INFLUENCE OF WEATHER ON TRANSPORT DEMAND: A CASE STUDY FROM THE VIENNA REGION

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ABSTRACT

In times of increasing travel demand urban transport systems are under continuous stress. Knowledge on the impact of weather on any given day needs to be obtained in order to efficiently operate such system. While it is expected that weather related impact will not dominate travel demand (e.g work trips cannot be easily omitted), trips may be delayed or different modes may be chosen. It is well known that transport systems that operate close to capacity react highly nonlinearly to an addition in demand. Thus changes in weather might lead to totally different settings for the management of the transport systems.

This paper provides evidence for the influence of weather on travel demand for the greater Vienna region. Long term household mobility surveys are used for a descriptive analysis of the influence of weather on travel behavior. Statistical modeling of smaller mobility surveys allows extrapolation to new situations as well as an analysis of the joint influence of several variables. We provide significant evidence that weather has a strong influence on the mobility choices of a large part of the population. The results emphasize that the weather impact depends heavily on mode and purpose of the trip and the characteristics of the traveler.

The results of the paper can be used on the aggregate level to predict the impact of weather on traffic demand. This information is important for the management of transport systems both in terms of supply management and demand management for ensuring efficiency of urban transportation systems.

1. INTRODUCTION

Ongoing urbanization tendencies pose serious problems for the limited resources in terms of transportation infrastructure. In some areas the rapidly growing demand for transportation is facing constant supply leading to growing congestion levels. Many systems are already performing close to capacity, hence even small reductions of supply or increases in demand may significantly increase traffic delays.

The high sensitivity of almost saturated systems with respect to small perturbations has been first documented for air traffic (Neufville, Odoni, 2003*(1)*), but can also be observed for urban transport (Wang et al, 2012 *(2)*). Therefore, transport planning and management must also pay attention to smaller factors influencing supply and demand which in the past were not in the focus.

On the other hand modern traffic management features many new tools that can be used to shape demand and supply. Due to modern communication means public transport can be more responsive to demand shifts as smart phone apps provide channels to communicate additional supply to the customers. For road traffic, congestion pricing (de Palma, Lindsey, 2011 *(3)*), high occupancy tolls (Lou et al. 2011 *(4)*) as well as reversible lanes (Zhao et al., 2014 *(5)*) and parking measures (Arnott, Inci, 2006 *(6)*) are recently introduced dynamic tools for managing both the demand and supply side of road traffic. These new tools require accurate measurements of traffic demand in order to exploit their potential in influencing traffic.

It was shown that in some urban areas weather has an impact on traffic conditions. In particular snow and ice significantly impact road safety (documented in the report of the EU-COST Action "Weather and Traffic" ,El Faouzi, 2010 *(7)*). Also impacts on saturation flow rates on intersections and driving behavior (Asamer et al., 2011 *(8)*) as well as on freeway capacities and speeds (Maze et al. 2006 *(5)*) were found. Furthermore, transport demand depends on weather conditions: Significant impact of heavy rain on Japanese highways has been reported in the magnitude of 9% of total demand (Chung et al., 2005 *(9)*). Travel behaviour was also studied with respect to effects of weather. In Cools et al. 2010 *(10)* a stated preference survey was used to study effects of weather on the frequency of trips as well as on purpose-dependent travel behaviour.

On an individual level Sabir, 2010 *(11)* investigates Dutch data reaching the conclusion that the dependence of weather on traffic demand heavily depends on the purpose of the trip and the particular means of transport. Not surprisingly bikes are found to be the most weather sensitive transport mean. This is also the result of a study in Toronto where a weather dependent mode choice model was estimated using data from a travel survey (Saneinejad et al., 2012 *(12)*).

Therefore, it is expected that weather conditions have an impact on mobility in terms of the number of trips taken, depending on the purposes of the trips and also on the means of transport used. Impacts of a particular weather situation cannot simply be evaluated using aggregate counts as potentially simultaneous shifts in the number of trips taken and between transportation modes mask the individual effects.

Therefore, in this paper a number of household surveys are used in order to obtain detailed information on the reactions of individuals on mode specific transportation demand disaggregated with respect to trip purpose. The database contains multi-year observations in the greater Vienna area with large sample sizes and low spatial resolution in combination with extensive detailed interviews ensuring that the observed weather conditions are not restricted by only observing a small number of days. In addition smaller sample sizes with high spatial resolution are used in order to estimate detailed models of the number of trips and the chosen modes incorporating the knowledge gained from the initial analysis.

