DEFINE

Development of an Evaluation Framework for the Introduction of Electromobility

Electromobility+

Project:

Development of an Evaluation Framework for the Introduction of Electromobility

Deliverable 3.2: Report on Microeconometric Results

Deliverable 3.3: Input to the General Equilibrium Model in Form of Elasticities

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1. Descriptive Statistics

This report is part of Working Package 3 of the DEFINE project. It is based on a survey and two discrete choice experiments[1], which allow us to conduct in-depth analysis on mobility behaviour in Austria and to calculate behavioural parameters for our macroeconomic model. The first section, comprising paragraphs 1.1 to 1.5, presents the results of the survey that are not connected to the choice experiments.

1.1 Background data

Table 1 compares the characteristics of the original and a weighted sample to the corresponding figures of the Austrian population.

The original sample includes 1449 respondents. In the weighted sample, data from the original sample was adjusted by applying individual weights to each respondent. Thus, additional weight was given to observations of respondents with characteristics being underrepresented - in comparison to the population - while simultaneously lowering the relative importance of responses from people with overrepresented characteristics[2]. In order to increase the representativeness of the sample the weighting process thus adjusts the aggregate values of the following variables: gender, age, educational attainment, employment status and federal state. It can be seen from the table below that while the original sample offers already a quite good fit, representativeness of the sample is further increased by weighting the data. The share of female respondents, for instance, which is close to 50% in the original sample, amounts to 52% in the weighted sample, which corresponds better to the characteristics of the population (table1). As a result our analysis will be based on weighted data, yet, keeping in mind the original sample. As regards the population, the comparing group is Austrian inhabitants who are 18 years or older, which in 2012 amounted to 6.933.029 people.

Furthermore, it is important to note that both samples, the original and the weighted one, include as a subsample a boost sample where only people (a) possessing a driving license and (b) having the intention to buy a car within the next three years were included. This means that the data used for the following descriptive analysis contains a somewhat higher share of car license owners, respectively car users and car owners, than it would be found in the actual population, which is important to keep in mind when interpreting some of the numbers presented in the following paragraphs. Regarding the discrete choice experiments (DCEs) discussed in part 2 of this text, people with no driving license or no car purchase intention had an equal probability to participate in the DCEs, with the corresponding elasticities thus being representative for the overall population.

[1] The survey and discrete choice experiments were carried out by the subcontractor GfK Austria.
[2] We use post-stratification weights as provided by GfK Austria.

Table 1: Comparison of original sample, weighted sample and population

	Samples		Population
	Original sample	**Weighted sample**	**Austria**
General information			01.01.2012
Number of respondents / inhabitants	1.449	1.400	8.443.018
Respondents / inhabitants who are at least 18	1.449	1.400	6.933.029
Gender			01.01.2012
Share of women in sample / population	50%	52%	52%
Age distribution			01.01.2012
18 - 29	18%	19%	19%
30 - 39	16%	16%	16%
40 - 49	21%	20%	20%
50 - 59	17%	17%	17%
60 +	28%	28%	28%
Education			01.01.2010 *
primary	16%	25%	25%
secondary	66%	63%	63%
tertiary	18%	12%	12%
Employment **			01.01.2012
Employment rate	72%	82%	73%
Average household size (people)			2009 / 10
	2,53	2,53	2,29
Median Personal Net Income (in €)			2011
	2.025	1.875	1.732
Household Income Distribution (in €) ***			2011
25% have less than…	1.327	1.275	1.123 ****
50% have less than…	1.700	1.700	1.493 ****
75% have less than…	2.175	2.100	1.940 ****
People living in...			01.01.2012 *
densely populated area	33%	31%	31%
intermediate density area	30%	29%	29%
thinly populated area	37%	40%	40%
People living in...			01.01.2012
Vienna	20%	21%	21%
Lower Austria	19%	19%	19%
Burgenland	4%	3%	3%
Upper Austria	17%	17%	17%
Styria	13%	15%	15%
Carinthia	7%	7%	7%
Salzburg	7%	6%	6%
Tyrol	9%	8%	8%
Vorarlberg	4%	4%	4%
Percentage of households that have...			2009 / 10
no car	6%	6%	23%
one car	47%	44%	51%
more than one car	47%	50%	26%
Number / Percentage of people who actually			

drive a car			
car drivers	1.383	1.326	-
percentage	95%	94%	-
Car purchase within next 3 years is...			
definitely planned	20%	20%	-
definitely planned or likely	59%	58%	-

* Figures calculated for people aged 20 and older.
** Figures calculated for people aged 15 to 65.
*** Equalised household incomes.
**** Monthly values were calculated by using a specific web-interface provided by the Austrian Ministry of Finance (http://onlinerechner.haude.at/bmf/brutto-netto-rechner.html).

As mentioned above, the gender distribution of the weighted sample perfectly resembles the Austrian population, with a share of females of 52%. Concerning the age distribution, the youngest respondent was 18 years old and the maximum age was 87 and we find a precise fit with the population's characteristics for both, the original and the adjusted sample.

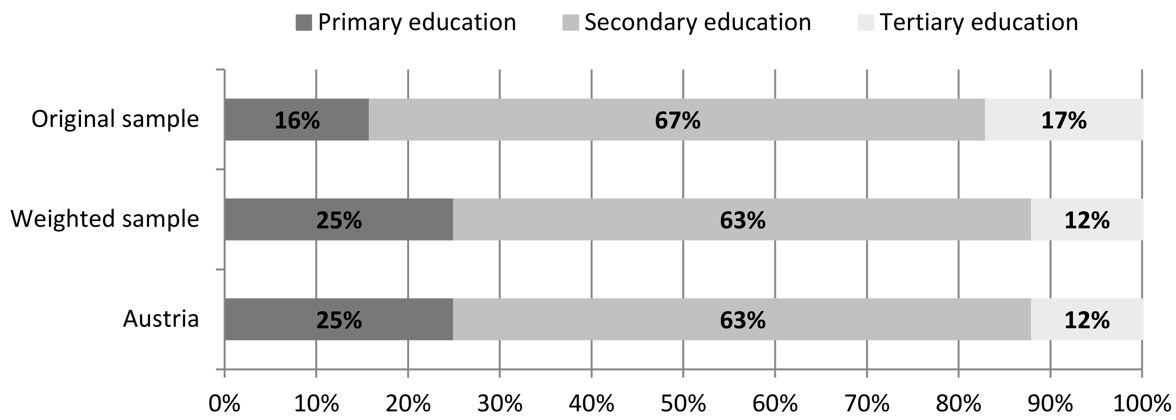
Education refers to the highest educational level a person has attained. One can look at educational levels either at the broad level of primary, secondary and tertiary education (table 1) or break education down more precisely. The more detailed classification was applied in table 2, where 'Basic education' corresponds to primary education, but secondary education is split up into Apprenticeship (Lehre), Vocational School (BMS), Higher general education (AHS), Higher vocational school (BHS) and tertiary education into College and University / FH. It can be seen that certain categories are underrepresented (e.g. Apprenticeship) and others are overrepresented (e.g. Higher general education, Higher vocational school), which still is the case with weighted data. This is because the applied weights correct only at the broad level of primary, secondary and tertiary education, thereby not adequately adjusting the individual educational subcategories that make up the respective categories of primary, secondary and tertiary education. This approach, however, seems to be justified as it is likely that different forms of secondary or tertiary education lead to similar educational levels.

Table 2: Highest educational attainment – distribution

	Original sample		**Weighted sample**		**Austria (thousands)**	
	Observations	%	Observations	%	Observations	%
Basic education	229	16	350	25	1.662	25
Apprenticeship	339	24	306	22	2.266	34
Vocational School	112	8	102	7	1.002	15
Higher general education	219	15	184	13	396	6
Higher vocational school	293	20	289	21	526	8
Some college	107	7	67	5	183	3
University, FH	150	10	102	7	619	9
Total	1.449	100	1.400	100	6.654	100

Applying the broader classification, we again see high representativeness of the weighted sample. This is demonstrated in graph 1, where the shares of primary, secondary and tertiary education are given for the original sample, the weighted sample and the population. It is easy to see that the weighted data provides a much better fit with the actual population than the original sample does, where the share of primary education is underestimated (16% compared to 25% in the population) and the respective shares of secondary and tertiary education are overestimated.

Graph 1: Highest educational attainment – Share of primary, secondary and tertiary education



Next, we consider employment status, which can either be looked upon for all ages or only for people at working age (15 – 64 years), with the second approach being the more common one. Following the latter approach, employment rates were calculated for people at working age. Employment comprises people working full time, part time, assisting in family business and women on maternity leave. It can be seen from table 1 that in the original sample the employment rate amounts to 72%, meaning that employed people are somewhat underrepresented in this sample (population: 73%). In contrast, in the weighted sample, the share of working people is higher (82%) than in the population, and employment seems to be overestimated. This is at least partly explained by the fact that the employment rate of the population also includes people between 15 and 18 years – which traditionally have very low employment rates – whereas that age group is completely missing in the sample due to the fact that the youngest survey respondent was already 18.

Table 3 splits up the original and weighted data by occupational status, thus giving additional insights and presenting the underlying individual numbers of the aggregated employment rates displayed in table 1.

Table 3: Occupational status - distribution

Occupational status *	Original sample		Weighted sample	
	Observations	%	Observations	%
Full time	648	54	735	61
Part time	183	15	218	18
Assistance in family business	8	1	8	1
Maternity leave	23	2	27	2
Unemployed	30	3	15	1
Pension	157	13	118	10
Working in household	25	2	17	1
Student, Apprenticeship, Military service	118	10	67	6

Total	1.192	100	1.205	100

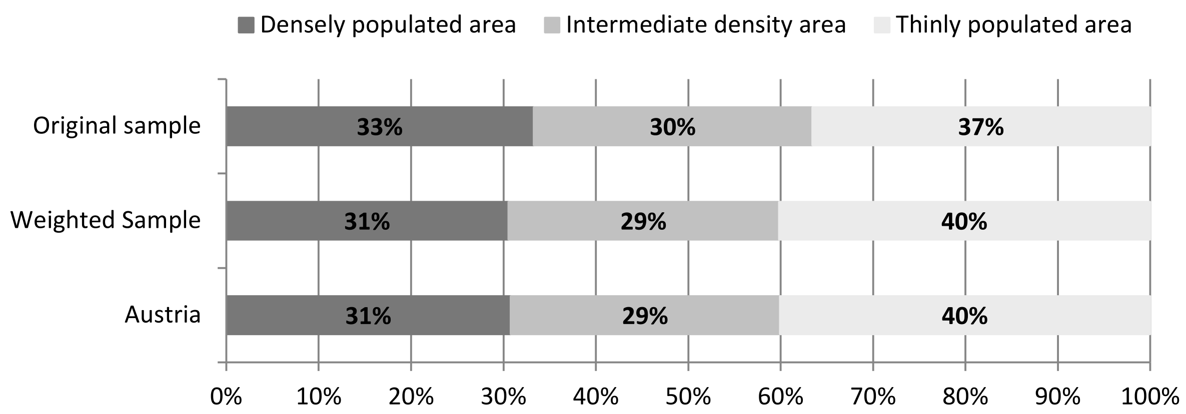
* Figures calculated for people aged 15 to 64.

