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Choosing the Mode of Transport - Case Study of Bratislava Region

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Abstract

We analyse commuting patterns in Bratislava's fast growing sub-urban region with sub-optimal developed infrastructure. Standardized discrete choice model is used to estimate demand for individual car transport as well as for public buses and trains and to obtain corresponding elasticities with respect to travel costs, times and income. We find low rate of substitution between available modes. Direct price elasticity for public modes is in accordance with often cited rule of thumb -0.3. Negative income elasticities of demand for buses and trains, together with low direct price elasticity for car transport can be hard to overcome when looking for solution of current traffic problems in the region. We use modelled demand to predict effects of two recently proposed policies - new parking system in Bratislava city and construction of highway D4R7. In case of first policy, we expect massive reduction in car usage due to increased costs for car commuters. On the other hand, new highway would have only limited impact on mode choice and could reduce number of train commuters.

Keywords: Elasticities, Mode-choice, Nested Logit Model, Transportation

JEL Codes: R41, R42, R48

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1 Introduction

Bratislava is the fastest growing region in Slovakia. Host of problems have occurred due to high pace of development, including sub-optimal development of new infrastructure, which is hard to solve among others due to lack of information on mobility and housing (the official statistics do not precisely describe the true migration, see Šveda and Barlík, 2018). As of 2019, infrastructure problems are intensified due to a long-term reconstruction of the nearby highway and its interchanges. The worst situation with is in a south-east part of Bratislava region, where the biggest town Šamorín is just 25 km from the capital's centre. However, according to GoogleMaps server, average travel time by car is 39 minutes during off-peak hours and 68 minutes in peak times. Moreover, the town has no direct connection to railway and due to an absence of bus lanes, public bus transport suffers due to same traffic jams as individual car transport.

In 2019, Slovak Ministry of Transport proposed a solution - new water transportation via nearby Danube river. A study which analysed potential costs and revenues was published in November 2019. As a part of the analysis, survey revealing preferences of commuters and inhabitants was conducted. In this paper, data from the survey are used for further analysis.

The main aim of the paper is to provide an understanding of commuting patterns in a fast growing sub-urban region with sub-optimal developed infrastructure. Furthermore, direct and cross elasticities with respect to travel costs, travel time and income are calculated and could be used to inform policy decisions.

A low rate of substitution between existing travel options is clear even from the descriptive statistics which are presented in the first part of the paper. This suggests low cross price and time elasticities. In case of direct price elasticities for existing modes our results are in line with published literature. Obtained direct elasticity with respect to travel costs for bus is very close to often cited rule of thumb -0.3. Furthermore, the negative income elasticities for public options (bus and train) confirm inferiority of these modes, found across other papers (see literature review). However, most importantly, direct price elasticity of demand for car transport close to zero brings only small hope for any easy solution to solve current traffic problems.

Estimated elasticities allow to predict outcomes of proposed changes in travel policies. In this paper we provide illustrative evaluation of two policy measures (which could easily be refined if more detailed data were available). We find that a parking policy, planned to be launched in 2021, could dramatically decrease in car commuting. Second, we conclude the scenario of new highway built along the original and the most problematic road number 63 would have only minimal effect on demand for travel modes since most commuters already use cars to commute. Only expected outcome of new highway, predicted by the model, is reduction in train travels, that is anything but desired.

2 Literature review

Methodology used in this paper is nowadays standard method of estimation of demand for transportation mode. Literature goes back to McFadden (1974) who introduced behavioral method for measurement of travel demand in the San Francisco Bay Area. As mentioned in the McFadden's paper, the problem of travel demand forecasting had been previously province of transportation engineers and *ad hoc methods* and models were usually used. Since McFadden's contribution, the whole area of economic literature based on behavioral theory has appeared. For example, Harker (1988) used demand model to analyse various forms of private market participation in urban mass transportation. The concept can be used not only to forecast demand for existing modes, but to evaluate potential investments and extensions (e.g. Wong, 2013, evaluates potential outcome of new high speed railway in Canada). To provide an overview of the existing literature, we focus on meta-analyses of studies of public transport.

Kremers et al. (2002) concludes that three types of models have been frequently used to investigate demand for modes of transport: (i) microeconomic, (ii) micro-econometric and (iii) discrete choice models. From mentioned, the first type of approach differs substantially and price elasticities estimated using microeconomic models were of higher value compared to other two methods.

Holmgren (2007) compares 81 studies which estimate price elasticity and 22 investigating income elasticity of public transportation. Mean price elasticity across papers is -0.38. This is in line with a frequently cited rule of thumb -0.3 (see e.g. Goodwin, 1992). In a case of income-elasticity, the mean value through studies is 0.17.

Elasticity of demand for car transport with respect to income has been summarised in Hanly et al. (2002). Short-run mean elasticity for car-km was 0.30. Furthermore, several other studies confirmed inelastic demand for car trips with respect to different variables of interest. For example, in De Jong and Gunn (2001) fuel price elasticity for car trips is -0.16 in case of short trips and slightly lower for long trips. The value of time elasticity is -0.60 for short trips and -0.26 for long-trips.

Price elasticities for train consumption were summarised in e.g. Wardman (2014). Even though only U.K. studies were compared, mean price elasticity was -0.57. Through all these studies, revealed preferences were used as a source of data and studies were based on mode choice models. Papers which analysed time-elasticity of demand for railway transport found rather lower values. In Fröidh (2008), time-elasticity of Swedish and Nordic high speed railway roughly of -2.0 is mentioned. However, such estimation high absolute value is more likely to be valid for long-distance high-speed railway rather than regional type of train transport which is subject of our study.

3 Methodology

To estimate direct and cross price elasticities we use nested multinomial logit (NMNL) model which is a generalization of multinomial logit (MNL) model. Both NMNL and MNL models assume that utility of consumer i of choosing alternative j can be expressed as:

$$U_{i,j} = \mathbf{z}'_{i,j}\boldsymbol{\beta} + \epsilon_{i,j}, \tag{1}$$

where $\mathbf{z}_{i,j}$ is a vector of alternative-specific and individual-specific characteristics, $\boldsymbol{\beta}$ is a vector of coefficients and $\epsilon_{i,j}$ is random error term. Vector $\mathbf{z}_{i,j}$ typically includes:

1. Time and costs of travel which are both alternative- and individual-specific.
2. Socio-economic characteristics such as income which are individual-specific but do not vary with j. These are typically interacted with dummy variables for different modes. This allows, for example, that high-earners prefer individual car transport over public transport.
3. Alternative-specific characteristics, for example dummy variables for different modes of transport to control for higher comfort of train over bus.

