Assessing the Impact of Public Holidays on Travel Time Expenditure

Differentiation by Trip Motive

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The impact of public holidays on the underlying reasons for travel behavior, namely, the activities people perform and the trips made, is seldom investigated. Therefore, the effect of 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 carried out in 2000. The zero-inflated Poisson regression approach is used; it explicitly takes into account the inherent contrast between travelers and nontravelers. The zero-inflated Poisson regression models yield findings that are harmonious with international literature: sociodemographic variables, temporal effects, and transportation preferences contribute significantly to unraveling the variability of travel behavior. In particular, it is shown that the effect of public holidays on daily travel behavior cannot be ignored. Triangulation of quantitative and qualitative techniques is a solid basis for insight into the underpinnings of travel behavior.

The importance of a thorough examination of the effect of public holidays on travel time expenditure was underlined by Liu and Sharma (*1*) and Cools et al. (*2, 3*), who stressed the need to incorporate holiday effects in travel behavior models. First, public holidays can influence both the demand for activities (e.g., on regular days, the demand for work activities is much larger than it is for periods during which most people plan their holidays) and the supply of activity opportunities in space and time (e.g., operating 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 and planes are scheduled to transfer people to popular holiday destinations). Finally, holidays can influence the supply of infrastructure and their associated management systems (e.g., during the summer holiday period, police often enforce driving in groups to limit traffic congestion).

The literature on holiday effects largely concerns two areas: the effect of holidays on traffic counts (*4, 5*) and on traffic safety (*6, 7*). The impact on underlying reasons for travel behavior, namely, the activities people perform and the trips made, is seldom investigated. Therefore, this study discusses the effect of public holidays on trips made, with a focus on attribute travel time.

It is important to differentiate travel time expenditure by trip motive. First, commuting (which is defined as work- and school-related trips), although the main reason for performing trips, accounts for only 26.8% of all trips (*8*). Thus, a focus on commuting trips would neglect almost three-quarters of all trips reported. Likewise, concentration of the analysis on shopping (defined as both daily and nondaily shopping, 20.5% of all trips) or leisure trips (14.2% of all trips) is to be avoided.

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

OVERVIEW OF DATA

Correspondence of Sample to Population

The data used for the analysis stem from a household travel survey in Flanders that was carried out in 2000 (*8*). This survey was done to investigate the travel behavior of people living in the Flanders area. Through stratified clustered sampling, 3,028 households were queried about their travel behavior. All household members older than 6 (7,625 persons total) were asked to report the trips they made during a particular day, which yielded information on about 21,031 trips.

To guarantee an optimal correspondence between the survey sample composition and the population, the observations in the sample were 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.

Dependent Variables: Travel Time Expenditure by Purpose

The daily travel time expenditure for each trip motive was calculated by adding the time spent on trips related to the specific

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motive. Both trips to the activity locations and trips back home were considered.

Explanatory Variables

Temporal Effects

The first category of explanatory variables used in the analysis is temporal effects; the first temporal effect considered is the day-of-week effect. Agarwal showed that there exists a significant difference between travel behavior on a weekday and travel behavior on a weekend day (*9*). This difference is further revealed by Sall and Bhat (*10*) and Schwanen (*11*) by demonstration of 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 of this study is 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 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 a Thursday, the Monday and weekend before and the Friday and weekend after, respectively, were also defined as a holiday, because often people have those days off and thus have a leave of several days, which may be used for a short holiday (*2*). The days in July and August not in the preceding holiday list were labeled as summer holidays.

Sociodemographics

In addition to temporal effects, sociodemographic variables were considered in the analysis, as they are commonly used in models that predict travel time (*12–14*). The following variables are considered for the analyses presented in this paper: age, gender, employment status, living conditions, and degree of urbanization.

Transportation Preferences

The final group of variables used for the analysis is frequency of use of various transport modes. The following modes were considered: use of scheduled-service bus and tramway, categorized as people who never, occasionally (a few times a year or month), and frequently (weekly or more often) use this service; use of the railroad system (same categorization as for bus); daily use of a bicycle (dummy variable that equals 1 if the respondent uses the bicycle daily); and daily use of a motorcycle (cf. daily bicycle use). Reports concerning the Flemish travel survey reveal that more than half the respondents never use buses or trams (*8*). The use of trains appears to be slightly more popular. In addition to various transportation uses, possession of a driving license is considered for the analysis.