Coming back to table 1, we see that the average household size is about 2,5 in the original and weighted sample, compared to 2,3 in the population.

The monthly median personal net income is 2.025€ in the original and 1.875€ in the weighted sample, with the corresponding median personal net income of the Austrian population being 1.732€ in 2011. Regarding the household net income 25% of the respondents report a monthly household income of 1.275€ or less, the median household net income is 1.700€ and 25% of the respondents display a household net income higher than 2.100€. Overall, the median personal and household net income are both a bit higher in the sample than in the Austrian population. This might be explained by the fact that car owners are overrepresented in our sample, assuming that people who (a) possess a driving license and (b) are planning a car purchase in the near future also display on average somewhat higher incomes than people who do not have a driving license and do not intend to buy a car.

When considering mobility behaviour, the degree of urbanisation of an area can be of great interest as areas with different population density provide different levels of infrastructure and feature different mobility needs. Graph 2 demonstrates that the distribution of people living in densely populated areas, intermediate density areas and thinly populated areas is exactly the same for the weighted sample and the Austrian population, with 40% of all people living in thinly populated areas, roughly 30% in intermediately populated areas and the remaining 30% living in densely populated areas.

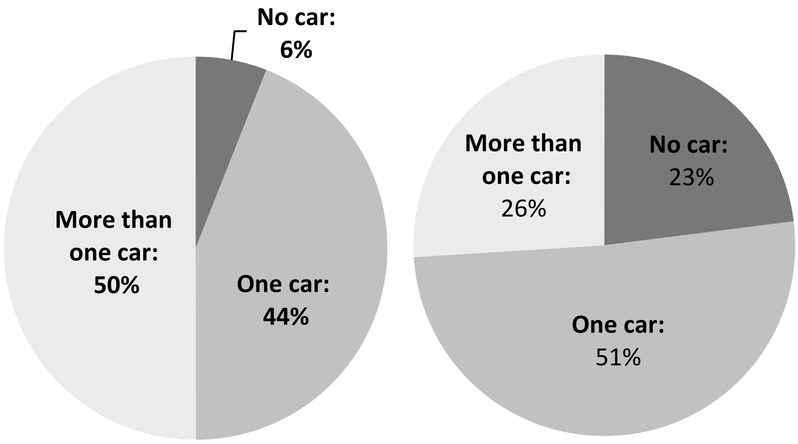
Graph 2: Degree of urbanisation – distribution



Likewise, the distribution among the different states in Austria provides very similar numbers for the weighted sample and the population, as can be seen from table 1.

Next, table 1 demonstrates the percentage of households in the sample and in the Austrian population that have no car, the percentage of all households that own exactly one car and the respective share of households owning more than one car. In comparison to the Austrian population households with no car are strongly underrepresented in the weighted sample (6% compared to 23%), while households with two or more cars are overrepresented in the sample (50% to 26%).

Graph 3: Weighted sample's (left) and population's (right) distribution of car ownership



This difference results from the fact that the focus of this survey was not only to analyse mobility behaviour but also to gain insights on vehicle demand, especially regarding alternative fuel technologies and as a result a boost sample exclusively with people who (a) possess a driving license and (b) find it likely to purchase a car within the next three years was included in our data set.

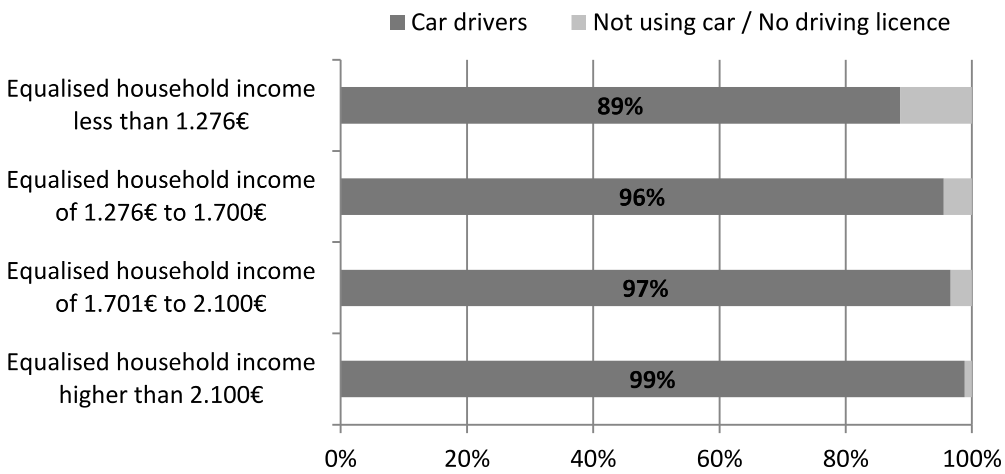
Finally, table 1 shows that 1383 out of a total of 1449 responses came from people actually driving a car at least from time to time, while 66 responses were made by people who either do not have a driving license or reported that they never use a car. Thus, approximately 95% of all respondents are drivers in the original as well as the weighted sample. Though there are no corresponding figures available for the Austrian population it is clear that car drivers are somewhat overrepresented due to the focus of the survey.

For reasons of better readability we will no longer refer to the original sample in the next paragraphs. Thus, if nothing different is explicitly stated, all further results will be derived from the weighted sample, whose superior properties have been discussed above.

1.2 Car use and ownership – general information

As already mentioned above, car drivers account for approximately 95% in our sample, with the remaining 5 % being made up of people either not having a driving license or simply never using a car. With regards to gender, we see certain differences between women and men with the share of non-drivers being more than double as high within female individuals (7%) than within male individuals (3%). Graph 4 gives additional insights on the distribution of drivers and non-drivers by splitting up the sample by monthly equalised household net income, with the four subgroups corresponding to income quartiles.

Graph 4: Car drivers and non-drivers by monthly equalised household net income



While it is clear that the share of car drivers is again somewhat overestimated compared to the figures we would actually find in the Austrian population, we can see an obvious trend in comparing the different income quartiles. There is a clear increase in the share of car drivers with rising incomes, indicating that the huge majority of non-driver are individuals with rather low (household) incomes, while in households with a monthly equalised net income higher than 2.100€ almost everybody is driving a car.

A similar trend can be seen when dividing the sample according to different degrees of urbanisation, where the number of car drivers is comparatively small in densely populated areas (89%), whereas in intermediate density (96%) and thinly populated (98%) areas a person that is not driving a car can hardly be found.

In the survey all car users were asked whether they are rather drivers or co-driver, with a huge majority of almost 90% stating to be the former (graph 5). The huge number of drivers and the simultaneously low figure for co-driving (10%) suggests that nowadays lots of capacities of our vehicles remain unused.

Graph 5: Car use

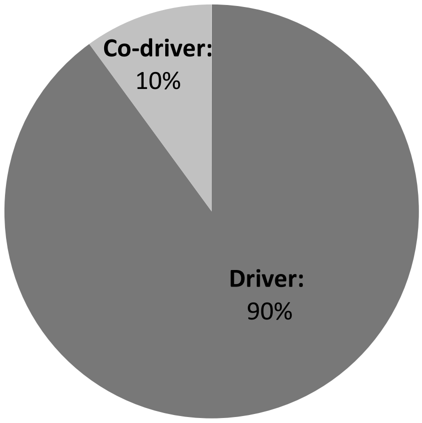


Table 4 indicates a somewhat higher share of co-drivers amongst younger (19%) and older (12%) people, with the corresponding value being exceptionally low for the 40 - 49 age cohort (5%).

Table 4: Share of drivers and co-drivers by age groups

Age	Rather driver	Rather co-driver
18 - 29	81%	19%
30 - 39	90%	10%
40 - 49	95%	5%
50 - 59	90%	10%
60 - 69	92%	8%
Over 70	88%	12%

Finally, table 5 demonstrates that being a co-driver is most common in Austria in areas with more than one million inhabitants, which is Vienna.

Table 5: Share of drivers and co-drivers by town size

Number of inhabitants	Rather driver	Rather co-driver
0 to 1000	93%	7%
1001 to 2000	91%	9%
2001 to 3000	94%	6%
3001 to 5000	90%	10%
5001 to 10000	90%	10%
10001 to 20000	94%	6%
20001 to 50000	91%	9%
50001 to 1 million	91%	9%
Over 1 million	83%	17%

The extent to which car users know and actively use the concept of car sharing[3] is another interesting issue. Table 6 shows that out of 1400 respondents in the sample only 5 (0,4%) reported to use car sharing on a regular basis, with another 37 respondents (2,6%) making use of car sharing at least from time to time. All in all, while about 3% of all respondents actively use car sharing and a broad majority knows car sharing, 38% still do not know this concept at all.

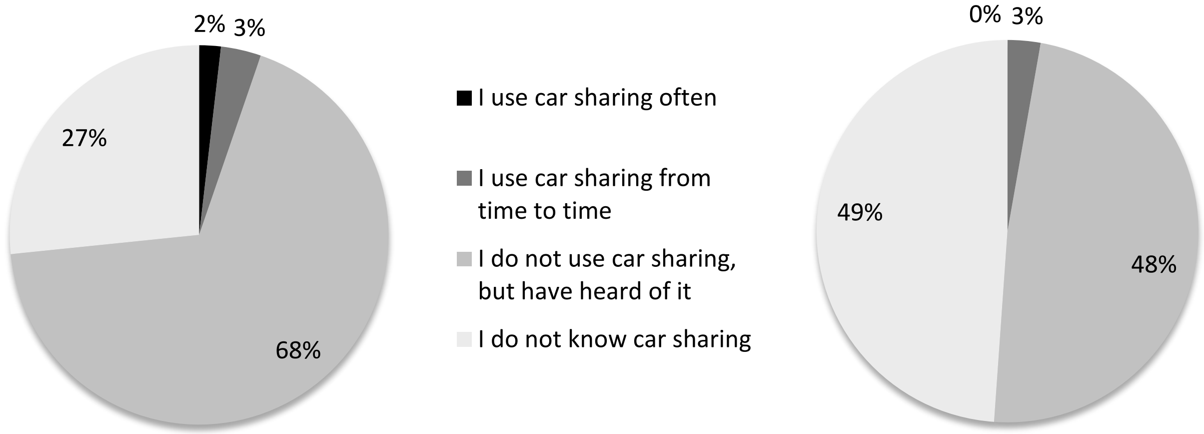
[3] Car sharing was defined as using cars that can be rent daily or hourly and can be parked at designated public parking areas.

