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The Impact of the Built Environment on Travel Behavior: The Swiss Experience based on two National Travel Surveys

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Abstract

This paper examines the effects of the built environment on travel behavior (i.e., number of trips and distance travelled) differentiated by mode of transport while statistically controlling for both mobility tool ownership and sociodemographic factors. The statistical analysis is based on two combined datasets stemming from the Swiss National Travel Surveys for 2010 and 2015. Our study provides an extensive view of the effects of the built environment on travel behavior in the Swiss context. One key finding is that high population and employment densities, frequent public transportation, low distances to points of interest (e.g., bars, cinema, sports facilities) and high-quality local recreation at one's place of residence reduce daily distances travelled by car. This finding underpins recent activities in spatial planning undertaken by the Swiss government in order to reduce energy consumption triggered by motorized individual travel. Finally, we recommend incorporating the attributes of individuals' residential self-selection into the framework of national travel surveys, an attribute still missing from Switzerland's Travel Census. This is of particular importance in order to statistically control the effect of the built environment using a further dimension that could enhance debates on transport policies and measures.

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Keywords: Built Environment; Travel Behavior; National Travel Surveys; Transport Policy

1. Introduction

Many countries have sought to develop a sustainable transport system that reduces the demand for travel, encourages greater use of public transport, and promotes cycling and walking. This can be done through the integration of land use and transport planning into policy engagement by governmental authorities. In order to provide efficient

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transport solutions, planners should pay greater attention to the fundamental principles of travel and the various dimensions that influence it, such as sociodemographic factors, mobility tool ownership and the built environment (Banister, 2008).

The planning of land use and transportation systems by governmental authorities mostly influences the last-named dimension, the built environment. In both academic and practical contexts, the central question is the size of the contribution of the built environment in relation to explaining variations in travel behavior when controlling for other influencing factors (e.g. individual attributes). Based on the statistical evidence, it can be assessed how great the change in travel behavior is by altering the built environment.

The built environment is described by means of notions such as density, usage mix, and accessibility. Numerous studies have examined the impact of the built environment on travel behavior over the last three decades (e.g., Ewing and Cervero, 2001, 2010, Handy, Cao, and Mokhtarian, 2005; Scheiner and Holz-Rau, 2007, Heinen, Steiner, and Geurs, 2015). Findings for residents' travel behavior show that better access to public transport infrastructure and improvements in urban design contribute to reducing travel by automobile and promote the use of public transport, cycling and walking (e.g. Olaru and Curtis, 2015). However, there is no consensus about the strength of this relationship between the objective conditions of the built environment and subjective travel behavior: some studies find profound impacts (Ewing and Cervero, 2001, 2010), while others report few effects (van Acker, 2016; van Wee, 2011).

From a European perspective, one drawback is that most existing studies of the relationship between the built environment and travel have been conducted in North America (e.g., see the two meta-analysis studies that include 250 studies by Ewing and Cervero, 2001, 2010; Handy, Cao, and Mokhtarian, 2005), a relatively few empirical studies having been carried out in Switzerland or elsewhere in Europe (e.g., Vance and Hedel, 2007; Scheiner and Holz-Rau, 2007; Simma, 2000 for Switzerland). A second drawback is that current studies tend to focus on a single mode of transport, mainly automobile travel or walking and cycling (Saelens and Handy, 2008). There has been much less work bringing together all modes of transport in a single empirical study to provide a comprehensive view. A third drawback is that there exist only a few studies whose findings draw on a national travel survey. The existing studies mainly focus on local contexts (e.g. Olaru and Curtis, 2015).

Against these backdrops, this paper examines the effects of the built environment on travel behavior (i.e., trips and distance) differentiated by modes of transport based on two datasets produced by the Swiss National Travel Survey. In fact, the analysis draws on a combined dataset based on the Swiss Micro-censuses on Mobility and Transport for 2010 and 2015, which includes a survey of 119,958 target persons representative of the Swiss population. These nationwide datasets on travel behavior were enriched by various built environment variables stemming from the Swiss Federal Office for Spatial Development (ARE). Based on these data, this paper aims to measure the size of the effects of the built environment while statistically controlling for both mobility tool ownership (e.g., car ownership, public transport season ticket) and sociodemographic factors.

