Exploring a potential downside of multi-modality by estimating the effect of the weather on travellers with different modality styles

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Abstract:

To inform policies aimed at more sustainable travel behaviour, previous research has looked into the concept of multi-modality. The notion underlying this research is that multi-modal travellers are more sustainable than unimodal travellers. This paper investigates a possible downside of more multi-modal travellers, which is their increased sensitivity to exogenous variation of the circumstances of the trip. The main idea of this paper is that multi-modal travellers resort to the use of the car more quickly when 'car-favouring' conditions present themselves. This idea is investigated by estimating the effects of the weather on mode choices of different segments of the population, using a latent class discrete choice model. Results show that the more multi-modal class is indeed more sensitive to changes in weather circumstances compared to the less multi-modal classes. To increase sustainability, more multi-modal behaviour then is not always desirable. Rather than the number of modes used, it is the sustainability of the modes that are part of the multi-modal behaviour that matters.

Keywords: Multimodality; Latent Class Choice Model; Modality Style; Weather

1. Introduction

With climate change becoming an ever more pressing concern, policy makers are trying to find effective climate change mitigation and adaptation strategies. As part of these efforts sustainability is becoming a key policy objective. Sustainable policies often seek to reduce greenhouse-gas emissions and/or decrease the dependency on non-renewable resources. Sustainability is also a key objective in the field of (personal) transportation, which has popularised policies aimed at increasing the use of non-motorised travel modes.

To inform policies that seek to increase the uptake of these sustainable travel modes, recent research has focused on the concept of multimodality, which is typically defined as the degree to which a person uses multiple distinct modes within a certain time period (Nobis, 2007). Based on the (implicit) notion that multi-modal travellers are more sustainable than the (strict) car user, recent research has focused on questions whether multi-modal travellers emit less CO_2 (Heinen & Mattioli, 2019b; Keskisaari, Ottelin, & Heinonen, 2017), use the car less (Heinen & Mattioli, 2019a), and are overall more sustainable (Nobis, 2007). In general, it is found that multi-modal travel patterns are more sustainable than single-mode travel patterns.

Multi-modality indeed seems an effective concept to increase sustainable travel. This paper argues that there is also a downside to the notion of multi-modality. Assuming that multimodal travellers consider the use of various travel modes (at least more deliberately than habitual unimodal travellers), it can be hypothesized that when "car-favouring" conditions present themselves, the travellers will resort to the use of the car. In short, the multimodal traveller runs a higher risk of falling back into an unsustainable car using pattern. On the other hand, unimodal *sustainable* travellers (e.g. those who exclusively use the bicycle) may be expected to keep travelling by their respective sustainable modes even in the face of such "car favouring" conditions.

In this paper this notion is examined by determining how travellers with different multimodality profiles react to variations in the weather, as the weather is an exogenous factor that changes the utility of using different modes on a daily and immediate basis. The expectation is that the unimodal travellers, i.e. those with a relative high baseline utility for a single mode, will be less affected by variations in the weather conditions (temperature, wind, etc.) than those with high baseline utility for multiple modes. The former group may be expected to keep travelling with their preferred mode (due to travel habits and/or structural constraints) while the latter group may be expected to deliberately take the weather into account in their decision to either travel by car in case of inclement weather or by bicycle or public transport in case of more favourable weather.

This idea is tested using a latent class mode choice model, in which alternative specific constants (ASC) of the considered modes and the parameters related to weather are freely estimated across the classes, while all other parameters (e.g. related to trip characteristics) are kept constant across the classes. Freely estimating the ASCs enables the effective capture of the existing multi- and unimodal preference profiles in the population. Freely estimating the weather parameters captures each latent group's sensitivity to the effects of the considered weather variables.

To estimate the model, data are used from the Netherlands Mobility Panel (MPN). The MPN is a longitudinal panel dataset, where respondents are tracked across multiple years (Hoogendoorn-Lanser, Schaap, & Olde-Kalter, 2015). The MPN consists of a travel diary survey and multiple questionnaires pertaining to, amongst other things, socio-demographic information and mode-attitudes of the respondents. Both parts are combined for this research. This research uses the first five waves of data from the MPN, which are collected from 2013 through 2017.

The remainder of this paper is organised as follows. First, previous literature on multi-modality, including modality styles, and the effect of weather on travel behaviour are described. This previous literature is used to establish a conceptual model. The research methods and data are described in the section thereafter, which is followed by the results section. Finally, the main conclusions and contributions are discussed.

