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Peer-reviewed author version

COOLS, Mario; MOONS, Elke & WETS, Geert (2010) Assessing the Impact of Public Holidays on Travel Time Expenditure Differentiation by Trip Motive. In: TRANSPORTATION RESEARCH RECORD, (2157). p. 29-37.

DOI: 10.3141/2157-04
Handle: http://hdl.handle.net/1942/11312

ASSESSING THE IMPACT OF PUBLIC HOLIDAYS ON TRAVEL TIME EXPENDITURE: DIFFERENTIATION BY TRIP MOTIVE

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Number of words = 5383
Number of Tables = 6
Words counted: 5383 + 6*250 = 6883 words

Revised paper submitted: November 13, 2009

ABSTRACT

The impact of public holidays on the underlying reasons of travel behavior, namely the activities people perform and the trips made, is seldom investigated. Therefore, in this paper the impact of public holidays on travel time expenditure in Flanders, differentiated by trip motive, is examined. The data used for the analysis stem from a household travel survey that was carried out in 2000. The main modeling approach that is employed is the zero-inflated Poisson regression approach, which explicitly takes into account the inherent contrast between travelers and non-travelers. The zero-inflated Poisson regression models yield findings that are harmonious with international literature: socio-demographic variables, temporal effects and transportation preferences contribute significantly in unraveling the variability of travel behavior. In particular it is shown that public holidays have a non-ignorable impact on daily travel behavior. Triangulation of both quantitative and qualitative techniques seems a solid roadway for further illumination of the underpinnings of travel behavior.

KEYWORDS: public holidays, travel time expenditure, trip motive, zero-inflated Poisson regression

1 INTRODUCTION

1.1 Relevance of Investigating Holiday Effects on Travel Time Expenditure

The importance of a thorough examination of the effect of public holidays on travel time expenditure is underlined by Liu and Sharma (*1*) and Cools *et al.* (*2*) stressing the need to incorporate holiday effects in travel behavior models. First, public holidays can influence both the demand for activities (e.g. during regular days the demand for work activities is much larger than during periods were most people plan their holiday) and the supply of activity opportunities in space and time (e.g. opening hours of amusement parks are often prolonged during holiday periods). Second, holidays can affect the supply of available transport options (e.g. during summer holidays, extra trains/plains are scheduled to transfer people to popular holiday destinations). Finally, they can influence the supply of infrastructure and their associated management systems (e.g. during the summer holiday period, the police often enforces driving in groups in order to limit traffic congestion).

State-of-the art literature concerning holiday effects mainly focused on two items, namely on the effects of holidays on traffic counts (e.g. *3*,*4*) and on traffic safety (e.g. *5*,*6*). The impact on the underlying reasons of travel behavior, namely the activities people perform and the trips made, is seldom investigated. Therefore, this study discusses the effect of public holidays on the trips made, and in particular the focus is devoted to the attribute travel time.

1.2 Importance of Examining Travel Time Expenditure Differentiated by Trip Motive

When travel time expenditure is investigated, it is necessary to acknowledge the importance of differentiating travel time expenditure by trip motive. First, commuting (which is defined as work and school related trips), although being the main reason for performing trips, only accounts for 26.8% of all trips (*7*). Thus, solely focusing on commuting trips would neglect almost three quarters of all trips reported. By analogy with this argument also the concentration of the analysis solely on shopping (defined as both daily and non-daily shopping; 20.5% of all trips) or leisure trips (14.2% of all trips) is to be avoided.

In addition, the differentiation by trip motive can trigger a refinement of the underlying relationships between travel behavior and explanatory factors. By dividing the travel time expenditure into trip motive dependant subparts, more complex relationships can be implicitly modeled: differentiation makes it feasible to incorporate explanatory factors that have an increasing/decreasing effect on a particular subpart, and have an opposite effect, a substitution effect or no effect at all on other subparts.

2 OVERVIEW OF THE DATA

2.1 Sample Correspondence to the Population

The data that are used for the analysis stem from a household travel survey in Flanders that was carried out in 2000 (*7*). The focus of this survey was to investigate the travel behavior of the people living in the Flanders area. Using stratified clustered sampling, 3,028 households were queried about their travel behavior. All household members older than 6 (in total 7,625 persons) had to report the trips they made during a particular day, yielding information on about 21,031 trips.

In order to guarantee an optimal correspondence between the survey sample composition and the population the observations in the sample are weighted. The weights were calculated by matching the marginal distributions of the sample with the marginal distributions of the population. Age, gender and civil state were the basis for this matching process.

2.2 Dependent Variables: Travel Time Expenditure by Purpose

The daily travel time expenditure for each trip motive is calculated by adding up the time spent on the trips related with the specific motive. Both the trips to the activity locations and the trips back home were considered.

2.3 Explanatory Variables

2.3.1 Temporal Effects

The first category of explanatory variables that is used in the analysis are temporal effects. The first temporal effect that is considered is the day-of-week effect. Agarwal (*8*) showed that there exists a significant difference between travel behavior on a weekday and travel behavior on a weekend day. This difference is even further unraveled by Sall and Bhat (*9*) and Schwanen (*10*) demonstrating a significant day-of-week effect. In the analysis the day-of-week effect is represented by a categorical variable with seven categories; the first category corresponding to a Monday, the last to a Sunday.

