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Investigating observed and unobserved variation in the probability of 'not travel' as a behavioural response to restrictive policies

Stefan Flügel*, Nils Fearnley, Marit Killi

Institute of Transport Economics, 0373 Oslo, Norway

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ABSTRACT

Besides technological improvements, restrictive car policies are likely to be the most effective measures for reducing greenhouse gas emissions from local passenger transport. Restrictive policies may lead some individuals to choose to not travel to otherwise useful or enjoyable activities. This paper therefore explores what factors drive the probability of 'not travel' as a behavioural response to restrictive policies.

Using stated choice data among car owners in the 10 largest cities in Norway, we investigate observed and unobserved taste variation for 'not travel' given different (hypothetical) policies. The empirical evidence suggests that the likelihood of 'not travel' (a) is lower for work-related trips; (b) is higher where respondents state they have no decent alternatives; (c) increases with trip distance; and (d) increases with the intensity of the policy. We perform Monte-Carlo simulations illustrating different predicted choice behaviour for car users and public transport users under different types of stylized policies (travel time changes versus travel cost changes).

1. Introduction

CO_2 emissions from the transportation of passengers have been the subject of considerable attention and study (Scholl et al., 1996; van Essen et al., 2019; Wang et al., 2011; Korzhenevych et al., 2014; Fearnley et al., 2016). Along the lines of these studies, for a given population, CO_2 emissions are the product of:

(1) the amount of travel per person
(2) the energy needed for that amount of travel
(3) the carbon intensity of that needed energy

Climate policies target—directly or indirectly—one or more of these. Subsidizing/incentivizing technological development and diffusion targets mainly point 3 (and, to a lesser extent, point 1), e.g. through telecommuting. Policies that incentivize dense development and the agglomeration of housing, working places and/or services target point 1 by reducing the need to travel long distances. Most policies that aim to change individuals' travel mode choice behaviour target point 2 by giving incentives to move from high energy-intensive travel modes (e.g. internal combustion engine cars) to low energy-intensive travel modes (e.g. metro and trains).

Among the latter, restrictive car policies are likely to be the most effective measures for reducing CO_2 emissions (see, e.g., Gärling

* Corresponding author.
E-mail address: sfl@toi.no (S. Flügel).

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and Schuitema, 2007; Tagliapietra and Zachmann, 2018) as well as other externalities associated with the private car, such as congestion and local emissions (see, e.g., Wu et al., 2016; Buehler, 2010; de Grange and Troncoso, 2011). Restrictive policies (i.e. 'sticks') such as road tolls are expected to have a larger effect on transferred demand from car to public transport (PT) than positive measures (i.e. 'carrots') for PT (as reductions in fares) (Fearnley et al., 2017; Wardman et al., 2018).

Besides mode choice changes, restrictive car policies can also alter the amount of travel per person (i.e. point 1, above). This can be by means of reduced travel distances as a result of changes in destination choice (e.g. road tolls provide incentives to run errands within the toll ring) and/or a reduction of travel frequency.

From an economic perspective, most changes in behaviour that result from restrictive policies are associated with a reduction in user benefits—while total social welfare may improve due to a possible reduction of external cost. This reduction in user benefit is likely to be severe for those travellers who opt to not travel at all after a restrictive policy is implemented (i.e. who stay at home or do not undertake an additional trip within a trip chain). This is because the restrictive policy may discourage otherwise useful/enjoyable activities. This may also lead to undesirable/costly changes in a person's time allocation (e.g. working less); in addition, it might be perceived as socially unfair, especially in scenarios of price increases that affect the welfare of low-income households and other disadvantaged groups most severely (see, e.g., Delbosc and Currie, 2011).

The above points suggest that 'not travel' (i.e. a reduction in trip frequency) is a contentious and unpopular effect of restrictive policies, and especially so if their primary aim is to affect mode choice. It is not surprising that official policy communication often excludes 'not travel'—and compromises in mobility in general—as a possible outcome of policies, exemplified in the statement 'Curbing mobility is not an option' in the EU's (2011) white paper on transport.

Douglas et al. (2003) point to a lack of understanding about what factors drive the probability of 'not travel' as a behavioural response to restrictive policies. Despite some recent empirical studies on trip-cancelling responses to policies and events (see section 2), there remains a lack of research that systematically investigates factors that drive the probability of 'not travel' as a behavioural response to restrictive policies. Such information may help with selecting more socially accepted climate policies in the transport sector.

In travel mode choice models, 'not travel' is often omitted as a choice alternative.[1] This is also the case for the Norwegian Greater Oslo model MPM23 (Flügel et al., 2016). When deriving cross-elasticities and cross-modal diversion factors with that model, as done in Flügel et al. (2018), one is likely to overestimate the cross-modal demand effects of policies because changes in total demand (i.e. supressed or induced travel) are not handled. Indeed, this limitation was one of the authors' motivations for the data collection and analysis for this paper.

In this paper, we are interested in estimating observed and unobserved taste variation for 'not travel'. For observed taste heterogeneity, we hypothesize the following regarding the likelihood of 'not travel':

(H1) Lower for work-related trips, since those trips are likely to be unavoidable
(H2) Increases with trip distance, as short distance trips can more easily be replaced with walking and cycling
(H3) Increases with the intensity/scope of the policy (e.g. doubling fares is likely to yield a higher probability of 'not travel' compared to a 10% fare increase)
(H4) Higher for situations where there is no (perceived) alternative to the current mode
(H5) Higher in situations where the currently used mode is unavailable (e.g. car is at the service station), rather than slower or more expensive

The likelihood or probability of 'not travel' can be measured absolutely (i.e. relative to all behavioural responses including to 'remain using the current travel mode', which still has some positive probability unless the restrictive policy makes the current travel mode completely unavailable) or relative to the probability of making a change in travel mode choice. In the latter case, the relative choice probability is referred to as the diversion factor towards 'not travel'.[2] We will perform hypothesis testing (Section 4) based on

[1] Many transport models do not account for 'not travel' explicitly. In four-steps models, 'not travel' is typically omitted from the choice set in the travel mode choice model component while effects of suppressed (and generated) transport are associated with changes predicted by a trip generation model. The prediction of behavioural changes towards 'not travel' given a policy/supply change is, in such models, based on the log-sum changes from the travel mode choice model. The marginal effect of changes in log-sum on trip frequency is typically measured with a generic coefficient (within each model segment) and is thereby independent of the size, direction and type of policy causing the change in log-sum. Heterogeneity regarding preferences or the likelihood towards 'not travel' is therefore not accounted for. In comparison, activity-based demand models (e.g. Castiglione et al., 2015) are in general better suited to accounting for heterogeneity with respect to 'not travel'. By modelling the utility of 'staying at home all day' and different variants of primary and secondary activities (as in Bowman and Ben-Akiva, 2001) one can also investigate how the propensity towards 'not travel' may vary with the daily activity pattern of an individual. Activity-based demand models are typically estimated based on (cross-sectional) travel survey data, a data source that (as discussed below) gives limited insights regarding how restrictive policies directly impact the probability of 'not travel'.