DESCRIPTIVE ANALYSIS

Dependent Variables: Travel Time Expenditure by Purpose

The distribution categories for travel time expenditure, differentiated by trip motive, are given in Table 1. The table shows 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, the means excluding zeros are tabulated. There are 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.

Explanatory Variables

Temporal Effects

Mean travel time expenditures according to trip motive for the categories of the temporal effects are given in Table 2. Time spent on commuting is considerably lower during holidays compared to regular days, and travel time expenditure on leisure trips is portentously higher during holiday periods. Less-pronounced differences are seen for shopping trips. There is a large discrepancy between weekdays and weekend days for commuting travel times, and a lesser discrepancy for leisure travel times. Shopping-related travel times appear to peak on Saturdays.

Sociodemographics

An exploratory analysis of the most dominant sociodemographical variables, shown in Table 2, reveals that the daily time spent on commuting increases with age, reaches its maximum at age category 35 to 44, and declines after people reach retirement age. The daily commuting time appears to be higher for males than for females, and the professionally active population spends more time commuting than the inactive population. Table 2 provides preliminary insight into the travel time spent on shopping trips: travel time increases with age, and females spend more travel time on shopping trips than males. For employment status, the inactive population spends more travel time on shopping then does the active. The overall picture for travel

TABLE 1 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 0s)	18.5 min	8.9 min	10.7 min
Mean (without 0s)	48.9 min	29.8 min	49.5 min

TABLE 2 Mean Travel Time Expenditure by Trip Motive

Explanatory Variable	Commuting (min)	Shopping (min)	Leisure (min)
Holiday			
No holiday	21.9	8.6	8.3
Holiday	11.3	9.6	15.7
Summer holiday	12.8	9.4	16.6
Day of week			
Monday	29.6	7.6	9.4
Tuesday	31.4	6.8	8.6
Wednesday	24.2	8.8	5.7
Thursday	28.5	8.7	7.7
Friday	25.7	8.0	11.6
Saturday	4.4	15.2	16.9
Sunday	3.0	7.0	24.3
Age, years			
6–12	10.8	5.3	14.4
13–15	21.0	3.8	12.1
16–24	27.1	6.1	13.4
25–34	27.7	8.8	9.9
35–44	28.0	8.8	10.7
45–54	24.0	10.7	10.4
55–64	10.0	12.4	13.4
65+	1.0	10.1	6.5
Gender			
Male	24.0	7.5	12.5
Female	13.4	10.2	9.1
Employment status			
Housekeeping	0.6	15.3	9.6
Unemployed	1.7	15.5	6.3
Retired	0.6	10.3	8.6
Disabled	1.1	9.1	8.8
Pupil, student	18.6	4.8	13.8
Worker	30.5	7.8	8.1
Employee	31.7	10.0	11.8
Executive	42.0	8.6	11.9
Liberal profession	15.5	5.2	18.5
Self-employed	20.3	6.1	11.6
Overall	18.5	8.9	10.7

time spent on leisure trips is less striking; however, travel time spent on leisure trips is higher for males than for females and is remarkably lower for the oldest age category (65+).

METHODOLOGY

Zero-Inflated Poisson Regression

The main modeling approach used for the analysis is zero-inflated Poisson (ZIP) regression. This modeling framework uses a ZIP 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 nontravelers, which could explain discrepancies between the means incorporating and disregarding zeros. 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 a Poisson regression model for predicting commuting times revealed that the Poisson regression model explained more of the variability in travel time expenditure on commuting (*15*). Therefore, accommodation of a Poisson model that takes into account the inherent contrast between travelers and nontravelers is a defensible approach. Although travel time expenditures are traditionally analyzed with Tobit models and hazard-based duration models (*16*), 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 individuals of the second type (the nontravelers), ω_i. Formally, the zero-inflated Poisson distribution can be represented as follows (*17*):