The focus in this study lies on the second temporal effect, namely the holiday effect. To evaluate the significance of public holidays on daily commuting time a special holiday variable is created, consisting of three categories: “normal days”, “holidays” and “summer holidays”. The following holidays are taken into account: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Sunday, Whit Monday, vacation of the construction industry (three weeks, starting the second Monday of July), Our Blessed Lady Ascension, fall break (including All Saints’ Day and All Souls’ Day), and finally Remembrance Day. Note that for all these holidays, the adjacent weekends, were considered to be a holiday too. For holidays occurring on a Tuesday or on a Thursday, respectively the Monday and weekend before, and the Friday and weekend after, were also defined as a holiday, because often people have a day-off on those days, and thus have a leave of several days, which might be used to go on a long weekend or on a short holiday (*2*). The days in July and August that were not in the above holiday list were labeled as “summer holidays”.

2.3.2 Socio-Demographics

Next to the temporal effects, also socio-demographic variables are considered for the analysis, as they are commonly used in models that predict travel time (*11-13*). The following variables are considered for the analyses presented in this paper: age, gender, employment status, living conditions and degree of urbanization.

2.3.3 Transportation Preferences

The final group of variables that is used for the analysis is the frequency of using different transport modes. The following transport modes were considered: the use of the scheduled service bus and tramway service, categorized in people who never, occasionally (a few times a year or month) and frequently (weekly or more often) use this service, the use of the railroad system (same categorization), the daily use of a bicycle (dummy variable which equals one if the respondent uses the bicycle daily) and the daily use of a motorcycle (cf. daily bicycle use). Reports concerning the Flemish travel survey (*7*) revealed that more than half of the respondents never use busses or trams. The use of trains seemed to be slightly more popular. In addition to the different transportation uses also the possession of a driving license is considered for the analysis. For an interpretation of the impact of transportation preferences the reader is referred to Section 5.

3 DESCRIPTIVE ANALYSIS

Before elaborating on the modeling methodology in Section 4, in this section some descriptive statistics are provided to gain a first insight into the data. First, information about the distributions of the different dependent variables (travel time expenditures by purpose) is displayed. Afterwards, the mean travel time expenditure by purpose is tabulated for the different categories of the explanatory variables.

3.1 Dependent Variables: Travel Time Expenditure by Purpose

The distribution categories for the travel time expenditure, differentiated by trip motive are displayed in Table 1. From this table one can observe that commuting is the most performed travel activity (it has the smallest percentage of no travel), followed by shopping and leisure trips. In addition to the overall means, also the means excluding zeros are tabulated. Marked are the large discrepancies between these two measures of central tendency, suggesting the need for a modeling approach that explicitly takes into account the excess of zeros.

TABLE 1 Distribution Categories for Travel Time Expenditure, Differentiated by Trip Motive

Descriptive measure	Commuting	Shopping	Leisure
Distribution category			
No travel	62.1 %	70.1 %	78.3 %
1-10 min	4.7 %	8.3 %	4.8 %
11-20 min	7.6 %	8.0 %	5.0 %
21-30 min	6.6 %	5.2 %	2.9 %
31-40 min	4.5 %	2.7 %	2.0 %
41-50 min	3.1 %	1.5 %	1.5 %
51-100 min	7.5 %	3.4 %	3.2 %
> 100 min	4.0 %	1.0 %	2.3 %
Central tendency			
Mean (with 0's)	18.5 min	8.9 min	10.7 min
Mean (without 0's)	48.9 min	29.8 min	49.5 min

3.2 Explanatory Variables

3.2.1 Temporal Effects

The mean travel time expenditures according to trip motive are displayed for the different categories of the temporal effects in Table 2. From this table one can descry that the time spent on commuting is considerably lower during holidays when compared to regular days, while travel time expenditure on leisure trips is portentously higher during holiday periods. Concerning shopping trips, less pronounced differences can be observed. Besides, one can note the large discrepancy between weekdays and weekend days for commuting travel times, and to a lesser extent for leisure travel times. Shopping related travel times appear to peak on Saturdays.

