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Estimating mode choice inertia and price elasticities after a price intervention – evidence from three months of almost fare-free public transport in Germany

Maria Fernanda Guajardo Ortega[a), *)] and Heike Link[a)]

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Abstract

This study analyses the behavioural response of travellers on a temporal reduction of public transport prices in Germany through the so-called 9 Euro Ticket during summer 2022. The focus is on the inertia effect, e.g. the resistance to change behaviour, on people's travel mode decisions for commuter trips. We estimate mixed logit models for nearly 7,000 commuter trips, based on GPS-tracking data collected as a panel dataset before and after the price intervention. We find significant inertia effects for all travel modes except walking, with negative effects for car and positive effects for public transport and cycling, indicating that car users are less willing to change travel mode while cyclists and public transport users tend to be less resistant. Cross-elasticities of car with respect to public transport attributes are higher than the cross-elasticities of public transport with respect to car attributes such as in-vehicle time and cost. This effect is even higher in the inertia model. Our modelling results suggest that car travel is inelastic and characterised by negative inertia, with a relationship between both effects. Future policy interventions such as the 49-Euro ticket should therefore not focus on price reductions alone, but need additionally to improve other attributes of public transport such as frequency, reliability, safety and comfort in order to incentivise motorists to shift from car to public transport.

Keywords: Inertia, Price elasticities, Revealed preference, GPS panel data, Mode choice

JEL classification: C23, C25, R41

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1. Introduction

When designing and implementing a transport policy measure, it is crucial to take into account the extent to which individuals' behavioural response is influenced by habit and inertia and thus affects the (expected and desired) effects of the measure. The phenomenon of habit, leading to the concept of inertia, has been discussed in transport behaviour research since the 1980s (see for example Goodwin 1977; Williams and Ortúzar, 1982 and Johnson and Hensher, 1982). These first studies on habit describe this effect as a source of resistance to change due to the tendency to repeat past behaviour by choosing the same alternative even when circumstances have changed (Goodwin 1977; Williams and Ortúzar, 1982). More generally, inertia describes the tendency of previous behavioural choices to influence present decisions. The rationale behind inertia refers on the one hand to individual's tendency to save transaction costs by repeating the previous choice, using routine and experience instead of evaluating a new or so far unknown travel alternative (Verplanken et al., 1997). On the other hand, inertia is also related to risk aversion and to the tendency to avoid uncertainty (Tversky and Kahnemann, 1991, Chorus and Dellaert, 2012). The inertia effect is especially relevant in daily mobility, as commuter trips tend to be repeated over time (Pendyala et al., 2001; Yañez et al., 2009).

Although inertia has been discussed in transport behaviour literature since the afore mentioned studies, most discrete choice models (DCM) and transport demand models (TDM) have ignored temporal effects in general and the existence of inertia in particular, as the majority of them are based on cross-sectional data (Yáñez et al. 2009; Ortúzar and Willumsen, 2011). Cross-sectional data does not allow to analyse behavioural responses to changing circumstances such as price interventions, the introduction of new travel modes or changes in frequency, comfort etc., as they capture a current situation at a specific point in time. These models have, consequently, overlooked individuals' behaviour history and any direct markers of habit (Cantillo et al., 2007). Addressing this, Cantillo et al. (2007) proposed a formulation of a discrete choice model incorporating the inertia effect as a randomly distributed variable. Yañez et al. (2009) extended this work and analysed the effect of inertia and shock on people's travel mode choices when a disrupted modification of the transport system occurs. González et al. (2017) and La Paix et al. (2022) have shown that estimating price elasticities without considering the effect of inertia on people's mode choices may lead to severe consequences when evaluating transport policies.

Accounting for inertia effects entails collecting information on individuals' travel behaviour over time, which implies the necessity of obtaining rich panel data. Acquiring a panel dataset is costly in general, as it requires observing the same sample of individuals over distinct periods. This process becomes even more intricate when attempting to capture inertia effects, as relevant data must be systematically collected at strategic intervals, encompassing periods both prior to and subsequent to changes in the system's conditions. The challenge lies not solely in the collection of panel data itself but also in the quantification of the attributes for every potentially available travel mode, most importantly travel time, travel cost and level-of-service attributes, which are relevant for individuals' mode choice.