Table 6: Usage of car sharing

	Observations	%
I use car sharing often	5	0,4
I use car sharing from time to time	37	2,6
I do not use car sharing, but have heard of it	824	59
I do not know car sharing	534	38
Total	1.400	100

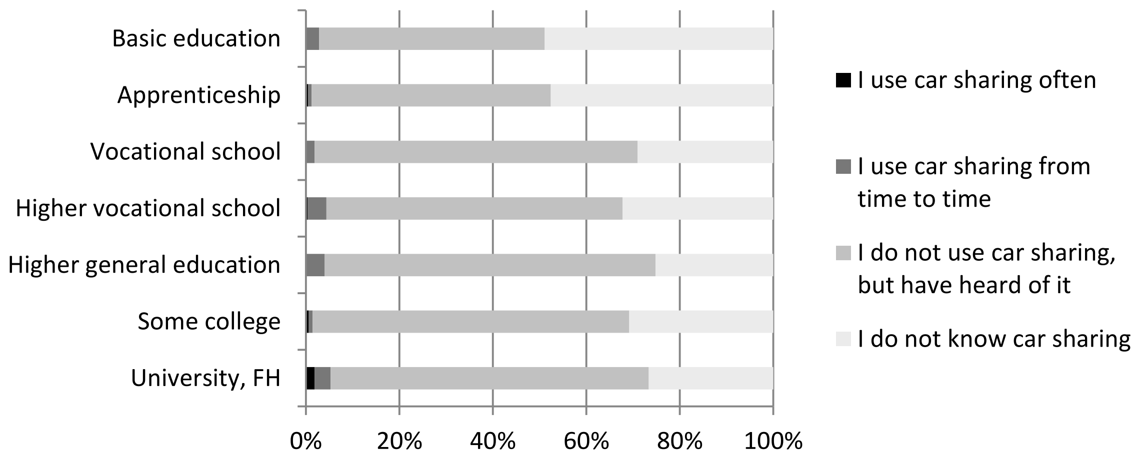
Graph 6 and 7 suggest that higher educational levels go together with more frequent use and higher knowledge of car sharing, with graph 6 comparing the use and knowledge of car sharing of respondents with a university / FH degree to respondents with basic education only.

Graph 6: Usage of car sharing among respondents with a university or FH degree (left) and respondents with basic education (right)



Generally, in our sample 50 % of all repondents that stated that they are using car sharing on a regular basis have a university / FH degree. Likewise, the share of repondents knowing this concept is the highest for people with higher general or university education (about 75%) and the lowest for respondents with basic education or an apprenticeship (about 50%).

Graph 7: Usage / Knowledge of car sharing by highest educational attainment



Last but not least, table 7 clearly demonstrates that car sharing occurs almost exclusively in densely populated areas while being almost never applied in thinly populated areas.

Table 7: Usage / Knowledge of car sharing by degree of urbanization

	Thinly populated area		Intermediate density area		Densely populated area	
	Observations	%	Observations	%	Observations	%
I use car sharing (CS) often	0	0	0,4	0,1	5	1
I use CS from time to time	4	1	7,6	1,9	25	6
I do not use CS, but have heard of it	292	52	239	58	293	69
I do not know CS	267	47	163	40	104	24
Total	563	100	410	100	427	100

In the final part of this chapter we discuss the number of cars per household.

Table 8: Summary on number of cars per household

Cars per household		
Mean	**Min**	**Max**
1,58	0	6

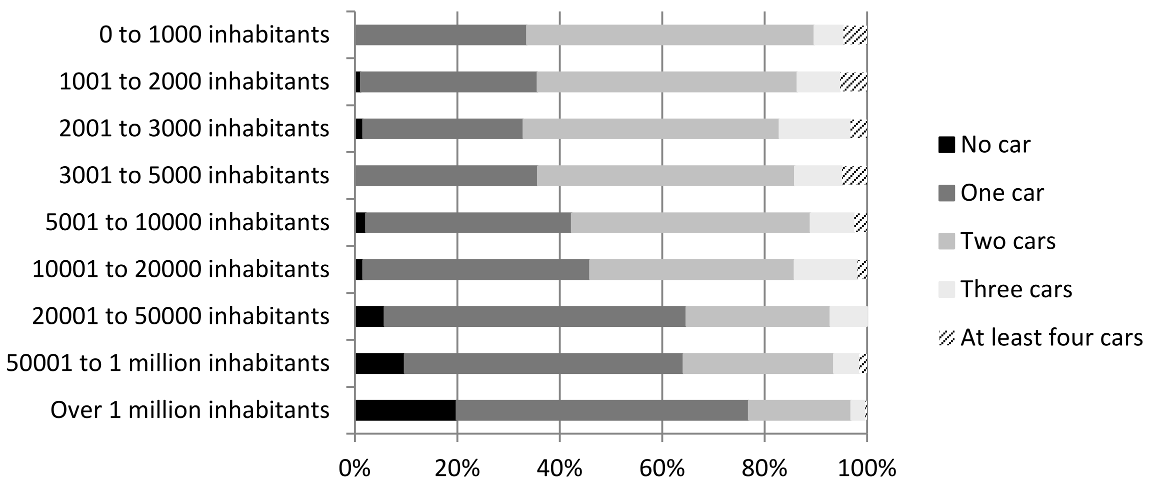
As indicated in table 8 the average number of cars per household is 1,58. The corresponding figure for cars per person is 0,6.

Table 9: Number of cars in household

	Observations	%
No car	89	6
One car	615	44
Two cars	553	39
Three cars	106	8
At least four cars	37	3
Total	1.400	100

As already discussed above, about 6% of the respondents do not have a car in their household and one can see from table 9 that in most households there is either one or two cars (together 83%). However, one has to keep in mind that our sample overestimates the number of car license owners and thus also car ownership to some extent.

Graph 8: Number of cars in household by town size



Finally, graph 8 shows that most respondents reporting to have no car in the household live in towns with at least 20,000 inhabitants. By contrast, there are virtually no households without a car in towns smaller than this and the share of households with three or more cars is much higher in small towns than in large cities, where households with four or even more cars hardly exist. All in all, there seems to be a negative relationship between the size of a town and the average number of cars per household, which can also be seen in table 10.

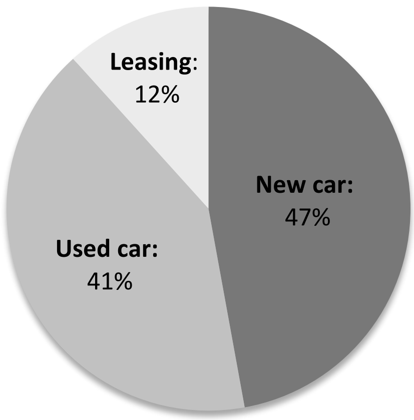
Table 10: Average number of cars in household by town size

Number of inhabitants	Average number of cars per household
0 to 1000	1,88
1001 to 2000	1,86
2001 to 3000	1,86
3001 to 5000	1,85
5001 to 10000	1,70
10001 to 20000	1,70
20001 to 50000	1,36
50001 to 1 million	1,35
Over 1 million	1,06

1.3 Car segment and purchase

Graph 9 demonstrates that about every second car purchase is a purchase of a new vehicle. Used cars account for roughly four out of ten purchases. Finally, leasing is chosen with approximately every 10th car.

Graph 9: Type of car purchase - main car



We differentiate car ownership by segment, ranging from mini cars to multi-purpose and sports cars. The classification used is the one applied by the European Commission. Cars are classified either as mini car (A), small car (B), medium car (C), large car (D), executive or luxury car (E, F), multi-purpose car (M) or sports utility car (J). It can be seen from table 11 that most cars are medium size cars, followed by large and small cars, which together account for three-fourths of all cars.

Table 11: Vehicle segments - distribution

Vehicle segment	Observations	%
A – Mini	123	5
B – Small	461	21
C – Medium	625	29
D – Large	539	25
E / F – Luxury	89	4
M – Multi-Purpose	213	10
J – Sports-Utility	125	6

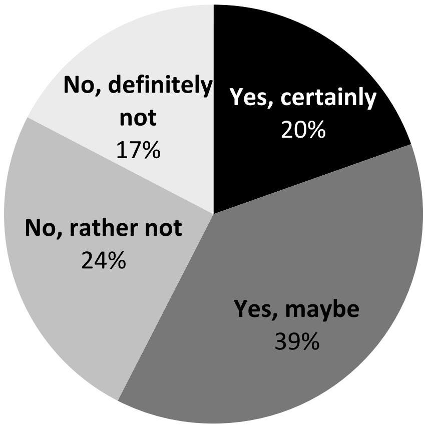
Table 12 displays the distribution amongst the different car segments for different levels of income. Overall there is not too much variation between the different income levels, but, as we would expect, the share of mini cars declines with raising personal net income, while simultaneously there is an increased consumption of luxury and sports cars. There is no significant difference regarding the segments when we compare commuters and non-commuters.

Table 12: Car segments by monthly equalized household net income

Equalised household income…	Mini	Small	Medium	Large	Luxury	Multi-Purpose	Sports-Utility
less than 1.276€	8%	24%	30%	22%	3%	11%	2%
of 1.276€ to 1.700€	7%	21%	30%	26%	3%	9%	5%
of 1.701€ to 2.100€	6%	22%	28%	25%	3%	11%	5%
higher than 2.100€	4%	18%	30%	26%	7%	9%	7%

Next, graph 10 gives some insights on the likelihood of future car purchases. Again, it must be considered that it is likely that our sample somewhat overestimates the number of future car purchases. In our sample one fifth of all respondents stated that they will certainly buy a new car within the upcoming three years. Another two fifths (39%) reported that it was quite likely that they would buy a car within the next three years or were at least considering it. On the contrary, 17% of the respondents are certain that they will not buy a car within this period and all in all about 40% of respondents will rather not make a car purchase within the next three years.

Graph 10: Likelihood of car purchase within next three years



The average construction year of the cars owned by the survey respondents is 2006. Thus, the average car in our sample is about 8 years old (as of July 1, 2013). Table 13 displays the average construction year for different groups within our sample. It can be seen that respondents with higher household incomes drive newer cars (7 years old on average). Regarding age groups, younger respondents drive older cars on average, which is again at least partially explained by incomes rising with age. Last but not least, the table shows that regarding different degrees of urbanization the newest cars are driven by people in intermediate density areas, including many suburban areas. What is interesting too is that those groups that already drive the newest cars still show the highest propensity to purchase a new car within the near future. Assuming that attitudes towards new car purchases were similarly distributed among the individual groups in the past, it makes perfect sense that the groups with the highest propensity for car purchases (e.g., intermediate density area, age 60 - 69, equalized household income higher than 2.100€) also possess the newest cars. On the other hand, given the fact that these groups already possess newer cars than the other groups, it is somewhat surprising that they still show the highest propensity for future purchases.