In an ordinary non-nested MNL model, probabilty of consumer i choosing alternative j is given by:

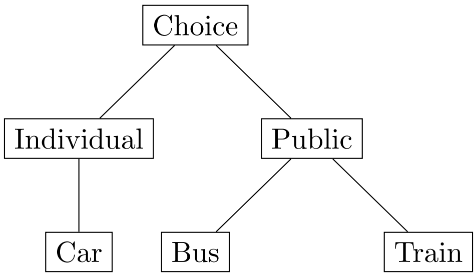
$$P(Y_i = j) = \frac{\exp(\mathbf{z}'_{i,j}\boldsymbol{\beta})}{\sum_{k=1}^{K} \exp(\mathbf{z}'_{i,k}\boldsymbol{\beta})}, \tag{2}$$

where Y_i is decision of consumer i and K is a number of alternatives. Expression (2) implies that ratio of probabilities of choosing two different alternatives j and k depends only on attributes of alternatives i and j (since $\frac{P(Y_i=j)}{P(Y_i=k)} = \frac{\exp(\mathbf{z}'_{i,j}\boldsymbol{\beta})}{\exp(\mathbf{z}'_{k,j}\boldsymbol{\beta})}$). This constitutes assumption of *independance of irrelevant alternatives* (IIA). *This assumption can hardly by satisfied when modelling choice of mode of transport.* McFadden (1974) illustrates this by the following example: Assume that consumer can chooses between two modes of transport - car and blue bus and assume that consumer choose car over blue bus with probability 0.5. Now assume that red buses are introduced. If consumers do not care about the colour of the bus, probability of choosing blue bus has to decrease which violates IIA.

Nested structure of NMNL model enables to relax IIA by allowing groups of alternatives (such as blue and red buses) to be similar to each other. Decision making in a NMNL model can be interpreted as sequential decision making. First, consumers choose group of alternatives, i.e. a *nest*. Second, they choose particular alternative within a chosen nest.

In this study, we divide modes of transport into two nests - (i) public transport and (ii) individual transport. Public transport includes two alternatives - (i/a) bus and (i/b) train, individual transport consists of a single alternative - car (see Figure 1).

Figure 1: Transport choice scheme



Utility of consumer i of choosing nest m is given by *inclusive value* $IV_{i,m}$:

$$IV_{i,m} = \log \sum_{j \in B_m} \exp\left(\frac{\mathbf{z}'_{i,j}\boldsymbol{\beta}}{\tau_m}\right), \tag{3}$$

where B_m is a set of alternatives within the nest m and τ_m is a dissimilarity parameter of nest m. Low value of τ_m indicates that alternatives within set m are similar, whereas high value signifies dissimilarity. If $\tau_m = 1$ for all m, model reduces to regular MNL.

Probability of consumer i choosing alternative j is given by

$$P(Y_i = j) = \frac{\exp(\mathbf{z}'_{i,j}\boldsymbol{\beta}/\tau_{n_j})}{\exp(IV_{i,n_j})} \frac{\exp(\tau_j IV_{i,n_j})}{\sum_{m=1}^{M} \exp(\tau_m IV_{i,m})}, \tag{4}$$

where n_j is nest in which alternative j is included and M is number of nests.

4 Data and travelling patterns

The main data source is a survey realized as a part of above mentioned research aimed to forecast an economic outcome of new water transportation mode on Danube river[1]. The survey is not representative of all inhabitants, but only of those commuting from south-east part of Bratislava region. However, the examined area can be considered as one of two main suburban regions of Bratislava. The final destination Bratislava is divided into 17 districts[2]. The survey provides information on in-vehicle and out-of-a-vehicle travel time, journey costs e.g. tickets in case of public mode or parking fees for cars. The fuel usage was not part of the original

[1]Authors of the paper were part of the original research team and therefore designed the survey themselves.
[2]The complete list of towns and cities in the region as well as Bratislava's districts can be find in the Appendix.

question. Furthermore, the socio-demographic characteristics (i.e. size of household, number of children and income), starting and ending point of travel as well as commuting frequency per week were obtained.

The sample consists of 412 commuters who travel at least once per week using one of three travel options - *car*, *bus* or *train*.

4.1 Descriptive statistics on commuter level

We begin a presentation of the data sample by descriptive statistics for commuters. Because several consumers use more than one mode, in the first stage of the analysis, *only the dominant mode is examined*. Later, we will provide descriptive statistics on individual journeys.

Shares of dominant modes used per week are presented in Table 1. The purpose of the statistics is to provide overview of overall commuting patterns. As can be seen, a car is far more popular than any of existing public options, two thirds of commuters use predominantly car transport.

Table 1: Shares of dominant modes per week

	Car	Bus	Train	Obs.
Freq.	275	64	73	412
Percent	66.75	15.53	17.72	100.00

Table 2 gives descriptive statistics for (i) car commuters (i.e. commuters who use predominantly car transport), (ii) bus commuters and (iii) train commuters. Observe that a fraction of commuters combines several transportation modes. For example, car commuters travel more than three times per week by car (3.33), while at the same time they use less than once bus or train (on average 0.23 and 0.42 per week). Same pattern of dominant choice can be seen for other modes. Such extreme difference between the prime option and other options suggests low rate of substitution. On average, more than 76 % of commuters use only one of available modes. From all commuters who use predominantly car transport, only 15 % use other mode of transport. On the other hand, approximately one third of all individuals using train use also some other travel mode to commute to Bratislava.

Observe also that bus commuters are most frequent commuters (travelling to Bratislava on average 0.23+3.89+0.13=4.22 times per week) followed by car commuters.