TABLE 2 Mean Travel Time Expenditure According to Trip Motive

Explanatory Variable	Commuting	Shopping	Leisure
Holiday			
No holiday	21.9 min	8.6 min	8.3 min
Holiday	11.3 min	9.6 min	15.7 min
Summer holiday	12.8 min	9.4 min	16.6 min
Day-of-week			
Monday	29.6 min	7.6 min	9.4 min
Tuesday	31.4 min	6.8 min	8.6 min
Wednesday	24.2 min	8.8 min	5.7 min
Thursday	28.5 min	8.7 min	7.7 min
Friday	25.7 min	8.0min	11.6 min
Saturday	4.4 min	15.2 min	16.9 min
Sunday	3.0 min	7.0 min	24.3 min
Age			
6-12	10.8 min	5.3 min	14.4 min
13-15	21.0 min	3.8 min	12.1 min
16-24	27.1 min	6.1 min	13.4 min
25-34	27.7 min	8.8 min	9.9 min
35-44	28.0 min	8.8 min	10.7 min
45-54	24.0 min	10.7 min	10.4 min
55-65	10.0 min	12.4 min	13.4 min
65+	1.0 min	10.1 min	6.5 min
Gender			
Male	24.0 min	7.5 min	12.5 min
Female	13.4 min	10.2 min	9.1 min
Employment status			
Housekeeping	0.6 min	15.3 min	9.6 min
Unemployed	1.7 min	15.5 min	6.3 min
Retired	0.6 min	10.3 min	8.6 min
Disabled	1.1 min	9.1 min	8.8 min
Pupil, student	18.6 min	4.8 min	13.8 min
Worker	30.5 min	7.8 min	8.1 min
Employee	31.7 min	10.0 min	11.8 min
Executive	42.0 min	8.6 min	11.9 min
Liberal profession	15.5 min	5.2 min	18.5 min
Self-employed	20.3 min	6.1 min	11.6 min
Overall	*18.5 min*	*8.9 min*	*10.7 min*

3.2.2 Socio-Demographics

An exploratory analysis of the most dominant socio-demographical variables, shown in Table 2, reveals that the daily time spent on commuting first increases with age, reaches its maximum at age category 35-44 and declines after people reach their retirement age. The daily commuting time seems to be higher for males than for females and obviously the professionally active population spends more time on commuting compared to the inactive population. Table 2 provides also preliminary insight into the travel time spent on shopping trips; the travel time increases with age and females spend more travel time on shopping trips than males. When employment status is considered, one could notice that the inactive population spends more travel time on shopping then the active one. The overall picture for travel time spent on leisure trips is less striking. Though, one could notice that travel time spent on leisure trips is higher for males than for females, and is remarkably lower for the oldest age category (65+).

4 METHODOLOGY

4.1 Zero-Inflated Poisson Regression

The main modeling approach that is used for the analysis is the zero-inflated Poisson (ZIP) regression approach. This modeling framework uses a zero-inflated Poisson distribution to deal with the excess of zeros. The approach assumes that the population consists of two types of individuals. The first type gives a Poisson-distributed count, which may be zero, whereas the second type always gives a zero count. This assumption can be supported by the inherent contrast between travelers and non-travelers, which could explain the discrepancies between the means incorporating and disregarding zeros, as identified in Section 3.1. The choice for the ZIP regression approach implies that the three types of travel time expenditures will be treated as count variables. The comparison of a linear regression and Poisson regression model for predicting commuting times revealed that the Poison regression model explained more of the variability in travel time expenditure on commuting (*14*). Therefore, the accommodation of a Poisson model that takes into account the inherent contrast between travelers and non-travelers certainly is a defensible approach. Although travel time expenditures are traditionally analyzed using Tobit models and hazard-based duration models (*15*), in this paper the suitability of the ZIP regression as an alternative modeling framework is illustrated.

The zero-inflated Poisson distribution has two parameters; the mean of the Poisson distribution λ_i and the proportion of the individuals that are of the second type (the non-travelers), ω_i. Formally, the zero-inflated Poisson distribution can be represented in the following way (*16*):

$$\Pr(Y_i = k) = \begin{cases} \omega_i + (1-\omega_i)e^{-\lambda_i} & \text{for } k = 0 \\ (1-\omega_i)\dfrac{e^{-\lambda_i}\lambda_i^k}{k!} & \text{for } k > 0 \end{cases},$$

where both the probability ω_i and the mean number λ_i depend on covariates. For the covariate matrices **B** and **G** of the models discussed in this paper, the parameters $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ satisfy the following equations:

$$\begin{cases} \log(\boldsymbol{\lambda}) = \mathbf{B}\boldsymbol{\beta} \\ \operatorname{logit}(\boldsymbol{\omega}) = \log\left(\boldsymbol{\omega}/(1-\boldsymbol{\omega})\right) = \mathbf{G}\boldsymbol{\gamma} \end{cases}.$$

Estimates for the unknown parameters are obtained by maximizing the log likelihood using a ridge-stabilized Newton-Raphson algorithm (*17*). The log-likelihood function for the zero-inflated Poisson distribution is given by:

$$\sum_{i=1}^{n} l_i, \qquad with \quad l_i = \begin{cases} w_i \log\left[\omega_i + (1-\omega_i)e^{-\lambda_i}\right] & k = 0 \\ w_i\left[\log(1-\omega_i) + k\log(\lambda_i) - \lambda_i - \log(k!)\right] & k > 0 \end{cases},$$

where n is the number of observations and where w_i are the weights calculated by matching the marginal distributions of the sample with the marginal distributions of the population. Note that in contrast to the ordinary Poisson regression model, no scale parameter can be included in the ZIP regression model to accommodate for over-dispersion (*17*).