Most studies in the literature on inertia have either studied inertia within a transport system without interventions (Gao et al., 2022; Bansal et al., 2022) or have focused on evaluating the introduction of a new travel mode into the transport system and the predisposition of people to change their travel mode, using combined SP and RP data (e.g., Cantillo et al., 2007; Chatterjee 2011; Cherchi and Manca 2011; González et al., 2017). To the best of our knowledge, there are only few papers in this literature which analyse a nationwide price intervention. Yañez et al. (2009) used geocoding of origin-destination pairs in an RP panel data to analyse the impact of the introduction of *Transantiago*, a new public transport system, in the capital of Chile. Recently, La Paix et al. (2022) used the Mobility Panel of the Netherlands to evaluate the cost sensitiveness and inertia effect in travel mode choice. In addition, Yang and Timmermans (2015) studied the co-variation between transport mode choice and travel duration regarding fuel price fluctuation using data collected through GPS devices.

This paper aims at analysing the impacts of a policy intervention in Germany which included both a reduction in public transport costs through the 9-Euro ticket and a reduction in fuel taxes. Based on RP panel data from a GPS-tracking experiment during the summer months of 2022, the descriptive analysis in Gaus et al. (2023) suggests a lower than envisaged and expected modal shift to public transport due to the price intervention for commute trips. This finding leads us to the hypothesis that inertia effects have strongly restricted modal shift in daily commute trips. In order to test for this hypothesis, we estimate and compare Mixed Logit (ML) models with and without inertia effects and assess whether the choice of a travel mode is significantly influenced by the individual's history. Furthermore, we are interested in the direct and cross elasticities for each travel mode in both models (with and without inertia effect). The remainder of this paper is organized as follows. Section 2 describes the policy intervention, focusing on the *9 Euro ticket* in Germany and section 3 summarises the main aspects of data collection. Section 4 explains the methodological framework of mixed logit models used in this study. Section 5 presents and discusses the results of the estimations. Section 6 concludes.

2. The study context

In March 2022, the German government launched a package of measures to offset the impacts of the Ukraine war on private households' cost of living. Amongst this package, two measures, implemented from June to August, were related to transportation costs: the 9-Euro ticket for public transport, and a decrease of fuel taxes to the minimum allowed by EU regulation. As a result of these measures, public transport was almost fare-free while the decrease of fuel taxes lowered fuel prices by around 10% during the same period.

The 9-Euro ticket was available for each of the three months of June, July, and August 2022. It granted nation-wide unlimited second-class access to busses, subways, trams, and regional trains throughout the respective month at a price of 9€. Long-distance public transport, such as ICE, Intercity and Eurocity trains, private long-distance trains and intercity buses, was excluded from this measure. Travelers could purchase the ticket independently for each of the three months at all venues selling public transport tickets such as vending machines, bus drivers, online etc. Seasonal tickets with a validity of more than one month (e.g., yearly passes or student tickets) were automatically valid as a 9-Euro ticket. Owners of such tickets received a compensation equal to the difference between their originally paid price and 9€.

With a strong negative shock to public transport prices followed by a symmetric positive shock three months later, when prices went back up to their initial level (and in some regions even higher due to price increases), the 9-Euro ticket provides a unique quasi-natural experiment for transportation research as it uncovers travellers' behaviour before, during, and after the availability of the ticket. In economic terms, the 9-Euro ticket in combination with the fuel tax decrease generated a temporal change in relative prices which complicates attempts to isolate the effects of the 9-Euro ticket. Our approach in this paper responds to the challenge of this twofold policy intervention in estimating a discrete choice model (DCM) that is capable of accounting for the change in relative prices and for inertia effects. However, it should be noted that with the DCM framework it is not straightforward possible to identify induced demand, which presumably has occurred immediately after the price intervention in June where a strong increase of leisure trips[1] was observed. Quantifying the occurrence and extent of induced demand would require other approaches such as causal inference methods or demand modelling.

[1] Even though not studied systematically, there is evidence from traveler surveys that part of these trips would not have been undertaken without the availability of the 9-Euro ticket.

3. Data Description

For our study, we had access to a panel of individuals representatively drawn from the German population by age, gender, household size and region. We used GPS tracking data from the mobile phones of this sample during the month of May 2022, prior to the public policy, and during the summer months when the 9-euro ticket was available (June, July and August 2022). For an extension of our analysis to the return of both public transport prices and fuel taxes to their level before the intervention, GPS tracking data from the same panel is available. In this paper, however, we are interested in the response to the price intervention and will therefore focus on the data from May to August. Additionally, we conducted three surveys to gather socioeconomic information on the individuals, such as age, gender, income groups, occupation and household size. The data were obtained from the market research provider *GIM Gesellschaft für innovative Marktforschung* and the GPS location information was pre-processed into single routes by the Swiss market research company *Intervista.* While GPS tracking offers a wealth of data, it requires extensive cleaning, data complementing and processing efforts (Axhausen et al., 2003) coming along with a significant loss of raw data. In our case, we conducted a data depuration process applying the following main criteria: Tracked individuals must have responded to the three surveys and travelled at least once a month[2]. As a result of this process, the initial sample of nearly 4,800 individuals and around 900,000 trips was reduced to nearly 860 individuals and 200,000 trips. Thorough consistency checks showed that this final data sample preserves the representative character of the initial sample with respect to spatial distribution and socioeconomic characteristics. More details on data processing and analysis are given in Link et al. (2023). In what follows we summarize the most important criteria and procedures used for data processing and the further filtering of the data for the analysis of inertia.