Table 2 also gives in-vehicle and out-of-a-vehicle travel times and costs. Since, for example, significant portion of car commuters do not use bus and/or train, average travel times and costs for bus/train in Table 2 are calculated *only according to responses of those car commuters who use bus/train at least once.* Same applies for bus commuters and train commuters. Respondents

Table 2: Statistics by dominant mode

	Observed Data			Adjusted Data		
	Car commuters	Bus commuters	Train commuters	Car commuters	Bus commuters	Train commuters
Car usage (per week)	3.33	0.23	0.42	-	-	-
	(2.03)	(0.68)	(0.86)			
Bus usage (per week)	0.14	3.89	0.11	-	-	-
	(0.54)	(1.92)	(0.36)			
Train usage (per week)	0.11	0.13	2.66	-	-	-
	(0.4)	(0.49)	(1.76)			
Time car (min.)	71.11	75.5	63.25	-	70.34	68.75
	(33.01)	(34.19)			(21.47)	(15.75)
Costs car (EUR)	0.82	0.50	1.30	0.48	0.48	1.03
	(2.34)	(0.71)	(2.47)	(1.63)	(0.71)	(1.33)
In-time bus (min.)	59.80	65.97	57.86	62.84	-	66.22
	(22.48)	(26.65)	(41.32)	(19.96)		(19.76)
Out-time bus (min.)	16.80	26.30	17.86	24.94	-	20.58
	(24.40)	(24.51)	(14.96)	(19.44)		(14.08)
Costs bus (EUR)	1.92	1.45	1.24	1.86	-	1.87
	(1.48)	(1.07)	(0.71)	(1.00)		(0.67)
In-time train (min.)	66.09	72.00	65.82	67.95	68.43	-
	(24.91)	(21.68)	(24.76)	(27.45)	(25.73)	
Out-time train (min.)	21.52	32.60	22.14	29.80	29.9	-
	(16.41)	(27.13)	(16.90)	(19.82)	(16.59)	
Costs train (EUR)	1.43)	1.90	1.25	1.47	1.51	-
	(1.33)	(1.86)	(1.34)	(0.82)	(0,84)	
Income (category)	2.69	2.25	2.05	-	-	-
	(1.52)	(0.84)	(0.7)			
Family members	1.00	0.20	0.43	-	-	
co-travelling (number)	(1.22)	(0.51)	(0.93)			
..out of which children	0.20	0.00	0.12	-	-	-
(number.)	(0.59)	(0.00)	(0.62)			
Transfers (numbers)	-	-	0.27			
			(0.45)			
Work	56 %	70 %	41 %	-	-	-
High School	0 %	5 %	3 %	-	-	-
University	2 %	3 %	0 %	-	-	-
Relax,culture, sport	3 %	0 %	3 %	-	-	-
Doctor	17 %	13 %	25 %	-	-	-
Others	22 %	9 %	28 %	-	-	-

Notes: Standard deviations can be found in parentheses. Kids variable is a subset to total number of family members. Furthermore, the commuting time by car was not distinguished between in- and out vehicle time. The Costs Cars in the table are only costs connected to using cars except fuel usage.

were not asked about travel times and costs of those transportation modes they do not use at all.

However, to use proposed methodology, it is necessary to have information about travel times and costs of all transportation modes including these which are never chosen by particular individual. Below, we explain how missing values are imputed using several sources.

In addition to travel times and costs of travel, socio-demographic characteristics of commuters were gathered. The income is categorical variable ranging from less than 500 EUR ($income = 1$) up to more than 6000 ($income = 13$), with intervals of 500. On average, the car users tend to have higher income. At the same time, they are travelling with more family members. Moreover, there is higher probability that the fellow-traveller is younger than 15 years.

The last part of the table shows purpose of travel, where, as expected, most of the respondents commute to work. For students, the bus option is often preferred (5% of bus commuters travel to high schools and 3% to universities). Moreover, students do not use train for travels to universities and cars for high schools (the second is mostly explained by restriction on driving age). Travels for doctor visit are frequently made by train[3]. Two explanations for such choice are at hand: First, the elderly commuters have option of free train tickets and the hospital (Kramáre) is not far from the main station in Bratislava. If a responded choose *other* as reason for commuting he/she was saked to report the reason. Mostly family or offices visits were reported (in addition to doctor visit as explained in the previous footnote). These travels are not on daily basis and are often made by car.

4.2 Imputing missing information for unrealized alternatives

In case of discrete choice models, it is necessary to have full information about all possible alternatives. Assume a train commuter, for whom researchers have to know all information including potential travel times and costs of transport in case he/she chose car or bus. However, not everybody from survey use all travel modes. Therefore, travel times and costs of transport for alternative options had to be calculated. Two sources were used to obtain missing values on unobserved choices:

1. If possible, average values across other commuters travelling from and to the same points were used.
2. Otherwise, data were calculated using:
    - GoogleMaps for missing informations on time travels for car transport,

[3] This option was not included in the original survey, howerver within an option *other* respondents often detailed a doctor visit as a reason for travelling to Bratislava. Therefore, such option was created as an individual category

- publicly available schedules for in-vehicle travel time and transportation costs of public transport,
- average across all commuters commuting to same district of Bratislava using given mode of transport (irrespective of starting point) for out-of-a-vehicle travel time for public transport

3. Further adjustments for daily commuters:

   - For commuters using either car or bus we used previous methods to calculate costs and times for train. However, for individuals who commute at least three times per week we discounted the price by factor 0.5. This reflects a fact that daily commuters in trains can use cheaper weekly or monthly tickets,
   - Total costs for car were divided between number of adult persons in vehicle.

As an example assume a commuter travelling daily from town A with an adult family member. Her dominant choice is a car. Furthermore, once a week she uses bus. Therefore, information about car and bus are both observed by researchers and complete information on times and costs are available. The missing train option was obtained from website providing times and costs for all bus and train connections in Slovakia where for train ticket we applied 50 % discount. The out-of-a-vehicle travel time of train was obtained by averaging same variable for other commuters from all starting points travelling to the same destination point by train[4]. Lastly, because she is commuting with other family member, costs of travel for car transport were divided by two.

Data adjusted in this way can be find in the right portion of Table 2. This leads to no adjustment in frequency of used modes (car, bus and train usage), socio-demographic characteristics, nor in travel times and costs of transport for dominant mode (except the car costs in case of shared journey). Therefore, these data are not replicated in second part of the table.