[2] In general, (cross-modal) diversion factors are the proportion of the change in demand for one mode that comes from, or goes to, another mode, or 'not travel' (Dunkerley et al., 2018). Diversion factors only relate to mode shift including 'not travel' but do not include such behavioural responses as changes in destination, trip timing, trip distance or route choice, cf. e.g., Noland and Lem (2002) and Bonsall (1996). When analysing competition and substitution between travel modes, the diversion factor is found to be more stable over time and between contexts, and hence more transferable, than cross-elasticities (Wallis, 2004; BAH, 2003; Fearnley et al., 2017; Flügel et al., 2018). However, diversion factors vary with the number of travel alternatives: Ceteris paribus, the diversion factor will be smaller the greater number of alternatives that exist and larger the fewer travel alternatives that exist (Flügel et al., 2018).

the former type, i.e. our model includes the option ‘remain using current travel mode’. However, when predicting choice probabilities (Section 5) we will focus mainly on diversion factors, as we expect that the risk of hypothetical bias of stated preference (SP) data is less profound with respect to diversion factors. This is because the probability of choosing the current option, which respondents may have the greatest incentives to over- or understate, is not considered by diversion factors.

We are not aware of other studies that have conducted similar hypothesis testing. Indeed, quantitative analyses of ‘not travel’ given restrictive policies seem rare, at least on an individual level. Reasons for this may include the fact that most case studies investigate positive (‘carrot’) measures (like most infrastructure projects) and thereby focus on induced demand (rather than suppressed demand). Of those studies that investigate restrictive measures, a majority seem to study the impact on modal shift and congestion relief rather than trip cancellation. In addition, the literature on diversion factors (see Section 2) typically assumes equivalence across the sign of attribute change, e.g. changing an attribute (say, ticket prices) by +10% or −10% implies the same diversion factors. Thus, one assumes the same demand effects (in absolute terms) of ‘carrot’ policies and ‘stick’ policies.

In general, it is difficult to obtain good revealed preference data on ‘not travel’ after restrictive policies are implemented. National travel surveys (NTS) usually routinely report individuals that did not travel on a given day (i.e. stayed at home).[3] However, these data provide little information regarding the question of suppressed demand and trip cancellation due to restrictive policies.[4] To obtain this information, one must survey people before and after a policy is introduced. These before–after studies are often costly to conduct. An alternative to revealed preference data, however, is the use of stated choice data—the approach taken in this study. Stated choice data is inherently connected to potential hypothetical biases, i.e. the danger that respondents over- or understate their utility/probability to with ‘not travel’ to (hypothetical) restrictive policies. This paper therefore focuses on factors influencing the probability of ‘not travel’ (using the proposed hypotheses above) and mainly discusses differences in probabilities between user groups (car user versus public transport users) and policies (travel time versus travel cost changes), rather than absolute values for choice probabilities or diversion factors.

The paper is structured as follows: Section 2 is a literature review, Section 3 presents the data, Section 4 documents the discrete choice modelling and estimation results, Section 4 presents the simulations of choice probabilities for some stylized policies, and Section 5 concludes the paper.

2. Literature review

This literature review is limited to quantitative studies on ‘not travel’ as a behaviour response to policies and events. The focus is on results rather than methods.

Regarding impact on *motorists’* trip cancellation, Marsden et al. (2016) described the 2015 four-week closure of the Forth Road Bridge in Scotland for regular car traffic, which caused a 12% reduction in work trips. This was mainly related to home working and more intense shift working. Social trips were also significantly reduced. With regards to *public transport* unavailability, a number of studies have analysed public transport strikes. Clark (2017), for example, reports the results of a large survey of nearly 234,000 US transit passengers. If their transit service were unavailable, 22% of these passengers would not travel, while one-third would switch to a car mode and another 20% would divert to other transit modes.

Van Exel and Rietveld (2001) reviewed 13 similar studies in Europe and the US and compared this review with their own findings from a short railway strike in the Netherlands. The 13 studies show large variation in the prevalence of trip suppression. However, the authors concluded that about 10–20% of commuting and school trips are cancelled following a public transport strike. A much larger share is to be found among elderly travellers and for trips. The same authors studied the effect of another one-day full railway strike in the Netherlands a few years later (van Exel and Rietveld, 2009). Their findings were considered to be comparable with previous studies of strikes, which showed that between one-third to half of the travellers cancelled their trip.

Nguyen-Phuoc et al. (2018a) interviewed 30 individuals and analysed their responses to a hypothetical short-term public transport removal. They report that ‘a lot of them stated that they would cancel their education-based trips’ (p. 6); that road traffic congestion would induce trip cancellations; and that they would cancel trips whose purposes were ‘not too important’ (p. 8). In a hypothetical long-term (10-year) removal of public transport services, however, none of their interviewees considered cancelling their trips. Nguyen-Phuoc et al. then (2018b) conducted a web-based survey (N = 640) that included a hypothetical question about a major public transport removal. Over 13% of respondents stated that they would cancel their trip. Higher shares of trip cancellations are associated with: female respondents; age over 50 years; lower income; no driving license; no car ownership; trips related to education; trips to CBD; and longer trips.

[3] Metz (2012) identified a remarkable stability in the average number of trips per person per year in Britain over a period spanning almost four decades, based on NTS. A similarly stable average number of trips per person per day of just over three is found in all Norwegian NTS from 1992 to 2013/4 (Vågane et al., 2011; Hjorthol et al., 2014; Denstadli and Hjorthol, 2002; Hjorthol, 1999). Regarding non-travel, 10–15% of Norwegian NTS respondents reported that they did not travel on the reference day. However, such NTS evidence does not provide insights into the question of induced and suppressed demand, or indeed of non-travel responses to policies or events, as acknowledged by Andersen et al. (2009, footnote 15). For example, although both the UK and the Danish NTS map reasons for not having made any trips, those reasons only refer to health and practical matters (Christiansen and Skougaard, 2013; Andersen et al., 2009) and not to such things as unavailability of transport modes or prohibitively high costs or travel times. The Norwegian NTS also places emphasis on health and practical reasons for non-travel but includes ‘bad weather’ and ‘no access to car or other modes’ as possible reasons for non-travel on the reference day (Hjorthol et al., 2014).

[4] Also, even an individual who makes multiple trips on a reference day may have cancelled one or more trips for some reason. Therefore, the number of trips recorded, be it zero or many, offer limited insight into trip cancellations due to unavailability or high money/time costs.

The volcanic ash cloud incident in 2010 shut down much of Europe's *aviation* between 17 and 22 April. Mazzocchi et al. (2010) cite various estimates of its impact, which includes 100,000 cancelled flights and 10 million cancelled passenger trips. While the alternative of 'not travel' was available to those who had not yet embarked on their journey, those who were stranded at their destinations and had their return flights cancelled either had to delay their trip home or find alternative modes of transport. During this time, Mazzocchi et al. observed increased demand for Eurostar and ferry services between Britain, France, the Netherlands and Spain.