The application of a discrete choice framework requires an appropriate dataset for which our revealed preference (RP) data had to be completed by identifying the non-chosen (available) alternatives for each observed route and by calculating attributes for the chosen and non-chosen alternatives. These attributes include trip cost, trip duration, and additional level-of-service attributes such as the access/egress and waiting times, the number of transfers, and the frequency of connections. In our case, the choice set consists of five modal alternatives: walking, bicycle, car, public transport (PT) with public transport comprising bus, tram and

[2] Expressed more precisely, their travel must have been recorded by the tracking device.

regional as well as long-distance rail[3]. For trips with more than one mode of transport (multi-modal trips), we followed a main-mode approach (Varela et al., 2018), e.g., the mode used for the major share of the total route (in km) was considered as the mode of transport for the entire route (main mode), while all other parts were considered as access and egress steps. Travel mode availability for each trip and individual was obtained by combining GPS data and additional information from the surveys such as owning a vehicle (for the case of bike and car), having access to sharing options or to public transport. The identification of non-chosen alternatives as part of the choice set was based on the observed distance of the chosen route and the information on mode availability from the survey, with distance thresholds.[4] With the information on the origin-destination and departure times of each trip, we used the *Application Programming Interface* (API) from *Maps Platform Google* to compute the best-estimated route for all available travel modes and computed the travel time for each travel mode. For public transport, we gathered further Level of Service (LOS) information, such as in-vehicle time (IVT) and out-vehicle time (OVT), the latter being disaggregated into access time, egress time, waiting time and transfer time.

Table 1: Travel mode share – commute trips

Mode share (%)	Car	Cycling	Public Transport	Walking
Wave 1	60.69	15.91	11.81	11.59
Wave 2	58.83	17.25	12.14	11.78
Availability	96.60	78.97	68.14	50.23

Notes: Number of observations: 352 individuals with 7056 trips. Wave 1: May 2022. Wave 2: June-August 2022.

Comprehensive calculations were necessary to obtain travel costs. To start with, we assumed zero cost for walking and bike owners; for non-bike owners, a cost of 0.10€ per minute was assumed for bike-sharing costs. For car users, we only considered the fuel cost, because short-term travel decisions may pay more attention to the perceived cost rather than to the full car ownership costs. Besides, as we could not deduce from the data if, for a particular trip, there was a parking cost associated, we assumed zero parking cost. We had no knowledge of the particular car fuel type for each trip of individual, so we considered the daily county-level average cost of gasoline and Diesel, available through *Tankerkönig API*. For non-car owners, we assumed an approximated cost of 0.30€ per minute for car sharing. Finally, for car users

[3] The full dataset described in Link et al. (2023) also contains flights which are not relevant in the context of commute trips as analysed here.
[4] These thresholds were set to 5km, 25km and 50km for walking, cycling and car, respectively. We did not impose any threshold on the public transport mode.

with a company car, we assumed zero cost. For public transport, we followed two main approaches. For the month of May, public transport prices were collected from the website of the *Deutsche Bahn* applying the corresponding discount for discount-card owners in interurban trips; for individuals with monthly or yearly inner-city public transport subscriptions, we considered zero cost, maintaining the same approach of perceived cost as for the other travel mode. On the other side, for the summer months, the cost per trip was set to zero for travellers owning a 9-Euro ticket and had an upper bound of 9€ for all others.