2. Conceptual and statistical model

In various studies, weather conditions have been shown to affect mode choice: typically, inclement weather with stronger wind speeds, more precipitation, and/or less comfortable temperatures, decreases the use of the more exposed active modes and are associated with an increase in the use of motorised modes (Böcker, Dijst, & Prillwitz, 2013; Liu, Susilo, & Karlström, 2017). In this study, this effect of weather on mode choice is assumed to be mediated by latent utilities of each mode. The trip purpose is generally found to moderate the effect of the weather (Cools, Moons, Creemers, & Wets, 2010; Helbich, Böcker, & Dijst, 2014), and is therefore included in the model as well. Interaction effects between weather and trip purpose are estimated for the bicycle, as usage of this mode is expected to be the most sensitive to weather. Finally, trip distances are also included in the model.

The effect of the weather on the utility of travel modes is estimated using a latent class choice model, in which the latent classes are assumed to be segments of the population with different behavioural predispositions. In this study, they pertain to the use of travel modes, so the latent classes can be interpreted as 'modality styles' (Vij, Carrel, & Walker, 2013). Based on previous research findings, the modality styles will be related to socio-demographics and mode attitudes (Diana & Mokhtarian, 2009; Molin, Mokhtarian, & Kroesen, 2016; Nobis, 2007).

The main hypothesis of this paper then is that modality styles moderate the relation between weather and mode utilities, meaning that the mode choices of people with different modality styles will respond differently to the same change in weather circumstances.

The above information is graphically presented in a conceptual model, which is given in Figure 1.

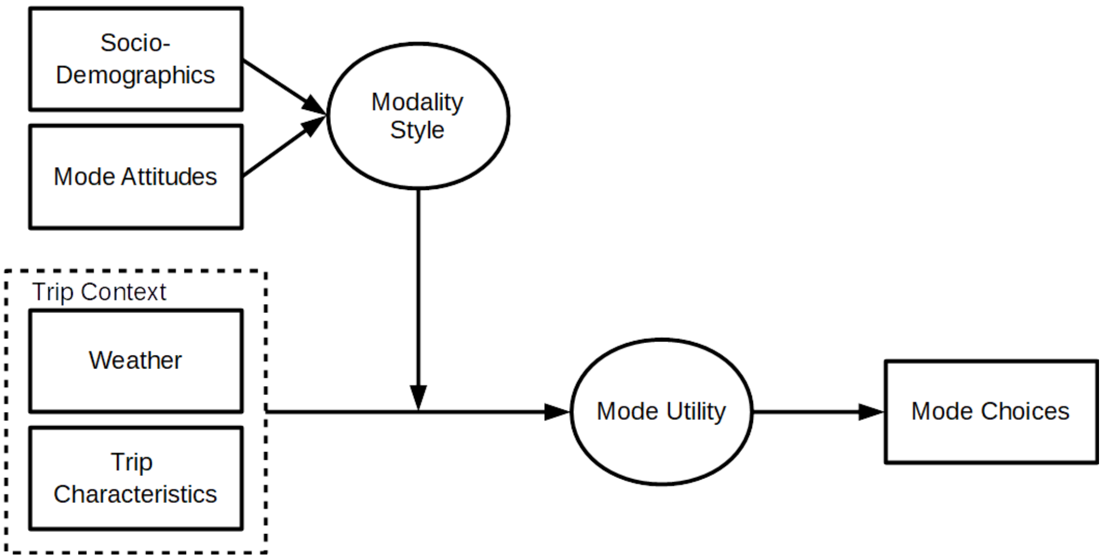

Figure 1 Conceptual model investigated in this research

3. Research Methods

Latent Class Choice Model

To analyse the effects of weather on mode choices and the differences of this effect between travellers with varying behavioural profiles a Latent Class Choice Model (LCCM) is estimated, in which the weather parameters and alternative specific constants are allowed to vary between classes.

Four alternatives are considered, namely car, public transport (PT), the bike, and walking. Trips using other modes were removed from the survey data. In total, the choice model is estimated using data pertaining to 59 820 trips made by 7054 individuals. When estimating choice models on revealed preference data, it is impossible to determine the alternatives that were actually considered by the respondent. This so-called choice set should consist of alternatives that are both mutually exclusive and collectively exhaustive (Ben-Akiva & Lerman, 1985). This research uses deterministic constraints based on the availability and consideration of travel modes to approximate the choice set (for more reading on choice sets the reader is referred to Calastri, Hess, Choudhury, Daly, & Gabrielli, 2017 and Ton et al., 2019).