The main contributions of the paper are the descriptive analysis and detailed quantification of weather related effects on mode and purpose specific transportation demand. Furthermore, detailed mobility models of Vienna were derived, such as the number of trips differentiated according to their associated activities and mode choices for trips of individuals depending on socio-demographic features and also weather conditions. The models allow deriving mode specific traffic demand variations as a function of weather related quantities such as precipitation, rain, temperature, and sunshine duration. These models build the basis for weather sensitive demand and supply management.

The paper is organized as follows: In the next section the data sets are described. Then explorative data analysis reveals the main dependencies and the magnitude of expected impacts. Subsequently detailed models are estimated. Finally the paper concludes by discussing the results and giving an outlook to future work as well as recommendations on the inclusion of weather models into traffic simulations.

2. DATA SETS

It is expected that impacts of weather conditions on traffic demand are most severe in extreme manifestation (defined as rare events). Therefore this work requires a large data base in order to ensure that sufficiently many different weather events are contained in the information set. Typically household surveys are only conducted on a small number of days and hence do not fulfill these requirements. However, socialdata (Institut für Verkehrs- und Infrastrukturforschung GmbH) and the Verkehrsverbund Ost Region (VOR; public transit operators in the greater Vienna region) have collected the mobility choices of the population in its domain of operation (Vienna, Lower Austria (which surrounds Vienna) and Burgenland (which borders on Lower Austria)) on a continuous base for many years. This data set provides much information on the mobility of individuals ranging from the number of trips per person to the mode of transport chosen. For each person socio-demographic information is recorded as well as mode choice related data. This dataset is ideal for generating aggregated descriptive statistics, to get a first impression about the way weather influences traffic demand. That overview is used within this paper to build traffic demand models. These are based on newer and smaller (in terms of time and number of individuals), but more detailed (in terms of trip characteristics) data set.

To get a more detailed insight in the relations between weather conditions and traffic demand, detailed weather data is necessary. Hence, weather data provided by UBIMET a leading provider of weather forecasts was used, and put in relation to the household survey data. In the following the data sets are described in more detail.

2.1 Long term household surveys

Socialdata has collected data in the KONTIV® design (Brög, 2000 *(13)*) during the last two decades. 23,697 people answered household surveys in Vienna (in spring 1993, autumn 1996 and constantly over the years 1998 – 2009) and 42,986 people from Burgenland and Lower Austria (from 1998 to 2009). On a given sample day of the survey period their mobility behavior was logged. Two different methods, one subjective and one from observations were used to include the weather into the survey. The first one uses subjective observations of participants, the second one uses measured weather conditions. In addition to the subjectivity of the assessment of weather conditions, the possible reactions to the weather usually depend on the trip purpose. A leisure trip probably can be postponed or cancelled more easily than the trip to work.

First long term data set - subjective approach

Data on respondents which did not perform a trip on the sample day was recorded stating the reason for staying home. One category in this respect was “extreme weather”. For a subsets of 2361 observations in Vienna and 2184 observations in Burgenland and Lower Austria, “extreme weather” was stated as the reason for immobility. There is no further information about the weather conditions, except that it prevented some people from traveling that day. The overall mobility on such “extreme weather” days is investigated below.

Second long term data set - weather data

For the period of 2006 - 2009, collected weather data was linked by day and postcode district with the household surveys. This resulted in a subset of data of 8,884 observed days in Vienna and 17,187 observed days in Lower Austria and Burgenland.

The results of Section 3 are based on this data. To eliminate possible biases due to a higher participation rate during a certain season of the year, the observations were weighted by the survey size per month.

2.2 Recent household surveys

Short term data set for Lower Austria and Vienna

For the mode and trip choice models, two data sets were used, one from Vienna, and another from Lower Austria and Burgenland. The latter was collected in the period from October till November 2008, where 4,506 people were interviewed about their mobility for one day each. Next to socio-demographic data (age, sex, home district) the participants were asked about their general availability of different travel modes (driving license, parking spaces at home and work, a transit pass, and availability of a car and/or bike). Within the period, information about 12,011 trips (TABLE 1shows the modal split) was collected, each with

- mode of transport,
- travelled distance,
- duration,
- purpose,
- origin and destination district,
- time of departure and arrival.

