial logit model as defined in Section 3.2.2. For all tickets, as expected, we find the generic cost coefficient to be negative. Additionally, we find positive shifts in the cost sensitivity for having good public transport access and having had a season ticket at the time of the survey. This is expected as those individuals are presumably less cost-sensitive. For example, having good public transport access at the household location might allow them to pay more as the benefits are higher; similarly, existing season ticket customers may already value the system's benefits and are, hence, willing to pay more. As expected, based on the reported effects in public media, we do not find an income effect for the "Deutschlandticket". Perhaps interestingly, we find a negative price shift for males for the distance fare attribute. Without a meaningful hypothesis, this effect may describe gender differences in variables we have not controlled for, e.g., car commuting distance.

Last, we use the estimates from Table 7 to estimate the sample's price elasticity of demand for the "Deutschlandticket". Here, we simulate the elasticity by increasing the price by 1% and compute the observed shares in both cases. The resulting price elasticity of demand is -1.6, meaning a 1% price increase decreases demand for the "Deutschlandticket" by 1.6%; alternatively, a 1% price drop would increase demand for the "Deutschlandticket" by 1.6%. Thus, demand is elastic, which is rather unusual for public transport demand elasticities (Litman, 2012). This finding allows us to put forward the hypothesis that a larger share of the population owns the "Deutschlandticket" as a (convenience) gadget for the particular price level of 49 euros and less of a pure mobility tool as more are willing to opt out of the ticket if its price

Table 7: Model estimates of the MNL model for modeling the stated preferences of “Deutschlandticket” ownership.

Variable	Alternatives (base category is “no pass”)							
	Local pass		Deutschlandticket		Long-distance pass		Distance fare	
	β	Rob. t	β	Rob. t	β	Rob. t	β	Rob. t
ASC	0.894	(4.861)	1.204	(3.947)	−1.058	(−2.117)	−1.452	(−5.597)
Price generic	−0.078	(−9.810)	−0.046	(−8.524)	−0.009	(−4.008)	−0.051	(−2.828)
Price shift good PT access	0.020	(2.263)	0.008	(2.023)	0.004	(2.803)		
Price shift season ticket ownership	0.088	(9.516)	0.034	(8.377)	0.008	(5.611)	0.095	(3.768)
Price shift male							−0.047	(−2.141)
λ income			−0.096	(−1.201)				
Number of parameters	17							
Number of individuals	567							
Number of observations	4522							
Log-likelihood (0)	−7277.88							
Log-likelihood (model)	−5027.32							
Adjusted ρ^2	0.307							
AIC	10088.64							
BIC	10197.73							

increases compared to the market averages.

5 Discussion

The undeniable value of the “Mobilität.Leben” data collection was the fact that it was real-time and in parallel to the two public transport fare innovations of the “9-Euro-Ticket” and the “Deutschlandticket”, i.e., reporting on actual changes in choice and travel behavior, this cannot hide the fact that this empirical data collection has limitations. First, uncertainty during data collection creates substantial noise in the data. For example, while a successor ticket was discussed and its consumer response was of interest, many attributes were discussed with the actual ones that were unknown to the decision-makers. Discussions about employer-subsidized were present, too, which could put some consumers in a wait-and-see attitude. Second, the real-time nature of the study created some urgency in data collection, i.e., a questionnaire had to be sent out this week, making it difficult for the analysis to formulate and test appropriate questions as they were faced with the same uncertainty as consumers. This noise in the questions is then propagated into the answers as well. Third, the recruiting and panel participation in the “Mobilität.Leben” combines a convenience sample for the part with the smartphone app while a representative sample from the external recruiting. The latter helped to obtain some validity for nationwide estimates, which have been exploited in this study. Fourth, the “Mobilität.Leben” study ended in December 2023, while some dynamics in “Deutschlandticket” ownership and use have been reported afterward (Deutsche Bahn AG and VDV, 2024), which is consequently not reflected in our analysis.