4.2 Model Performance Assessment

To assess the appropriateness of the zero-inflated Poisson distribution, the Van den Broek score test for testing zero inflation relative to a Poisson distribution (*18*) will be performed. The statistic is based on a comparison of the actual zeros to those predicted by the model:

$$S = \frac{\left[\sum_{i=1}^{n}\left\{\frac{I(y_i = 0) - p_{0i}}{p_{0i}}\right\}\right]^2}{\sum_{i=1}^{n}\left\{\frac{1-p_{0i}}{p_{0i}}\right\} - n\bar{y}},$$

where S is the score, $I(y_i = 0)$ is an indicator function that is one if a given observation equals zero, and zero otherwise; p_{0i} the probability of a zero for observation i under the null distribution (regular Poisson distribution), $\bar{y}$ the mean of the observations and n the number of observations. Note that the probability is allowed to vary by observation. The S score is assumed to follow a chi-squared distribution with one degree of freedom.

Next to computing the score test, also two model selection criteria, that balance model fit against model parsimony, will be tabulated. The first measure is the corrected Akaike information criterion (*AICC*), given by:

$$AICC = -2LL + 2p\frac{n}{n-p-1},$$

where p is the number of parameters estimated in the model, n the number of observations and LL the log likelihood evaluated at the value of the estimated parameters (SAS Institute Inc. 2004). A second, yet similar measure is the Bayesian information criterion (*BIC*) defined by:

$$BIC = -2LL + p\log(n).$$

The AICC and BIC are useful criteria in selecting among different models, with smaller values representing better models. For an extensive discussing about the use of AICC and BIC with generalized linear models the reader is referred to Simonoff (*19*).

5 RESULTS

5.1 Overall Results

The variables that were used in the final zero-inflated Poisson regression models, together with their likelihood ratio (LR) statistics are displayed in Table 3. From this table, it can be seen that all three categories of variables (socio-demographic variables, temporal effects and transportation preferences) are contributing significantly in the unraveling of daily travel time. The final models also take into account interdependencies between trips, as the travel time spent on a certain type of trip, significantly influences the likelihood of performing other trips, as well as the travel time of these other trips, especially in the case of commuting trips.

TABLE 3 Likelihood Ratio (LR) Statistics for the Zero-Inflated Poisson Regression Models

Selected variables	DF*	Commuting		Shopping		Leisure	
		Chi²	p-value	Chi²	p-value	Chi²	p-value
Model predicting λ							
Holiday	2	84.2	<0.001	7.7	0.021	2052.4	<0.001
Day-of-week	6	401.0	<0.001	95.8	<0.001	615.2	<0.001
Age	7	1291.7	<0.001	330.2	<0.001	664.9	<0.001
Gender	1	15.4	<0.001	46.2	<0.001	70.3	<0.001
Interaction Age*Gender	7	1388.2	<0.001	238.7	<0.001	896.9	<0.001
Employment status	9	845.1	<0.001	383.5	<0.001	1534.4	<0.001
Living conditions	4	--------	--------	223.6	<0.001	1164.2	<0.001
Degree of urbanization	3	120.0	<0.001	219.9	<0.001	863.0	<0.001
Uses of bus/tram	2	931.8	<0.001	497.6	<0.001	117.2	<0.001
Uses of trains	2	3272.5	<0.001	29.1	<0.001	27.6	<0.001
Daily use of motorcycle	1	86.0	<0.001	--------	--------	99.3	<0.001
Daily use of bicycle	1	341.4	<0.001	--------	--------	--------	--------
Driving license	1	30.0	<0.001	--------	--------	211.4	<0.001
Other type trips made	1	1911.8	<0.001	927.4	<0.001	7125.9	<0.001
Model predicting ω							
Holiday	2	218.3	<0.001	--------	--------	6.4	0.041
Day-of-week	6	909.1	<0.001	136.5	<0.001	204.8	<0.001
Age	7	--------	--------	17.5	0.014	15.5	0.030
Gender	1	11.7	<0.001	22.3	<0.001	30.5	<0.001
Employment status	9	1400.6	<0.001	68.1	<0.001	29.2	<0.001
Living conditions	4	--------	--------	--------	--------	14.3	0.006
Driving license	1	--------	--------	17.9	<0.001	7.8	0.005
Time spent on other type trips	1	357.4	<0.001	89.4	<0.001	60.3	<0.001
Performance measure							
AICC		75489		46880		70572	
BIC		75908		47344		71088	
Score-test (p-value)		<0.001		<0.001		<0.001	

* DF: Degrees of freedom, -------- indicates that the variables is not included in the final model

Concerning the covariates in the Poisson regression part of the model, one could note that the holiday effect, the day-of-week effect, age, gender, employment status, degree of urbanization, the use of buses and trams, the use of the trains, and the indicator of making other type trips play a significant role in all three models. With respect to the explanatory variables in the zero-inflation part of the model, one could observe that the day-of-week effect, gender, employment status, and the time spent on other type trips are the covariates that are significant in all three models. The degree of urbanization did not contribute significantly to any of the zero-inflation parts. Except for the covariate driving license, all other explanatory variables representing transportation preferences were left out of the zero-inflation part in order to prevent convergence problems in the estimation procedure.