It is likely that imputing data using above mentioned technique introduces considerable measurement error. The web service calculates very optimistic, almost optimal travel times. Moreover, it is likely that some commuters *do not choose given travel mode precisely because travel times would be unusually high* and this *true* travel times are known only by commuters themselves. Combination of these two factors leads to the fact that imputed travel times for modes not chosen are most likely biased downwards and true potential travel times are higher.[5]

[4]Data on destinations were distinguished to 5 groups of districts of Bratislava as explained in Table 5

[5]Measurement error most likely produces certain bias in our estimates. However, direction of the bias is not clear. On the one hand, measurment error tend to bias estimates of coefficients towards zero. On the other hand, as explained, in our case measurement error is not random. Measured differences in times and costs between chosen and not chosen alternatives are most likely *smaller* than true differences. Therefore, it seems that even small differences in travel times and costs of travel are capable to motive commuters to change the travel mode which is consistent with relatively high absolute value of coefficients. However, if true differences are higher, true absolute value of coefficients might by smaller. It would be possible to determine true direction of the bias by Monte Carlo experiment, however, this is outside the scope of this study (Hultkrantz and Savsin, 2018, use

4.3 Descriptive statistics on journey level

NMLM model is based on assumption that each individual chooses between alternatives only once. However, when choosing a mode of transport, each commuters have to make a choice possibly five times a week (when commuting daily). As already mentioned, some consumers mix two and on occasion even all three modes of transport. Therefore, we create a dataset of individual journeys. If, for example, an individual commutes to Bratislava four times per week, once using a train, three times using a car, she occurs in the dataset four times. In one case, train is listed as chosen option, three times it is car.

The frequency of journeys are presented in following table (that can be compared to Table 1). There is almost no change in car usage. On the other hands, there is a switch within the public modes. While train was more often dominant public mode on commuter level, in case of individual journeys bus are chosen more often. This was observable already in rows two and three of Table 2 by differences in means. More people travel by train, however, bus commuters travel more often.

Table 3: Shares of journeys by modes per week

	Car	Bus	Train	Obs.
Freq.	956	283	225	1464
Percent	65.30	19.33	15.37	100.00

Table 4 presents average in-vehicle and out-of-vehicle travel times, costs and socio-demographic characteristics for journeys by car, bus and train. Therefore, the interpretation is following: the average total time of travel by car is 70 minutes, compared to 93 by bus and only 54 minutes by train (summing up in-vehicle and out-of-a-vehicle travel times). Car is frequently shared (see rows 5 and 6 for family members and children in vehicle). The share of commuting to work is raised due to the higher frequency of their travels and a share of visits of doctor or other reasons that are not on daily bases naturally decreased.

experiment to compare valuation of time calculated according to (i) and (ii) revealed preferences and conclude that results based on stated preferences tend to be substantially lower than the informations from revealed preferences). There is another way to obtain information about unobserved options - to directly ask commuters in survey about their estimation of travel times and travel costs. In such case, it is possible consumers might overestimate both travel times and costs.

Table 4: Statistics by journeys

	Observed Data		
	Car	Bus	Train
In-Time (minutes)	69.48	65.99	40.99
	(30.95)	(27.81)	(15.43)
Out-Time (minutes)	0.00	26.22	23.26
	(0.00)	(25.96)	(17.05)
Costs (EUR)	0.46	1.55	1.33
	(1.98)	(1.06)	(1.20)
Income (category)	2.85	2.32	2.23
	(1.68)	(0.87)	(0.75)
Family traveling (numbers)	0.65	0.21	0.23
	(1.04)	(0.55)	(0.66)
Kids traveling (numbers)	0.15	0.02	0.13
	(0.54)	(0.17)	(0.63)
Work	75.6 %	79.5 %	64 %
High School	0.5 %	5.7 %	2.7 %
University	1.3 %	3.9 %	1.8 %
Relax,culture, sport	3.6 %	0.3 %	4.9 %
Doctor	7.5 %	5.3 %	12 %
Other	11.5 %	5.3 %	14.6 %

5 Results including counter-factuals

5.1 Model specification and estimation results

Variables used to specify the model are summed up in Table 5. Using these variables enables not only to control for effects of travel costs, travel time and socio-demographic characteristics. Interacting $school_{i,j}$ with bus_j enables to control for increased tendency of students to travel by bus. Similarly, interacting $locality_i^5$ with $train_j$ allows (for example) controlling for lower tendency to commute by train when travelling to Petržalka and so on.

Travel times, costs and income enter the model in logarithms. Since out-of-a-vehicle travel times as well as costs are often equal to zero, we transform data into $\log(1 + time)$ and $\log(0.1 + price)$.

Estimation results are given in Table 6. Observe that coefficients corresponding to travel times

Table 5: Variables description

$time^V_{i,j}$	In-vehicle time of travel (in minutes)
$time^O_{i,j}$	Out-of-a-vehicle time of travel (in minutes)
$price_{i,j}$	Travel costs (EUR)
$change_{i,j}$	Dummy variable equal to 1 if $j = train$ and there is no railway station located in town in which households i lives
$income_i$	Income of household i
$family_i$	Number of co-travelling adult family members
$kids_i$	Number of co-travelling children
$work_i$	Dummy variable equal to 1 if reason for commuting is work (*not* included in the model to avoid perfect multicollinearity).
$school_i$	Dummy variable equal to 1 if reason for commuting is school attendance
$doctor_i$	Dummy variable equal to 1 if reason for commuting is visit of a doctor
$other_i$	Dummy variable equal to 1 if reason for commuting is other than work, school attendence, visit of a doctor
$locality^k_i$	Dummy variable equal to 1 if household i commutes to locality k Five localities are distinguished: $k = 1$ for Staré Mesto and Nové Mesto, $k = 2$ for Ružinov, Vrakuňa and Podunajské biskupice, $k = 3$ for Rača, Vajnory, Karlova Ves, Dúbravka and Lamač, $k = 4$ for Devín, Devínska Nové Ves and Záhorska Bystrica, $k = 5$ for Petržalka, Jarovce, Rusovce and Čunovo (variable $locality^1_i$ is not used in the model to avoid perfect multicollinearity).
car_j	Dummy variable equal to 1 if $j = car$ (*not* included in the model to avoid perfect multicollinearity).
bus_j	Dummy variable equal to 1 if $j = bus$.
$train_j$	Dummy variable equal to 1 if. $j = train$
$individual_j$	Dummy variable equal to 1 if $j = car$ (*not* included in the model to avoid perfect multicollinearity).
$public_j$	Dummy variable equal to 1 if $j = bus$ or $j = train$.

and costs are negative what indicates that utility of a given mode decreases with longer times of travel and higher costs. Coefficient corresponding to $change_{i,j}$ is also negative - consumers dislike combining several modes of travel. Observe that the value of the coefficient is especially high, the need to commute to the nearest railway station and than to switch to train is almost prohibitive and corresponds more 25.5 EUR (using specification (4) $-0.358 \log(0.1 + 25.5) = -1.161$) or 923 minutes of travel ($-0.170 \log(1 + 923) = -1.161$). Only in case of 82 journeys (roughly 5% of all travels) commuters switch to train from other mode. A good example of such low tendency is town Šamorín which is only 7 minutes (4.8 km) away from the nearest railway station which is situated in town Kvetoslavov. However, only 20 journeys out of 330 from Šamorín use train, compared to 36% from Kvetoslavov itself. Moreover, average travel time by train from Šamorin is 54 minutes compared to 81 minutes by car.