The remainder of the paper is structured as follows. First, we present a literature review of the impacts of the built environment on travel behavior. Secondly, we introduce our methodology and modeling approach. Thirdly, we analyze empirically the effects of the built environment (BE), sociodemographics (SD) and mobility tool ownership (MT) on selected travel figures based on mode of transport using both trip generation and distance traveled. The article ends with a ranking of the main effects stemming from these three dimensions with a special focus on distances travelled by car. Finally, we make a recommendation to incorporate the attributes of individuals' residential self-selection into the framework of national travel surveys that is still missing from Switzerland's Travel Censuses. The inclusion of this information in national travel surveys should increase the power of analysis on the effects of the built environment on travel behavior.

2. Literature review

2.1. Definitions of land use, the built environment and the seven D-Variables

Research on the relationship between the built environment and travel behavior has long been one of central topics in transportation studies. However, these studies do not always clearly define key terms such as *land use* and the *built* *environment*. Thus, before discussing the impacts of the built environment on travel behavior, we briefly present definitions of these central notions.

According to van Acker (2016: 386-387), *land use* refers to "the spatial distribution of functions such as living, working, shopping and recreating, and determines the relative proximity of different types of activities." The *built environment*, also called the *urban form*, is a broader concept than *land use*. Built environments "combine land use patterns with characteristics of the transport system and urban design features" (van Acker 2016: 386).

Thus, the *built environment* is characterized by a range of variables. The most important and most frequently mentioned variables are **d**ensity, **d**iversity, and **d**esign (the 3 Ds as developed by Cervero and Kockelman (1997)), which were followed later by **d**estination accessibility and **d**istance to public transportation (Ewing and Cervero, 2001), known as the 5 Ds.

Density variables (1st D), such as residential density and employment density, refer to the intensity of activities of living and working in a certain area (e.g. persons per hectare). Diversity (2nd D) refers to the mixture of different types of activity and their proximity to each other. Design (3rd D) can be defined as the aesthetic and visual details of the built environment, particularly the design of buildings and streetscapes. Destination accessibility (4th D) refers to the ease with which activities or locations can be reached by means of a (combination of) travel mode(s). According to Ewing and Cervero (2010), distance to public transportation (5th D) is generally measured by an average of the shortest street routes from the residences or workplaces in an area to the nearest public transport connection.

Some studies add **d**emand management (e.g. parking supply and cost) as a 6th D (Cervero, 2003). To control confounding influences, a 7th D, **d**emographics, is included in many travel studies, though it is not part of the built environment (Ewing and Cervero, 2010).

2.2. Effects of D-Variables

Meta-analyses have been conducted by Ewing and Cervero (2001, 2010) in an attempt to investigate the effects of the built environment on key travel behavior outcomes. Ewing and Cervero (2001) reviewed fifty empirical studies on this topic. Their main findings were as follows:

Trip frequencies are primarily influenced by the socioeconomic characteristics of travelers' households and are only secondarily influenced by the built environment. **Trip lengths** are primarily influenced by the built environment and are secondarily influenced by the socioeconomic characteristics of travelers' households. Trip lengths are shorter in urban than in rural settings. Central locations with high land-use mixes and grid-like street networks of dense neighborhoods are expected to produce shorter trips. In other words, trip lengths are shorter at locations that are more accessible, have higher densities or feature mixed uses. This holds true for both home-end and non-home-end trips (e.g., working, shopping).

Vehicle miles traveled (VMT) and **vehicle hours traveled (VHT)** depend on both the socioeconomic characteristics of travelers' households and the built environment. VMT is more elastic with regard to destination accessibility than the three other D variables, that is, density, diversity, and design. **Destination accessibility** is the dominant environmental influence on trip length. **Mode choice** is predominantly affected by local land-use patterns. **Public transportation use** depends primarily on local densities and only secondarily on the degree of land-use mixing. **Walking** is more prevalent in dense urban neighborhoods and depends as much on the degree of land-use diversity. For both **public transportation** and **walking**, employment densities at destinations are as important as population densities at origins.