For the three different types of trips considered, each time the best model was chosen using the AICC and BIC criteria. The corresponding values for these criteria are displayed in the lower part of Table 3. The necessity of using a zero-inflated Poisson model rather than a regular Poisson model is formally tested using the Van den Broek score test. For all three models the corresponding p-value is smaller than 0.001 indicating that a zero-inflated Poisson distribution seriously outperforms a regular Poisson distribution for these models.

5.2 Commuting Time

The parameter estimates of the zero-inflated Poisson regression model for predicting the travel time expenditure on commuting are shown in Table 4. A distinction has to be made between the parameters in the model predicting the mean response λ and the parameters for estimating the probability of the zero-inflation ω. The parameters of the Poisson part of the zero-inflated Poisson model (λ) should be interpreted as multiplicative effects. Take as an example the parameter estimates for daily users of a motorcycle. The multiplicative effect of being a daily motorcycle user instead of a non-(daily) motorcycle user can then be calculated in the following way: exp(-0.441 – 0) = exp(-0.441) = 0.643. This means that the commuting time of daily motorcycle users is only 64.3% of the commuting of non-(daily) motorcycle users, given that they share the same characteristics for all the other variables. The parameters of the logistic part of the zero-inflated Poisson model (ω) could be seen as log odds ratio multiplicative effects. Take as an example the parameter of the time spent on other type trips: an increase of one minute travel time spent on other type trips has as a consequence that the odds of non-commuting (a zero for travel time expenditure on commuting trips) equals exp(0.016) = 1.02 times the odds of commuting.

When certain covariates are used for modeling both the mean response λ and the probability of zero-inflation ω, the assessment of the overall effect is not straightforward. When both parameters support the same conclusion, the multiplicative effect of the Poisson parameter is elevated by the zero-inflation parameter. Take as an example the comparison between regular days and days within the summer holiday period: the parameters of the Poisson parameter indicate that the average commuting time on a regular day is 1.13 (=exp(0+0.120) times the commuting time during a day within the summer holiday period, and this effect is enlarged by the zero-inflation part indication that the odds of commuting are 4.33 for regular days compared to summer holidays. On the other hand, when both parameters support opposite effects, the assessment of the overall effect remains inclusive. Consider for instance the difference between Saturdays and Sundays: while the Poisson parameters indicate that the commuting time on Sundays is 1.03 (=exp(-0.203+0.230) times the commuting time on Saturdays, the zero-inflation parameters, on the other hand, indicate that the odds of commuting on a Saturday versus a Sunday are 1.87 (=exp(3.205-2.573)).

Examination of the temporal effects provides the insight that the traditional organization of the modern society in 5-day workweeks predominates the travel time expenditure on commuting: the likelihood of commuting and the average time spent on commuting are considerably larger during weekdays than during weekend days. This finding is consistent with the results reported by Bhat and Misra (*20*) and Sall and Bhat (*9*), who indicated the importance of incorporating day-of-week effects to account for variability in travel times. Furthermore, the travel time expenditure is significantly lower during holidays and summer holidays.

TABLE 4 ZIP Regression Parameter Estimates for Travel Time Expenditure on Commuting

Parameter	Est.	S.E.	Parameter	Est.	S.E.	Parameter	Est.	S.E.
Poisson Model λ								
Intercept	3.699	0.020	*Gender & Age*			*Use of buses/trams*		
Holiday			Male, 06-12 years	-0.429	0.031	Frequently	0.337	0.011
Regular Day	0.000		Male, 13-15 years	-0.658	0.033	Occasionally	0.125	0.008
Holiday	-0.061	0.009	Male, 16-24 years	-0.494	0.021	Never	0.000	
Summer Holiday	-0.120	0.015	Male, 25-34 years	-0.193	0.019	*Use of trains*		
Day-of-week			Male, 35-44 years	0.000		Frequently	0.531	0.012
Monday	0.000		Male, 45-54 years	0.093	0.022	Occasionally	-0.038	0.008
Tuesday	-0.063	0.010	Male, 55-64 years	-0.256	0.034	Never	0.000	
Wednesday	-0.087	0.010	Male, 65+ years	9.004	3.747	*Daily use of motorcycle*		
Thursday	-0.037	0.010	*Employment status*			Yes	-0.441	0.044
Friday	-0.046	0.010	Housekeeping	0.039	0.079	No	0.000	
Saturday	-0.230	0.018	Unemployed	-0.340	0.059	*Daily use of bicycle*		
Sunday	-0.203	0.024	Retired	-0.012	0.042	Yes	-0.143	0.008
Gender			Disabled	-0.456	0.093	No	0.000	
Male	0.456	0.014	Pupil, Student	-0.117	0.018	*Driving license*		
Female	0.000		Worker	0.000		Yes	0.081	0.014
Age			Employee	0.136	0.009	No	0.000	
06-12 years	-0.367	0.028	Executive	0.200	0.011	*Other type trips made*		
13-15 years	0.275	0.028	Liberal profession	-0.142	0.038	Yes	-0.293	0.007
16-24 years	0.247	0.019	Self-employed	-0.134	0.017	No	0.000	
25-34 years	0.086	0.016	*Degree of urbanization*					
35-44 years	0.000		Metropolitan area	-0.155	0.014			
45-54 years	-0.072	0.019	Urban area	0.018	0.008			
55-64 years	0.188	0.030	Suburban area	-0.049	0.012			
65+ years	-8.891	3.747	Rural area	0.000				
Zero inflation ω								
Intercept	-2.032	0.162	*Day-of-week*			*Employment status*		
Holiday			Friday	0.060	0.151	Retired	4.703	0.306
Regular Day	0.000		Saturday	2.573	0.163	Disabled	4.235	0.528
Public Holiday	1.245	0.103	Sunday	3.205	0.203	Pupil, Student	0.407	0.128
Summer Holiday	1.473	0.154	*Gender*			Worker	0.000	
Day-of-week			Male	-0.290	0.090	Employee	-0.088	0.130
Monday	0.000		Female	0.000		Executive	-0.383	0.179
Tuesday	-0.107	0.160	*Employment status*			Liberal profession	1.031	0.368
Wednesday	0.116	0.150	Housekeeping	4.970	0.500	Self-employed	1.043	0.191
Thursday	0.077	0.152	Unemployed	3.785	0.362	*Time spent on other trips*	0.016	0.001