Brechan (2010) analysed impacts of the ash cloud incident in Norway. Approximately 0.8 m trips were lost and the net reduction was about 0.65 m trips. Around one-quarter of Brechan's respondents made the journey by means of alternative transport modes, which included different flight (45%), train (26%), bus (24%), boat (15%) and private or rented car. Consequently, about three-quarters postponed their journey or cancelled it altogether.

The most recent and comprehensive study regarding diversion factors to 'not travel' was conducted by Dunkerley et al. (2018), who recommend diversion factors to 'no travel' of 10–25% based on a review of 1009 reported diversion factors from 45 studies. However, Dunkerley et al. (2018) did not analyse the evidence beyond cross-tabulations of average values with standard errors. Hence, there is no evidence of differences in diversion factors by type of intervention (pricing, infrastructure, service, etc.) or between improvement vs deterioration.[5]

In Norway, a recent research programme has evaluated major transport infrastructure and service shocks in and around the city of Oslo, and has provided some empirical evidence relevant to the 'not travel' response (see Fearnley et al., forthcoming a,b; Tennøy et al., 2015a, 2015b, 2016). The picture that emerges from their surveys of former passengers on discontinued bus and metro services and of car commuters through closed tunnels is that non-travel is a relatively limited behavioural response to unavailability and a considerable worsening of the transport service.[6]

3. Data

Our data stem from an online self-administered questionnaire (SAQ) conducted in May/June 2017. Respondents were recruited from the membership base of the Norwegian Automobile Association (NAF), whose members comprise almost 10% of Norway's adult population. Of those members with a home address in one of Norway's 10 largest cities, 60,000 were randomly selected and invited to participate. Of these, 6853 completed the questionnaire, which corresponds to a response rate of 11.4%. Table 1 compares our sample with that of the population. The public transport modal share is rather low in our sample compared to more representative survey data. Correspondently, the car share is higher, which is probably due to the high representation of car owners and driver's license holders in our sample. Due to self-selection bias towards NAF, our sample almost entirely consists of individuals that have a drivers' licence (99.7%) and at least one car at their disposal in the household (99.9%). These high shares made it impossible to weight observations to make them representative for the total travel population in the 10 cities. Our sample is therefore a sample of car owners/users and not a sample of travellers, or the population, in general. This is, however, very useful given the current policy push towards zero-growth in car use in Norwegian urban areas (Norwegian Government, 2017).

Comparison with a more representative sample of car users from the NTS shows, furthermore, that our sample of NAF members consists of many elderly people and is predominantly male, especially in the older age groups. We therefore weight observations in each of the following analyses by age and gender, such that the weighted distributions fit with those observed in the NTS.

At the core of the survey, there are six stated choice tasks where respondents are asked to recall a trip they had taken the day before the interview (the 'reference trip'), and asked how they would have chosen in cases of hypothetical policies/situations, as outlined in Table 2. Choice alternatives included car, public transport, walk, cycle, and 'not travel'. For the response alternative of continuing to use their current mode of transport, the text describing the choice alternative was formulated 'remain using [mode]'. Fig. 1 is a screenshot of a test interview and shows how the choice tasks were presented to respondents.

For the choice task with index '1b (car)' in Table 2, those whose reference trip was a car trip would be asked about their behavioural response to a hypothetical 50% increase in car costs (for petrol and road tolls). Of the 1723 respondents who were asked

[5] It appears uncertain whether evidence of induced demand (given improvements/carrot measures) like new infrastructure or reduced prices can be transferred to predict suppressed demand (given deteriorations/restrictive policies). Indeed, arguments made by behavioural economists that humans tend to regard losses as more severe than corresponding gains suggest that the effects and/or underlying factors are different. Income and time budget restrictions are another reason why deterioration may be considered differently from improvements. Regarding 'not travel' it should intuitively—at least on an individual level—matter in which direction the policy goes, as taking an extra trip is fundamentally different from not taking a trip at all.

[6] Bus route 57 closed down on 4 April 2016. Six weeks later, its former passengers responded to a survey (N = 120). About 11% stated that they travelled less often (and 1% travel more often). A similar survey was sent to passengers who used to travel the 'Østensjøbanen' metro line, which closed down for nearly a year for major refurbishment (N = 132). 11% stated that they travelled less often (and 5% travel more often). The same research programme analysed a number of temporary (between a few months and up to two years) tunnel closures on main arteries and ring roads in and around Oslo, Norway. Among commuters who were affected by the 2015 'Smestadtunnelen' ring road tunnel (AADT ~ 50,000) closure, 54% reported no behavioural response; 29% changed trip timing (i.e. they started their trips earlier or later); 8% reported mode shift; and 6% said they had chosen another route. Only four per cent worked from home more often, which can be considered a 'no travel' response. A tunnel closure with much farther-reaching consequences, but which only closed 50% of its lanes at a time, is the Bryn tunnel (AADT ~ 66,000). During its 2016 closure, 41% of commuters who had previously used the Bryn tunnel stated that they had made no behavioural changes; 33% had changed timing; 22% had changed routes; and 13% had changed mode. Again, only a fairly small share, seven per cent, stated that they worked from home more often.

Table 1
Geographical distribution of sample.

Index	Urban area (based on reported postal code)	Population			Our sample (unweighted)		
		Inhabitants (1000 s)*	Inhabitants per sqm*	Share PT**	N	Percent	Share PT
1a	Oslo city	653	4 982	26	215	3.1%	33.9%
1b	Oslo suburban	605	2 040	12	549	8.0%	17.8%
2a	Bergen city	270	2 804	16	453	6.6%	11.3%
2b	Bergen suburban	93	1 383	7	237	3.5%	5.9%
3a	Trondheim city	181	3 047	12	424	6.2%	8.3%
3b	Trondheim suburban	55	1 648	7	197	2.9%	5.2%
4	Stavanger	131	3 143	10	711	10.4%	10.4%
5	Nedre Glomma	123	1 812	8	657	9.6%	6.7%
6	Drammen	66	2 767	8	521	7.6%	11.5%
7	Tønsberg	40	1 967	8	435	6.3%	5.9%
8	Grenland	83	1 746	8	445	6.5%	2.5%
9	Kristiansand	85	2 316	8	629	9.2%	3.7%
10	Tromsø	65	2 876	8	755	11.0%	8.8%
0	Others (rural)	Na	Na	Na	87	1.3%	8.2%
0	Unknown	Na	Na	Na	539	7.9%	9.8%
Total					6 853	100%	9.4%

* Source: Statistics Norway.
** "Share PT" refers to public transport mode share. Source: National Travel Survey (Hjorthol et al., 2014).

Table 2
Choice responses (weighted) on stated preference (SP) tasks.