Design variables appear to have a more ambiguous relationship to travel behavior than the density and diversity variables. Any effect of design variables is likely to reflect a collective effect involving multiple design features. A typical example of this collective design effect is the composite measures in the urban design factor, which is a function of design attributes (mostly related to walkability, e.g. footpaths, pedestrian rights-of-way, the presence of trees, vegetation and benches), intersection density, residential density and employment density (for details, see Parsons, Brinckerhoff, Quade Douglas, 1993).

In their study from 2010, Ewing and Cervero (2010) updated their previous analysis of 2001 by reviewing two hundred studies quantitatively examining the correlation between the characteristics of the built environment and travel measures (e.g. trip frequencies, VMT). These two hundred studies of the built environment and of travel were mostly completed between 2001 and 2009 (since Ewing and Cervero's review 2001). The authors especially use more than fifty of these two hundred studies, which all statistically control for confounding influences (e.g. sociodemographic influences) on travel behavior and for measuring the effect sizes of built environment characteristics on travel measures (i.e. elasticities, in this context a measurement of how a transport behavior variable responds to a change in another variable, e.g. the built environment). These authors use individual elasticities from original studies to compute weighted average elasticities for dependent/independent variable pairs representing travel outcomes and the attributes/characteristics of the built environment.

In sum, the latter work of Ewing and Cervero (2010) confirms the main findings of Ewing and Cervero (2001). In addition, they find that **VMT** is most strongly associated with measures of accessibility to destinations and only secondarily to street network design variables (i.e. the distance to downtown areas, the design metrics intersection density, and street connectivity). Short blocks and many interconnections are likely to shorten travel distances. **Walking** is primarily affected by measures of land-use diversity, intersection diversity, and the number of destinations within walking distance. Intersection density, the jobs-housing balance, and distance to stores have the greatest elasticities on walking. Intersection density has a greater influence on walking than street connectivity. The jobs–housing balance has a stronger association with walking than the more commonly used land-use mix variable. Job density is less strongly correlated with walking than population density. Having many **public transportation** stops nearby may encourage **walking** (see also Ryan and Frank, 2009). **Bus and train use** are primarily and equally influenced by proximity to public transportation and street network design variables, being only secondarily influenced by land-use diversity. High intersection density and dense street connectivity shorten access distances and provide more routing options for transit users and transit providers. **Population and job densities** are weakly associated with travel behavior when other variables are controlled for. This suggests that density is an intermediate variable which is often manifested by the other D variables, for example, dense settings which commonly have mixed uses, short blocks, and central locations. Linking where people live and work stimulates walking more than increasing multiple land uses around a neighborhood. The elasticities provided by this meta-analysis by Ewing and Cervero (2010) are subject to some limitations, such as small sample sizes, the small number of studies controlling for residential preferences and attitudes, and the lack of confidence intervals around the results.

2.3. Critics of recent findings and the range of influencing variables

Despite the evidence presented above, the findings on the impact of the built environment on travel behavior have been criticized. Based on a further meta-review research project, Saelens and Handy (2008) concluded that there is still not enough empirical evidence to confidently support the causal relationship between the built environment and walking due to limitations in research methodologies.

As an example, studies conducted at different geographical scales tend to produce contradictory findings. For example, using a case study of the Seattle metropolitan region, Hong, Shen, and Zhang (2014) show that residential density significantly affects the vehicle miles traveled (VMT) of work trips only at an aggregated traffic analysis zone level, not at a smaller one-kilometer buffer level or an individual level. Similarly, Zhang et al. (2012) find that the magnitude of the impact of the built environment on VMT varies depending on city size.

With regard to individual characteristics, in their micro-analysis of land and travel in five neighborhoods in the San Francisco Bay area, Kitamura, Mokhtarian, and Laidet (1997) reported that socioeconomic variables explain travel behavior to a substantially larger extent than spatial structural properties do.