TABLE 1 Modal Split of recent household survey in Lower Austria and Burgenland

Travel Mode	Frequency	Share in percent
Train/Subway	593	4.9
Bus	387	3.2
Foot	2086	17.4
Motorbike	79	0.7
Car-driver	6305	52.5
Car-passenger	1722	14.3
Bicycle	654	5.4
Other	68	0.6
Underground/Tram	117	1

Short term data set for Vienna

The Vienna data set contains an average of 29.7 weekly trips from 193 persons from 113 households. For data ascertainment each trip was linked with one activity (e.g. way to work), and consisted of several trip-legs. Also for this dataset socio-demographic characteristics and the availability of mobility options were surveyed.

Data collection took place between April and June of 2012, guaranteeing some variance in weather conditions. To analyze how weather affects the mobility behavior, the following information about the weather was added to the data set for the starting time of each trip:

- The amount of rain during the last 2 hours
- The amount of rain during the last 2 hours, compared to observed values in previous years at the same day and time
- The amount of rain at the day, compared to observed values in previous years at the same day
- The lowest temperature of the day
- The wind speed during the last 10 minutes before the start of the trip

For both surveys, the chosen modes were recorded in travel diaries. Given information about the driver's situation, plausible mode alternatives were modeled. The approach takes the individual's availability of travel modes into consideration. The modal split of the considered journeys in this urban setting was

- Car (30%)
- Foot (36%)
- Bicycle (9%)
- Public transport (25%)

Determining mode alternatives and the corresponding attributes for each trip was a fundamental step for further research. Two different methods were used. On the one hand public transport (PT) routes were created by inquiries to the public transport timetable information system (EFA) of the Viennese public transport provider VOR. On the other hand non-public transport routes were calculated using the Ariadne routing service (Prandtstetter et al., 2013 *(14)*).

To evaluate the modelled alternatives, the trips were also generated for the revealed modes. Therefore, a comparison of actually stated and calculated travel times was possible. It shows that for most car, bike and PT trips stated travel times were longer compared to the generated ones. One explanation could be that people tend to overestimate travel time, another that parking time and access/ egress times were not considered in the trip generation. To compensate this systematic bias, a robust linear model (Least Trimmed Squares) was fitted, for each mode separately. The empiric, stated travel time was regressed onto the generated travel time.

FIGURE 1 shows the stated travel time vs. generated counterpart for all car trips. The 45-degree line is plotted in green, and the regression line in red. The intercept (of about 4 minutes) can be interpreted as the parking time, which people automatically add, when they state the travel time, or a systematic overestimation of time. However, the generation process neglects this. Since the slope is nearly 1 (exactly 1.0833), the generic travel time fits the stated nearly independently of trip length. The outliers are probably caused by a combination of wrong statements in the drivers` diaries, and the modelling process of the trips' origins. Since a driver only states the destination, each trip's origin is modelled as a function of former trips by the same person and her home address. This can cause misleading results, if the driver forgets to record a trip. Another reason for outliers is layovers (e.g. a short stop at the supermarket on the way home), which are not correctly listed in the diaries.

In mode choice modelling travel time is one of the main factors. To guarantee comparable travel times for all modes in the choice set the stated travel times were replaced by generated travel times, adjusted for the bias, using the regression model. Observations with overly large regression errors (either the generated or stated travel time was implausible for due to one of the mentioned reasons) were disregarded for further analyses. After the above preprocessing, missing weather data for certain trips and the selection of alternatives modes described in section 4.3, the remaining number of choice situations for the mode choice modelling was 1840, i.e. an average of 9.5 trips per person.