Table 13: Average year of construction and likelihood of car purchase within next three years by monthly equalised net household income, age and degree of urbanisation

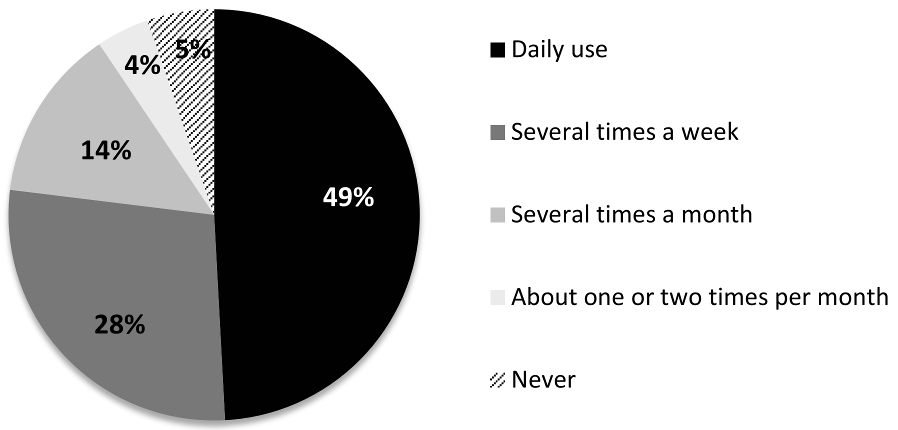
	Average year of construction	Age of car as of July 1, 2013 (in years)	Respondents planning / thinking of car purchase within next 3 years
Total	2006	8	59%
Equalised household income less than 1.276€	2004	9	51%
Equalised household income of 1.276€ to 1.700€	2005	8	55%
Equalised household income of 1.701€ to 2.100€	2006	7	58%
Equalised household income higher than 2.100€	2007	7	71%
18 - 29	2005	9	55%
30 - 39	2005	8	52%
40 - 49	2006	8	59%
50 - 59	2006	7	56%
60 - 69	2006	7	63%
Over 70	2006	8	6%
Thinly populated area	2006	8	54%
Intermediate density area	2006	7	61%
Densely populated area	2005	8	60%

1.4 Frequency and purpose of car use

In order to further analyse mobility patterns in Austria, the following paragraph discusses usage frequency and purposes of car driving.

Graph 11 demonstrates that about half of the respondents use their car on a daily basis. In addition, corresponding shares are observed for the following categories: multiple uses a week (28%), multiple uses a month (14%), rare use of car (4%) and no car usage at all (5%). Again, it is possible that our sample slightly overestimates the real amount of car usage.

Graph 11: Frequency of car usage



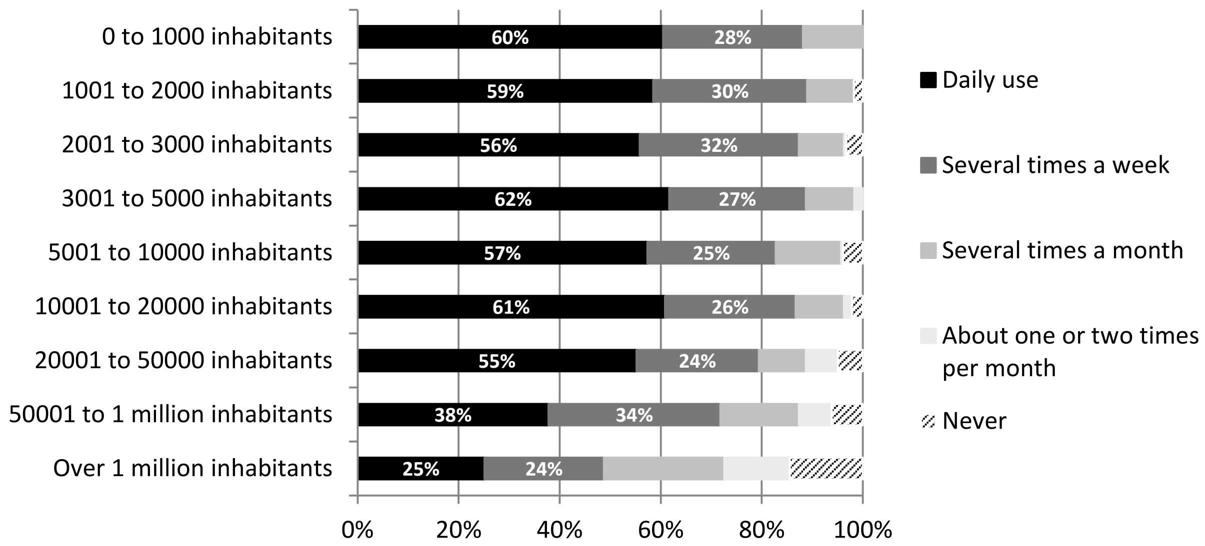
Analysis of the frequency of car usage by different socio-demographic characteristics reveals that the frequency is not much different between women and men, though women use the car somewhat less frequent. Furthermore, apart from Vienna and Burgenland, variation in the frequency of car usage between different Austrian federal states is small. In Burgenland, which has many commuters, the share of people using their car every day (71%) is higher than in other states while Vienna follows a different pattern because it is made up of a huge urban area (daily use of car accounts for only 25%). There is no clear relationship between frequency of car use and education, but regarding income we see that the share of daily car users increases together with income. Variation in the share of people using their car daily exists also amongst different age groups (table 14).

Table 14: Share of daily car use by age cohort

Age	Daily use
18 - 29	43%
30 - 39	56%
40 - 49	67%
50 - 59	53%
60 - 69	36%
Over 70	26%

The share of daily usage initially increases with age. It then peaks at the age of 40 to 49 with two third of all respondents in this age groups reporting a daily usage, before falling to about one quarter for people over 70. Below, graph 12 demonstrates that the frequency of car usage is different for various town sizes, with the share of daily users being much lower and the share of non-drivers significantly higher in high density areas.

Graph 12: Frequency of car usage by town size



In table 15 we distinguish between people using their car for going to work and those who report other purposes only (e.g. shopping or transportation of people). It can clearly be seen that the share of daily users is much higher with the former group (77% versus 28%).

Table 15: Frequency of car usage amongst respondents that use their car for going to work and respondents who use the car for other purposes only

Frequency of car usage	Car is used, amongst others, for going to work		Car is not used for going to work	
	Observations	%	Observations	%
Daily use	511	77	177	28
Several times a week	123	19	266	43
Several times a month	28	4	162	26
About one or two times per month	1	0	17	3
Total	663	100	622	100

Last but not least it should be mentioned that the share of people driving the car on a daily basis is also significantly higher in households with children, with the exact number of children in the household, however, not making much of a difference.

The survey does not only comprise information on the frequency of car use, but also on the purpose of driving. All car users were asked to indicate for which of the following purposes (Going to work, Official use / Business use, Going to an educational institution / school, Shopping, Private use, Transportation of people, Leisure) they used their car, with multiple answers being allowed. Graph 13 graphically presents the number of responses out of 1.285 (car users only) that were reported for each of the seven categories mentioned above.

Graph 13: Use of main car – number of responses

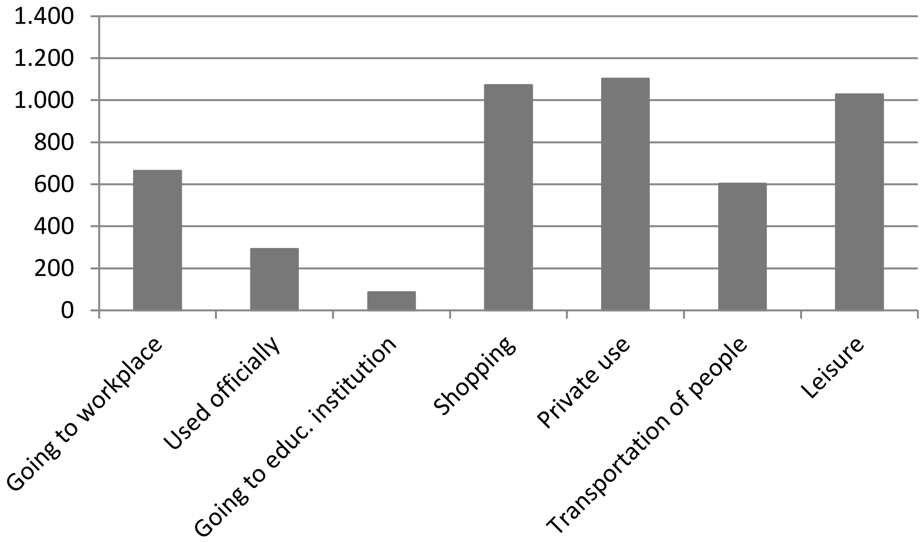


Table 16 uses the same data as graph 13 and shows that 52 % of all car users in the sample indicate that they are using their main car for going to the workplace (amongst other things). Furthermore we can see that almost everybody is using his or her car for shopping, private use and leisure.

Table 16: Percentage of car users using main car for indicated purpose

Purpose	Percentage of car users using main car for indicated purpose
Going to workplace	52%
Used officially / Business Purposes	23%
Going to an educational institution	7%
Shopping	83%
Private use	86%
Transportation of people	47%
Leisure	80%

1.5 Mobility

In contrast to the last paragraphs the following analysis is no longer focused exclusively on cars, but includes various means of transport.

Table 17 provides information about the number of kilometres that people travel (on various means of transport) on a typical workday. On average, respondents of the survey travel 39 kilometres on a normal workday, with 10% of respondents traveling less than 5 kilometres per day and 25% travelling less than ten kilometres. All of these figures are higher for commuters, which travel a mean distance of 64 kilometres per day.

Table 17: Summary of kilometres travelled on a typical workday - total sample and commuters

Distance travelled on a typical workday (km)						
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**
Total sample	39	5	10	20	50	80
Commuters only	64	22	35	50	80	120

Table 18 provides more detailed insights on average kilometres travelled on a workday. One can see that the average kilometres travelled are not quite the same for all states and that respondents from Lower Austria and Burgenland travel more kilometres a day, on average, than people from other states.

Table 18: Average kilometres travelled per workday by state

Average distance travelled on a typical workday (km)	
Vienna	26
Lower Austria	52
Burgenland	52
Styria	42
Carinthia	43
Upper Austria	34
Salzburg	39
Tyrol	43
Vorarlberg	28

There is also a considerable difference in average daily kilometres travelled between different degrees of urbanisation, with people from densely populated areas travelling much fewer kilometres a day than their counterparts in thinly populated areas (table 19).