Index	SP task	Weighted Count*	Car	PT	Cycle	Walk	Not travel	Sum 'change mode'
*Current **car** users:*								
1a (car)	10% increased car costs (petrol and road tolls)	1665	**89.7%**	4.6%	2.6%	1.5%	**1.6%**	**8.7%**
1b (car)	50% increased car costs (petrol and road tolls)	1723	**83.2%**	6.0%	5.2%	2.0%	**3.6%**	**13.3%**
1c (car)	100% increased car costs (petrol and road tolls)	1771	**75.0%**	9.9%	6.9%	3.0%	**5.2%**	**19.8%**
2a (car)	10% increased travel time	1723	**90.3%**	7.6%	1.0%	0.7%	**0.4%**	**9.3%**
2b (car)	50% increased travel time	1771	**84.9%**	9.0%	2.5%	0.4%	**3.2%**	**11.9%**
2c (car)	100% increased travel time	1665	**76.1%**	13.4%	3.9%	0.5%	**6.2%**	**17.7%**
3 (car)	Car not available at all	4788	NA	48.1%	18.4%	6.6%	**27.0%**	**73.1%**
For current PT users:								
1a (PT)	10% increased ticket prices	214	18.8%	**73.4%**	2.9%	4.7%	**0.3%**	**26.3%**
1b (PT)	50% increased ticket prices	192	29.8%	**49.5%**	15.7%	3.2%	**1.7%**	**48.7%**
1c (PT)	100% increased ticket prices	187	34.8%	**48.0%**	9.7%	3.4%	**4.1%**	**47.9%**
2a (PT)	10% increased travel time	192	7.4%	**92.0%**	0.6%	0.0%	**0.0%**	**8.0%**
2b (PT)	50% increased travel time	187	29.9%	**58.8%**	8.4%	0.8%	**2.0%**	**39.1%**
2c (PT)	100% increased travel time	214	43.2%	**39.4%**	13.5%	1.3%	**2.6%**	**58.0%**
3 (PT)	PT not available at all	579	69.1%	NA	18.1%	5.4%	**7.4%**	**92.6%**

* Weights are not rescaled within segments. That is why the sum does not equal the (unweighted) number of observations in Table 4.

this question, 83.2% stated that they would continue using a car in this scenario. Six per cent would switch to public transport, 5.2% would cycle, 2% would walk and 3.6% would not make that trip ('not travel').

The option 'not travel' was only included in restrictive policy scenarios, on which we focus in this paper. A description of responses to carrot measures, like free public transport, is provided in Fearnley et al. (2018).

Since the survey was designed for short-distance transport (and thus 'air' was not given as a possible alternative), we excluded all trips longer than 100 km (about five per cent of the sample).

The SP tasks included in this paper are presented in Table 2 alongside the corresponding response shares.

Looking at the response shares in Table 2, we see a consistent pattern regarding the intensity of the policy. The bigger the change, the lower the share that remains using the current transport mode and the higher the share of stating 'not travel' and 'change mode' (the latter is given in the last column in Table 2 as the sum of shares to other (non-reference) transport modes). If the intensity is 'absolute', i.e. when the current mode is assumed unavailable (choice task with index 3), shares of 'not travel' and 'change mode' are high.

Car users are more likely to choose 'not travel' compared to PT users (who, in our sample, own a car), especially in choice task 3. Even greater differences between car and PT are found in the choice to remain using the current mode and to change the transport mode. Car users are less likely to change their transport mode. This partly relates to the fact that PT users in our sample are also car owners and have a decent alternative (the car) available. Those of our respondents who used PT for their reference trip state a mode switching response that is very large compared with the general evidence of the demand effects of price and travel time changes (cf. Balcombe et al., 2004).

Fig. 1. Screenshot of choice task: 'Imagine that your car trip took 9 min longer. Your total travel time becomes 28 min. What would you have chosen?' Alternative responses are: continued with car; public transport; bicycle; walk; I would not travel.

While it is perfectly within expectation that our car-owning sample would react stronger to an increase in fares or travel time than the average PT passenger, it is clear that SP studies (alone) typically lack external validity to infer own- and cross-elasticities of demand. As mentioned earlier, we therefore do not focus on absolute market shares and absolute derived elasticities. Instead, since this study has strong internal validity—i.e. the ability to explain variation across the sample in a meaningful way, as indicated by the expected pattern of response in Table 2—our focus is on cross-sectional variation.

Tables A1 and A2 in the Appendix A show the response pattern for work-related and non-work trips. As expected, the share of respondents replying 'not travel' is considerably larger in the non-work sample (for the related hypothesis testing, we refer to the next section).

4. Discrete choice modelling and estimation results

Discrete choice models—logit models, in particular—are the standard method to investigate choice probabilities among finite, exhaustive and mutually exclusive alternatives. For our data, we define the choice alternatives to be

(1) Remain using current transport mode (R)
(2) Change transport mode (C)
(3) Not travel (NT)

This compact and generic specification of the choice set allows us to run identical models for the car and the PT segments.

The bold numbers in Table 2 show the aggregated choice responses. Note that 'remain current transport mode' is not an alternative in SP task 3 where current mode is not available.

The purpose of the estimation models is to investigate the hypotheses stated in the introduction section. The utility function for NT is therefore parameterized with different explanatory variables (see below). By investigating the size and significance of the related beta coefficients we can investigate which variables are important drivers behind the propensity to choose 'not travel' as a consequence of restrictive policies and the event that the current mode is unavailable.

Our models are mixed logit models for panel data (see, e.g., Train, 2009) that include normally distributed error components with mean zero and to-be-estimated variance. They are designed to capture unobserved taste variation towards certain alternatives across respondents, i.e. taste variation that is not already explained by the explanatory variable. As shown in many applications in the field of transport and other disciplines, mixed logit models (MXL) typically outperform multinomial logit models (MNL). This relates to the fact that the stochastic part of the MNL is only captured by identical and independent Gumbel-distributed error terms, whereas additional error components in the MXL models capture how individuals have different tastes beyond what is captured by observable explanatory variables.

The choice probability (P) for 'not travel' of respondent n in choice task t is formally given as:

$$P_{NT,n,t} = \frac{e^{V_{NT,n,t}}}{e^{V_{NT,n,t}} + e^{V_{R,n}} + e^{V_{C,n}}} \tag{1}$$

The probability function for 'remain' (R) and 'change' (C) correspond. Since all three probabilities need to sum up to 100%, explanatory variables that affect the utility of 'non-travel' will also affect the probability of R and C.

The systemic utility function of the three alternatives are further specified as:

$$V_{R,n} = \beta_{R,0} + \varphi_{R,n} \quad with \quad \varphi_{R,n} \sim N(0, \sigma_{R,n}) \tag{2}$$

$$V_{C,n} = \beta_{C,0} + \varphi_{C,n} \quad with \quad \varphi_{C,n} \sim N(0, \sigma_{C,n}) \tag{3}$$

$$V_{NT,n,t} = \beta_{NT,0} + \sum_k \beta_k * X_{k,n,t} + \varphi_{NT,n} \quad with \quad \varphi_{C,n} \sim N(0, \sigma_{NT,n}) \tag{4}$$

where the constant terms capture the average effect of the stochastic part of the utility. The phi-terms in Eqs. (2)–(4) are the above-mentioned error components with a mean value of zero and to-be-estimated standard error ofσ_n. Note that these terms are constant over choice task t for respondent n.