Table 2: Descriptive statistics – commute trips

	Mean		Std. deviation		Minimum		Maximum	
Variable	Wave 1	Wave 2	Wave 1	Wave 2	Wave 1	Wave 2	Wave 1	Wave 2
In-vehicle time (IVT)								
Car	12.46	12.48	8.85	8.88	1.02	0.90	49.44	49.50
Bicycle	27.01	27.11	25.81	25.88	1.68	1.68	125.76	125.76
PT	16.75	16.63	15.08	15.62	0.50	0.50	108.00	117.00
Walking time	30.68	30.69	20.35	20.27	6.00	6.00	143.28	88.86
Access time	7.59	8.31	7.19	8.38	0.00	0.00	51.78	53.90
Egress time	6.12	6.06	5.97	6.18	0.00	0.00	39.45	52.45
Waiting time	4.45	4.78	8.72	9.70	0.00	0.00	111.85	112.55
Travel cost								
Car	1.20	1.14	1.42	1.36	0.00	0.00	10.10	10.10
Cycling	1.79	1.80	2.44	2.45	0.00	0.00	12.03	12.20
PT	2.82	1.67	2.27	2.12	0.00	0.00	15.16	9.00

Notes: Number of observations: 352 individuals with 7056 trips. Wave 1: May 2022. Wave 2: June-August 2022.

As the main objective of this paper is to measure the effect of inertia on daily mobility, further data processing and filtering was necessary. We focused on commuter trips as one major type of daily and repeated mobility, which comprise in our raw data both work and education trips. Under this definition, commuting represents around 20% of all trips in our dataset. To quantify the effect of the 9-Euro ticket on travel behaviour, we aggregated the data into two waves: prior to the intervention and during the intervention. In order to enable an appropriate identification of inertia effects, equivalent amounts of trips with similar characteristics had to be defined and filtered out of the sample. Therefore, trips per individual were constrained to the minimum number of the trips undertaken by the individual in one of both waves. To aggregate the trips per person with similar characteristics we considered three main criteria: similar distance (with a maximum difference of 5 km), similar departure time (morning: from 5:00 until 12:00, evening: from 12:00 until 19:00 and night: from 19:00 until 5:00) and day of the week (weekday or weekend). The final sample used for this paper consists of 352 individuals with 7,056 trips, where individuals have an average age of 44 years which is – due to the focus on commuter trips – slightly lower than in the full sample (see Link et al., 2023). With 55% men are slightly over-represented and the household size is with 2.5 persons slightly higher than in the full sample (2.3 persons). As expected, our subsample for the inertia analysis in this paper has a higher share of fulltime workers (78%) than the entire sample (58.9%).

Table 1 shows the travel mode share in commute trips in wave 1 and wave 2. We can see that during the 9-Euro ticket months, the public transport, cycling and walking modes had an increase in their mode share, while car suffered a decrease in use. Table 2 presents descriptive statistics on travel times (in minutes) and costs (in euros). The main changes can be seen in the travel costs in public transport and cars from wave 1 to wave 2, as the main implications of the public policy were related to those costs.

4. Methodology

Our modelling approach is based on discrete choice models that have been applied as a workhorse in transport behaviour research. Discrete choice models are within the framework of random utility theory (McFadden, 1974), where individuals aim to maximize their utility when choosing an alternative among a finite set of discrete alternatives, assuming they are rational and have perfect information. The probability of choosing an alternative is affected by the attributes of the alternatives and by the individual's characteristics (Ortúzar and Willumsen, 2011). The perceived utility U_{jq} of an alternative j for an individual q includes a systematic component V_{jq} and a stochastic term ε_{jq} (Ortúzar and Willumsen, 2011):

$$U_{jq} = V_{jq} + \varepsilon_{jq} \tag{1}$$

The systematic utility function, defined by the modeler, is typically represented as a linear combination of the measurable and quantifiable attributes that characterize the alternative, as in Equation (2). This formulation assumes that the estimated parameters θ_{jk} of the attributes are constant across individuals.

$$V_{jq} = \sum_{k} \theta_{jk} \cdot X_{jkq} \quad (2)$$

To allow for diverse attribute parameters across the population, *systematic variations in taste* can be incorporated. These enable the derivation of distinct parameters for a specific attribute based on individual characteristics (such as socioeconomic status, age, among others). Equation 3 presents the example from Ortúzar and Willumsen (2011) to illustrate how distinct parameters can be obtained for different attributes, depending on the socioeconomic characteristics of the individuals.

$$V_{jq} = (\alpha_0 + \sum_{l} \alpha_l \cdot s_{lq}) \cdot t_{iq} + (\beta_0 + \sum_{l} \beta_l \cdot s_{lq}) \cdot c_{iq} + (\gamma_0 + \sum_{l} \gamma_l \cdot s_{lq}) \cdot f_{iq} \; (i = 1,2) \quad (3)$$

Individuals will attempt to maximize their utility by selecting the alternative with the highest perceived utility, as shown in Equation (4).

$$P_{jq} = Prob\{U_{jq} \geq U_{iq}, \forall \, Ai \; \in A(q)\} \quad (4)$$

As the modeller can decompose the perceived utility of an individual into a systematic utility and a stochastic term, Equation (4) can be expressed as

$$P_{jq} = Prob\{V_{jq} + \varepsilon_{jq} \geq V_{iq} + \varepsilon_{iq}, \forall \, Ai \; \in A(q)\} \quad (5)$$