Table 19: Average kilometres travelled per workday by degree of urbanisation

Average distance travelled on a typical workday (km)	
Densely populated area	27
Intermediate density area	37
Thinly populated area	49

The survey also collects information on the average number of different routes travelled on a single day. 11% of the respondents travel only one route a day, while the vast majority covers two (42%) or three (30%) routes (return trips do not count separately).

In the next paragraphs analysis will be focused on the respondent's main trip, defined as the trip that is travelled most often. Table 20 demonstrates that for 27% of all respondents the main trip is less than five kilometres. For another 21% it is less than ten kilometres. The median distance of the main trip is 12 kilometres and on average it is 27 kilometres.

Table 20: Distance of main trip

Distance	Observations	%
0 - 5 km	371	27
6 – 10 km	290	21
11 – 20 km	285	20
21 – 30 km	159	11
31 – 50 km	140	10
51 – 100 km	104	7
More than 101 km	51	4
Total	1.400	100

Table 21 shows that for more than half of all respondents (53%) the purpose of their main trip is going to work. In addition, shopping and private use account for another quarter of the recorded main trips, with the remaining quarter being made up by purposes such as transportation of other people, going to an educational institution or leisure activities.

Table 21: Purpose of main trip

Purpose	Observations	%
Going to workplace	738	53
Used officially / Business purposes	110	8
Going to an educational institution	58	4
Shopping	153	11
Private use	187	13
Transportation of people	60	4
Leisure	94	7
Total	1.400	100

As mentioned above, the main trip is on average 27 kilometres. This figure, however, varies with the purpose of the trip. This is demonstrated in table 22, where we see that the average length of a trip is rather high if its purpose is going to work or business use, while the number of average kilometres travelled is much lower in case the underlying purpose is transportation of people or shopping.

Table 22: Average distance of main trip by purpose of main trip

Purpose	Average distance (km)
Going to workplace	28
Used officially / Business purposes	59
Going to an educational institution	23
Shopping	19
Private use	17
Transportation of people	13
Leisure	20

Graph 14 shows the individual shares of different means of transport chosen as central mode of travelling for a respondent's main trip. In 71% of all cases the car is the main means of transport, followed by walking (9%) and underground or tram, accounting for some 7%.

Graph 14: Mainly used means of transport for main trip

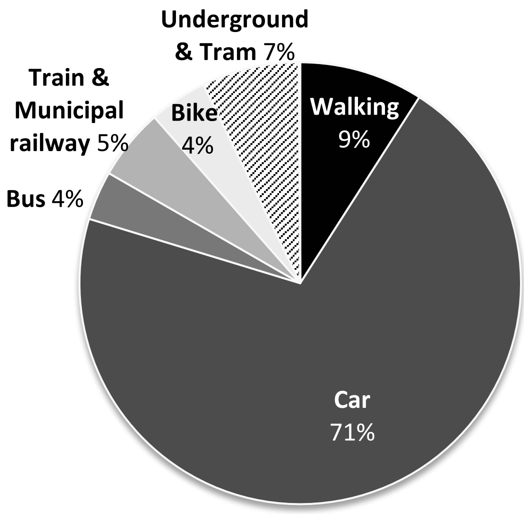


Table 23 shows the extent to which a certain means of transport is chosen for the main trip, broken down by distance. It can be seen that the car is clearly the dominant means of transport for all distances larger than two kilometres. Walking presents the most common mode of travelling for short range distances. It still plays an important role for distances up to 5 kilometres, but its importance quickly falls with growing distances. Bikes are most relevant for distances up to 10 kilometres, where they account for about 7 - 9 %. Buses, tram and underground are most important for distances up to 20km. For distances greater than 20 kilometres people choose almost exclusively cars or trains as means of transportation.

Table 23: Mainly used means of transportation for main trip by distance

Distance of main trip	Means of transportation					
	Walking	Car	Bus	Train & Municipal railway	Bike	Under-ground & Tram
0 - 1km	30 51%	13 22%	6 10%	1 1%	3 5%	7 11%
1 - 5km	59 19%	173 56%	13 4%	4 1%	29 9%	34 11%
6 - 10km	13 5%	212 73%	10 3%	7 2%	19 7%	28 10%
11 - 20km	14 5%	220 77%	15 5%	10 4%	3 1%	23 8%
21 - 50km	0 0%	256 86%	5 2%	25 8%	5 2%	6 2%
More than 51 km	0 0%	115 78%	2 1%	28 18%	1 1%	3 2%

Table 24 demonstrates that the relative importance of certain modes of travelling varies greatly with the purpose of travelling. It can be seen that walking has a relevant stake if the purpose of travelling is leisure, shopping or going to an educational institution, but is rather insignificant as a mean of going to work, with only 4% of all going-to-work trips being covered by walking. Transportation of other people is almost exclusively dependent on the car and the car is also the dominant means of transportation for going to work. While the car is highly relevant for almost all purposes, it accounts only for 27% of all trips to educational institutions, a purpose where bus (17%) and train (25%) play a crucial role. The bike is most relevant for leisure activities (11%) and underground and tram are relatively most important when the purpose of the main trip is either going to an educational institution (14%) or to work (9%).

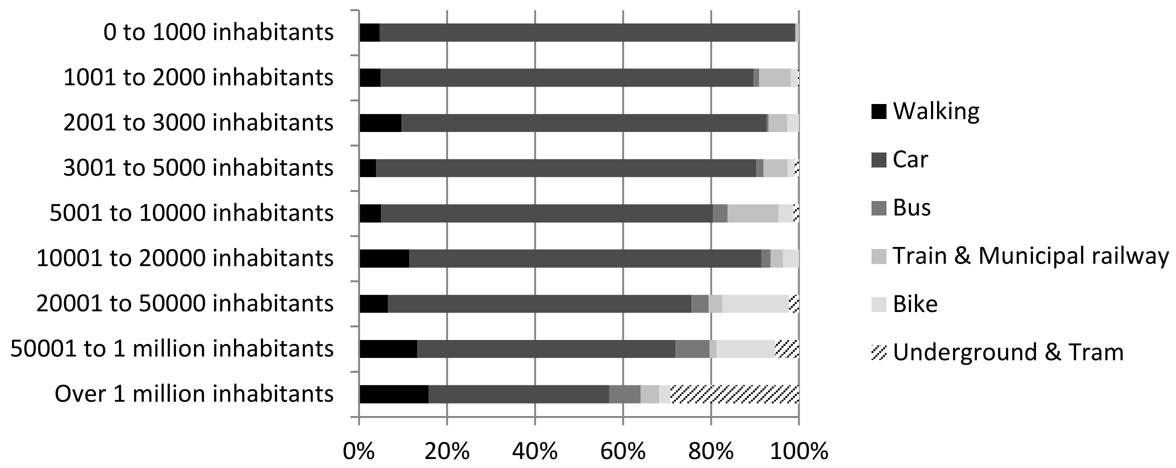
Table 24: Mainly used means of transportation for main trip by purpose of main trip

Purpose of main trip	Means of transportation					
	Walking	Car	Bus	Train & Municipal railway	Bike	Under-ground & Tram
Going to workplace	32 4%	525 71%	33 5%	53 7%	30 4%	64 9%
Used officially / Business purposes	7 7%	95 86%	0 0%	0 0%	1 1%	6 6%
Going to an educ. Institution / school	6 11%	16 28%	10 17%	15 25%	3 5%	8 14%
Shopping	29 19%	109 71%	4 2%	1 1%	6 4%	5 3%
Private use	25 13%	137 74%	4 2%	2 1%	8 4%	11 6%
Transportation of people	6 10%	52 86%	0 0%	1 1%	1 2%	0 1%
Leisure	22 24%	55 59%	0 0%	1 1%	10 11%	5 5%

Next, graph 15 displays the shares of different means of transportation for various town sizes. It is demonstrated that the relative importance of certain modes of travelling varies not only with distance and purpose of the main trip, but with different town sizes too.

While in small towns the vast majority of trips is conducted by car (94%), importance of walking, bus, bike, underground and tram rises quickly with increasing town sizes. The train and municipal railway seem to be relatively most important for medium size towns and the bike is most prominent in cities with 20.000 to 50.000 inhabitants.

Graph 15: Mainly used means of transportation for main trip by size of town



This descriptive analysis is concluded by looking at 'distance to workplace' and the distribution of commuting allowances ("Pendelpauschale"). Table 25 gives detailed information on the distance to workplace, which is 18 kilometres on average. Furthermore, it shows that 25% of all respondents stated that the distance to their workplace is not more than 1 kilometre and for the majority of respondents distance to workplace is not more than 5 kilometres.

Table 25: Distance to workplace

Distance to workplace (km)					
Mean	**p10**	**p25**	**p50**	**p75**	**p90**
18	0	1	5	15	35

By looking at table 26, however, one can see that the average distance to work is significantly higher for people living in intermediate density areas (23 km), which can at least partly be explained by the fact that most suburban areas, comprising lots of people commuting to nearby cities, fall in this category. On the other hand, average distance to workplace is rather low in densely populated areas (7 km).

Table 26: Average distance to workplace by degree of urbanisation

Average distance to workplace (km)	
Thinly populated area	10
Intermediate density area	23
Densely populated area	7

Next, table 27 presents the share of people in the sample receiving commuting allowances. Moreover, one can also see from table 27 that there exist seven different categories of commuting allowances.

Table 27: Distribution of commuting allowances amongst total sample

	Observations	%
Commuting allowance small (20 km, €58/month)	100	7
Commuting allowance small (40 km, €113/month)	36	3
Commuting allowance small (60 km, €168/month)	17	1
Commuting allowance large (2 km, €31/month)	29	2
Commuting allowance large (20 km, €123/month)	41	3
Commuting allowance large (40 km, €214/month)	10	1
Commuting allowance large (60 km, €306/month)	14	1
No commuting allowance	732	52
Unknown	421	30
Total	1.400	100

To finish, table 28 presents the share of respondents that receive commuting allowance by federal states. It can be seen that the share of people receiving commuting allowance varies considerably from state to state and that the highest shares are found in Burgenland, Lower Austria and Upper Austria.

Table 28: Percentage of respondents receiving a commuting allowance by federal states

State	Share of respondents receiving a commuting allowance
Vienna	3%
Lower Austria	26%
Burgenland	28%
Styria	18%
Carinthia	17%
Upper Austria	26%
Salzburg	15%
Tyrol	18%
Vorarlberg	13%

2. Discrete Choice Experiments

In addition to the descriptive information described in the previous chapter, the survey also included two discrete choice experiments (DCE). That is to say, a subset of the survey respondents were asked to address a set of hypothetical choice situations designed to analyse individual mobility behaviour. In order to match the requirements of the macroeconomic computable-general-equilibrium (CGE) model, which is being developed in work package (WP1), we included choice experiments addressing two distinct aspects of mobility behaviour: *vehicle purchase* decisions and choice of *transportation mode*.