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

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:

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

Estimates for the unknown parameters are obtained by maximizing the log likelihood by using a ridge-stabilized Newton–Raphson algorithm (*18*). The log likelihood function for the zero-inflated Poisson distribution is given by

$$\sum_{i=1}^{n} l_i$$

where

$$l_i = \begin{cases} w_i \log\left[\omega_i + (1-\omega_i)e^{-\lambda}\right] & k = 0 \\ w_i\left[\log(1-\omega_i) + k\log(\lambda_i) - \lambda_i - \log(k!)\right] & k > 0 \end{cases}$$

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 overdispersion (*18*).

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 (*19*) will be performed. The statistic is based on a comparison of the actual zeros to those predicted by the model:

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

where

S = score,
$I(y_i = 0)$ = indicator function that is 1 if a given observation equals zero and is zero otherwise,
p_{0i} = probability of a zero for observation i under the null distribution (regular Poisson distribution),
$\bar{y}$ = mean of the observations, and
n = number of observations.

The probability is allowed to vary by observation. The S score is assumed to follow a chi-squared distribution with one degree of freedom.

Two model-selection criteria that balance model fit against model parsimony are tabulated. The first measure is the corrected Akaike information criterion (AICC), given by

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

where

p = number of parameters estimated in the model,
n = number of observations, and
LL = log likelihood evaluated at the value of the estimated parameters (*18*).

A second, similar measure is the Bayesian information criterion (BIC), defined by

$$\text{BIC} = -2\text{LL} + p\log(n)$$

AICC and BIC are useful criteria for selecting among different models, with smaller values representing better models. Simonoff offers an extensive discussion about the use of AICC and BIC with generalized linear models (*20*).

RESULTS

Overall Results

The variables used in the final zero-inflated Poisson regression models and their likelihood ratio statistics are given in Table 3. The table shows that all three categories of variables (sociodemographic variables, temporal effects, and transportation preferences) contribute significantly to 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 and the travel time of these other trips, especially in the case of commuting trips.

Concerning the covariates in the Poisson regression part of the model, the holiday effect, the day-of-week effect, age, gender, employment status, degree of urbanization, use of buses and trams, use of trains, and the indicator of making other types of trips play a significant role in all three models. For explanatory variables in the zero-inflation part of the model, the day-of-week effect, gender, employment status, and time spent on other types of trips are significant covariates 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

TABLE 3 Likelihood Ratio Statistics for ZIP Regression Models

		Commuting		Shopping		Leisure	
Selected Variable	df[a]	Chi^2	p-Value	Chi^2	p-Value	Chi^2	p-Value
Model predicting λ							
Holiday	2	84.2	<.001	7.7	.021	2,052.4	<.001
Day of week	6	401.0	<.001	95.8	<.001	615.2	<.001
Age, years	7	1,291.7	<.001	330.2	<.001	664.9	<.001
Gender	1	15.4	<.001	46.2	<.001	70.3	<.001
Interaction age * gender	7	1,388.2	<.001	238.7	<.001	896.9	<.001
Employment status	9	845.1	<.001	383.5	<.001	1,534.4	<.001
Living conditions	4	—	—	223.6	<.001	1,164.2	<.001
Degree of urbanization	3	120.0	<.001	219.9	<.001	863.0	<.001
Uses of bus or tram	2	931.8	<.001	497.6	<.001	117.2	<.001
Uses of trains	2	3,272.5	<.001	29.1	<.001	27.6	<.001
Daily use of motorcycle	1	86.0	<.001	—	—	99.3	<.001
Daily use of bicycle	1	341.4	<.001	—	—	—	—
Driving license	1	30.0	<.001	—	—	211.4	<.001
Other type trips made	1	1,911.8	<.001	927.4	<.001	7,125.9	<.001
Model predicting ω							
Holiday	2	218.3	<.001	—	—	6.4	.041
Day of week	6	909.1	<.001	136.5	<.001	204.8	<.001
Age, years	7	—	—	17.5	.014	15.5	.030
Gender	1	11.7	<.001	22.3	<.001	30.5	<.001
Employment status	9	1,400.6	<.001	68.1	<.001	29.2	<.001
Living conditions	4	—	—	—	—	14.3	.006
Driving license	1	—	—	17.9	<.001	7.8	.005
Time spent on other type trips	1	357.4	<.001	89.4	<.001	60.3	<.001
Performance measure							
AICC		75,489		46,880		70,572	
BIC		75,908		47,344		71,088	
Score-test (p-value)		<.001		<.001		<.001	