The probability of selecting alternative *j* by an individual q is subsequently defined as:

$$P_{jq} = Prob\{\varepsilon_{iq} \leq \varepsilon_{jq} + (V_{jq} - V_{iq}), \forall \, Ai \; \in A(q)\} \quad (6)$$

The commonly used Multinomial Logit Models (MNL) assumes that the stochastic terms ε_{iq} are independent and identically (iid) Gumbel distributed. When assuming this distribution, the choice probability is shown in Equation (7) and the parameter β is usually normalized as it cannot be estimated separately from the θ.

$$P_{jq} = \frac{\exp(\beta V_{jq})}{\sum_{A_i \in A(q)} \exp(\beta V_{iq})} \quad (7)$$

An extension of the MNL model is the Mixed Logit model (ML). It accounts for the more general case where the attributes of an alternative do not equally affect all individuals. It provides more flexibility than systematic taste variations. These models assume that parameters follow a probability distribution, allowing attributes to impact individuals differently. The probability is then defined by integrating over the parameter distribution of the standard Logit probabilities.

$$P_{jq} = \int L_{jq}(\theta)f(\theta)d\theta \tag{8}$$

When considering longitudinal data (panel data) for the estimation of models, as in our application, several stochastic terms must be considered, such as: the error component specific to the alternative υ_{jq}, an error component specific to wave *w* of the panel ς_j^w, and a random component ε_{jq}^w assumed usually with independent and identically (iid) Gumbel distribution. As in other studies (Cantillo et al., 2007; La Paix et al., 2022), we will assume $\varsigma_j^w = 0$ and consider ξ_{jq}^w , the random component, and the υ_{jq} error component of the alternative as normally distributed random variables. A described above, the systematic utility function V_{jq}^t described by the modeler is expressed as a linear combination between the tangible and quantifiable attributes that define the alternative, LOS variables and socioeconomic characteristics of the individual (SE). The extended definition of the perceived utility considering the inertia effect on individuals' choice used in our analysis, is based on Cantillo et al. (2007) and the generalisation by Yañez et al., (2009):

$$U_{jq}^w = V_{jq}^w - I_{jq}^w + \upsilon_{jq} + \varepsilon_{jq}^w \tag{9}$$

The inertia I_{jq}^w is defined as the valuation of the available alternatives compared to the chosen alternative of the previous situation (previous wave). The inertia component is only present from the second wave onwards, as we assume that the travel mode choice is influenced by the previous wave. Based on Cantillo et al. (2007) and Yanez et al. (2009), we will consider inertia as a randomly distributed variable within the population (Equation 10).

$$I_{jrq}^w = \left(\beta_{Ij}^w + \delta_{Iq} \cdot \sigma_{Ij}^w + \beta_{I_{SE}} * SE_I\right) \cdot (V_{rq}^{w-1} - V_{jq}^{w-1}) \tag{10}$$

The inertia term is generally assumed as normal randomly distributed variable with the population mean β_{Ij}^{w} , the standard deviation σ_{Ij}^{w} , and with the socioeconomic variables SE_I for systematic variation. A positive inertia component indicates that the individual would tend to maintain the chosen alternative of the previous wave. A negative inertia component would indicate the opposite effect, namely that individuals would be less resistant to change, thus increasing travel mode change probabilities.

The probability of choosing an alternative i in wave w is now defined as the person's sequence of choices, expressed as the joint probably product of the probabilities between waves evaluated at all values of the parameters (La Paix et al., 2022):

$$P_{ni}^{w} = \int_{\omega} \prod_{wt} L_{ni}(\omega_{ni}) f(\omega_{ni}) d\omega \tag{11}$$

Apart from identifying the existence and size of inertia, our study focuses on identifying the extent of mode shift due to the price intervention, notably the price elasticities. The direct point elasticity refers to the change in the probability of choosing an alternative in wave w when an attribute of the alternatives increases, and is defined based on Train (2009) as

$$E_{iz_{ni}}^{w} = \frac{\partial P_{ni}^{w}}{\partial z_{ni}} \frac{z_{ni}}{P_{ni}^{w}} \tag{12}$$

The cross elasticities refer to the change in the probability of choosing an alternative i in a wave w when an attribute z_{nj} from another alternative j changes, and is given as

$$E_{iz_{ni}}^{w} = \frac{\partial P_{ni}^{w}}{\partial z_{nj}} \frac{z_{nj}}{P_{ni}^{w}} \tag{13}$$