Another issue that may give rise to ambiguity regarding the relationship between the built environment and travel behavior that is discussed broadly in research about residential self-selection. In this context, self-selection is understood as individuals locating themselves in places that provide them with conducive conditions for their preferred way of travel and thus mitigate the effect of the built environment (e.g., Ettema and Nieuwenhuis, 2017). Cao, Mokhtarian, and Handy (2009) argue that, thanks to residential self-selection, the true effects of spatial structural conditions on travel behavior are often smaller than the apparent effects, although the true effects are still present, and in many cases they appear to be larger than those of self-selection. For example, in their empirical investigations, Kamruzzaman et al. (2013) and Timmermans et al. (2003) both found that settlement structure does not significantly influence travel behavior in most cases and that the attitudes of residents towards their locality have a greater influence. Other authors also claim that attitudes to travel reflect the choice of residential location, being shaped by mobility needs, the availability of modes of transport, and travel culture, all of which are defined by residential neighborhoods (Naess, 2014; van Wee, 2009; van Wee and Boarnet, 2014).

Hence, many authors still question the strength of the relationship between the built environment and travel behavior and call for further investigations (e.g. Aditjandra, 2013; Hong, Shen, and Zhang, 2014). Nonetheless, Cao et al. (2009) reviewed 38 empirical studies and found that they all conclude that the built environment still has a statistically significant influence after controlling for residential self-selection. The paper finds first that, even after accounting for residential self-selection, the built environment nearly always still has a significant impact. Secondly, most of the studies reviewed did not specify which factor had the stronger influence, residential self-selection or the built environment; among the ten that did, the built environment was stronger in eight of them. This correlation was also investigated by Boarnet et al. (1996), who found a smaller degree of correlation between spatial structure and traffic behavior when controlling for processes of self-selection. They recommend that place of residence and its spatial structure should not be treated as exogenous (explanatory) variables but as endogenous variables in models of traffic behavior. This suggests the importance of considering the effects of self-selection when examining the effects of spatial factors on traffic behavior or when designing appropriate measures. According to the Transportation Research Board (TRB) (Transportation Research Board, 2005:134-135), “If researchers do not properly account for the choice of neighborhood, their empirical results will be biased in the sense that features of the built environment may appear to influence activity more than they in fact do.”

Furthermore, cognitive emotional factors (e.g. attitudes towards environmental protection and public transport) are found to have a greater influence on travel behavior than spatial structural factors. In this context, time scales in research design seem to lead to ambiguous findings. For instance, a quasi-longitudinal research design by Handy, Cao, and Mokhtarian (2005) shows significant associations between travel behavior and the built environment when attitudes are controlled for. Using cross-sectional data to examine the same relationship, they find that changes in travel behavior are mostly explained by attitudes and that the effect of the built environment on travel behavior largely disappears. Likewise, van Acker, van Wee, and Witlox (2010) claim that lifestyle, perceptions, attitudes, and preferences should be included when modeling the impacts of the built environment on travel behavior.

The results of the literature analysis show that the empirical findings lead to debates about the strength of the impact of the built environment if the influence stemming from attitudes, residential self-selection or sociodemographics is controlled in statistical analysis (Cao, 2014; Cao et al., 2009; Naess, 2014; Schwanen and Mokhtarian, 2005). This is why research within this field has shifted from modeling travel behavior determined solely by spatial characteristics towards a broader understanding of travel behavior that is also influenced by other factors, such as sociodemographic and sociopsychological factors (Ewing and Cervero, 2010; van Acker, 2016) and life-course events (Beige and Axhausen, 2017; Zhang, 2014). Likewise, Cao et al. (2009). Other scholars suggest that, in order to obtain more accurate results, researchers should also incorporate travel attitudes and sociodemographic variables into their investigations (Naess, 2014; van Wee, 2009; van Wee and Boarnet, 2014).

In the following, these results will be discussed against empirical findings from Swiss data that incorporate findings for the interrelationships between travel behavior, built environment, mobility tool ownership and sociodemographic characteristics.