[a]df: degrees of freedom; indicates that the variables are not included in the final model.

variables representing transportation preferences were left out of the zero-inflation part to prevent convergence problems in the estimation procedure.

For the three different types of trips considered, the best model was chosen each time by 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 by 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.

Commuting Time

The parameter estimates of the zero-inflated Poisson regression model for predicting travel time expenditure on commuting are shown in Table 4. A distinction must 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 nondaily 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 nondaily motorcycle users, given that they share the same characteristics for all 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 types of trips: an increase of 1 min travel time spent on other types of trips has as a consequence that the odds of noncommuting (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

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

Parameter	Est.	SE	Parameter	Est.	SE	Parameter	Est.	SE
Poisson Model λ								
Intercept	3.699	0.020	Gender & age, years			Use of buses or trams		
Holiday			Male, 6–12	−0.429	0.031	Frequently	0.337	0.011
Regular day	0.000		Male, 13–15	−0.658	0.033	Occasionally	0.125	0.008
Holiday	−0.061	0.009	Male, 16–24	−0.494	0.021	Never	0.000	
Summer holiday	−0.120	0.015	Male, 25–34	−0.193	0.019	Use of trains		
Day of week			Male, 35–44	0.000		Frequently	0.531	0.012
Monday	0.000		Male, 45–54	0.093	0.022	Occasionally	−0.038	0.008
Tuesday	−0.063	0.010	Male, 55–64	−0.256	0.034	Never	0.000	
Wednesday	−0.087	0.010	Male, 65+	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, years			Employee	0.136	0.009	No	0.000	
6–12	−0.367	0.028	Executive	0.200	0.011	Other type trips made		
13–15	0.275	0.028	Liberal profession	−0.142	0.038	Yes	−0.293	0.007
16–24	0.247	0.019	Self-employed	−0.134	0.017	No	0.000	
25–34	0.086	0.016	Degree of urbanization					
35–44	0.000		Metropolitan area	−0.155	0.014			
45–54	−0.072	0.019	Urban area	0.018	0.008			
55–64	0.188	0.030	Suburban area	−0.049	0.012			
65+	−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

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. However, when both parameters support opposite effects, the assessment of the overall effect remains inclusive. Consider the difference between Saturdays and Sundays: whereas 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 indicate that the odds of commuting on a Saturday versus a Sunday are 1.87 (= exp(3.205 − 2.573)).

Examination of temporal effects shows that the traditional organization of modern society into 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 (*21*) and Sall and Bhat (*10*), who indicated the importance of incorporating day-of-week effects to account for variability in travel times. Furthermore, travel time expenditure is significantly lower during holidays and summer holidays.

Investigation of the sociodemographic effects indicates that males have a higher propensity to commute than females. To calculate the overall effect of age and gender, the main effects of age and gender as well as the interaction effects must be tallied. Furthermore, males (25+) make longer commutes than their female counterparts. This observation can be explained by the persistence of traditional patterns: taking care of children still is most frequently done by females, and correspondingly, females better align home and work locations. When employment status is considered, it can be seen that the occupationally active population has a higher likelihood of commuting and spends more time on commuting, than do occupationally inactive people. The higher the position held within a company, the more daily time a person spends on commuting and the higher the probability of commuting. Consequently, executives spend the most time on commuting.

Conclusions that can be drawn from exploring the parameter estimates are that frequent users of public transport (bus, train) commute up to 1.7 times longer than do people who seldom or never use public transport. Daily users of a motorcycle spent on average 35.7% less time on commuting than nondaily users. Also, there is a 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 do people who make only commuting trips, and moreover the likelihood 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 (*22, 23*).