Investigation of the socio-demographic effects points out that males have a higher propensity to commute than females. Note that to calculate the overall effect of age and gender, the main effects of age and gender, as well as the interaction effects have to be added up. Furthermore, males (25+) commute longer than their female counterparts. This can be explained by persistence of the traditional role patterns: taking care of children still is most frequently done by females, and correspondingly females gear home and work locations better to one another. When the employment status is considered, it can be seen that the occupationally active population quite logically has a higher likelihood to commute and spends more time on commuting than occupationally inactive people. Interesting is the fact that the higher the position people hold within a company, the more daily time they spend on commuting and the higher the probability of commuting. Consequently, executives spend the most time on commuting.

Final conclusions that can be drawn from exploring the parameter estimates are the fact that frequent users of public transport (bus, train) commute up to 1.7 times longer than people who seldom or never use public transport. Daily users of a motorcycle spent on average 35.7% less time on commuting than non-(daily) users. Also noteworthy is the significant interdependency of travel time expenditure on the remainder of the travel time budget: people making other kinds of trips commute on average 25.4% less than people who only make commuting trips, and moreover the chance of commuting decreases when other type of trips are made. This is a consequence of the substitution effect caused by the travel time frontier, the intrinsic maximum amount of time that people are willing to allocate to travel (*21*,*22*).

5.3 Time Spent on Shopping Trips

The parameter estimates of the zero-inflated Poisson regression model for predicting the travel time expenditure on shopping trips are displayed in Table 5. Recall the distinction between the parameters in the model predicting the mean response λ and the parameters for estimating the probability of the zero-inflation ω. For the analysis there was no distinction made between daily and non-daily shopping, as only one-day trip diary data were available. The analysis of the temporal effects yields the conclusion that in general the time spent on shopping trips is lower during holidays than during regular days. Saturday appears to be the most preferred day for performing shopping trips: both the likelihood for performing shopping trips and the travel time expenditure exceed those of other days. This can be accounted for by the fact that on Saturdays there are fewer work-related obligations, and more available time to perform non-work related activities. The importance of incorporating temporal effects to account for differences in travel time variability is also acknowledged by Srinivasan and Guo (*23*) and Habib and Miller (*24*).

Exploration of the socio-demographic effects reveals that females have a much larger propensity to perform shopping trips than males (odds ratio equals 1.37), which can be explained by the fact that household related activities are primarily performed by females (*25*). The assessment of the effect of age is not that straightforward. Notwithstanding, adults in the age category 25-64 have the largest probability of performing shopping trips. When the effect of the employment status is evaluated, it can be seen that the finding of Gould and Golob (*11*), indicating that the occupationally active population spends less travel time on shopping than occupationally inactive people, is more variegated in this study: on the one hand occupationally active people have a decreased likelihood of performing shopping trips, on the other hand - when they do make the trip - they spent more time than occupationally inactive people. Although the overall effect remains inconclusive, an important finding is that people performing a liberal profession have a lower verisimilitude to perform shopping trips (irrespective of self-employed people) and a clearly lower travel time (28% less than executives) than other occupationally active people.