Our specification of the utility formulas for the four travel modes (walking, cycling, car and public transport) is detailed in Table 3. Each mode is associated with an alternative specific constant, set to zero for the walking mode. In-vehicle time is specific for each travel mode. For cycling we defined an absolute taste variation with in-vehicle time and a binary variable for heavy rain (considering heavy rain as rain over 5 mm per hour[5]). We defined a generic walking time parameter; for public transport, the latter encompasses access and egress time. For walking time, we used an absolute taste variation with a binary variable that indicates if the person is a women or not. The waiting time is defined only for public transport as a specific parameter. Each alternative has a generic cost parameter, except for walking (as its cost is assumed to be zero). We specify a normally distributed random inertia variable specific to each alternative (starting with wave 2). As those variables are continuous, there is no identification issue (Cantillo et al., 2007). Finally, we describe a serial correlation for the alternatives.

Table 3: Model specification

	ASC	IVT	Walking time	Waiting time	Cost	Inertia	Serial correlation
Walking			G			S	
Cycling	S	S			G	S	S
Car	S	S			G	S	S
Public Transport	S	S	G	S	G	S	S

ASC: Alternative-specific constant. IVT: In-vehicle time. G: generic parameter. S: specific parameter.

For estimating mixed logit models, usually simulations are applied, whereby the number of draws is a trade-off between computation time and estimation accuracy. We used the Python package Biogeme (Bierlaire, 2003).

5. Results

Table 4 shows the estimated coefficients for mixed logit models without inertia effects (Model ML1 – base model) and for a mixed logit model that incorporates alternative-specific inertia components (Model ML2) as defined in section 4. Both models were estimated using a sample with 352 individuals and 7052 observations (trips) in total. The models were estimated simultaneously for both waves. In the absence of a closed-form solution for the choice probabilities in an ML context, a simulated log-likelihood estimation with 250 Halton draws was used.

Several specifications and definitions of waves were considered during the modelling process. We started with estimating Multinomial Logit models (MNL) for each month

[5] This data was obtained from the Climate Data Center (CDC) which offers extensive weather data from local measuring stations (see https://cdc.dwd.de/portal/).

separately, followed by estimating simultaneously ML models with the first month (May) and second month (June). We continued by aggregating all summer months (June, July and August) into one wave (wave 2) and estimated two-wave models, e.g combining the first wave (May, before the policy intervention) with the second wave (June, July, August, during the policy intervention). In none of these specifications we found access and egress times being significantly different from each other. Furthermore, we did not find a significant difference between a specific public transport walking parameter and the general walking parameter. Therefore, we finally specified a generic parameter for walking. In-vehicle time (IVT) was defined as a mode-specific variable, although IVT for car and public transport were not found to be significantly different from each other (t-test for ML1: -0.267 and t-test for ML2: -0.288).

Table 4 shows that all parameters estimated in ML1 (and almost all parameters in ML2) are significant and plausible. An exception is the absolute taste variation of cyclists' IVT with rain (same as in model ML2). Since the negative sign is as expected, meaning that heavy rain impacts negatively and leads to a worse perception of IVT, we decided to maintain it in the specification. The taste variation of women in walking time is in line with expectations: The estimated parameter is significant for both models, and we can conclude that walking time affects men by nearly 38% (ML1) and 30% (ML2) more negatively than women. Walking time as access/egress to public transport affects individuals more negatively than waiting time and IVT, as expected. In ML1, the negative impact of IVT in public transport on utility is of comparable size as the estimated value of the waiting time parameter. In contrast to the results from ML1, the parameter for IVT in PT estimated in ML2 has a stronger negative effect than waiting time, which seems more plausible and is also in line with literature (Ortúzar and Willumsen, 2011).

When discussing the estimated inertia parameters, one must keep in mind that inertia effects are defined negatively in the utility function, meaning that a negative parameter has to be interpreted as a positive impact on individuals' utility. Our main result is that the inertia component for car is significant and negative (table 4), indicating that car users have a resistance to change travel mode. This finding is consistent with other studies such as González et al. (2017) and La Paix et al. (2022) and was expected, as more attractive modes generally have negative inertia parameters (Yáñez et al. 2009). For cycling, the inertia parameter is positive and significant, indicating that cyclists are more willing to change their habitual travel mode. For pedestrians, no significant inertia effect was found. For public transport users, the inertia effect is significant with only 85% confidence level, which leads us to the cautious interpretation that public transport users seem to have a tendency of changing their travel mode.