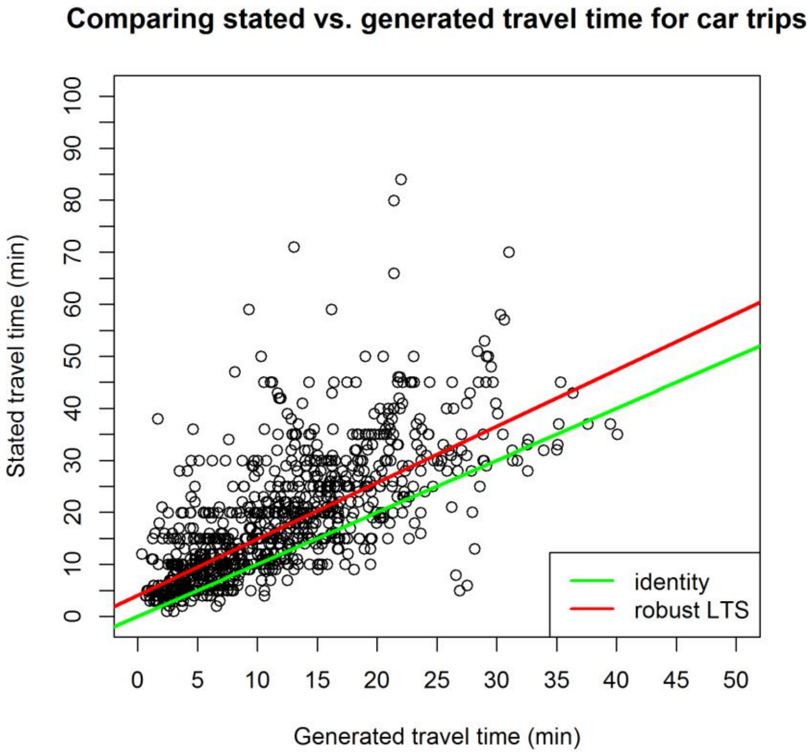


FIGURE 1 Modelling travel time for car trips. The green line denotes the 45° line and the red line the linear model.

3. DESCRIPTIVE RESULTS

As a first step the long term dataset was used to generate descriptive measures on the impact of weather on the transport system. The results in this section are of interest on their own and also build the basis for the specification of the models in the next section. The investigation has been performed using the two different long term data sources described above. The first dataset contains more data on mobility related issues, however, no detailed data on weather conditions could be matched. Thus for this data weather impact is inferred from people indicating that the reason for staying home were 'weather conditions'. In this way the potential impact of weather conditions can be estimated.

Additionally the second long term data set is used in order to investigate the impacts of particular weather conditions in terms of out-of-home-activities, number of trips, characteristics of trips (such as trip duration and trip distances) and finally mode choice.

3.1 Out-of-home activities

The percentage of people leaving their home on any given day is one of the main determinants for traffic demand. In the Vienna region approximately 81% of the population lists at least one trip on any given day. On days with people stating that they stayed home due to weather (in the following called "weather days") this percentage drops to 76% implying a reduction of 6%. On weekends the drop in percentage is larger reaching 12%. This is a first indication that bad weather leads to a significant reduction in mobility.

Moreover there is a strong impact of age on the reduction in mobility. Among the very young (younger than 6) and the elderly (older than 64) the percentages of people leaving their home drops by approximately 18% while for the remaining population the percentage only drops by 2%.

One factor in the reduction of mobility is precipitation: In Vienna the percentage of out of home activities drops from 83% without precipitation to 78% with precipitation, in the greater Vienna region from 80% without precipitation to 78% with precipitation.

Temperature also has an effect on active days, reducing the percentages of out of home activities in the city from 83% for hot weather (temperatures higher than 24° Celsius (C), 75.2° Fahrenheit (F)) to 73% for temperatures below 0° C (32° F). For the greater Vienna region the impact of temperature is concave reaching a high of 80% at temperatures ranging from 5°C to 15°C (41°F - 59°F) being reduced to 77% for temperature below 0°C and above 24°C.

The other weather related variables (wind, sunshine duration) did not show any impact.

3.2 Number of Trips

Similarly to the out of home activities also the number of trips is affected at weather days. The number of trips is reduced by 9% on weather days overall. The effect is different for different activities related to the trips. Not surprisingly trips to/from work are not affected by the weather, while work-related-business-trips drop by 26%, service trips by 17% and leisure trips by 16%. One possible interpretation of these facts is that trips with some freedom to choose the timing are scheduled to fit the weather impacts.

This is also supported by the fact that the number of trips drops by 12% on weekends, which is mostly due to persons not leaving home and hence potentially postponing trips. Again age is a main influencing factor with a reduction of 16% for young kids and a reduction of more than 25% by persons aged over 64.

The changes in the number of trips show differences between urban and suburban settings, as the increase on bad weather days in Vienna is only 3% for regular trips (work and education), and 16% for leisure or 12% for non-regular trips, while the numbers for the greater Vienna region show a 9% decrease for regular trips and 10% for the rest.

In terms of temperature, work related trips increase on very hot days. Leisure trips show the highest intensity between 10° and 24°C (50°F-75.2°F). As expected, the number of trips decreases with increasing rain, where the impact on leisure trips is largest. In the greater Vienna region trips accompanying someone occur more often with increasing rain.