The aforementioned challenges with the “Mobilität.Leben” data propagate further into the discrete choice modeling. While undoubtedly, using discrete choice methods is the appropriate method to investigate consumer behavior to investigate the overarching research questions, the particular methodological approaches can be enhanced. For example, it can be expected that much (random) heterogeneity may exist with respect to “Deutschlandticket” ownership, given the huge variety of purposes why individuals obtain this ticket. Accounting for such factors with finite mixtures (e.g., Kim and Mokhtarian, 2023), latent variables (Becker *et al.*, 2017) or mixed logit approaches (e.g., Paulssen *et al.*, 2013) can be a viable option. Nevertheless, although these approaches may improve model fit, it can be argued that these advanced approaches might not be able to accommodate or even correct the aforementioned challenges in the data generation process with its implications for the model design. Here, recent contributions in modeling averaging in travel behavior research could be a promising approach (Hancock *et al.*, 2020). There might be further unobserved correlation structures among different related choices, e.g., between ownership and use (Loder and Axhausen, 2018) and even further in spatial dependencies (Bhat *et al.*, 2016).

6 Conclusions

In this paper, we investigated the choice to adopt the “Deutschlandticket” using revealed and stated preference data. The data comes from the “Mobilität.Leben” study, a large-scale panel survey that observed from 2022-2023 the “9-Euro-Ticket” and the “Deutschlandticket”, two radical public transport fare innovations in Germany with questionnaires and semi-passive travel diaries utilizing waypoint tracking. The revealed preference data, collected before and after the “Deutschlandticket”’s introduction, provided information about the intention to buy the ticket and who eventually subscribed to the “Deutschlandticket”.[1] The stated preference data resulted from a discrete choice experiment where the choice was among different public transport tickets, including the “Deutschlandticket”. Using discrete choice models, we found that the intention for and ownership of the “Deutschlandticket” can be explained primarily by spatial typology, access to public transport, and previous public transport use, and not with socio-economic attributes. Nevertheless, the choice models also showed that a substantial share of the observed choices could not be explained with deterministic factors, i.e., they can be considered rather individual factors that can barely be captured by typical choice model parameters. Further, we found that the price elasticity of demand is around -1.6, i.e., a price increase most likely results in a decrease in the overall revenue from ticket sales for the public transport operators.

Considering that consumer behavior and market environments since the introduction of the “Deutschlandticket” have changed, future research is advised to perform another data collection, especially about the price sensitivity and updated choice behavior of the ticket’s alternatives, e.g., integration in mobility bundles and budgets. Here, integrating more attitudinal questions linked to the fare innovation and mobility policy in Germany would allow for, e.g., building hybrid choice models that may deepen the insights into the choice process (Ben-Akiva *et al.*, 2002; Abou-Zeid and Ben-Akiva, 2024). Further, the novel data source of semi-passive travel diaries with waypoint tracking has not yet been fully exploited, where the integration of this rich data into appraisal has just started (e.g., Tsoleridis *et al.*, 2022). Consequently, future research has to develop methods across the entire process chain, from data collection to model estimation,

[1] The “Deutschlandticket” is only available as a subscription.

to make these new data meaningful for policy making. Furthermore, utilizing actual trip data might reveal discrepancies between stated and revealed travel choices in research surveys, where it is well known that common household travel surveys suffer from an underreporting of trips (Stopher *et al.*, 2007), or alternatively, from an applied perspective that is helpful in guiding commuters to individually more optimal travel choices and ticket options.

In closing, the "Deutschlandticket" is well received by large parts of the German public (Deutsche Bahn AG and VDV, 2024), and initial welfare assessments suggest net benefits of this fare innovation (Krämer, 2024). Nevertheless, the ongoing debate in public and politics about the ticket's future shows that society is still undeceived as to whether to perceive public transport as a public or private good. As for similar tickets in Austria and Switzerland, the "Deutschlandticket" is surely not a policy for everyone, yet the rather high price elasticity of demand found in this study of -1.6 compared to literature reporting rather an inelastic demand (Litman, 2012), suggests that some may got the ticket as a gadget and not as a mobility tool based on economics; this leads to the promising hypothesis that this ticket through its very public good pricing nature may conserve more carbon emissions - by substituting at least some car trips - than by a having a more user-pays principle.

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