Table 4: Model estimation results

	ML1		ML2	
	Value	t-test	Value	t-test
In-vehicle time (IVT)				
Car	-0.068	-3.34	-0.022	-1.20
Bicycle	-0.083	-7.97	-0.035	-5.25
PT	-0.072	-5.05	-0.037	-2.89
Walking time	-0.120	-9.94	-0.036	-3.81
Waiting time	-0.070	-2.94	-0.027	-3.56
Interactions				
Rain Bicycle	-0.007	-0.84	-0.002	-0.32
Women walking time	0.046	2.52	0.011	1.75
Travel cost	-0.149	-2.76	-0.051	-1.38
Inertia car (mean)			-2.936	-2.06
Inertia bicycle (mean)			8.706	4.27
Inertia PT (mean)			3.229	1.49
Inertia walking (mean)			0.879	0.70
Inertia car (st.dev)			3.851	-1.11
Inertia bicycle (st.dev)			0.247	-0.03
Inertia PT (st.dev)			1.228	-1.06
Inertia walking (st.dev)			0.071	0.32
υ Car	2.242	12.14	1.793	5.54
υ Bicycle	2.294	10.27	-0.835	-1.67
υ PT	1.755	8.92	-0.614	-2.87
ASC Car w1	-1.218	-4.02	0.093	0.42
ASC Car w2	-1.333	-4.62	0.485	0.31
ASC Bicycle w1	-1.939	-7.27	-1.369	-6.35
ASC Bicycle w2	-1.875	-7.17	3.547	4.60
ASC PT w1	-1.375	-5.98	-0.727	-1.72
ASC PT w2	-1.505	-6.49	0.403	0.52
Sample size	352		352	
Observations	7056		7056	
Number of draws	250		250	
N° of estimated parameters	17		25	
Log likelihood	-11 294.43		-10 525.99	
p2	0.218		0.271	

In both models, all standard deviations of the estimated error components are significant. In terms of model performance, we used the Likelihood Ratio test (LR) to compare both model´s performance to an unrestricted version of the model (Armstrong et al., 2001). The value of the LR test for the model with against the model without inertia is 1,536.88, larger than the critical value $\chi^2_{95\%,8} = 15.507$, so we can reject the null hypothesis that both models are identical.

Given our study context which aims at analysing whether the price intervention was capable to induce mode shift to public transport, we calculated for each observation in wave 1 the elasticities with Biogeme. Table 5 shows the average values of the disaggregate elasticities which tend to be higher in the model with inertia (ML2) than in the model without inertia, in particular for car and walking and – to a lower extent – for bicycle. The use of the main mode approach and the definition of public transport mode as a composite mode, imply that we only obtain a generic direct travel cost elasticity for all PT modes without distinction between bus, underground railway, tram, rail, and others. When comparing this generic value with values from the literature (Goodwin, 1992), we can conclude that our direct elasticity of travel cost is within the ranges of bus and underground railway, but smaller in magnitude when compared with rail. As we only considered commuter trips, which tend to be urban and shorter in distance, a more appropriate comparison would be with the values of bus and underground railway. As travel cost of car was constructed as the fuel cost per minute of driving, we compare our estimated value with the elasticity of vehicle-km with respect to short-term fuel price presented in the literature (Goodwin et al., 2004), and observe that our values are smaller but reasonable.

Our general result from both models is that users of all transport modes are rather inelastic to price changes. PT users are the least inelastic whereas car users are the most inelastic, which is consistent with other studies (González et al., 2017; La Paix et al., 2022). When incorporating inertia, only small changes in own price elasticities are found, ranging from a decline in inelasticity by 6% for cyclists to an increase in inelasticity by 3% for public transport users and by 6% for motorists. The cross-price elasticities suggest that a price change for public transport has a higher effect on mode shift to/from car than a price change of car on public transport. These effects, although all of them confirm the inelasticity of demand, are stronger in absolute terms when incorporating inertia, and incorporating inertia leads to stronger effects on cross-price elasticities than the own-price elasticities.

Turning to time elasticities, cyclists and public transport users are more sensitive to IVT than car users. This result is expected, as being inside a private car tends to be perceived as more comfortable than being in public transport vehicles or cycling. Regarding cross-elasticities, we obtain similar effects as González et al. (2017), namely that the cross-elasticities of car with respect to PT attributes are higher than the cross-elasticities of PT with respect to car attributes (such as IVT and cost). This suggests that the probability of changing to car is high when an attribute of the public transport alternative increases, whereas the probability of changing to public transport is low when an attribute of the car alternative increases. This effect is even more pronounced in the inertia model.