For Vienna somewhat surprisingly high mobility for precipitation below 5°C (41°F) is observed while for days with degrees below zero the number of trips is greatly reduced. In terms of trip purpose, days with rain and 10°C-15°C (50°F-59°F) turn out to be ideal for shopping in Vienna, leisure trips are attractive on days with and without rain for higher temperatures.

With respect to distance covered and duration of trips there are no clear patterns except for the obvious that both drop on bad weather days. Other than that no strong impact of weather conditions could be discovered.

3.3 Mode Choice

In terms of mode choice considering the overall modal split changes are small. When looking more closely a number of facts can be seen, however.

As expected the bike is most sensitive mode. For weekends on weather days the number of trips is almost halved and drops by 41%. For regularly occurring trips the drop on weather days still amounts to approximately 30%.

On the contrary public transport gains on weather days. On weekends an increase of 15% is observed which most likely is transferred from walking or biking in the most part. For regular trips still an increase of 5% is observed. For the remaining modes smaller changes are observed.

As reasons for these observed changes a number of factors can be found: For example it is observed from the Vienna datasets that walking on particularly hot days is reduced from 0.77 trips per person on days between 5°C and 10°C (41°F-50°F) to 0.66 trips on days above 24°C (75.2°F).

Biking is reduced from 0.24 trips on average between 15°C to 20°C (59°F-68°F) to 0.03 trips below 0°C (32°F) and 0.19 for very hot days.

A similar but less pronounced trend is also observed for public transport in Vienna, which is most utilized up to 15°C (59°F) and less below 0°C (32°F) and above 15° (59°F). In the greater Vienna region by contrast public transport trips occur also for cold temperatures..

Precipitation can be shown to have the anticipated effect: Walking decreases with increasing precipitation, biking also but more sensitively, car driving is almost unaffected, car passenger trips are more observed for heavy levels of precipitation as are public transit trips in Vienna. On the contrary, in the greater Vienna region heavy rain reduces public transit trips presumably because of problems with the access legs.

Similarly, in the small Lower Austria data (TABLE 1), it can be seen that for temperatures below zero bike trips reduce from 5% to 3% and to 4% for periods with precipitation. However, these numbers are less reliable due to small sample size for these weather conditions.

4. TRAFFIC DEMAND MODELS

Based on the results of the last section detailed models for transportation demand are derived for two main reasons: first the descriptive analysis of the last section does not allow extrapolation that is the evaluation of expected demand for a given situation. And secondly the analysis only considers effects ceteris paribus, one factor at a time. Therefore in this section models are estimated using a discrete choice setting incorporating all influential variables jointly.

Three groups of results are presented below: First the percentage of people engaging in out-of-home activities is modelled. Second, the number of trips split into different trip purposes is investigated. Finally mode choice is examined.

For the results the short term data sets for Vienna and the greater Vienna region are used for out-of-home activities and number of trips. As these two datasets have been collected in different times of the year (the Vienna dataset in April-June, the greater Vienna region in fall), they contain a rich set of different weather conditions. However, regional differences cannot be detected as the Vienna dataset contains only spring and summer observations while the greater Vienna region dataset fall and winter. This limits the information content in the data and thus in the models.

For mode choice the dataset in the greater Vienna region does not include enough spatial resolution to allow the computation of characteristics of trips for alternative means of transport and as a result only the Vienna dataset was used for that model.

4.1. Out-of-home activities

For the percentage of people engaging in out-of-home activities on a given day a binary choice model that can take two values 1 if the person is not active and 2 otherwise is specified and estimated. Here the socio-demographic variables age, sex, occupation status, driving license, public transit time cards are used, weekdays versus weekends, daily minimum temperature at home location, daily maximum temperature, rain intensity (in terms of quantiles with respect to the location and month), sunshine duration. Finally a dummy variable for differentiating Vienna from the greater Vienna region is used.

Since the corresponding set of potential regressors is large, model selection techniques were used in order to compute the final model. Backward selection based on eliminating the regressor with the worst p-value until all regressors show a p-value of at least 0.2 (somewhat arbitrarily chosen) is used in all cases. Other ways of model selection including information criteria were tried, however, did not lead to good results.