2.1 Subgroups and Data Collection

The original sample of 1449 respondents was divided into three subgroups on the basis of screening questions and a randomized selection procedure. Since only a fraction of the respondents might in fact be considering a vehicle purchase in the upcoming future, we had to ensure that only those individuals had to answer the corresponding DCE. Therefore we first asked respondents whether (a) they had a driver’s license at the time of the survey and (b) whether they are considering making a vehicle purchase in the near future. From the pool of those individuals who answered both questions positively we randomly assigned a certain fraction to answer the DCE on vehicle purchases. Through this procedure we could thus ensure that, on the one hand, the DCE were actually related to upcoming purchase decisions in real life. On the other hand, randomised selection implied that the respondents with driver’s license and purchase intention had the same positive probability of ending up in the group with the DCE on transportation mode choice. This procedure thus allowed us to divide respondents into subgroups without unnecessarily introducing bias.

Table 29: DCE Subgroups

		DCE: Transportation Mode Choice		
		no	yes	total
DCE: Vehicle Purchase	No	0	662 *(46%)*	662 *(46%)*
	Yes	511 *(35%)*	276 *(19%)*	787 *(54%)*
	Total	511 *(35%)*	938 *(65%)*	1.449 *(100%)*

Table 29 shows how the original sample of 1449 respondents is divided into the three subgroups. The majority of respondents, 1173 individuals, had to address only one DCE, resulting in a total survey duration of approximately 20 minutes. A fraction of 276 individuals were selected into a group with survey duration of about 30 minutes, implying that they had to answer both DCE. In total 787 respondents had to address the vehicle purchase DCE. Since each respondent was asked to answer 9 independent choice scenarios, the estimated models of vehicle demand were based on 7083 stated preference observations. In case of the transport mode DCE we include not only stated preference data in the form of 9 choice sets per respondent, but also information on revealed preferences relating to a recent trip. However, as some respondents gave only incomplete information on their recent trip (or reported that there was no choice in transportation mode on their trip) we lost 73 revealed preference observations. In total the mode choice models thus use 865 revealed (RP) and 8442 stated preference (SP) observations.

2.2 DCE: Vehicle Purchase

This DCE focuses on consumer choice between vehicles with different propulsion technologies. We use a labelled experimental design including four choice alternatives referring to one propulsion technology each: conventional vehicles (CV), plug-in hybrid-electric vehicles (PHEV), hybrid-electric vehicles (HEV) and electric vehicles (EV). Each of the alternatives is described by the following attributes: purchase price (PP), power (PS), fuel costs (FC), maintenance costs (MC), full driving range (RA). In addition to these attributes, the EV is further characterised by the following attributes: availability of loading stations (LS) and purchase incentive (IM).

To strengthen the link between the hypothetical choice scenarios and the real purchase decision we collected additional information on the segment of each respondent's prospective vehicle purchase, as summarized in table 30.

Table 30: Vehicle Segments

Vehicle Segment	Observations	%	Reference Price (Euro)	Reference Power (PS)
A – Mini	39	*5*	10.000	67
B – Small	154	*20*	15.000	70
C – Medium	197	*25*	23.000	105
D – Large	218	*28*	25.000	105
E / F – Luxury	21	*3*	56.000	170
M – Multi-Purpose	85	*11*	28.400	105
J – Sports-Utility	73	*9*	32.500	140
	787	*100*		

To condition each respondent's choice sets according to the segment of his or her next vehicle we developed a pivot-design using the experimental design software NGENE (ChoiceMetrics, 2012). Based on the vehicle classification described in Hanappi et al. (2012) we first define a conventional reference vehicle for each segment in terms of purchase price and power (table 30). Attribute levels of the alternative vehicles are then defined in relative terms, i.e. as percentage of the corresponding reference attribute. However, the remaining attributes (fuel and maintenance cost, full driving range, loading station network and incentives) are allowed to vary independent of the reference alternative. To further individualise the choice sets we account for individual driving behaviour by customizing running costs, fuel and maintenance, in terms of a yearly average value for each respondent. To do this we simply multiply costs per kilometre by the average kilometres of each respondent, as reported in the survey and shown in table 31. Since the full driving range is fixed for most vehicle types (CV, PHEV, HEV) we vary this attribute only in case of electric vehicles.

Table 31: Average Driving Distance per Year

Average Distance / Year	Observations	%
Below 5000 KM	44	*6*
5000 - 10000 KM	201	*26*
10000 - 15000 KM	244	*31*
15000 - 20000 KM	147	*19*
20000 - 30000 KM	98	*12*
Above 30000 KM	53	*7*
	787	100

To define the choice sets we used an efficient experimental design as described e.g. by Bliemer (2008). As a-priori parameters we used the estimation results from our preceding study on vehicle demand in Vienna metropolitan area (Hanappi et al. 2012). Table 32 summarizes attribute variation in the final design.

Table 32: Attribute Variation (Vehicle Purchase DCE)

Attribute	CV	HEV	PHEV	EV
Purchase Price	-	140	140	140
(% of reference)	-	130	130	130
	-	120	120	120
	-	110	110	110
	100	100	100	100
	-	90	90	90
	-	80	80	80
Power	100	100	100	100
(% of reference)	-	95	95	-
	-	90	90	90
	-	85	85	-
	-	85	80	80
	-	-	-	70
	-	-	-	60
Fuel Costs	0,10	0,10	0,10	-
(Euro/KM)	0,09	0,09	0,09	-
	0,08	0,08	0,08	-
	0,07	0,07	0,07	-
	0,06	0,06	0,06	0,06
	0,05	0,05	0,05	0,05
	0,04	0,04	0,04	0,04
Maintenance Costs	0,060	0,060	0,060	0,060
(Euro/KM)	0,055	0,055	0,055	0,055
	0,050	0,050	0,050	0,050
	0,045	0,045	0,045	0,045
	0,040	0,040	0,040	0,040
Full Driving Range	500	500	500	-
(KM)	-	-	-	350
	-	-	-	280
	-	-	-	210
	-	-	-	140
	-	-	-	70
Loading Station Availability	100	100	100	Low
(% or qualitative)	-	-	-	Medium
	-	-	-	High
Incentive Measure	none	none	none	none
(qualitative)	-	-	-	P&R
	-	-	-	Invest. Sub.
	-	-	-	Pub. Trans.

2.3 DCE: Transport Mode Choice

In this DCE we analyse transport mode choice in Austria with a specific focus on the decision between public (PT) and motorised individual (MIT) transport.

As part of the survey we collected information on *revealed transport preferences* based on a recent and typical trip (i.e. a 'main' trip as described in previous chapters). Relating to this trip, each respondent gave us information on its length and the chosen mode of transport (table 33). Depending on their mode of transport, each respondent was then asked to provide details on travel time, costs, number of changes, time in congested travel and waiting time associated with their actual trip. In addition we also asked the respondents to give us information on these attributes in case they would have chosen another mode of transport, i.e. either motorised individual transport or public transport. Instead of introducing an undefined 'none' option, we included a third alternative corresponding to non-motorised individual transport such as e.g. walking or cycling.

Table 33: Observed Transport Choices

	Observed Choices		
	Observations	%	Avg. KM
Motorised-Individual Transport	597	*69*	25
Public Transport: Bus or Train	165	*19*	20
Non-Motorised Individual Transport	103	*12*	15
	865	*100*	

As in the other DCE the analysis of transport mode choices also included 9 choice sets aimed at eliciting *stated transport preferences* of the respondents. As this stated preference part allowed us to control attribute variation through the experimental design, we were able to include two distinct public transport alternatives as well as several more fine-grained attributes. Each choice set represented a decision between four transport modes: car (i.e. corresponding to motorised-individual transport), bus and train (both corresponding to public transport) as well as a non-motorised alternative which was labelled either as bike, e-bike or walking. The car alternative was described by travel time in free flow, congested travel time, toll cost, fuel costs and parking costs. Public transport options were described by travel time, number of changes, interval and costs, whereas non-motorised individual transport is characterised by total travel time one of the three labels (walking, bike or e-bike).

As in the previously described DCE, we also conditioned the choice sets according to individual responses to specific survey questions. In this DCE the main conditioning variable was the trip length associated with the respondent's main trip. As has been described above, trip length varies considerably among respondents, with an average of 22 kilometres among those in the mode choice subgroup (938 individuals). Depending on the length of their main trip, respondents were thus further subdivided into three groups: a short distance group corresponding mainly to inner city trips (1-3 kilometres), a more heterogeneous medium distance group (4-15 kilometres) and a long distance group with mostly rural or suburban trips of 16 or more kilometres. To increase behavioural relevance we developed a distinct experimental design for each of these groups. While these designs had the same underlying features (i.e. number of alternatives, attributes and levels), the travel time and cost variables were defined such that the overall values matched the trip length of the associated reference trip (1, 5 or 25 kilometres). Table 34 summarizes attribute variation by subgroup, where we have (a) excluded waiting time for public transport and (b) aggregated congested and free flow travel time (for cars) in order to facilitate comparison. Table 35 has corresponding results with regard to overall costs, thus aggregating toll, fuel and parking costs associated with motorised-individual transport. However, non-motorised transport was further described by a qualitative attribute labelling this alternative as either walking, cycling or going by e-bike. Therefore, no costs were associated with this alternative.

Table 34: Variation in Total Travel Time (Mode Choice DCE)

Total Travel Time (Min)	**Short Distance: Reference 1 KM**						
	Observations	Mean	Min	p25	p50	p75	Max
Motorised-Individual	161	6,59	2	5	6	8	12
Public Transport (Train)	161	7,33	4	5	7	10	10
Public Transport (Bus)	161	7,37	4	5	7	10	10
Non-Motorised Indiv.	161	11,30	8	9	12	14	14
	Medium Distance: Reference 5 KM						
	Observations	Mean	Min	p25	p50	p75	Max
Motorised-Individual	432	23,29	12	18	22	30	34
Public Transport (Train)	432	26,17	18	20	28	32	32
Public Transport (Bus)	432	26,69	18	22	28	31	32
Non-Motorised Indiv.	432	30,62	20	24	32	36	36
	Long Distance: Reference 25 KM						
	Observations	Mean	Min	p25	p50	p75	Max
Motorised-Individual	345	37,28	16	24	36	48	60
Public Transport (Train)	345	40,06	18	30	42	54	54
Public Transport (Bus)	345	41,45	18	30	48	54	54
Non-Motorised Indiv.	345	76,59	60	68	76	84	88

Table 35: Variation in Total Travel Costs (Mode Choice DCE)

Overall Costs (Euro)	**Short Distance: Reference 1 KM**						
	Observations	Mean	Min	p25	p50	p75	Max
Motorised-Individual	161	3,05	0,06	1,34	3,42	4,22	5,82
Public Transport (Train)	161	1,01	0	0	1	2	2
Public Transport (Bus)	161	1,01	0	0	1	1,5	2
	Medium Distance: Reference 5 KM						
	Observations	Mean	Min	p25	p50	p75	Max
Motorised-Individual	432	4,18	0,8	3,05	4,6	5,8	7,3
Public Transport (Train)	432	1,05	0	0	1,5	2	2
Public Transport (Bus)	432	0,96	0	0	1	2	2
	Long Distance: Reference 25 KM						
	Observations	Mean	Min	p25	p50	p75	Max
Motorised-Individual	345	8,76	3,6	6,8	8,4	11,25	13,9
Public Transport (Train)	345	5,28	1,8	3	5,4	7,8	9
Public Transport (Bus)	345	5,55	1,8	3	5,4	7,8	9

While overall time and cost values were thus dependent on the subgroup, we included more attribute levels as in the previous DCE, typically ranging between 6 and 10 levels per attribute. As mentioned above we used the experimental design software NGENE to create efficient designs for each subgroup. In this case, however, we had to define a-priori parameter values based on an extensive literature review.