3. Methodology

3.1. Data bases and preparation

Since 1974, Switzerland has conducted a survey of its population’s travel behavior every five years. The latest survey was conducted for the reference year of 2015 by the Federal Statistical Office (BfS) and the Federal Office for Spatial Planning (ARE). The Micro-censuses on Mobility and Transport (MCMT) 2015 (BfS and ARE, 2017) has a net sample size of 57,090 target persons. These households were interviewed by telephone about their travel habits. The survey gathered data on daily mobility patterns (number of trips and stages, duration of travel, distance traveled, purpose of trips, mode of transport used) and ownership of mobility tools (vehicles, driving license, public transport travel tickets). All the household data are available using geocoded residential addresses so that all respondents could be allocated to a specific geolocation in order to add variables representing the built environment. In fact, attitudes towards the neighborhood as a way of controlling for residential self-selection are not included in the framework of this national travel survey.

For purposes of data analysis, we used two data sources (pooled data): sociodemographic and travel data from the 2010 and 2015 MCMTs, and spatial structure data to operationalize the built environment taken from the GIS (Geographical Information System) dataset of the Swiss Federal Office for Spatial Development, also for 2010 and 2015. The analysis draws on the travel habits of over 119,958 target persons surveyed in total.

3.2. Modeling approach

The following analytical dimensions are used for the modeling approach as independent variables: the built environment characteristics of the place of residence, ownership of or access to mobility tools, e.g. car, public transport season ticket, and various sociodemographic characteristics (individual and household level). The dependent variables are patterns of travel behavior, including daily distance traveled by different modes of transport and trip frequency by different modes of transport. Table 1 summarizes the independent and dependent variables for the statistical analysis.

These statistical models for the impacts of the built environment, mobility tools and sociodemographic factors on travel behavior are based on linear regression models with logarithmic transformations of the dependent variable (linear-log models) (see Christensen, 2000). Therefore, the coefficient values of these models are predicted for logarithmic transformations of dependent variables. These logarithmic transformations are necessary to satisfy the assumptions of regression analysis (mainly multivariate normality). Due to this transformation of data, the statistical models only represent those among the target population that reported trips on the survey date, which includes 90% of the sample.

Furthermore, we controlled for the error correlations for the different models. The correlation matrices revealed that there is no correlation higher than Pearson $r > 0.6$ among the metric independent variables.

Each model was estimated in three different variants:

- **Variant 1** includes all the dimensions of independent variables, i.e. built environment, mobility tool ownership, socio-demographics (total).
- **Variant 2** includes only built environment variables as factors influencing travel behavior (subset of variant 1, only built environment).
- **Variant 3** includes only socio-demographics and mobility tool ownership (also subset of variant 1, only MT and SD).

Using these modeling steps, we are able to compare and contrast the explained variance of these three model variants. In fact, the goodness of fit measure R-squared presents a statistical measure of how well the regression predictions approximate the real data points. We compare R-squared of the three model variants instead of adjusted R-squared because R-squared does not control for the number of predictors.

In a further step, we interpret the effect size of the built environment by statistically controlling for socio-demographics and mobility tool ownership based on Variant 1 models. To compare the effect size of the built environment, and for ease of interpretation, we estimated 95% confidence intervals on predicted impacts based on Variant 1 models. Based on these, we can simulate the effects of the built environment on travel behavior and are able to demonstrate and rank the effect sizes more clearly. We applied the Duan smearing estimate that uses a nonparametric retransformation method to receive an unbiased estimator for the mean based on log-transformed dependent variables (Duan, 1983). This is calculated based on the average of the exponential of the residuals from the OLS regression multiplied by the exponential transformation of the predicted value of the log-transformed dependent variable. For more information on this procedure, see Duan (1983) for how to obtain an unbiased estimator based on linear-log models (see Christensen, 2000).

Table 2 presents the operationalization of data, measurement, and sample characteristics.