A categorized box plot for the corresponding estimates is presented in FIGURE 2 below. It gives the values the model takes in case of a person being active or not. It shows that the model takes lower values for inactive persons on average. With the model using a threshold of 50% to classify the predictions the percentage of true predictions of 84.5% only narrowly exceeds the naïve predictor of all people being active by 0.28 percent.

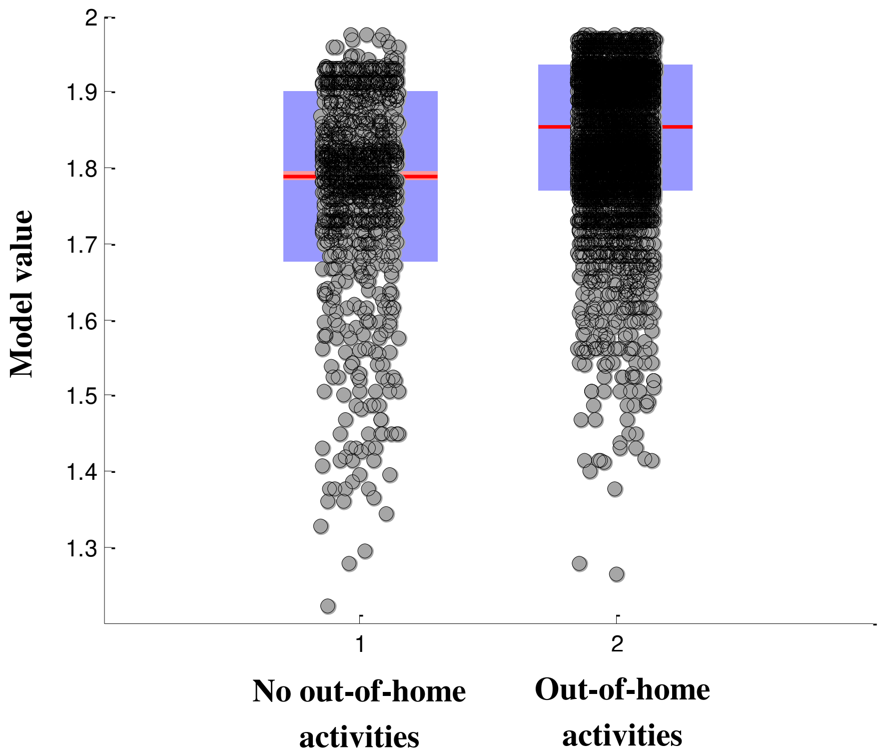


FIGURE 2 Categorized boxplot of the estimated utility values: 1 refers to no out-of-home activity while 2 refers to people participating in out-of-home activities. If the model value is above 1.5 the model predicts that the person is active.

In terms of weather related quantities the model only contains the variables of minimum temperature (with a positive influence of warmer temperatures and a large penalty for minimum temperature below zero for older people), heavy rain in conjunction with age over 70 years, as well as cold weather in conjunction with people aged 70 and older, i.e. predicting lower participation only for older people in case of severe rain or cold weather reestablishing findings from the descriptive analysis. Additionally also rain itself has a slightly negative impact with increasing level for higher temperatures. No other model parameters were significantly different from zero.

4.2. Number of Trips

For the number of trips ordered logit models are used. The model assumes that the choice of the number of trips is done relying on some underlying utility function depending on a weighted sum of the regressors plus a random term distributed according to a Gumbel distribution:

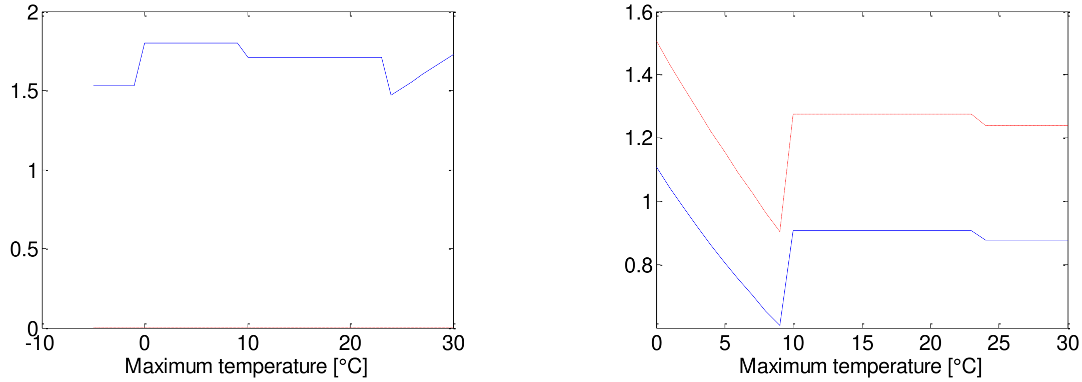
$$U_i = X_i\beta + e_i, i = 1, \ldots, n.$$