$X_{k,n,t}$ are the explanatory variables (some of which vary with t) and β_k are the corresponding beta parameters measuring the marginal effect of the variables on the utility of 'not travel'.

Because utility has no natural scale, we need to normalize one constant term so as to identify all parameters; we apply $\beta_{R,0} = 0$. For the SP tasks with index 3 (current mode unavailable), and Eq. (1) reduces to $P_{NT,n,t} = \frac{e^{V_{NT,n,t}}}{e^{V_{NT,n,t}} + e^{V_{C,n}}}$.

The explanatory variables of the X-vector are described in Table 3, while Table A1 in the Appendix A reports descriptive statistics of the explanatory variables.

The square root transformation of the intensity variables was introduced because a pre-test showed that linear (non-transformed) specifications tend to overpredict behavioural changes at large intensities (100% increases in the attributes).

We tested some other variables like age and a dummy for respondents living in larger cities, but those were omitted from the final model because these variables had low t-statistics in both the car and the PT model already in the MNL version of the models. In general, we are limited to the available variables from the survey; the geographical information about the trip in the survey was not detailed enough to import reliable information from network models. Note that the inclusion of additional error components partly captures the effects of omitted variables (unobserved attributes).

The models are estimated in Biogeme (Bierlaire 2003) by maximizing the weighted simulated log-likelihood using 1000 Halton draws. Table 4 shows the estimation results.

The models have a decent goodness-of-fit (adjusted rho-square of 0.482 for the car model and 0.396 for the PT model). However, much is associated with the alternative specific constants ($\beta_{C,0}$ and $\beta_{NT,0}$), as seen by the relative low value of the adjusted rho-square statistic (Adj. rho square (c)). The contributions of the explanatory variables alone therefore appear modest (see Tables A4 and A5 in Appendix A for the reduced models). This is likely related to the fact that the explanatory variables describe a choice alternative ('not travel') that has a relative low market share to begin with. It may therefore not be surprising that the explanatory variables, despite being largely statistically significant, do not contribute that much to the overall likelihood of the observed choices.

It is worth mentioning that the model specification was not chosen to achieve the highest possible fit, but rather to investigate the hypothesis relating to 'not travel' in the most direct way. For the PT model, the contributions of the unobserved heterogeneity are larger than those from observed heterogeneity: going from Final-LL of -319.864 in the 'constant only' model (compare with Table A5 in the appendix) to -313.311 in the multinomial logit model (MNL) where $\varphi_{R,n}$, $\varphi_{C,n}$ and $\varphi_{NT,n}$ are assumed fixed to zero, to

Table 3
Explanatory variables in utility function of "not travel".

Short name	Variable name	Type of variable	Varies with	Explanation
Dist.	Distance	Continuous in km	n	Self-reported distance of reference trip
Male	Male	Dummy	n	1 if gender of respondent is male
Work	Work-related	Dummy	n	1 if trip purpose commuting or business
Bad	Bad_alternatives	Dummy	n	1 if respondents ticked 'other alternative are unacceptable' for their motivation of the reference mode
Una	Unavailable	Dummy	t	1 if choice task index 3
C_time	Constant_time	Dummy	t	1 if choice task index 2
I_time	Intensity_time_sqr	Continuous in %	t	% increase in the time attribute (choice index 2); square root transformed
I_cost	Intensity_cost_sqr	Continuous in %	t	% increase in the cost attribute (choice index 1); square root transformed

Table 4
Estimation results of mixed logit models that explain the probability of 'not travel'

		Car		PT	
Observations/respondents		15308/5236		1620/544	
Final-LL		−2619.114		−304.406	
Adj. rho square (0)		0.482		0.396	
Adj. rho square (c)*		0.091		0.014	
Parameter	**Short explanation**	**Value**	**Robust T-stat**	**Value**	**Robust T-stat**
$\beta_{C,0}$	Mean value of change transport mode	−2.98	−23.29	−0.587	−4.32
$\sigma_{C,n}$	Sigma value of change transp. mode	1.84	16.48	−1.17	−5.15
$\beta_{R,0}$	Mean value of remain transport mode	0	fixed	0	fixed
$\sigma_{R,n}$	Sigma value of remain transp. mode	1.05	3.87	0.0381	0.19
$\beta_{NT,0}$	Mean value of not travel	−6.17	−13.27	−8.24	−4.02
$\sigma_{NT,n}$	Sigma value of not travel	1.33	6.47	2.00	4.58
Dist.	Distance of reference trip	0.0265	8.53	0.0301	2.85
Male	Male respondent	0.135	0.148	0.0142	0.03
Bad	Other alternatives perceived as bad	0.883	5.69	0.296	0.38
Una	Current mode not available	1.21	2.88	3.48	2.17
I_time	Scope of the time change	0.199	3.98	0.404	2.34
I_cost	Scope of the cost change	0.408	7.07	0.35	2.2
C_time	Policy is travel time related	−1.78	−2.74	0.0715	0.04
Work	Commuting/business trips	−1.71	−10.25	−1.29	−2.43

* Computed against the Final-LL of the "MNL_ASC" model in the appendix, i.e. a model that just includes the constant terms.

−304.406 in the mixed logit model. In the car model, we observe a similar pattern for the contributions.[7]

Looking at the explanatory variables, we see that distance has a positive effect on the probability of 'not travel'. As this result is statistically significant (with *t*-stats beyond the critical limit of 1.96 for a 95% level of confidence), we have empirical support for hypothesis H2 stated above.

When respondents stated that 'other alternatives were unacceptable' for their reference trip (dummy 'Bad_alternative' = 1), we see that the likelihood of 'not travel' increases. The effect is lower for PT compared to car (0.296 vs 0.883), and in the case of PT it is not statistically significantly different from zero; this may be partly due to the low number of respondents who reported this motivation for their choice of reference mode (6.4% as shown in Table A3 in the Appendix A). From the car model, we do get support for hypothesis H4, suggesting that 'not travel' may be more likely in situations without any good options besides the current transport mode.

Choice task 3, where the current mode is assumed to be not available, has—as expected from the observed choice responses presented in Table 2—a strong positive effect on 'not travel', giving clear support for hypothesis H5.

Both variables 'Intensity_cost_sqr' and 'Intensity_time_sqr' are statistically significant (in both models), supporting hypothesis H3 that the intensity or severity of the policy affects the likelihood of 'not travel'. The numerical values of the two variables need to be seen together with the 'Constant_time' variable. We refer to the next sections for analysis as to the degree to which the intensity influences the probability of 'not travel' for time and cost changes.