Time Spent on Shopping Trips

The parameter estimates of the zero-inflated Poisson regression model for predicting 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, no distinction was made between daily and nondaily shopping, as only 1-day trip-diary data were available. Analysis of temporal effects yields the conclusion that, in general, time spent on shopping trips is less during holidays than during regular days. Saturday appears to be the most preferred day for shopping trips: both the likelihood for performing shopping trips and the travel time expenditure exceed those of other days. An explanation is that on Saturdays there are fewer work-related obligations and more time is available to perform non-work-related activities. The importance of incorporating temporal effects to account for differences in travel time variability was acknowledged by Srinivasan and Guo (*24*) and Habib and Miller (*25*).

Exploration of sociodemographic effects reveals that females have a much larger propensity to perform shopping trips than do males (odds ratio equals 1.37), probably because household-related activities are performed primarily by females (*26*). Assessment of the effect of age is not as straightforward. Adults in the age category 25 to 64 years have the largest probability of performing shopping trips. When the effect of employment status is evaluated, it can be seen that the finding of Gould and Golob (*12*), which indicated that the occupationally active population spends less travel time on shopping than do 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 do occupationally inactive people. Although the overall effect remains inconclusive, an important finding is that people performing a liberal profession have a lower likelihood to perform shopping trips (irrespective of self-employed people) and a clearly lower travel time (28% less than executives) than other occupationally active people.

People living in nontraditional situations spend considerably less time on shopping trips. An explanation is that shopping trips for people in living conditions such as rest homes and institutions are performed by staff, instead of by individuals themselves.

One can infer that the degree of urbanization has a decreasing effect on travel time expenditure for 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 kinds of trips. This is again a consequence of the travel time frontier. Note that the interdependency of shopping trips and work trips was incorporated by Lee and Timmermans (*27*).

Time Spent on Leisure Trips

The parameter estimates of the zero-inflated Poisson regression model for predicting travel time expenditure for 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 modern society: during weekends and holidays, more time is available to perform leisure activities.

Investigation of sociodemographic effects reveals that males have a higher propensity to perform leisure trips and in general spend more time on leisure trips than do females, which was also demonstrated by Schlich et al. (*26*). People 65 and older are least likely to execute leisure trips and also spend the least time on leisure trips. This is in part because people 65 and older are more likely to have physical disabilities, which limit leisure activities. People who live together have a clearly lower probability and lower travel time expenditure on leisure than people who live alone. Coupling constraints clearly

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

Parameter	Est.	SE	Parameter	Est.	SE	Parameter	Est.	SE
Poisson Model λ								
Intercept	3.579	0.030	Age, years			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, years			Partner	–0.039	0.017
Summer holiday	–0.001	0.017	Male, 6–12	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 or 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, years			Disabled	–0.356	0.041	Frequently	0.134	0.024
6–12	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, years			Employment status		
Day of week			6–12	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

play an important role here. The importance of incorporating land use and density variables, denoted by Bhat and Gossen (*28*), is also shown by this study: in metropolitan and urban areas, significantly more time is spent on leisure trips, compared to rural areas. Finally, the interdependency of travel time expenditure on differently motivated trips can be observed for leisure trips.

CONCLUSIONS AND FURTHER RESEARCH

This paper showed that sociodemographics, temporal effects, and transportation preferences contribute significantly to understanding variability in daily travel time expenditure. It was shown that the effect of public holidays on daily travel behavior cannot be ignored. The zero-inflated Poisson regression models, which were used to accommodate the Poisson models to the excess of zeros caused by nontravelers, yielded findings that were harmonious with international literature.

The findings reported in this paper should be translated into transportation models. Incorporation of the effect of public holidays on travel demand models will likely result in more-precise travel demand forecasts, and consequently policy makers can develop and fine tune their policy measures on the basis of more-precise assumptions.