The choice models are estimated using the Apollo package for R (Hess & Palma, 2019b, 2019a). The number of classes used within the latent class choice model is exogenous to the estimation procedure. Models with two to four latent classes were estimated and compared with one another based on model fit (AIC & BIC) and behavioural interpretability. The four-class model performed best based on model fit, but the three class model provided more behaviourally distinguishable classes and was selected for this reason.

Attitudes

Attitudes towards travel modes were collected using six indicator questions per mode, which were collected in both wave 2 and wave 4 of the MPN. The indicators pertain to the perceived comfort, prestige, and performance of travel modes. Respondents that did not participate in either wave 2 or wave 4 are removed from the analysis. For respondents who participated in both waves the responses from wave 4 were used.

A factor analysis is used to derive the value of the latent attitude underlying the indicator responses for each individual. For each of the modes, only one factor has an Eigenvalue larger than 1, resulting in the extraction of just this singular factor (which corresponds to one underlying attitude).

The latent factor is calculated as a weighted sum of the indicators, where the weights are the factor loadings. The resulting values are standardized so that the mean and standard deviation of each factor are 0 and 1 respectively. The reliability of the scale is calculated using Cronbach's Alpha. For all factors, this reliability score was higher than 0.8, indicating a reliable scale. The factor labels, scale statistics, and correlations between factors are given in Table 1.

Table 1 Summary of attitudinal factor scores

Factor Label	Cronbach's Alpha	Explained Variance (%)	Correlations			
			1. Car	2. Train	3. BTM	4. Bicycle
1. Car Attitude	0.881	60	1	-0.102	-0.113	0.052
2. Train Attitude	0.864	64		1	0.667	0.240
3. BTM Attitude	0.894	66			1	0.170
4. Bicycle Attitude	0.873	62				1

Weather Data

For this paper, objectively measured weather data provided by the Royal Netherlands Meteorological Institute (KNMI) is used. The data-set contains information on 45 different weather attributes, ranging from rainfall to solar radiation, as collected by 50 different weather stations placed throughout the Netherlands. The data is collected every 10 minutes.

The weather data needs to be matched to travel behaviour based on spatial and temporal dimensions, with the objective of assigning weather values to trips based on the weather that impacted the mode choice decision. The location of the trip origin is used to locate the closest weather station. From this weather station the daily weighted average values for the day of the trip are collected, where the weights are the overall number of trips made in a given hour.

Temperature, wind speed, rain intensity, and solar radiation are the weather variables used in this research. To give an indication for the weather in the Netherlands during the sampling period, descriptive statistics for the weather variables as connected to the trips in the MPN are given in Table 2. The variables are all standardized in the model, so that the mean value is 0 and the standard deviation is 1.

Table 2 Descriptive statistics of weather variables

Variable	Min	Max	Mean	Median	St. D
Temperature (°C)	0.97	20.9	11.4	11.7	3.79
Wind Speed (m/s)	0.28	18.4	4.01	3.61	0.284
Rain Intensity (mm/h)	0.00	1.95	0.0921	0.00383	0.185
Solar radiation (W/m^2)	8.42	300	107	90.4	68.9

4. Results

The results from the latent class choice model estimation with three latent classes are described in this section. First, the classes will be interpreted, followed by an interpretation of the effects of the weather variables on the mode choices for each latent class.

The modality styles can be interpreted straightforwardly by using the estimated choice probabilities for each mode in average weather conditions. This gives the behavioural predisposition towards the use of certain modes, given weather conditions, trip purpose, and trip distance. These probabilities are displayed in Table 3.

Table 3 Estimated choice probabilities of travel modes in average weather conditions

	Leisure Trips				Work Trips				Educational Trips			
	Car	PT	Bike	Walk	Car	PT	Bike	Walk	Car	PT	Bike	Walk
Class	Distance: 11 km											
1	0.81	0.10	0.08	0.01	0.57	0.27	0.16	0	0.14	0.62	0.24	0
2	0.67	0.03	0.30	0	0.41	0.07	0.52	0	0.11	0.14	0.75	0
3	0.97	0.01	0.02	0	0.93	0.02	0.06	0	0.66	0.11	0.23	0
	Distance: 5 km											
1	0.57	0.07	0.19	0.16	0.41	0.18	0.36	0.05	0.09	0.37	0.49	0.04
2	0.4	0.02	0.57	0.02	0.20	0.05	0.77	0	0.04	0.09	0.87	0
3	0.92	0	0.06	0.01	0.82	0.01	0.16	0	0.43	0.07	0.49	0.01