The random utility is compared to threshold points p_k, defining intervals. Then k trips are chosen, if U_i falls into interval $[p_k, p_{k+1})$. The corresponding probability can be calculated using the logit-function. In this way also the expected number of trips follows. It is this value that will be compared to the true choice in order to evaluate the accuracy of the model.

In terms of different types of activities the models for work related trips provide a better predictive power reaching R^2 values of 0.44 for work related trips and 0.54 for education related trips. Leisure trips reach 0.17 while the remaining considered trip purposes only reach R^2 values less than 0.15 and hence do not provide much explanatory power.

For work related trips as also confirmed by the preliminary analysis weather has a minor impact. Only the temperature showed an impact with “bad” weather increasing the number of trips slightly. As an example the expected number of work trips of a 35 year old male (full time employee with driving license) with no rain and average sunshine duration as a function of maximum temperature is given in the right plot of FIGURE 3.

For comparison reasons also the expected number of trips from a 75 year old retired person with all other characteristics being equal is also provided, which unsurprisingly equals zero throughout.



Number of work trips, no rain, average sunlight Number of leisure trips, no rain, average sunlight

FIGURE 3 Number of trips as a function of maximum daily temperature. Left plot: work trips, right plot: leisure trips. Blue line: 35 year old male with driving license, full time worker. Red broken line: 75 year old retiree.

For leisure trips on the other hand all weather conditions have some influence on the predicted number of trips. During weekdays the right plot in FIGURE 3 shows that the average number of leisure related trips for the 35 year old male is well below the numbers for the 75 year old retiree. On weekends this difference disappears (not shown). It is noticeable that the number of trips drops sharply below 10 degrees and recovers for temperatures close to zero.

However, different specifications of the regressors lead to different results in particular for the leisure related trips. Hence these results are not seen to be reliable due to small sample sizes and their interpretation needs to be done carefully. In particular for small temperatures estimates correspond to only a small number of days as only in the greater Vienna region in fall such low temperatures occur.

4.3. Mode Choice

Due to the results described in section 3 it can be seen that weather has an effect on mode choice. To see if it is possible to quantify some of these influences a mixed logit model including weather variables was estimated. As in the case of number of trips model, a utility maximization based approach was chosen, where the utility of user n choosing mode i for a trip is

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \sum_{k=1}^{m} \beta_{ik} x_{nik} + \varepsilon_{ni}$$

where x_{nik} are the observed attributes of the chosen mode for the route and β_{ik} are m parameters that are estimated. The unobserved attributes are included in the extreme value distributed random variables ε_{ni}. Since the set of decision makers is heterogeneous some of the parameters are normally distributed such that $\beta_{ik} \sim N(\mu_{ik}, \sigma_{ik})$ where μ_{ik} and σ_{ik} are the mean and standard deviation of the normal distribution. The parameters are chosen to be distributed if σ_{ik} is estimated to be significantly different from zero and are fixed otherwise. They are estimated using a simulated maximum likelihood approach. The probability P_{ni} of decision maker n to choose mode i is given by

$$P_{ni} = \frac{exp(V_{ni})}{\sum_j exp(V_{nj})}.$$

The included modes in the mode choice were walking, bike, car and PT and the choice set was determined in the following way:

Walking was added as an alternative whenever the distance between starting and endpoint was below 5 km.

A public transportation alternative was included whenever the EFA server was able to create a public transportation trip that started within 45 minutes (setting somewhat arbitrarily 45 minutes as an acceptable upper bound) after the stated departure of the real trip.

A bike trip was added when the decision maker owned a bike and the trip was going to start at his or her home or when the last bike trip had ended at the starting place of the new trip..

A car trip was added as an alternative whenever the decision maker had a driving license and a car was available to him or her, i.e when the trip was started at home and there was a car available in this household at the starting time or when the last car trip had ended at the starting point of the next trip.