2.4 Econometric Specification

As described for instance in Train (2009) we use these datasets to estimate standard discrete choice models corresponding to the following general form: $U_{nj} = V(x_{nj}, z_n) + \varepsilon_{nj}$. In this specification $V_{nj} = V(x_{nj}, z_n)$ denotes the systematic part of utility derived by decision maker *n* from choosing alternative *j*. While this part of the utility function can be modeled by the researcher on the basis of the observed attributes x_{nj} and socio-economic variables z_n, the stochastic part of utility, ε_{nj} , is not directly observed and is thus assumed to be distributed according to an Extreme-value distribution. The corresponding model specifications thus belong to the group of multinomial logit models and are estimated using a maximum likelihood approach.

So far the estimated parameters are based on the simple multinomial logit specification and are used to derive the simulation results which will serve as intermediary inputs to the macroeconomic-model (see next sections). However, preliminary results show that mixed multinomial specifications would allow for considerable improvements in goodness of fit (as captured for instance by likelihood ratio tests), since these class of models is better able to capture unobserved heterogeneity across individuals. We plan to incorporate these improvements in our final model specifications.

While the vehicle demand model is thus estimated based on a comparatively simple specification, the mode choice model requires some further comment as in this case we have to deal with a combined RP-SP dataset. To perform a joint estimation based on two distinct datasets, i.e. RP and SP data, we first estimate both models separately (see next section) and then present the estimation results of the joint RP-SP model. In the latter model we therefore introduce and estimate an additional scale parameter which allows us to account for the fact that the variance of the error terms has to be the same in both models (Hensher et al., 2005, or Greene, 2008).

2.5 Estimation Results

The estimated parameters for the vehicle demand model are collected in table 36. While controlling for a wide range of relevant socioeconomic variables, such as e.g. age, income, education and regional variables, we are mainly interested in the attribute-specific parameters. Purchase prices are measured in units of 10.000 Euro. The corresponding parameter estimates thus measure the effect of a one-unit change on the probability to choose the respective alternative. As expected, these parameter estimates have negative effects, which seem to be somewhat stronger for HEV and PHEV. Running costs, i.e. fuel and maintenance costs, are customized according to individual driving behaviour and measured in Euro values per year. These parameters have a negative and significant effect on choice probabilities, although maintenance costs appear to have only marginal effects on EV purchases. Similarly, vehicle power appears to have no effect on EV purchases, although increases in PS seem to affect purchase decisions regarding the other three vehicle types. Increases in the full driving range, on the other hand, have strong effects on the choice probabilities for EV, as would be the case with a strong increase in the loading station network. Specific incentive measures targeting the demand for EV seem to have no effects (PR: park and ride; OEV: public transport subsidy; INV: investment subsidy for loading stations).

Table 36: VEHICLE PURCHASE MNL

Name	Value	Std. Error	t-test	p-value
ASC_CV		*reference*		
ASC_EV	0,141	0,415	0,340	0,730
ASC_HEV	0,347	0,302	1,150	0,250
ASC_PHEV	0,587	0,345	1,700	0,090
FuelCosts_CV	-0,001	0,000	-9,120	0,000
FuelCosts_HEV	-0,001	0,000	-10,730	0,000
FuelCosts_PHEV	-0,001	0,000	-8,690	0,000
FuelCosts_EV	-0,002	0,000	-7,360	0,000
MaintenanceCosts_CV	-0,001	0,000	-7,010	0,000
MaintenanceCosts_HEV	-0,001	0,000	-5,250	0,000
MaintenanceCosts_PHEV	-0,001	0,000	-5,700	0,000
MaintenanceCosts_EV	-0,000	0,000	-1,590	0,110
PurchasePrice_CV	-1,220	0,114	-10,700	0,000
PurchasePrice_HEV	-1,740	0,083	-21,050	0,000
PurchasePrice_PHEV	-1,770	0,096	-18,520	0,000
PurchasePrice_EV	-1,300	0,100	-13,030	0,000
Power_CV	0,016	0,004	3,860	0,000
Power_HEV	0,022	0,003	7,040	0,000
Power_PHEV	0,026	0,004	6,970	0,000
Power_EV	0,000	0,002	0,000	1,000
DrivingRange_EV	0,003	0,000	8,730	0,000
Incentive_NONE		*reference*		
Incentive_INV	-0,087	0,126	-0,690	0,490
Incentive_OEV	0,134	0,121	1,100	0,270
Incentive_PR	-0,203	0,127	-1,600	0,110
EV_LS_Low		*reference*		
EV_LS_Medium	0,059	0,126	0,470	0,640
EV_LS_High	0,603	0,114	5,310	0,000
AGE_CV		*reference*		
AGE_HEV	-0,013	0,002	-5,420	0,000
AGE_PHEV	-0,019	0,003	-7,450	0,000
AGE_EV	-0,023	0,003	-7,720	0,000
Commuting_CV		*reference*		
Commuting_HEV	-0,189	0,102	-1,850	0,060
Commuting_PHEV	-0,250	0,106	-2,350	0,020
Commuting_EV	0,117	0,125	0,930	0,350
Income_CV		*reference*		
Income_HEV	0,000	0,000	-0,760	0,450
Income_PHEV	0,000	0,000	1,610	0,110
Income_EV	0,000	0,000	0,470	0,640

HouseholdIncome_CV		*reference*		
HouseholdIncome_HEV	0,000	0,000	2,010	0,040
HouseholdIncome_PHEV	0,000	0,000	-1,720	0,090
HouseholdIncome_EV	0,000	0,000	1,540	0,120
LowSkilled_CV		*reference*		
MediumSkilled_HEV	0,390	0,134	2,900	0,000
MediumSkilled_PHEV	0,090	0,138	0,650	0,510
MediumSkilled_EV	0,349	0,171	2,050	0,040
HighSkilled_HEV	0,537	0,150	3,580	0,000
HighSkilled_PHEV	0,176	0,152	1,160	0,250
HighSkilled_EV	0,357	0,188	1,900	0,060
CitySize1_CV		*reference*		
CitySize2_HEV	0,238	0,135	1,760	0,080
CitySize3_HEV	0,002	0,142	0,020	0,990
CitySize4_HEV	-0,338	0,159	-2,120	0,030
CitySize5_HEV	-0,614	0,191	-3,200	0,000
CitySize6_HEV	-0,384	0,192	-2,000	0,050
CitySize2_PHEV	0,045	0,147	0,310	0,760
CitySize3_PHEV	0,132	0,153	0,860	0,390
CitySize4_PHEV	-0,124	0,154	-0,800	0,420
CitySize5_PHEV	-0,810	0,210	-3,850	0,000
CitySize6_PHEV	-0,583	0,222	-2,630	0,010
CitySize2_EV	0,123	0,171	0,720	0,470
CitySize3_EV	0,176	0,172	1,020	0,310
CitySize4_EV	-0,118	0,189	-0,620	0,530
CitySize5_EV	-1,040	0,272	-3,820	0,000
CitySize6_EV	-0,151	0,249	-0,610	0,540
Urban_CV		*reference*		
Rural_HEV	-0,516	0,189	-2,720	0,010
Rural_PHEV	-0,680	0,214	-3,180	0,000
Rural_EV	-0,327	0,244	-1,340	0,180
Suburban_HEV	-0,204	0,141	-1,450	0,150
Suburban_PHEV	-0,592	0,176	-3,370	0,000
Suburban_EV	-0,402	0,188	-2,140	0,030

Estimation results for the mode choice models are shown in tables 37, 38 and 39. While the former two tables show results for the separate RP and SP models, respectively, we are more interested in the combined RPSP model which is described in table 39 and subsequently used to derive the elasticities. In order to match the definitions used in the macroeconomic model we estimated only a single parameter for costs and travel time, thus ignoring differential impacts of e.g. free flow and congested travel or toll, fuel and parking costs. These issues will be further explored when compiling the microeconomic results for the final report. Relatedly, we also combine different levels of schooling into three categories relating to the set-up of the macroeconomic model (low skilled: basic education; medium skilled: apprenticeship, (higher) vocational schooling, higher general schooling, college (i.e. 'Kolleg'); high skilled: universities (including 'Fachhochschule'). To ensure consistency between the RP and the SP model we do not distinguish between the bus and train alternatives.

In general, estimated parameters in the RP model have somewhat lower significance levels (table 37), which seems to be plausible due to the fact that variation in attribute levels is much lower than in the SP model. However, cost parameters have the expected negative effects and are all highly significant. Travel time, on the other hand, seems to have significant negative effects only regarding public transportation modes. As expected, the result from the SP model allow for a more precise estimation of the behavioural parameters (table 38).

As mentioned in the previous section, the joint estimation based on the combined RP-SP dataset implies that we have to add an additional scale parameter to ensure that the error terms are the same in both models (table 39). In this model, we again control for sociodemographics such as age, income, education and regional variables. The behavioural parameters are highly significant, showing the expected effects on choice probabilities. Travel time is measured in minutes and has a negative effect, which is somewhat stronger in case of motorised transport. The cost parameters also have negative effects, however, this parameter seems to be more relevant for the public transport alternatives. To further account for inertia in past choices, we include a corresponding parameter for motorised individual and public transport. This is simply an indicator variable capturing the effect of the observed RP choice on the corresponding SP alternative. Both parameters are positive and highly significant, implying that individuals are in fact more likely to stick with the chosen alternative from the RP data. Table 40 shows summary statistics for all four models presented in this section.