Table 5: Cross and direct point elasticities for travel cost and in-vehicle time

	ML 1			ML2		
		Price elasticities				
Car	-0.047	0.012	0.014	-0.045	0.009	0.016
Bicycle	0.022	-0.189	0.005	0.017	-0.199	0.004
Public transport	0.038	0.009	-0.356	0.048	0.006	-0.345
		Time elasticities (IVT)				
Car	-0.249	0.066	0.064	-0.232	0.047	0.077
Bicycle	0.183	-1.532	0.047	0.138	-1.629	0.037
Public transport	0.111	0.029	-1.020	0.140	0.022	-0.989

Notes: Number of observations: 352 individuals with 7056 trips. ML1: Mixed Logit model without inertia. ML2: Mixed Logit model with inertia. All elasticities were estimated for the first wave (May).

6. Conclusion

This paper was motivated by the need for a deeper analysis on the impacts of the 9-Euro Ticket and of the fuel tax reduction, both implemented during June-August 2022 in Germany, on mode choice in daily commuting. The rather low mode shift from car to public transport for commute trips, which amount at around 20% of all trips, has led to the research question whether inertia effects, known for being particularly relevant when analysing daily (repeated) mobility, are responsible for this disappointing effect of the policy intervention. This paper has therefore analysed the incorporation of temporal effects, in particular the inertia effect, on people's travel mode decisions following a disruption in the transport system. We have estimated mixed logit models using GPS-tracking data collected as a panel dataset before and after the start of the intervention.

The Mixed Logit model with mode-specific inertia parameters has given significant and plausible estimates for the relevant modal attribute such as travel cost, in-vehicle time, waiting and walking time, and has shown a better fit than a model without inertia. We found significant inertia effects for all travel modes except walking, with negative effects for car and positive effects for public transport and cycling. The policy conclusion from this is that car users are less willing to change travel mode while cyclists and public transport users tend to be less resistant to travel mode change. The estimated elasticities in our inertia model differ from the model without inertia, as shown in other studies (González et al. 2017; La Paix et al., 2022).

This is a critical result, as not considering inertia may lead to significant consequences in the *ex ante* evaluation of transport policies (La Paix et al., 2033).

Furthermore, for car and walking the elasticities obtained in the model with inertia tend to be higher than in the model without inertia and lower for cycling. Car users are more inelastic to travel cost compared to cyclists and public transport users, and therefore less sensitive to price variations. On the other hand, public transport users and cyclists are more sensitive to variations of in-vehicle time compared to car users. Finally, similar to González et al. (2017) we found that the cross-elasticities of car with respect to PT attributes are higher than the cross-elasticities of PT with respect to car attributes (such as IVT and cost). This means that the probability of changing to car is high when a public transport attribute increases, whereas the probability of changing to public transport is low when a car attribute increases. This effect is even higher in the inertia model.

Our major policy conclusion is that the (temporal) price intervention alone has not provided a sufficient incentive for a modal shift of commute trips from car to public transport. Our modelling results suggest that the reasons for this are the inelastic car demand on the one hand, and the existence of negative inertia on the other hand, with a relationship between both effects. This means for future policy interventions such as the 49-Euro ticket that apart from travel cost, other attributes of public transport such as frequency, reliability, safety and comfort have to be positively experienced by travellers in order to incentivise motorists to shift from car to public transport. This requirement is at a conceptual level reinforced by Chorus and Dellaert (2012) who show that not only saving transaction costs leads travellers to repeat past choices: in addition, and even independently from the wish to save cognitive resources, it is risk aversion and avoidance of uncertainty associated with a so far non-chosen alternative, that leads to inertia effects. The resistance of motorists to shift to public transport even at almost zero cost during the 9-Euro ticket experiment might be explained by such aversion against uncertainty and risk regarding the quality of public transport (such as feeling not safe in public transport, disliking lack of cleanness, scenery and crowding, especially after seeing pictures of crowded trains in the media etc.). This opens avenues for future research where the GPS tracking data should be complemented by surveys on the afore-mentioned less tangible attributes such as reliability, crowding and personal safety, allowing to study in more detail the reasons for inertia effects. While this requires new data collection efforts, we also have potential to extend the analysis with the existing dataset. First, a third panel wave for September 2022, e.g. the period after the policy intervention could be included into model estimation, allowing to analyse whether a symmetric behavioural response has occurred. Furthermore, other trip purposes than commuting should be studied. For instance, shopping trips, which account for around 16% of all trips, might be subject to inertia effects. Finally, interesting insights could be gained from a model extension that includes inertia and shocks in the fashion of Yañez et al. (2009), accounting for the two price shocks from May to June and from August to September and that studies the shock effects separately for each month of a five-months panel.

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