TABLE 5 ZIP Regression Parameter Estimates for Travel Time Expenditure on Shopping Trips

Parameter	Est.	S.E.	Parameter	Est.	S.E.	Parameter	Est.	S.E.
Poisson Model λ								
Intercept	3.579	0.030	*Age*			*Living conditions*		
Holiday			55-64	0.087	0.025	Alone	0.000	
Regular Day	0.000		65+	0.064	0.029	Others (No partner)	-0.045	0.021
Public Holiday	-0.034	0.011	*Gender & Age*			Partner	-0.039	0.017
Summer Holiday	-0.001	0.017	Male, 06-12	0.081	0.046	Partner and others	-0.189	0.017
Day-of-week			Male, 13-15	-0.736	0.075	Other conditions	-0.509	0.075
Monday	0.000		Male, 16-24	-0.425	0.041	*Degree of urbanization*		
Tuesday	0.015	0.021	Male, 25-34	-0.003	0.032	Metropolitan area	-0.186	0.022
Wednesday	0.019	0.019	Male, 35-44	0.000		Urban area	-0.159	0.011
Thursday	0.057	0.019	Male, 45-54	-0.085	0.033	Suburban area	-0.016	0.019
Friday	-0.013	0.019	Male, 55-64	-0.031	0.034	Rural area	0.000	
Saturday	0.119	0.017	Male, 65+	-0.140	0.033	*Use of buses/trams*		
Sunday	-0.021	0.021	*Employment status*			Frequently	0.406	0.017
Gender			Housekeeping	-0.062	0.023	Occasionally	0.087	0.011
Male	0.095	0.023	Unemployed	0.005	0.025	Never	0.000	
Female	0.000		Retired	-0.159	0.025	*Use of trains*		
Age			Disabled	-0.356	0.041	Frequently	0.134	0.024
06-12	0.300	0.046	Pupil, Student	-0.380	0.033	Occasionally	0.053	0.011
13-15	0.394	0.054	Worker	0.000		Never	0.000	
16-24	0.197	0.029	Employee	-0.009	0.017	*Other type trips made*		
25-34	-0.161	0.022	Executive	-0.027	0.022	Yes	-0.299	0.010
35-44	0.000		Liberal profession	-0.359	0.061	No	0.000	
45-54	0.086	0.021	Self-employed	0.016	0.030			
Zero inflation ω								
Intercept	1.345	0.168	*Age*			*Employment status*		
Day-of-week			06-12	0.300	0.243	Retired	-0.539	0.176
Monday	0.000		13-15	0.445	0.285	Disabled	-0.239	0.250
Tuesday	-0.043	0.130	16-24	0.300	0.171	Pupil, Student	0.000	0.210
Wednesday	-0.295	0.121	25-34	-0.121	0.105	Worker	0.000	
Thursday	-0.315	0.123	35-44	0.000		Employee	-0.307	0.108
Friday	-0.423	0.121	45-54	0.047	0.110	Executive	-0.124	0.145
Saturday	-1.070	0.116	55-64	-0.008	0.142	Liberal profession	0.188	0.337
Sunday	-0.041	0.129	65+	0.431	0.183	Self-employed	0.417	0.184
Gender			*Employment status*			*Driving license*		
Male	0.318	0.069	Housekeeping	-0.870	0.161	Yes	-0.600	0.105
Female	0.000		Unemployed	-0.840	0.192	No	0.000	
						Time spent on other trips	0.004	0.001

Other conclusions that can be formulated are the fact that people living in non-traditional living conditions spend considerable less time on shopping trips. This can be explicated by the fact that shopping trips for people living in ‘other’ living conditions such as rest homes and institutions are performed by personnel of these organizations instead of by the individuals themselves. Next, one can infer that the degree of urbanization has a decreasing impact on travel time expenditure on shopping trips. A possible reason is the increased number of shopping locations in a more urban context. Furthermore, one could ascertain the interdependence of shopping trips and other kind of trips. This is again a consequence of the travel time frontier. Note that the interdependency of shopping trips and work trips was also incorporated by Lee and Timmermans (*26*).

5.4 Time Spent on Leisure Trips

The parameter estimates of the zero-inflated Poisson regression model for predicting the travel time expenditure on leisure trips are shown in Table 6. Examination of the temporal effects indicates that both the travel time expenditure on leisure trips and the odds of making these trips are higher during holiday periods and weekends. This can again be explained by the traditional organization of the modern society: during weekends and holidays more time is available to perform leisure activities.

Investigation of the socio-demographic effects reveals that males have a higher propensity to perform leisure trips and in general spend more time on leisure trips than females, which was also demonstrated by Schlich *et al.* (*25*). People in the age category 65+ have the smallest likelihood to execute leisure trips and also spend the least time on leisure trips. This can be partially accounted for by the fact that people aged 65+ are more likely to have physical disabilities limiting the opportunity to perform leisure activities. People living together with other people have a clearly lower probability and lower travel time expenditure on leisure than people living alone. Coupling constraints clearly seem to play an important role here. Besides, the importance of incorporating land use and density variables, denoted by Bhat and Gossen (*27*), is also evidenced in this study: in metropolitan and urban areas significantly more time is spent on leisure trips when compared to rural areas. Finally, the interdependency of travel time expenditures on differently motivated trips can also be observed for leisure trips.