The attributes included in the utility model were travel time (where the travel times were calculated according to section 2), costs for travel (cost of walking and cycling were chosen to be zero, cost of a car trips 0.0822 Euro/km (0.1323 Euro/mile) (Kölbl et al.(9)) and cost of a PT trip 0 if person owns a time-pass and 2 Euro otherwise (cost of a standard fare) as well as weather and socio demographic variables. For the distance of the trip the distance stated by the participant was chosen for all modes. The weather variables were chosen according to the results described in section 3.4 and include variables indicating the strength of wind, rain as well as temperature categories.

The data used for the mode choice model was the relatively small household survey from Vienna. Due to the small sample size of 193 persons the models only give an indication on how weather influences mode choice and a larger, more comprehensive data set needs to be collected for a more general result. The data from lower Austria was unusable for this purpose since it has a poor geographical resolution. Positions were just marked by postcodes areas which in this rural setting are large. Hence the calculation of travel times for alternative routes was not reliable enough to create a useful input data set. The results of the model estimation are given in TABLE 2.

TABLE 2 Estimated parameters significantly different from zero of the mode choice model

Parameter	Estimated parameter value	Standard Deviation
Travel time: μ_{tt} σ_{tt}	-0.1057 0.3026	0.0443 0.0596
Distance Car: μ_{dCar} σ_{dCar}	0.9994 0.5557	0.3034 0.2329
Distance Walk: μ_{dWalk} σ_{dWalk}	-4.7590 1.6867	0.7395 0.3358
Distance PT: μ_{dPT} σ_{dPT}	0.4962 0.6824	0.1374 0.2666
Age 25-55:Car	4.4315	1.1559
Age 56+:Car	4.3809	1.1661
Age 25-55: Bike	3.6345	0.8970
Age 56+ : Bike	3.3740	0.8816
Heavy Rain: Bike	-1.3626	0.8510
Strong Wind: Walk	1.3544	0.5878
ASC Car	*-2.3357*	*1.1370*
ASC Walk	*6.8048*	*1.1390*
ASC PT	*-1.569*	*0.7526*

The parameters denoted for example by Heavy Rain:Bike are dummy variables that are one when both conditions are met and zero otherwise. The only distributed parameters are those for travel time and distance for different travel modes.

One can see that all the sign of all parameters are consistent with the findings in section 3. Longer distances shift trips from biking and especially walking to car and PT and strong rain reduces bike trips. The cost parameter turned out not to be significantly different from zero in this setting.

Also weather does play a role in the model. Strong rain reduces biking compared to the other modes and strong winds increases walking. This is close to the results in section 3 where heavy rain was one of the influencing factors. The other influencing factors like the combination of cold temperatures and rain might not be apparent in the small data set collected in Vienna.

5. CONCLUSIONS AND FUTURE WORK

The results in this paper show that certain weather conditions have a non-negligible influence on transport choices and consequently on the transport system of a city, since this runs close to capacity. The influence of weather on demand was shown both using descriptive analysis of a multiyear data set of travel surveys from the greater Vienna region, as well as using traffic demand models for some smaller data sets from the same region.

The descriptive analysis shows that weather has an influence on the mobility and immobility of people. The highest reduction of activity was found for precipitation and hot as well as cold weather . Regarding the number of trips a substantial decrease is caused by bad weather. This affects mostly leisure trips that are influenced by hot and cold temperatures. Concerning mode choice the presumption was confirmed, that biking and to a lesser degree walking are the most effected modes, while car trips are not strongly influenced by weather.

To enable the modelling and extrapolation of the effects of weather on demand and to combine different weather scenarios three different models were estimated on smaller data sets. The first models “out of home activities”, the second “the number of trips” for different activities and the third “mode choice” for given trips. In all three models it can be seen that weather has a significant effect on the dependent variable. It has to be noted that the data set for the mode choice model was collected from April to June and hence does not contain very low temperatures which do influence the mode choice according to the descriptive analysis.

While the modelling results do suggest an influence of weather, in particular the number of trips model has to be taken with some care as the sample size for the model estimation is rather small.

In future the modeling methodology should be applied to larger data sets that were collected year round to get more reliable models. In addition to the research in this paper, starting time choices as well as route choices and their reaction to weather need to be analyzed to get a complete picture.

Finally, since a sizeable influence of weather was found, weather effects should be incorporated into traffic simulation models to be able to truly see the influence of weather on congestions for all modes. This, together with previous knowledge about the influence of weather on capacities and speeds, would in turn enable to study the effects of weather on complex urban transport systems.

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