Table 1. Summary of variables for modeling

Independent variables		
Built environment	**Data description**	**Data source**
Population density	Population density at place of residence (persons per hectare)	BFS (STATPOP)
Employment density	Employment density at place of residence (persons per hectare)	BFS (STATENT)
Points of interest (Kilometers)	Routing distance from place of residence to various facilities (mean distance): • entertainment (theater, museum, cinema, café, pub, bar, discotheque); • services (drugstore, restaurant, school, bank, medical practices, library, work office); • retail trade (retail, small store, large store, small supermarket, large supermarket, consumer shop); • places for leisure activities (tennis, golf, sports center)	ARE GIS
Local natural recreation (Index)	Index value for the quality of local natural recreational attributes (park, green area, lake, etc.) at place of residence. The index is estimated based on spatial properties in a radius of 1,000 meters (maximum).	Kienast et al. (2012)
Public transportation (Quality Classification A-E)	Classification of public transport connection at place of residence (based on distance and service quality) • A: Very good connection (<300 m) • B: Good connection (300 m – 500 m) • C: Average connection (500 m – 750 m) • D: Poor connection (750 m – 1,000 m) • E: Limited or no connection	ARE GIS
Mobility tools		
Car availability	Frequent or constant access to car (Yes/No)	MCMT
Bicycle availability	Constant access to bicycle (Yes/No)	MCMT
Public transport season tickets	General-, year-, month-, and week-ticket (Yes/No)	MCMT
Sociodemographic characteristics		
Gender	Men / Women	MCMT
Age	Age group: below 17; 18-35; 36-64; 64+	MCMT
Gross household income (Swiss Francs, CHF)	Low (< 4,000); average (4,001-10,000); High (>10000)	MCMT
Household structure	Family household Multi-person household Single-person household	MCMT
MCMT		
Year	2010, 2015 (dummy variable to control for level effects)	MCMT
Dependent variables		
Distance traveled per day in total and by mode	Distance traveled (total, human-powered mobility, car, public transport)	MCMT
Trip frequency per day in total and by mode	Number of trips (total, human-powered mobility, car, public transport)	MCMT

Table 2. Operationalization: data, measurement, and sample characteristics

	Measurement level and type, statistics				
Built Environment					
Population density	Metric – **M**ean **= 25.35** persons/hectare				
Employment density	Metric – **M = 19.40** persons/hectare				
Points of interest	Metric – **M = 5.0** km				
Local natural recreation	Metric – **M = 480.15** (Index)				
Public transportation	Nominal – 5 categories:				
	A	B	C	D	E
	13.4%	20.6%	22.0%	23.6%	20.4%
Mobility Tools					
Car availability = Yes	Nominal: 0 = No – 31.5% 1 = Yes – 68.5%				
Bicycle availability = Yes	Nominal: 0 = No – 24.7% 1 = Yes – 75.3%				
Public transport season tickets = Yes	Nominal: 0 = No – 66.6% 1 = Yes – 33.4%				
Sociodemographic Characteristics and Travel Behavior					
Gender = Man	Nominal: 0 = Woman – 51.1% 1 = Man – 48.9%				
Age	Ordinal – 4 categories:				
	Below 17	18-35	36-64	64+	
	14.8%	19.7%	44.4%	21.1%	
Gross household income (Swiss Francs, CHF)	Ordinal – 3 categories (low, middle, high):				
	< 4,000 (low)	4,001-10,000 (middle)	>10,000 (high)		
	19%	56%	25%		
Household structure	Nominal – 3 categories:				
	Family	Multi-person (no Family)	Single-person		
	51.5%	31.1%	17.4%		
MCMT Year = 2015	Nominal: 0 = 2010 – 47.9% 1 = 2015 – 52.1%				
Distance traveled per day	Metric – **M =** 35.65 kilometers on average (also differentiated by mode)				
Trip frequency	Metric – **M =** 3.36 on average (also differentiated by mode)				

4. Results

For ease of interpretation, we summarize the ranked results of the variant 1 models of the impacts of the built environment, mobility tools, and sociodemographics on daily distance traveled and trips (per mode of transport) in Figures 1 and 2. The size effects of the coefficients were therefore standardized, compared and then ranked.

A negative effect is indicated as a minus (-) and a positive effect as a plus (+).

For reasons of simplification we ranked the significant effects according the effect size from significantly weak (- or +) to significantly strong (----- or +++++).

The dependent variables are divided into daily distance (in total), only human-powered mobility, i.e. walking and cycling (HPM), only car and only public transportation (PT).