The estimated probabilities in Table 3 show three distinct patterns. Class 1 is more multi-modal, both within and across trip purposes and travel distances. At lower distances, this class shows sizeable shares of walking, whereas both other classes' predicted walking share is very close to zero. The PT share is also higher than for the other two classes, especially for non-leisure trips. The estimated probabilities for class 2 meanwhile point to the use of either the car or the bicycle for almost all trips during average weather circumstances. Use of the other modes is very limited, especially for non-educational trips. Class 3 is the most unimodal, with very high estimated probabilities for the use of the car. Only educational trips are relatively multi-modal for this group, although the estimated probability for the car is still very high compared to the other two classes.

These findings are based on observed mode choices. They can be complemented by an interpretation of the class-membership model, which shows how mode attitudes and socio-demographics impact the likelihood of being a part of a class. The class-membership parameter estimates are given in Table 4.

Table 4 Class-membership parameter estimates

	Class 2	Class 3
Delta	2.30	1.16
Male	-0.019	-0.051
Age	-0.14	-0.027
Employed	-0.21	0.52
Education	-0.079	-0.13
Urban Density	-0.072	-0.13
Owns E-bike	0.27	-0.14
Owns Car	-0.32	0.69
Owns Driver's License	-0.21	1.61
Car Attitude	-0.19	0.34
Train Attitude	0.12	-0.14
BTM Attitude	-0.25	-0.11
Bike Attitude	0.73	-0.31

Class 1 is the reference alternative. The parameters for this class were fixed to zero.

Some observations can be made based on the class membership estimates. First, one can see that there are more people in classes 2 and 3 compared to class 1 based on the delta values. In total, 19% of people are assigned to class 1 and 43% and 37% to classes 2 and 3 respectively.

Secondly, mode availability and mode attitudes have a significant effects on the class-membership probabilities. This is expected, given the identification of the latent classes as modality styles. Bicycle and car attitudes increase the likelihood of the respondent being part of classes 2 and 3 respectively. Attitudes towards public transport are a bit more ambivalent, with local transport (Bus, Tram and Metro) attitudes leading to increased probability of being part of class 1 while train attitudes mostly result in an increased probability of being part of class 2. The mode attitudes are thus congruent with the observed mode choice behaviours as given in Table 3.

The above analyses lead to the conclusion that the latent classes identified by the model can be described as modality styles, conform the expectations set out in the conceptual model. The classes are all of a different modality style. The interpretations given to the classes in the remainder of this research are the following: class 1 is multi-modal, class 2 is 'bike + car', and class 3 is 'car mostly'.

The objective set out in the introduction of this paper is to identify whether these modality styles moderate the effect of the weather on travel behaviour. The estimates are given in Table 5. To complement the parameter estimates and give an indication for the effect of the weather for each latent class, the estimated choice probabilities are calculated for reference weather scenarios. These choice probabilities are given in Table 6 and concern a trip to work with a distance of 5 km.

Table 5 Parameter estimates for the effect of weather on travel mode utility

Class		PT	Walk	Bike (leisure)	Bike (work)	Bike (edu)
1: Multi-Modal	Temperature	-0.13	**0.15**	**0.15**	0.10	0.026
	Wind	0.13	**-0.17**	-0.095	**-0.40**	-0.25
	Rain	**-0.15**	-0.060	**-0.23**	-0.022	-0.14
	Solar Radiation	-0.025	0.041	0.093	0.057	0.17
2: Bike + Car	Temperature	0.060	**0.10**	**0.13**	**-0.050**	0.02
	Wind	0.044	-0.0034	**-0.067**	0.0003	-0.0082
	Rain	0.086	**-0.084**	**-0.13**	-0.11	-0.10
	Solar Radiation	0.044	**0.11**	**0.12**	0.080	0.038
3: Car mostly	Temperature	0.11	0.00	**0.19**	0.027	**-0.23**
	Wind	0.017	-0.012	**-0.20**	0.11	0.34
	Rain	-0.049	-0.018	-0.082	-0.070	0.0021
	Solar Radiation	**-0.38**	0.10	0.084	0.093	0.045

Bold parameters are significant at the 5% threshold level
The car is the reference alternative. The parameters for this mode were fixed to zero.