Interaction terms reveal that consumers commuting to school and to visit a doctor are more likely to use public modes of transport than those commuting to work. Opposite effect is detected for those commuting for *other* reasons.

Coefficients corresponding to terms interacting bus_j and $train_j$ with locality dummies are all negative. This signifies that consumers commuting to locality 1, i.e. to Staré Mesto and Nové

Table 6: Estimation results

	(1)	(2)	(3)	(4)
$\log\left(1+time^V_{i,j}\right)$	-0.134	-0.131	-0.173**	-0.170**
	(-0.084)	(-0.094)	(-0.078)	(-0.084)
$\log\left(1+time^O_{i,j}\right)$	-0.164***	-0.186***	-0.114***	-0.128***
	(-0.035)	(-0.038)	(-0.033)	(-0.037)
$\log\left(0.1+price_{i,j}\right)$	-0.348***	-0.398***	-0.322***	-0.358***
	(-0.041)	(-0.046)	(-0.042)	(-0.047)
$change_{i,j}$	-1.169***	-1.285***	-1.080***	-1.161***
	(-0.153)	(-0.169)	(-0.145)	(-0.155)
$bus_j \times school_i$	-	1.227***	-	1.768***
		(-0.405)		(-0.408)
$train_j \times school_i$	-	1.667***	-	2.050***
		(-0.352)		(-0.372)
$bus_j \times doctor_i$	-	0.576**	-	0.621**
		(-0.292)		(-0.293)
$train_j \times doctor_i$	-	0.706**	-	0.519*
		(-0.302)		(-0.291)
$bus_j \times other_i$	-	-0.538**	-	-0.653***
		(-0.223)		(-0.226)
$train_j \times other_i$	-	-0.939***	-	-0.852***
		(-0.255)		(-0.245)
$bus_j \times locality^2_i$	-	-	-0.395***	-0.517***
			(-0.153)	(-0.159)
$bus_j \times locality^3_i$	-	-	-0.625***	-0.671***
			(-0.237)	(-0.242)
$bus_j \times locality^4_i$	-	-	0.940***	0.972***
			(-0.215)	(-0.222)
$bus_j \times locality^5_i$	-	-	-0.509**	-0.811***
			(-0.219)	(-0.239)
$train_j \times locality^2_i$	-	-	-0.742***	-0.867***
			(-0.158)	(-0.166)
$train_j \times locality^3_i$	-	-	-0.710***	-0.757***
			(-0.232)	(-0.237)
$train_j \times locality^5_i$	-	-	-0.796***	-1.029***
			-(0.229)	(-0.247)
$public_j \times \log(income_i)$	-1.070***	-1.137***	-1.117***	-1.162***
	(-0.165)	(-0.171)	(-0.169)	(-0.176)
$public_j \times family_i$	-0.788***	-0.797***	-0.817***	-0.845***
	(-0.095)	(-0.099)	(-0.097)	(-0.101)
$public_j \times kids_i$	-0.446***	-0.334**	-0.429***	-0.293**
	(-0.145)	(-0.150)	(-0.142)	(-0.148)
bus_j	1.445***	0.983***	1.563***	1.290***
	(-0.192)	(-0.300)	(-0.203)	(-0.302)
$vlak_j$	2.009***	1.704***	2.238***	1.910***
	(-0.224)	(-0.320)	(-0.234)	(-0.322)
τ_{public}	0.463***	0.539***	0.383***	0.419***
	(-0.071)	(-0.084)	(-0.064)	(-0.072)
N	4371	4371	4371	4371

Note: standard errors in parentheses; ***, **, * denote significance on 1%, 2% and 5% level; since no consumer in the sample use train to commute to locality 4, coefficient corresponding to $train_j \times locality^4_i$ cannot be estimated

Mesto, are more likely to use public mode of transport, especially train. This is due to the fact that two main railway stations in Bratislava are located in Staré Mesto and Nové Mesto. Trains from Danube region which is investigated in this study have their terminal stop in main railway station in Staré Mesto and do not continue to Petržalka.

Consumers with higher income and more co-travelling family members are less likely to use public modes of transport.

Finally, parameter of dissimilarity τ_{public} is close to one half in all specification. This signifies that consumers consider train and bus to be relatively close substitutes.

To demonstrate the importance of interaction terms, Table 7 gives predictive power of models (1)-(4). First row gives information about how many times when car is chosen for a journey, model predicts that $P(Y_j = car)$ is higher than both $P(Y_j = bus)$ and $P(Y_j = train)$. Percentages given in the second row indicate how many times public mode was chosen (bus *or* train) and model predicts that $P(Y_j = bus)$ *or* $P(Y_j = train)$ is higher than $P(Y_j = car)$.

Observe that success rate of correctly predicting public mode without interaction terms is lower than in full specification (4). This is especially important for buses. Including interaction terms enables to improve success rate from 16.3% to 37.8%.

Table 7: Correct predictions

	(1)	(2)	(3)	(4)
Correctly predicted car = C. p. individual mode	91.4%	90.5%	90.5%	88.9%
Correctly predicted public mode	29.7%	36.6%	34.6%	42.3%
Correctly predicted bus	16.3%	25.4%	27.2%	37.8%
Correctly predicted train	36.0%	38.7%	35.6%	36.4%
Correctly predicted all modes	68.4%	69.9%	69.8%	71.0%

Table 8 gives actual demand and predicted demands for modes of transport. These are approximately the same in all four specifications.