TABLE 6 ZIP Regression Parameter Estimates for Travel Time Expenditure on Leisure Trips

Parameter	Est.	S.E.	Parameter	Est.	S.E.	Parameter	Est.	S.E.
Poisson Model λ								
Intercept	4.575	0.032	*Gender & Age*			*Living conditions*		
Holiday			Male, 06-12	-0.225	0.031	Other conditions	0.970	0.058
Regular Day	0.000		Male, 13-15	-0.144	0.044	*Degree of urbanization*		
Public Holiday	0.361	0.009	Male, 16-24	0.422	0.031	Metropolitan area	0.507	0.017
Summer Holiday	0.415	0.014	Male, 25-34	-0.316	0.030	Urban area	0.100	0.010
Day-of-week			Male, 35-44	0.000		Suburban area	0.189	0.015
Monday	0.000		Male, 45-54	0.133	0.031	Rural area	0.000	
Tuesday	0.166	0.020	Male, 55-64	0.434	0.032	*Use of buses/trams*		
Wednesday	-0.197	0.021	Male, 65+	0.370	0.035	Frequently	-0.162	0.017
Thursday	-0.104	0.019	*Employment status*			Occasionally	-0.110	0.010
Friday	0.122	0.017	Housekeeping	0.131	0.026	Never	0.000	
Saturday	0.021	0.016	Unemployed	-0.607	0.036	*Use of trains*		
Sunday	0.056	0.016	Retired	0.127	0.026	Frequently	-0.065	0.020
Gender			Disabled	0.435	0.038	Occasionally	0.046	0.010
Male	0.001	0.021	Pupil, Student	-0.006	0.028	Never	0.000	
Female	0.000		Worker	0.000		*Daily use of motorcycle*		
Age			Employee	0.311	0.017	Yes	-0.981	0.129
06-12	0.166	0.035	Executive	0.237	0.021	No	0.000	
13-15	0.192	0.042	Liberal profession	0.556	0.035	*Driving license*		
16-24	-0.058	0.032	Self-employed	0.518	0.024	Yes	-0.292	0.017
25-34	0.141	0.022	*Living conditions*			No	0.000	
35-44	0.000		Alone	0.000		*Other type trips made*		
45-54	-0.032	0.023	Others (No partner)	-0.581	0.020	Yes	-0.783	0.009
55-64	-0.038	0.028	Partner	-0.154	0.015	No	0.000	
65+	-0.544	0.033	Partner and others	-0.385	0.015			
Zero inflation ω								
Intercept	1.953	0.225	*Age*			*Employment status*		
Holiday			06-12	-0.274	0.243	Employee	-0.379	0.124
Regular Day	0.000		13-15	-0.019	0.272	Executive	-0.442	0.159
Public Holiday	-0.111	0.081	16-24	-0.312	0.193	Liberal profession	-0.688	0.337
Summer Holiday	-0.264	0.126	25-34	0.017	0.124	Self-employed	0.042	0.203
Day-of-week			35-44	0.000		*Living conditions*		
Monday	0.000		45-54	0.194	0.128	Alone	0.000	
Tuesday	0.189	0.155	55-64	0.258	0.176	Others (No partner)	0.147	0.159
Wednesday	0.026	0.144	65+	0.627	0.232	Partner	0.209	0.134
Thursday	-0.190	0.141	*Employment status*			Partner and others	0.368	0.135
Friday	-0.544	0.135	Housekeeping	-0.383	0.197	Other conditions	2.036	0.706
Saturday	-0.868	0.128	Unemployed	-0.350	0.229	*Driving license*		
Sunday	-1.162	0.132	Retired	-0.211	0.215	Yes	-0.364	0.125
Gender			Disabled	0.463	0.353	No	0.000	
Male	-0.408	0.075	Pupil, Student	-0.558	0.210	*Time spent on other trips*	0.005	0.001
Female	0.000		Worker	0.000				

6 CONCLUSIONS AND FURTHER RESEARCH

In this paper it is shown that socio-demographics, temporal effects and transportation preferences are contributing significantly in the unraveling of variability in daily travel time expenditure. In particular it was shown that public holidays have a non-ignorable impact on daily travel behavior. The zero-inflated Poisson regression models, which were used to accommodate the Poisson models to the portentous excess of zeros caused by non-travelers, yielded findings that were harmonious with international literature.

It is essential that the findings reported in this paper are acknowledged and translated into transportation models. An explicit incorporation of the effect of public holidays in travel demand models will most likely result in more precise travel demand forecasts, and consequently policy makers can develop and fine-tune their policy measures on more precise assumptions.

From a methodological point of view, further research should assess the need for accommodating over-dispersion in zero-inflated models. A possible framework tackling both over-dispersion and the excess of zeros is the zero-inflated negative binomial approach. A comparison of zero-inflated Poisson regression models with zero-inflated negative binomial regression models would provide a thorough assessment. In addition, it would be worthwhile to compare the suggested modeling approach with the classical techniques such as Tobit models and hazard-based duration models. Inclusion of social interaction variables and spatial variables in the analyses could further intensify the understanding of differences in travel time expenditure. Moreover, the use of multi-day data can improve the analysis even further by for instance differentiating random and routine behavior (*28*). Triangulation of both quantitative (e.g. statistical analysis) and qualitative techniques (e.g. mental models) seems a solid roadway for further illumination of the underpinnings of travel behavior.

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