There are a couple of especially interesting observations that can be made here. First, on a general level the results show that temperature and solar radiation have a positive effect on the use of active modes, whilst wind and rain negatively affect the shares of these modes. The effect on public transport use differs more between the classes. For the multi-modal class use of public transport is much more sensitive to weather changes. For the 'bike + car' class strong effects can only be seen for rainy conditions, when public transport use drastically increases. Other weather variables have a negligible effect.

Table 6 Estimated choice probabilities for an average distance commute trip under various weather conditions

	Weather				Class 1: Multi-Modal				Class 2: Bike + Car				Class 3: Car Mostly			
	Temp (°C)	Wind (m/s)	Rain (mm/h)	Sun (W/m²)	CR	PT	BC	WK	CR	PT	BC	WK	CR	PT	BC	WK
Mean	11.4	4.01	0.092	107	0.41	0.18	0.36	0.05	0.19	0.03	0.78	0.00	0.82	0.01	0.16	0.00
Rainstorm	10	15	1.5	25	0.71	0.23	0.06	0.01	0.34	0.11	0.55	0.00	0.83	0.02	0.15	0.00
Overcast	10	3	0	10	0.39	0.19	0.37	0.04	0.20	0.03	0.77	0.00	0.84	0.02	0.14	0.00
Wind, Rain	10	7	1	100	0.58	0.16	0.24	0.02	0.28	0.07	0.66	0.00	0.85	0.01	0.13	0.00
Near-freezing	2	4	0	100	0.41	0.27	0.28	0.04	0.17	0.02	0.81	0.00	0.83	0.01	0.15	0.00
Mild, clear	15	2	0	150	0.33	0.12	0.49	0.06	0.18	0.03	0.79	0.00	0.82	0.01	0.16	0.01
Warm, sunny	20	2	0	250	0.29	0.09	0.55	0.07	0.18	0.03	0.79	0.00	0.80	0.01	0.18	0.01

Second, the effects of the weather variables vary markedly across the classes. The effect on public transport use is greatest for the multi-modal class by far, which makes sense given the fact that this class uses public transport (much) more frequently than the other classes. For commute trips specifically, the stability of predicted choice probabilities for both the 'bike + car' and 'car mostly' classes contrasts sharply to the variation that can be seen for the multi-modal class. The effect is clearest for the two most extreme days given here. For the rainstorm day, the predicted use of the bicycle is reduced from 0.36 to 0.06 for the multi-modal class, which is accompanied by an increase of the car share from 0.41 to 0.71. The bike + car segment also sees a decrease of the bike share, but it is relatively much smaller (from 0.78 to 0.55). On the other end of the weather spectrum, warm and sunny weather induces multi-modal travellers to use the bicycle more often (0.36 to 0.55), an effect that is not visible for both the 'bike + car' and the 'car mostly' modality styles.

5. Conclusion & Discussion

This paper set out to investigate whether travellers with a more multi-modal modality style are more sensitive to changes in the weather circumstances of their travels. This idea is investigated by the use of a latent class choice model, which estimates separate effects of the weather for different parts of the population, segmented by modality style.

The results show that the effects of weather conditions on mode choices do indeed differ between three revealed modality styles. The identified modality styles can be summarised as (1) multi-modal; (2) car + bike and (3) car mostly. For the more multi-modal first class, the use of the sustainable modes is more strongly affected by weather conditions when compared to the second less multi-modal class. Inclement weather (wind, rain) in particular has a much greater impact on the use of the bicycle for the first class. Simultaneously, the least sustainable third modality style, which mostly consists of car use, is also affected to a lesser extent by weather conditions. More pleasant weather conditions are for the most part unable to entice people within this segment to use more sustainable modes.

These findings shed a new light on the concept of multi-modality, as they suggest that multi-modality should perhaps not be seen as a primary goal of transport policies. More multi-modal travellers are less likely to keep using sustainable modes after an exogenous shock has decreased the utility of these modes, in contrast to less multi-modal travellers. From the perspective of sustainability the less multi-modal 'bike + car' group is more preferable compared to the multi-modal segment. Policies aimed at increasing more unimodal behaviour, given that this mode is sustainable, would then be more effective. On the other hand the results also show that the least sustainable behaviour is the modality style revolving around singular use of an unsustainable mode. Exogenous (weather) variation is unable to meaningfully increase sustainable behaviour of this group. Increasing the multi-modality of this group could be beneficial. The concept of multi-modality thus can still be useful, but should be applied with more reference to the actual sustainability of the modes in question.

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