Table 8: Actual and predicted demand

	Actual	(1)	(2)	(3)	(4)
Demand for car tr. = D. for individual mode	65.3%	65.1%	65.1%	65.1%	65.1%
Demand for public modes	34.7%	34.9%	34.9%	34.9%	34.9%
Demand for bus transport	19.3%	18.8%	18.9%	18.7%	18.9%
Demand for train transport	15.4%	16.1%	15.9%	16.2%	16.0%

5.2 Price, time and income elasticities

To calculate direct and cross price elasticities as well as time and income elasticities we use full specification (4) and we proceed in the following way:

1. We calculate fitted values of $\hat{P}_0(Y_i = j)$ according to (4).
2. For all journeys we increase variable of interest x (for example costs of commuting by car) by one percent[6])
3. We calculate adjusted fitted values $\hat{P}_1(Y_i = j)$.
4. Demand elasticity in case of journey i for transport mode j with respect to variable x is calculated as:
$$e^x_{i,j} = 100 \times \left[\log \hat{P}_1(Y_i = j) - \log \hat{P}_0(Y_i = j)\right]$$
5. Market demand elasticity for transport mode j with respect to variable x is calculated as:
$$e^x_j = 100 \times \left[\log \sum_i \hat{P}_1(Y_i = j) - \log \sum_i \hat{P}_0(Y_i = j)\right]$$

Calculated market elasticites are given in Table 9. Observe that direct price (and time) elasticities are negative, whereas cross elasticities are positive. Importantly, elasticities of demand for car travel are lower than those of demand for public modes. This indicates that consumers travelling by car are less willing to change the mode of transport when facing higher costs and/or travel times. On the other hand, those traveling by public modes are more willing to change the way they commute to Bratislava when travel times or costs get higher.

Table 9: Direct and cross elasticities with respect to price, time and income

Market elasticity of... ..with repect to	Car	Bus	Train
$price_{car}$	-0.095	0.194	0.160
$price_{bus}$	0.056	-0.363	0.199
$price_{train}$	0.039	0.169	-0.359
$time^V_{car}$	-0.045	0.092	0.076
$time^V_{bus}$	0.027	-0.173	0.095
$time^V_{train}$	0.019	0.081	-0.171
$income$	0.309	-0.628	-0.518

[6]More specifically, in case of travel times we increase $1 + time$ by one percent, in case of costs we increase $0.1 + price$ by one percent. This means that if reported costs associated with, for example, commuting by car are 0 EUR, we increase costs by 0.001 EUR (one percent of $0.1 + price$).

Not surprisingly, income elasticities of demand for car travel are positive, whereas negative values in case of bus and train transport indicates that those travel modes are inferior goods.

Figures 2-4 give individual elasticities plotted against income category. Observe that direct price (and time) elasticities of demand for car transport tend to decrease (in absolute value) with higher income. On the other hand, demand for train transport tend to be more elastic with higher income. However, this is due to the fact that high-earners commute by train very rarely and therefore even small change in probability of using train manifests as high elasticity.

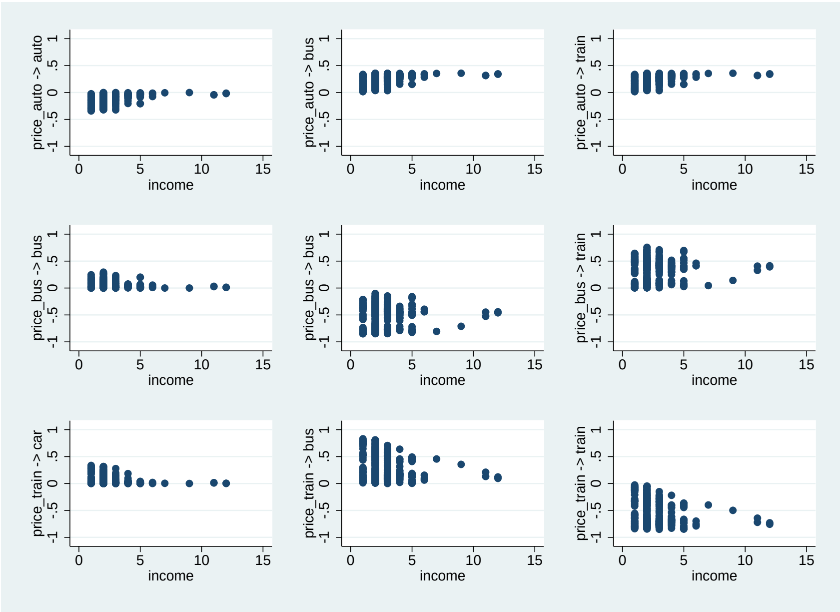


Figure 2: Individual price elasticities

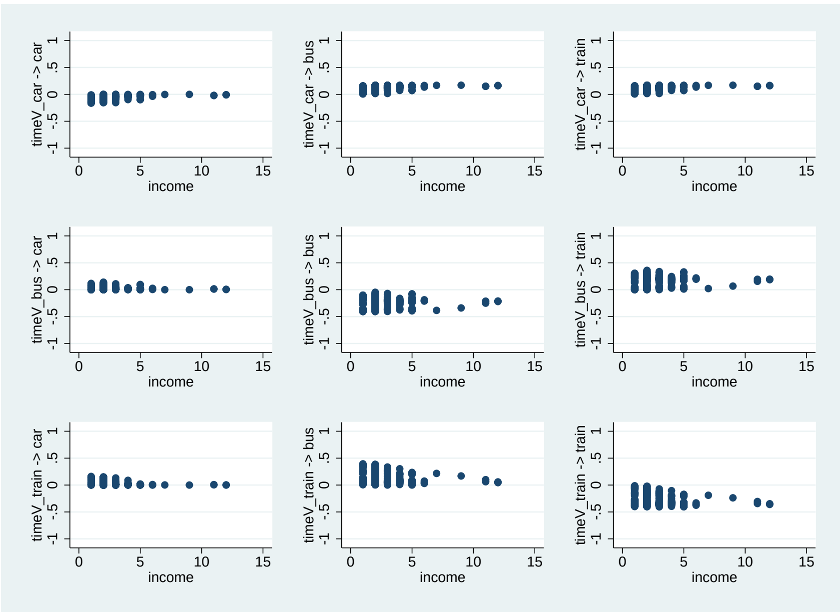


Figure 3: Individual time elasticities

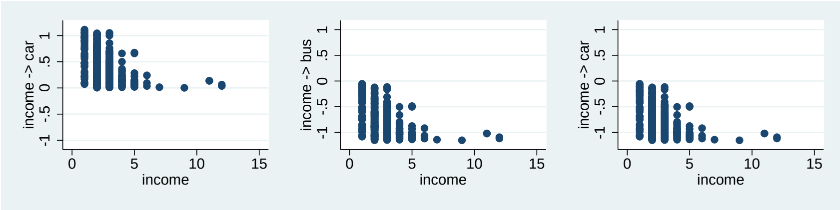


Figure 4: Individual income elasticities

5.3 Illustrative evaluation of changes in travel policy and infrastructure

In this subsection we give illustrative evaluation of two possible changes in Bratislava region:

New parking policy and rising costs for car commuters: Currently Bratislava municipality is preparing new parking policy, that is expected to be launched in 2021. Basic idea is to reduce usage of cars by new and uniform system of parking fees. First, the Bratislava's residents will have opportunity to buy a resident card starting from 39 EUR/year. Second, for non-residents prices are shown in Table 10

Table 10: Parking price per hour

Zones	Price	Locality
Zone A	2.00 EUR/h	$k = 1$
Zone B	1.50 EUR/h	$k = 2, 3$
Zone C	1.00 EUR/h	$k = 4$
Zone D	0.50 EUR/h	$k = 5$

Where Zone A is a district with the highest demand (exact streets belonging to particular zones have not been detailed yet). On an aggregated level the zones can correlate with localities specified in Table 5. These are shown in the third row of Table 10. Furthermore, the fees do not necessary be active 24 hours per day, but only during a peak time.