Further research should assess the need for accommodating overdispersion in zero-inflated models. The zero-inflated negative binomial approach is a possible framework for tackling both overdispersion and the excess of zeros. A comparison of zero-inflated Poisson regression models with zero-inflated negative binomial regression models would provide a thorough assessment. It also 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 understanding of differences in travel time expenditure. Moreover, the use of multiday data can improve the analysis by, for instance, differentiating random and routine behavior (*29*). Triangulation of both quantitative (e.g., statistical analysis) and qualitative techniques (e.g., mental models) is a solid approach for gaining insight into the underpinnings of travel behavior.

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

Parameter	Est.	SE
Poisson Model λ		
Intercept	4.575	0.032
Holiday		
Regular day	0.000	
Public holiday	0.361	0.009
Summer holiday	0.415	0.014
Day of week		
Monday	0.000	
Tuesday	0.166	0.020
Wednesday	–0.197	0.021
Thursday	–0.104	0.019
Friday	0.122	0.017
Saturday	0.021	0.016
Sunday	0.056	0.016
Gender		
Male	0.001	0.021
Female	0.000	
Age, years		
6–12	0.166	0.035
13–15	0.192	0.042
16–24	–0.058	0.032
25–34	0.141	0.022
35–44	0.000	
45–54	–0.032	0.023
55–64	–0.038	0.028
65+	–0.544	0.033
Gender & age, years		
Male, 6–12	–0.225	0.031
Male, 13–15	–0.144	0.044
Male, 16–24	0.422	0.031
Male, 25–34	–0.316	0.030
Male, 35–44	0.000	
Male, 45–54	0.133	0.031
Male, 55–64	0.434	0.032
Male, 65+	0.370	0.035
Employment status		
Housekeeping	0.131	0.026
Unemployed	–0.607	0.036
Retired	0.127	0.026
Disabled	0.435	0.038
Pupil, student	–0.006	0.028
Worker	0.000	
Employee	0.311	0.017
Executive	0.237	0.021
Liberal profession	0.556	0.035
Self-employed	0.518	0.024
Living conditions		
Alone	0.000	
Others (no partner)	–0.581	0.020
Partner	–0.154	0.015
Partner and others	–0.385	0.015
Living conditions		
Other conditions	0.970	0.058
Degree of urbanization		
Metropolitan area	0.507	0.017
Urban area	0.100	0.010
Suburban area	0.189	0.015
Rural area	0.000	
Use of buses or trams		
Frequently	–0.162	0.017
Occasionally	–0.110	0.010
Never	0.000	
Use of trains		
Frequently	–0.065	0.020
Occasionally	0.046	0.010
Never	0.000	
Daily use of motorcycle		
Yes	–0.981	0.129
No	0.000	
Driving license		
Yes	–0.292	0.017
No	0.000	
Other type trips made		
Yes	–0.783	0.009
No	0.000	
Zero Inflation ω		
Intercept	1.953	0.225
Holiday		
Regular day	0.000	
Public holiday	–0.111	0.081
Summer holiday	–0.264	0.126
Day of week		
Monday	0.000	
Tuesday	0.189	0.155
Wednesday	0.026	0.144
Thursday	–0.190	0.141
Friday	–0.544	0.135
Saturday	–0.868	0.128
Sunday	–1.162	0.132
Gender		
Male	–0.408	0.075
Female	0.000	
Age, years		
6–12	–0.274	0.243
13–15	–0.019	0.272
16–24	–0.312	0.193
25–34	0.017	0.124
35–44	0.000	
45–54	0.194	0.128
55–64	0.258	0.176
65+	0.627	0.232
Employment status		
Housekeeping	–0.383	0.197
Unemployed	–0.350	0.229
Retired	–0.211	0.215
Disabled	0.463	0.353
Pupil, student	–0.558	0.210
Worker	0.000	
Employment status		
Employee	–0.379	0.124
Executive	–0.442	0.159
Liberal profession	–0.688	0.337
Self-employed	0.042	0.203
Living conditions		
Alone	0.000	
Others (no partner)	0.147	0.159
Partner	0.209	0.134
Partner and others	0.368	0.135
Other conditions	2.036	0.706
Driving license		
Yes	–0.364	0.125
No	0.000	
Time spent on other trips	0.005	0.001

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