The dummy for male is not statistically significant and is not further discussed here. Finally, the coefficient for the dummy for work-related trips is significantly negative, supporting our intuition that 'not travel' is less likely for work-related trips (hypothesis H1).

In summary, our assessment of the hypothesis stated in the introduction section is as follows:

H1 Lower for work-related trips as those trips are likely to be unavoidable: Supported. The coefficient for work-related trips is significantly negative, meaning that 'not travel' is less of an alternative for work trips.
H2 Increases with trip distance: Supported. We found that distance has a significantly positive effect on the likelihood of 'not travel'.
H3 Increases with the intensity/scope of the policy: Supported. There is a significant effect of higher intensity of the change. Higher costs and longer travel times give higher probabilities for 'not travel'.
H4 Higher for situations where there is no (perceived) alternative to the current mode: Partly supported. When respondents state that 'other alternatives were unacceptable' for their reference trip, we see that the likelihood of 'not travel' increases. This effect is found to be significant for the car user subsample but not for the PT user sample (possibly because of the low number of PT users stating 'other alternatives were unacceptable').
H5 Higher in (hypothetical) scenarios where the current mode is unavailable: Supported. When the current mode is assumed to be unavailable, we find a significant, strong positive effect on 'not travel'.

[7] Going from Final-LL of −2895.779 in the 'constant only' model to −2750.275 for the multinomial logit model to −2.619.114 in the mixed logit model for car.

5. Monte-Carlo simulations

In this section, we simulate choice probabilities and diversion factors regarding ‘not travel’. The purpose of this application is to illustrate the effect of some stylized policies for different subgroups of the population. The intention is also to get a better understanding of possible different outcomes of cost versus time increases. Because of the square-root-transformation in the choice model, possible differences were not straightforwardly detectable from the estimation results alone.

We repeat that the focus in this paper is on cross-sectional variation (not absolute choice probabilities) and we therefore do not calibrate the choice model with external data. The Monte-Carlo (MC) simulations are based on the estimated parameters from the previous section alone. This includes the standard deviation of the additional error terms, capturing the effects of unobserved attributes and unobserved taste heterogeneity.

The MC simulations are performed by taking sets of draws d from the distributions $N(0, \sigma_{R,n})$, $N(0, \sigma_{C,n})$ and $N(0, \sigma_{NT,n})$ in Eq. (1) given the point estimates for the variances, as presented in Table 4. We apply 30 sets of draws per respondent n in each of the two subsamples. The average simulated choice probability over N individuals (weighted by w_n) and D draws are given as:

$$\bar{P_{NT}} = \frac{1}{N*D}\sum_{n}\sum_{d}\left(w_n\frac{e^{V_{NT,n,d}}}{e^{V_{NT,n,d}} + e^{V_{R,n,d}} + e^{V_{C,n,d}}}\right) \tag{5}$$

We also calculate average diversion factors towards ‘not travel’ as:

$$D\bar{F}_{NT} = \frac{1}{N*D}\sum_{n}\sum_{d}\left(w_n\frac{e^{V_{NT,n,d}}}{e^{V_{NT,n,d}} + e^{V_{C,n,d}}}\right) \tag{6}$$

These diversion factors can be interpreted as the choice probability for ‘not travel’ given that one is no longer using the existing transport mode. An underlying (and somewhat restrictive) assumption of the applied models is that choice probabilities are independent of each other, such that the relative choice probabilities do not change when one alternative is removed from the choice set.

Table 5 gives the average simulated choice probabilities (by formula 5) and diversion factors for ‘not travel’ (by formula 6) given different stylized policies. Naturally, the diversion factors to ‘not travel’ are larger than the choice probabilities because diversion factors are only relative to the choice probability of ‘changing transport mode’.

The bold numbers in Table 5 can be directly compared to the response shares from Table 2. The simulated average probabilities fit the observed shares well over the range of policies, which suggests that the applied square-root-transformations are appropriate.

Current car users have—on average—a higher probability of stating ‘not travel’ as a behavioural response to a policy. The effect of the intensity variable is larger for car time increases compared to car cost increases. However, the effects for time increases start at a lower level and first when applying very high changes (75%) we see a greater absolute effect for the time attribute. For PT users, the differences in the time- and cost attribute are not statistically significant (the confidence intervals of ‘intensity_time’ and ‘intensity_cost’ in Table 4 are overlapping).

The effects of policy intensity on probability is roughly linear, indicating that the square-root-transformation and the S-shape of the logit probability functions are levelling each other out to some degree.

Looking at average diversion factors, the difference between car users and PT users becomes even more apparent. This relates to the fact that ‘changing transport’ mode is much more likely for PT users in our sample (cf. Table 2).

Results in Table 5 are averages over all trips within the two subsamples. Table 6 segments the results for given policies (here, 50% increases for time and cost) by 6 subgroups defined by trip purpose and travel distance. We see a great variation, as the segment with the largest effect (non-work trips over 20 km) have a more than 3-times higher average probability towards ‘not travel’ compared to

Table 5
Outcome of the Monte-Carlo simulation by policy.

Simulated policy	Average probability of “not travel”		Average DFs towards 'not travel'	
	Car users	PT users	Car users	PT users
Cost increases by				
5%	1.55%	0.29%	19.19%	1.19%
10%	**1.81%**	**0.40%**	20.87%	1.60%
25%	2.45%	0.77%	24.45%	2.78%
50%	**3.41%**	**1.55%**	28.86%	4.96%
75%	4.35%	2.57%	32.48%	7.45%
100%	**5.31%**	**3.86%**	35.66%	10.22%
Time increases by				
5%	0.48%	0.28%	9.76%	1.14%
10%	**0.68%**	**0.37%**	12.03%	1.48%
25%	1.32%	0.65%	17.61%	2.40%
50%	**2.69%**	**1.20%**	25.61%	4.02%
75%	4.46%	1.89%	32.85%	5.82%
100%	**6.65%**	**2.72%**	39.52%	7.78%

Table 6
Average diversion factors towards 'not travel'. Outcome of the Monte-Carlo simulation for subgroups for given policies.

Trip purpose	Trip distance	50% cost increases		50% time increases	
		Car users	PT users	Car users	PT users
Work-related	< 5 km	13.15%	2.49%	11.09%	1.97%
	5–20 km	15.87%	2.78%	13.53%	2.19%
	> 20 km	25.64%	6.86%	22.50%	5.61%
Non-work	< 5 km	30.98%	5.39%	27.43%	4.29%
	5–20 km	34.98%	6.01%	31.21%	4.91%
	> 20 km	46.52%	13.90%	42.46%	11.71%

the group with the lowest effect (work-related trips below 5 km). This underlines a rather high observed heterogeneity in preference in the sample.

It must be remembered that these are average values and that there is a high variation of individual probabilities within these groups. This is illustrated in Fig. 2, which shows the cumulative distribution functions of the individual diversion factors given a 50% increase in car costs.