The detailed statistics of the modelling result can be assessed in Tables 4 and 5 in the Appendices.

Fig. 1. Impact of built environment, mobility tool ownership and sociodemographics on daily distances

	Effect Direction	Ranked Effect Size: Daily Distance	...only HPM	...only Car	...only PT
Built Environment					
Population density	When more densely	- - - - -	++	- - - -	-
Employment density	When more densely	- -	++	- - -	+
Points of interest	When further away	+	-	++	n.s.
Local natural recreation	When better	-	+	-	n.s.
Public transportation quality	A	-	n.s.	-	n.s.
	B	-	n.s.	-	+
	C	-	+	-	+
	D	n.s.	n.s.	n.s.	n.s.
	Ref.: E				
Mobility Tools (MT)					
Car availability	Yes	+++++	- - - - -	+++++	- - - - -
Bicycle availability	Yes	+	+++++	- -	++
PT season tickets	Yes	+++	+++++	- - - - -	+++++
Sociodemographic Characteristics (SD)					
Gender	Man	+++	-	+++	n.s.
Age	Up to 17	+++++	n.s.	++++	++++
	18-35	+++++	- -	++++	+++
	36-64	++++	n.s.	+++	++
	Ref.: 65+				
Household income (CHF)	Up to 4,000	- - - - -	-	- - - -	- -
	above 4,000 to 10,000	- - -	-	- -	- -
	Ref.: above 10,000				
Household structure	Family	- - -	-	-	- - -
	Multi-person household	- -	n.s.	-	-
	Ref.: Single-person household				
Year 2015	Ref: 2010	n.s.	n.s.	+	-
Explained Variance (R^2) in %	Total	7.01	5.78	19.66	26.58
	Only built environment	2.51	1.60	7.10	1.25
	Only MT and SD	11.25	3.82	18.04	22.72

n.s.= not significant, Ref. = Reference category, Significance level of .05 (5%)

Fig. 2. Impact of built environment, mobility tool ownership and sociodemographics on trip frequency

	Effect Direction	Ranked Effect Size			
		Trips	...only HPM	...only Car	...only PT
Built Environment					
Population density	When more densely	+	n.s.	n.s.	n.s.
Employment density	When more densely	n.s.	+++	- -	n.s.
Points of interest	When further away	n.s.	n.s.	n.s.	n.s.
Local natural recreation	When better	+	++	-	-
Public transportation quality	A	n.s.	+++	- - - -	+++
	B	n.s.	++	- - -	++
	C	n.s.	++	- -	++
	D	n.s.	+	-	n.s.
	Ref.: E				
Mobility Tools (MT)					
Car availability	Yes	+++	- - -	+++++	- - - -
Bicycle availability	Yes	++	++	-	n.s.
PT season tickets	Yes	- -	-	- - - - -	+++++
Sociodemographic Characteristics (SD)					
Gender	Man	n.s.	-	+	-
Age	Up to 17	+++	n.s.	- -	+++++
	18-35	+	-	+	+
	36-64	n.s.	n.s.	+	n.s.
	Ref.: 65+				
Household income (CHF)	Up to 4,000	- -	+	-	-
	above 4,000 to 10,000	n.s.	n.s.	n.s.	n.s.
	Ref.: above 10,000				
Household structure	Family	n.s.	n.s.	+	-
	Multi-person household	- -	-	n.s.	-
	Ref.: Single-person household				
Year 2015	Ref: 2010	-	-	- - - - -	- -
Explained Variance (R^2) in %	Total	1.10	1.87	8.74	9.58
	Only built environment	0.09	1.30	3.98	1.81
	Only MT and SD	3.20	2.59	7.45	7.92

n.s.= not significant, Ref. = Reference category, Significance level of .05 (5%)

4.1. Effects on distance traveled by mode of transport per day (Figure 1)

Based on Variant 1 Models (including all categories of built environment, socio-demographics, and mobility tool ownership), we identify the following (see comparison of explained variance (R^2) in Figure 1). With regard to daily distance in total, we see that the model including only MT and SD (Variant 3) is the best (11.25% of explained variance). This indicates that MT and SD can handle the variance of distance travelled better without including variables of the built environment. However, if the models are differentiated according to mode, all Variant 1 Models have the highest shares of explained variance. Here we can assume the following: with regard to the models that are differentiated according to mode the built environments increase the share of explained variance, but the majority of the explained variation stems from MT and SD.