Table 37: MODE CHOICE MNL / RP

Parameter	Value	Std. Error	t-test	p-value
ASC_MIT		*reference*		
ASC_NMT	-0,062	0,571	-0,110	0,910
ASC_PUB	3,340	0,410	8,140	0,000
PUB_TravelTime	-0,012	0,006	-2,120	0,030
PUB_COST	-0,017	0,007	-2,580	0,010
MIT_TravelTime	0,003	0,008	0,320	0,750
MIT_COST	-0,009	0,003	-2,920	0,000
NMT_TravelTime	0,000	0,002	-0,190	0,850
MIT_Age	0,007	0,010	0,670	0,500
MIT_Male	0,350	0,280	1,250	0,210
MIT_LowSkilled		*reference*		
MIT_MediumSkilled	0,032	0,304	0,110	0,920
MIT_HighSkilled	-0,335	0,369	-0,910	0,360
NMT_Urban		*reference*		
MIT_Rural	3,200	0,407	7,860	0,000
MIT_Suburban	1,380	0,285	4,840	0,000
PUB_Age	-0,052	0,011	-4,760	0,000
PUB_Male	0,112	0,323	0,350	0,730
PUB_LowSkilled		*reference*		
PUB_MediumSkilled	-0,235	0,346	-0,680	0,500
PUB_HighSkilled	-0,745	0,446	-1,670	0,090
NMT_Urban		*reference*		
PUB_Rural	1,070	0,442	2,420	0,020
PUB_Suburban	-0,420	0,355	-1,180	0,240

Table 38: MODE CHOICE MNL / SP

Parameter	Value	Std. Error	t-test	p-value
ASC_MIV		*reference*		
ASC_BAHN	-0,958	0,206	-4,650	0,000
ASC_BUS	-0,833	0,205	-4,060	0,000
ASC_NMT	0,409	0,249	1,640	0,100
MIT_TravelTime	-0,063	0,003	-22,310	0,000
MIT_COST	-0,140	0,009	-16,300	0,000
PUB_TravelTime	-0,042	0,002	-19,390	0,000
PUB_COST	-0,253	0,012	-21,730	0,000
PUB_CHANGES	-0,366	0,020	-18,580	0,000
NMT_TravelTime	-0,095	0,003	-30,990	0,000
NMT_EBIKE	0,797	0,118	6,780	0,000
NMT_BIKE	-0,223	0,068	-3,300	0,000
MIT_INERTIA	1,270	0,073	17,430	0,000
PUB_INERTIA	0,837	0,078	10,750	0,000
MIT_Age	0,002	0,002	0,800	0,420
MIT_Male	-0,558	0,074	-7,580	0,000
MIT_Commuting	0,305	0,174	1,750	0,080
MIT_Income	0,000	0,000	4,250	0,000
MIT_HouesholdIncome	0,000	0,000	-3,280	0,000
MIT_MediumSkilled	-0,234	0,088	-2,650	0,010
MIT_HighSkilled	-0,050	0,116	-0,430	0,670
NMT_CitySize1		*reference*		
MIT_CitySize2	-0,237	0,152	-1,560	0,120
MIT_CitySize3	-0,118	0,166	-0,710	0,480
MIT_CitySize4	-0,801	0,166	-4,820	0,000
MIT_CitySize5	-0,648	0,198	-3,270	0,000
MIT_CitySize6	-0,492	0,201	-2,450	0,010
NMT_Urban		*reference*		
MIT_Rural	-0,315	0,188	-1,680	0,090
MIT_Suburban	-0,061	0,133	-0,460	0,650
PUB_Age	0,006	0,002	2,710	0,010
PUB_Male	-0,549	0,072	-7,670	0,000
PUB_Commuting	0,570	0,173	3,290	0,000
PUB_Income	0,000	0,000	2,970	0,000
PUB_HouseholdIncome	0,000	0,000	-2,420	0,020
PUB_MediumSkilled	0,130	0,088	1,470	0,140
PUB_HighSkilled	0,199	0,116	1,720	0,090
NMT_CitySize1		*reference*		
PUB_CitySize2	-0,089	0,154	-0,580	0,560
PUB_CitySize3	0,072	0,170	0,420	0,670
PUB_CitySize4	-0,334	0,167	-2,000	0,050
PUB_CitySize5	-0,576	0,211	-2,740	0,010
PUB_CitySize6	0,263	0,206	1,280	0,200
NMT_Urban		*reference*		
PUB_Rur	0,291	0,189	1,540	0,120
PUB_Sub	0,155	0,129	1,200	0,230

Table 39: MODE CHOICE MNL / RPSP

Parameter	Value	Std. Error	t-test	p-value
ASC_RP_MIT		*reference*		
ASC_RP_NMT	-68,500	119,000	-0,580	0,560
ASC_RP_PUB	-63,100	91,700	-0,690	0,490
ASC_SP_MIT		*reference*		
ASC_SP_BAHN	-0,951	0,206	-4,600	0,000
ASC_SP_BUS	-0,826	0,206	-4,020	0,000
ASC_SP_NMT	0,396	0,250	1,590	0,110
MIT_TT	-0,063	0,003	-22,250	0,000
MIT_COST	-0,141	0,009	-16,490	0,000
PUB_TT	-0,042	0,002	-19,370	0,000
PUB_COST	-0,255	0,012	-21,690	0,000
PUB_CHANGE	-0,367	0,020	-18,570	0,000
NMT_TT	-0,094	0,003	-30,580	0,000
NMT_EBIKE	0,804	0,118	6,820	0,000
NMT_BIKE	-0,223	0,067	-3,310	0,000
MIT_INERTIA	1,270	0,073	17,390	0,000
PUB_INERTIA	0,837	0,078	10,750	0,000
MIT_Age	0,002	0,002	0,820	0,410
MIT_Male	-0,556	0,074	-7,560	0,000
MIT_Commuting	0,319	0,175	1,820	0,070
MIT_Income	0,000	0,000	4,250	0,000
MIT_HouseholdIncome	0,000	0,000	-3,270	0,000
NMT_LowSkilled		*reference*		
MIT_MediumSkilled	-0,233	0,088	-2,650	0,010
MIT_HighSkilled	-0,051	0,116	-0,440	0,660
NMT_CitySize1		*reference*		
MIT_CitySize2	-0,238	0,152	-1,570	0,120
MIT_CitySize3	-0,118	0,166	-0,710	0,480
MIT_CitySize4	-0,803	0,166	-4,830	0,000
MIT_CitySize5	-0,650	0,198	-3,280	0,000
MIT_CitySize6	-0,497	0,201	-2,480	0,010
NMT_Urban		*reference*		
MIT_Rural	-0,310	0,188	-1,650	0,100
MIT_Suburban	-0,058	0,133	-0,440	0,660
PUB_Age	0,006	0,002	2,680	0,010
PUB_Male	-0,547	0,072	-7,640	0,000
PUB_Commuting	0,586	0,174	3,360	0,000
PUB_Income	0,000	0,000	2,960	0,000
PUB_HouseholdIncome	0,000	0,000	-2,420	0,020
NMT_LowSkilled		*reference*		
PUB_MediumSkilled	0,130	0,088	1,470	0,140
PUB_HighSkilled	0,197	0,116	1,700	0,090
NMT_CitySize1		*reference*		
PUB_CitySize2	-0,091	0,154	-0,590	0,560
PUB_CitySize3	0,072	0,170	0,430	0,670
PUB_CitySize4	-0,334	0,167	-2,000	0,050

PUB_CitySize5	-0,578	0,211	-2,740	0,010
PUB_CitySize6	0,259	0,206	1,260	0,210
NMT_Urban		*reference*		
PUB_Rural	0,291	0,189	1,540	0,120
PUB_Suburban	0,153	0,129	1,180	0,240
Scale	0,020	0,030	-32,86	0,000

Table 40: Summary Statistics

	Vehicle Purchase	Mode Choice	Mode Choice	Mode Choice
Model	MNL	MNL	MNL	MNL
Data	SP	RP	SP	RP-SP
Observations	64	19	41	44
Estimated Parameters	7083	865	8442	9307
Initial Log-likelihood	-9819,123	-950,300	-11703,097	-12653,397
Final Log-likelihood	-6667,117	-545,475	-9050,384	-9751,858
Likelihood-Ratio Test	6304,012	809,649	5305,425	5803,077
Rho Squared	0,321	0,426	0,227	0,229
Adjusted Rho Squared	0,314	0,406	0,223	0,226

2.6 Elasticities

As intermediary inputs to the development of the macroeconomic computable-general-equilibrium model we use the microeconometric models described in the previous section to compute elasticities at various levels of aggregation. Specifically, we use model 1 for the simulation of the demand elasticities and model 4 for the simulation of the mode choice elasticities. To do this we first predict choice probabilities in the base scenario, and then simulate 1- and 10-% increases in the relevant cost parameter. As a result we obtain the predicted choice probabilities after the price increase which can then be used to compute the corresponding percentage change on individual level. However, since (alternative-specific) parameter estimates differ from one alternative to the other, we obtain specific elasticities for each cost parameter that is increased, i.e. a 10% price increase has a different impact on the corresponding market share depending on which mode of transport is affected. In order to be able to account for these differences within the framework of the CGE-model, we provide micro-level elasticities for the full range of possible price increases (20 simulations). This includes 1- and 10-% increases of purchase prices or running costs for each of the 4 vehicle types (16 simulations), as well as 1- and 10-% increases in the costs of motorised-individual and public transport (4 simulations).

These outputs are delivered via a set of STATA-datasets including the complete set of variables from the baseline survey as well as the corresponding individual elasticities. In order to aggregate the individual elasticities so as to match macro-level requirements additional STATA-codes are provided, thus allowing for complete flexibility in the aggregation of these results.

As a sample output we provide two additional tables (41 and 42), so as to get a first idea about the type of outputs we provide as well as the underlying empirical results. Table 41 depicts results from an increase in purchase prices of conventional vehicles by 10% grouped by degree of urbanisation and educational level. In the next table we use the same grouping to summarize the effects of a 10% cost increase in motorised-individual transport. While these two tables offer only a limited glance at the whole range of simulation results, it can still be seen that these outputs capture considerable diversity regarding behavioural reactions.

Table 41: Elasticities (Sample Output #1)

10% increase in purchase prices of conventional vehicles			
	Urban	Suburban	Rural
Low Skilled	-10,7%	-8,3%	-9,6%
Medium Skilled	-12,3%	-10,6%	-11,8%
High Skilled	-13,6%	-11,4%	-12,0%

Table 42: Elasticities (Sample Output #2)

10% increase in costs of motorised-individual transport			
	Urban	Suburban	Rural
Low Skilled	-1,4%	-1,6%	-1,8%
Medium Skilled	-1,3%	-1,8%	-1,9%
High Skilled	-1,2%	-1,7%	-1,9%

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