As a reading example for Fig. 2, we derive that about 80% of respondents within the subgroup 'work trips below 5 km' (the black-dotted uppermost line in the graph) have diversion factors of below 20%, while the corresponding share of respondents with a diversion factor lower than 20% for longer distance non-work trips (the grey solid downmost line at the bottom of the graph) is 30%.

In all subgroups, some respondents have relative probabilities (i.e. diversion factors) of 'not travel' close to 0% and others have probabilities close to 100%. As we hold the policy constant and control for observed subgroups, this variation within subgroups is largely associated with unobserved heterogeneity in preferences (besides distance variation within the subgroups and possible different shares of people stating that they did not have decent alternatives).

6. Conclusions and implications

As pointed out in the introduction, implementing policies towards a 'green mode shift' may have the undesirable effect of supressing certain trips. This is strongly supported by our data. Our data showed further that the probability for 'not travel' as a

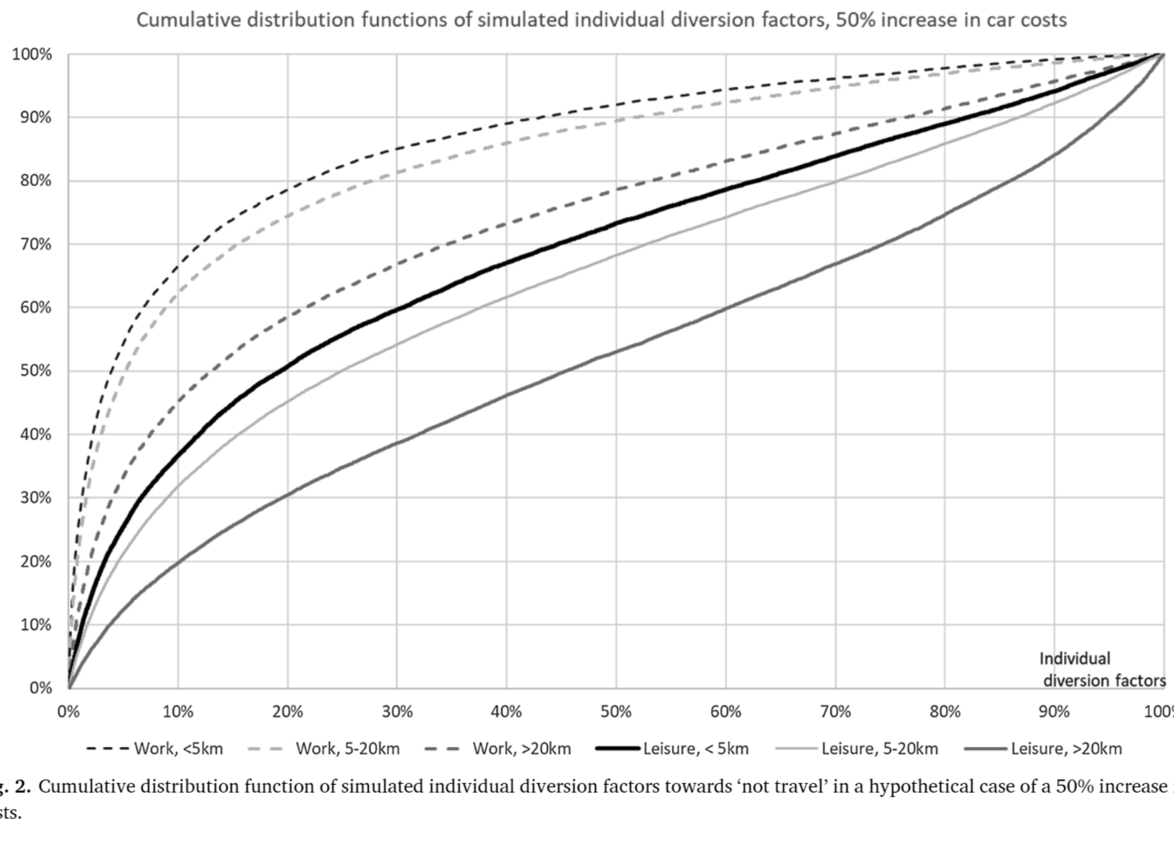

Fig. 2. Cumulative distribution function of simulated individual diversion factors towards 'not travel' in a hypothetical case of a 50% increase in car costs.

consequence of restrictive policies varies with several observable variables. In particular, it (a) is lower for work-related trips; (b) is higher where respondents state they have no decent alternatives; (c) increases with trip distance; and (d) increases with the intensity of the policy. In addition, our analysis identifies a large unobserved variation across individuals. Our paper therefore adds to the literature, where 'not travel' has—to our knowledge—not been subject to anything but aggregate analysis and average numbers.

Our data, and the simulated choice probabilities from the presented models, indicate also that car users are more prone to react with 'not travel' to restrictive policies compared to PT users. An important caveat for our study is that (almost) all respondents in our sample live in a car-owning household (recall that they were recruited from the Norwegian Automobile Association's membership base), thus it can be expected that a rather high share of the respondents that currently use PT has at least one good travel alternative (the car) available as an alternative. This has likely lead to a somewhat downwards bias in the response to 'not travel' for PT users.

The patterns in the empirical results and the results of the hypothesis testing presented in this paper are largely as expected a-priori. They may therefore be consistent with the intuitions of politicians and transport planners guiding the formulation of policies. Still, we believe a short discussion of practical implications of our results is in order. For the sake of argument, assume that decision-makers are interested in reducing CO_2 emissions (or other negative externalities) from local transport and consider restrictive car policies an effective strategy. However, they want to minimize the extent of suppressed trips (i.e. trips not undertaken) resulting from the restrictive policies. In this setting it seems vital to offer travel alternatives that are perceived as acceptable (cf. H4). This suggests that many restrictive car policies should go hand-in-hand with improvements ('carrots') for public transport, walking or cycling—not so much for the isolated effect of the carrot measure on mode choice, but to sustain the level of mobility for citizens.

Regarding the intensity of policy (cf. H3) there seems to be a clear trade-off. More severe restrictive car policy (e.g. higher road tolls) will have a larger effect on environmentally-friendly mode shift but are also likely to limit mobility to a larger degree. Reducing PT fares may be an equitable way to offset that mobility loss due to restrictive car policies that typically impact individuals from low-income households.

Of course, for some types of travel, PT is not a realistic alternative. In this situation, an implication (cf. H2) is to aim at policies that target short car trips (compared to long ones), as short car trips can in many situations be replaced by walk and cycle trips. Increasing fees for parking may be such a policy since parking fees have a relatively higher impact on total travel cost for short distance trips.

Another implication (cf. H1) could be to aim specifically for work trips, e.g. by restricting workplace parking availability or having higher road tolls in commuting hours, as our analysis shows that work trips are significantly less likely to be suppressed.

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Appendix A

See Tables A1–A5.

Table A1
Choice responses (weighted) on stated preference (SP) tasks, work related trips only.