D4R7 highway and decreasing in-time for car and bus commuters: Within a specified region new highway named D4R7 is planned to be built until 2020. The total length of highway is 59 km, with 4 possible interchanges in towns of Holice, Šamorín, Dunajská Lužná and Rovinka. The highway is therefore planned along the problematic road number 63. According the GoogleMaps server the average difference between peak and off-peak in-vehicle time for selected towns for the whole region of interest (see Appendix) is 21 minutes, that is roughly 41% rise in relative term.

To evaluate new parking policy, we assume parking time of 10 hours if commuting to work or school and 3 hours when commuting for other reasons. Therefore, we increase travel costs associated with commuting by car by:

- Commuting to work or to school: 20 EUR (2.00 EUR times 10 hours estimated parking time) if journey is into locality 1, by 15 EUR if destination is locality 2 or 3 (1.50 EUR times 10 hours estimated parking time) and so on. We divide this value by number of adult family members.
- Other reasons: 6 EUR per adult family member (2.00 EUR times 3 hours estimated parking time) if journey is in locality 1, by 4.5 EUR if destination is locality 2 or 3 (1.50 EUR times 3 hours estimated parking time) and so on. We divide this value by number of adult family members.

Subsequently, we recalculate probabilities according to (4) and calculate market demand for all transport modes. Results are given in the left graph of Figure 5. On the horizontal axis is extent of policy application, for example, if $policy = 0.5$, we assume that parking costs are only half of those given in Table 10.

In case of full policy application, model predicts drastic decrease in car commuting, from over 60% to only slightly more than 20%. This is hardly surprising, parking costs of 20 EUR per day are indeed prohibitive. Model predicts that car commuters will more likely switch to public buses. This is mainly due to the fact that commuting by train without first travelling to the nearest railway station by car or bus is not possible for many commuters. As mentioned above, one of the biggest towns in the area, Šamorín, does not have a railway station.

However, we would like to emphasise that this scenario does not take into account possibility of new parking lots build away from the city centre where commuters would be able to park before switching to public urban transport. Modelling this complicated scenario would require knowing where new parking lots will be located and how public transport would be adjusted. This task is therefore outside the scope of this study.

To evaluate potential effects of D4R7 highway we assume that ins-vehicle travel times for consumers commuting to work and school by car and bus will decrease. Maximum potential time saves are calculated according to differences between peak and off-peak travel times given by GoogleMaps (for list of maximum potential time saves see Table 12 in Appendix).

Results are given in the middle graph of Figure 5. In case of $policy = 0.5$ we assume that actual time saved is only half of the potential save given by GoogleMaps. Observe that reductions in time travel have only minimal effect on demand for travel modes. This is due to the fact that most consumers already choose to travel by car *despite* long travel times. If anything, D4H7 will reduce number of train commuters.

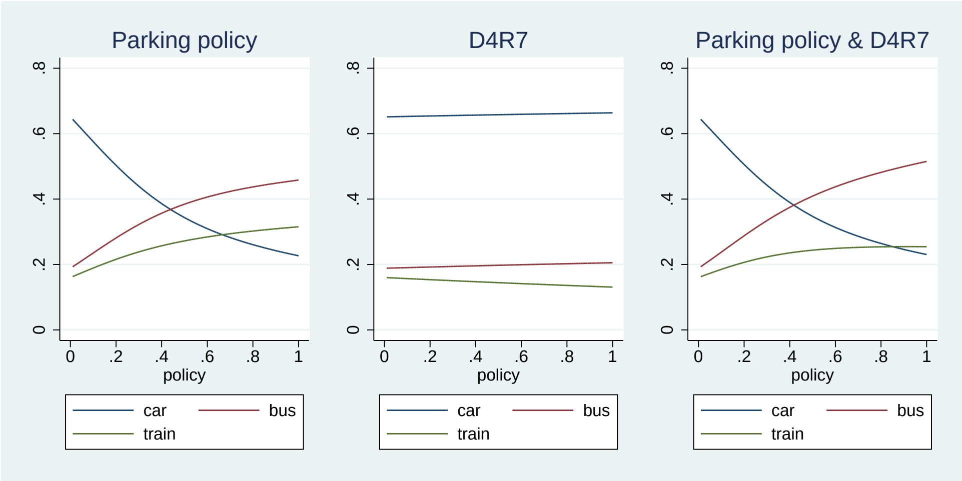


Figure 5: Effects of new policies on demand for travel modes

Finally, scenario depicted in the right graph of Figure 5 is calculated under assumption that both policies take place. Combining new highway with new parking policy will affect mainly commuting by bus which would benefit by new infrastructure, but will not be harmed by parking policy. Our model predict substantive increase in number of bus commuters. However, we would like to stress once again that this does not take into account possibility of new parking lots and changes in public transport within Bratislava.

6 Conclusion

This paper generalizes findings from recent study for proposed water transportation on Danube river. Data for revealed preferences of commuters from south-east part of Bratislava region were collected during the study. These information are used to understand commuting behaviour as well as choice patterns within region of interest. The standardized methodology of discrete choice model, particularly nested logit model, is used to estimate demand for existing modes of transport.

First, data for 412 commuters suggest low substitution between public and individual private modes. Roughly 76% of commuters use only one of available modes. Unsurprisingly, socio-demographic characteristics reveal that car users tend to have higher income and greater probability of sharing journey with other family members.