Index	SP task	Weighted Count	Car	PT	Cycle	Walk	Not travel	Sum 'change mode'
Current car users:								
1a (car)	10% increased car costs (petrol and road tolls)	735	90.7%	4.6%	3.4%	1.1%	0.2%	9.1%
1b (car)	50% increased car costs (petrol and road tolls)	757	82.7%	6.5%	6.7%	2.4%	1.7%	15.6%
1c (car)	100% increased car costs (petrol and road tolls)	740	70.7%	13.4%	9.4%	2.7%	3.7%	25.6%
2a (car)	10% increased travel time	757	88.9%	8.8%	1.2%	0.9%	0.1%	10.9%
2b (car)	50% increased travel time	740	85.3%	9.7%	3.4%	0.4%	1.2%	13.5%
2c (car)	100% increased travel time	735	75.4%	16.7%	4.0%	0.5%	3.4%	21.2%
3 (car)	Car not available at all	2067	NA	55.9%	23.8%	4.6%	15.7%	84.3%
For current PT users:								
1a (PT)	10% increased ticket prices	171	21.3%	71.7%	3.4%	3.5%	0.0%	28.3%
1b (PT)	50% increased ticket prices	137	32.2%	50.7%	13.0%	3.2%	0.9%	48.3%
1c (PT)	100% increased ticket prices	136	34.8%	47.2%	10.0%	3.4%	4.7%	48.2%
2a (PT)	10% increased travel time	137	8.3%	90.9%	0.9%	0.0%	0.0%	9.1%
2b (PT)	50% increased travel time	136	33.8%	52.8%	11.3%	0.7%	1.3%	45.8%
2c (PT)	100% increased travel time	171	42.9%	37.1%	16.7%	0.8%	2.4%	60.4%
3 (PT)	PT not available at all	437	70.7%	0.0%	21.1%	2.2%	6.0%	94.0%

Table A2
Choice responses (weighted) on stated preference (SP) tasks. non-work trips only.

Index	SP task	Weighted Count	Car	PT	Cycle	Walk	Not travel	Sum 'change mode'
*Current **car** users:*								
1a (car)	10% increased car costs (petrol and road tolls)	930	88.9%	4.6%	2.0%	1.8%	2.7%	8.3%
1b (car)	50% increased car costs (petrol and road tolls)	966	83.6%	5.6%	4.1%	1.6%	5.0%	11.4%
1c (car)	100% increased car costs (petrol and road tolls)	1031	78.1%	7.3%	5.1%	3.2%	6.3%	15.6%
2a (car)	10% increased travel time	966	91.4%	6.6%	0.8%	0.6%	0.7%	8.0%
2b (car)	50% increased travel time	1031	84.7%	8.6%	1.8%	0.4%	4.6%	10.8%
2c (car)	100% increased travel time	930	76.6%	10.8%	3.8%	0.4%	8.4%	15.0%
3 (car)	Car not available at all	2721	NA	42.0%	14.2%	8.1%	35.7%	64.3%
For current PT users:								
1a (PT)	10% increased ticket prices	43	8.6%	80.0%	0.6%	9.2%	1.5%	18.5%
1b (PT)	50% increased ticket prices	55	24.0%	46.6%	22.6%	3.1%	3.7%	49.8%
1c (PT)	100% increased ticket prices	51	35.0%	50.3%	8.7%	3.5%	2.5%	47.2%
2a (PT)	10% increased travel time	55	5.2%	94.8%	0.0%	0.0%	0.0%	5.2%
2b (PT)	50% increased travel time	51	19.4%	74.9%	0.5%	1.3%	3.9%	21.2%
2c (PT)	100% increased travel time	43	44.6%	48.2%	0.6%	3.2%	3.3%	48.4%
3 (PT)	PT not available at all	143	64.5%	NA	8.8%	15.1%	11.6%	88.4%

Table A3
Explanatory variables in utility function of 'not travel'.

	Car users			PT users		
	Mean	Min	Max	Mean	Min	Max
Distance (km)	19.970	0	100	22.996	1	100
Male	0.728	0	1	0.653	0	1
Work-related	0.387	0	1	0.706	0	1
Bad_alternatives	0.283	0	1	0.064	0	1
Unavailable	0.316	0	1	0.328	0	1
Constant_time	0.342	0	1	0.336	0	1
intensity_time (%ˆ0.5)*	2.302	0	10	2.227	0	10
Intensity_cost (%ˆ0.5)*	2.303	0	10	2.310	0	10

* Included 0% for choice task 3.

Table A4
Reduced models for car users.

	ASC_model		MNL_models		MNL_fixed	
Observations	15,308		15,308		15,308	
Final-LL	−2895.779		−2750.275		−2768.427	
Adj. rho square (0)	0.43		0.457		0.454	
Adj. rho square (c)			0.046		0.043	
	Value	Robust T-stat	Value	Robust T-stat	Value	Robust T-stat
β_(C.0)	−1.89	−41.15	−1.82	−38.2	−2.97	−16.9
β_(R.0)	0	–fixed–	0	–fixed–	0	–fixed–
β_(NT.0)	−2.98	−58.11	−4.88	−13.83	−5.65	−24.2
Distance			0.0182	8.88	0.027	–fixed–
Male			0.157	1.61	0.162	–fixed–
Bad_alternatives			0.709	7.13	0.916	–fixed–
Unavailable			1.84	5.33	0.632	–fixed–
Intensity_cost_sqr			0.179	4.15	0.014	–fixed–
Intensity_time_sqr			0.344	6.48	0.0279	–fixed–
Constant_time			−1.43	−2.31	−1.06	–fixed–
Work-related			−1.19	−11.21	−1.74	–fixed–
Homogeneity parameter					0.657	−9.22

Table A5
Reduced models for public transport users.

	ASC_model		MNL_models		MNL_fixed	
Observations	1620		1620		1620	
Final-LL	−319.864		−313.311		−313.502	
Adj. rho squ (0)	0.387		0.384		0.397	
Adj. rho square (c)			−0.005		0.014	
	Value	Robust T-stat	Value	Robust T-stat	Value	Robust T-stat
β_(C.0)	−0.472	−4.35	−0.455	−4.17	−0.663	−16.85
β_(R.0)	0	–fixed–	0	–fixed–	0	–fixed–
β_(NT.0)	−3.21	−15.96	−6.11	−4.67	−7.84	−21.97
Distance			0.0201	2.59	0.0301	–fixed–
Male			−0.0219	−0.06	0.0142	–fixed–
Bad_alternatives			0.0904	0.15	0.296	–fixed–
Unavailable			3.18	2.56	3.48	–fixed–
Intensity_cost_sqr			0.346	2.43	0.404	–fixed–
Intensity_time_sqr			0.334	2.32	0.35	–fixed–
Constant_time			−0.158	−0.09	0.0715	–fixed–
Work-related			−0.834	−2.11	−1.29	–fixed–
Homogeneity parameter					0.696	−1.98

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