To correctly estimate demand, interaction terms with purpose of travel as well as the destination were used. Students and commuters travelling for *other* (not work, school or visiting a doctor) reasons tend to use more public modes of transport. On the other hand, travellers commuting to work typically choose individual option, i.e. car. Furthermore, importance of in-town train stations was revealed. Commuters dislike combining several modes and therefore the probability of choosing train if railway station is not in their starting and ending destination is low. As expected, coefficients corresponding to travel times and costs are all negative. The model has been able to correctly predict 71% of all modes.

All direct price and time elasticities are negative (since corresponding coefficients are bellow zero). Moreover, price elasticity for cars is approximately four times lower than for public options. In case of elasticity with respect to time it is 3.8 times lower. This indicates that while car travellers are less willing to change the mode of transport when facing higher costs or travel times, users of public modes are more willing to switch the way they commute. Lastly, elasticities with respect to income are negative for public modes, that suggests inferiority of these options.

According to results, outcomes for planned infrastructure policies within the region were predicted. First, the new system for parking fees was evaluated. Second, potential outcome of new highway R7D4 was calculated. In case of parking policy, travel costs for car commuters were increased up to 20 EUR per car per day. Such costs would reduce share of car commuters from current 60% to more than 20%. However, the scenario do not take into consideration possible parking lots around Bratislava where commuters would be able to switch to public transportation. Second, the predicted effect of new highway has only limited outcome and if anything, would reduce number of train commuters.

Low tendency to switch between modes, together with inelastic demand with respect to time and costs (however, still in line with published literature) and strong socio-demographic preferences are hard obstacles for any 'quick and easy' policy. However, some of our results offer hope. First, the current view of public modes as an inferior option can be soften by increasing quality and comfort. Furthermore, drastic increase in costs can overwhelm even inelastic demand for cars. Lastly, reducing the out-of-a-vehicle time connected to changes between modes of transport can bring more commuters to trains what is certainly desired outcome.

References

De Jong, G. and H. Gunn (2001). Recent evidence on car cost and time elasticities of travel demand in europe. *Journal of Transport Economics and Policy (JTEP) 35*(2), 137–160.

Fröidh, O. (2008). Perspectives for a future high-speed train in the swedish domestic travel market. *Journal of Transport Geography 16*(4), 268–277.

Goodwin, P. B. (1992). A review of new demand elasticities with special reference to short and long run effects of price changes. *Journal of transport economics and policy*, 155–169.

Hanly, M., J. Dargay, and P. Goodwin (2002). Review of income and price elasticities in the demand for road traffic. *Department for Transport, London*.

Harker, P. T. (1988). Private market participation in urban mass transportation: application of computable equilibrium models of network competition. *Transportation science 22*(2), 96–111.

Holmgren, J. (2007). Meta-analysis of public transport demand. *Transportation Research Part A: Policy and Practice 41*(10), 1021–1035.

Hultkrantz, L. and S. Savsin (2018). Is referencing a remedy to hypothetical bias in value of time elicitation? evidence from economic experiments. *Transportation 45*(6), 1827–1847.

Kremers, H., P. Nijkamp, and P. Rietveld (2002). A meta-analysis of price elasticities of transport demand in a general equilibrium framework. *Economic Modelling 19*(3), 463–485.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of public economics 3*(4), 303–328.

Šveda, M. and P. Barlík (2018). Daily commuting in the bratislava metropolitan area: case study with mobile positioning data. *Papers in Applied Geography*, 1–15.

Wardman, M. (2014). Price elasticities of surface travel demand a meta-analysis of uk evidence. *Journal of Transport Economics and Policy (JTEP) 48*(3), 367–384.

Wong, B. (2013). *Modelling Intercity Travel Demand in the Quebec City–Windsor Corridor: A Study on the Effects of Local Accessibility Utilizing a Geographically Disaggregated Web-based Approach.* Ph. D. thesis.

Appendix

Table 11: List of cities and towns in region of interest

#	Town	Off-peak	Peak	Diff.	#	Town	Off-peak	Peak	Diff.
1.	Báč	44	73	0.60	22.	Šamorín	39	68	0.57
2.	Bodíky	44	51	0.86	23.	Veľká Paka	41	64	0.64
3.	Dolný Bar	60	82	0.73	24.	Vrakúň	58	64	0.90
4.	Kostolné Kračany	57	84	0.68	25.	Blatná na Ostrove	49	77	0.63
5.	Kvetoslavov	35	60	0.58	26.	Dobrohošť	38	46	0.82
6.	Lúč na Ostrove	53	82	0.64	27.	Dunajská Streda	53	77	0.68
7.	Malé Dvorníky	58	80	0.73	28.	Holice	51	79	0.64
8.	Michal na Ostrove	45	69	0.66	29.	Horný Bar	52	79	0.65
9.	Ohrady	60	81	0.73	30.	Kútniky	57	79	0.72
10.	Orechová Potôň	48	70	0.68	31.	Mad	60	88	0.68
11.	Trstená na Ostrove	55	82	0.67	32.	Mierovo	35	59	0.60
12.	Veľké Dvorníky	57	80	0.72	33.	Rohovce	47	75	0.62
13.	Vojka nad Dunajom	38	47	0.82	34.	Trnávka	47	75	0.62
14.	Baka	57	61	0.95	35.	Veľké Blahovo	48	71	0.68
15.	Gabčíkovo	52	59	0.89	36.	Vydrany	50	73	0.69
16.	Hviezdoslavov	34	58	0.59	37.	Hamuiakovo	33	62	0.53
17.	Kráľovičove Kračany	53	83	0.64	38.	Kalinkovo	30	61	0.49
18.	Kyselica	49	77	0.63	39.	Dunajská Lužná	26	56	0.45
19.	Macov	45	68	0.66	40.	Rovinka	21	43	0.50
20.	Ňárad	59	64	0.91	41.	Miloslavov	31	57	0.54
21.	Povoda	58	87	0.67	42.	Čunovo	25	34	0.74

The table includes all towns from the region of interest together with in-vehicle times in minutes obtained from server GoogleMaps during peak and off-peak hours. The relative difference is calculated in column Diff.

Table 12: List of Bratislava's districts

#	District		
1.	Staré Mesto	10.	Lamač
2.	Ružinov	11.	Devín
3.	Vrakuňa	12.	Devínska Nová Ves
4.	Podunajské Biskupice	13.	Záhorská Bystrica
5.	Nové Mesto	14.	Petržalka
6.	Rača	15.	Jarovce
7.	Vajnory	16.	Rusovce
8.	Karlova Ves	17.	Čunovo
9.	Dúbravka		