Thus, the built environment only serves to explain travel behavior if the focus lies on a differentiated perspective when mode of transport is taken into account. If doing so, the built environment is most relevant in explaining car travel and comes second after MT and SD. Here the built environment has relevant impacts on distance traveled by car. High population and employment densities, as well as good-quality local natural recreation, combined with good public transportation service quality in residential areas, reduces distance traveled by car. The added variance of the built environment in case of HPM and PT is of only limited importance.

If effect sizes are taken into account, the following can be observed. The built environment has a particularly minor impact on distance traveled by PT (Figure 1). Whereas population density at the place of residence reduces distance with PT, on the same level it will be increased by the employment density. With regard to HPM, high densities of population and employment and better local natural recreation in residential areas promote walking and cycling (positive effect on HPM distance). If the points of interest are further away, this reduces travel distance by HPM. The quality of public transportation is less important in terms of effect size in comparison to density measures.

The dimensions of MT and SD have a higher importance with regard to effect size for Car and PT, whereas the built environment is of higher importance for HPM than SD.

Car ownership and owning PT season tickets have strongly positive impacts on distance traveled by mode of transport per day. Those who own these mobility tools tend to travel longer distances (52.70 kilometers on average) than those who had no access to them (21.77 kilometers on average). Distance traveled by walking and cycling is influenced most strongly by ownership of mobility tools. While car ownership has negative impacts, bicycle ownership and PT season tickets have positive impacts on distance traveled by walking and cycling. Similarly, mobility tools have their strongest impacts on distance traveled by car. It is obvious that owning a car increases the distance traveled by car, whereas owning a bicycle and PT season tickets reduce that distance.

Sociodemographic factors have minor influences on distance traveled by walking and cycling: as mentioned above the built environment is of greater importance, whereas the ownership of mobility tools is most important. Men seem to travel longer distances in general than women, but they walk and cycle less, while young people travel longer distances than older people. Young people are likely to travel longer distances by PT than older people. Incomes and household structures also have positive impacts on trip lengths. People from low-income households travel shorter distances than those from high-income households. Family and multi-person households are less mobile than single-person households. Family and multi-person households prefer to travel by PT less in comparison with single-person households.

In general, the 2015 MCMT reports longer distances for cars and shorter ones for public transport.

The ranking of effects is thus that MT and SD are stronger than the built environment for total, car and PT. In the case of HPM the ranking is MT, BE followed by SD.

4.2. Effects on trip frequencies by mode of transport per day (Figure 2)

Based on Variant 1 Models (including all categories of built environment, socio-demographics, and mobility tool ownership), we identify the following overall effects if we compare with other variants (2 and 3). With regard to explained variance, the best models in case of trips in general and by HPM are based on MT and SD variables. Only in the case of car travel and PT does the built environment have added value with regard to explaining variance. The added variance if variables of the built environment are included in the models is highest in the case of car travel, followed by PT.

With regard to trips in general, the frequencies are influenced primarily by access to mobility tools and the sociodemographic characteristics of travelers and only secondarily by the built environment. The only significant effect for population density and local natural recreation can be observed: if the area is more densely populated and has a higher quality of natural recreation, people are more mobile in terms of trips. Again, ownership of mobility tools, together with sociodemographic characteristics, has greater explanatory power for trip frequencies than built environment factors. Since in total trip generation is quite a stable measure (three trips per day and person), the separation according to mode is more relevant for the analysis.

Concerning the built environment separated by mode, population density and point of interest have no significant impacts on trip frequencies by specific modes of transport. In contrast, employment density, local natural recreation, and public transportation do affect trip frequencies by specific modes of transport. A high employment density, attractive local natural recreation, and good-quality public transportation increase the number of trips by walking and cycling (HPM) but reduce the number of trips by car. The better the quality of public transportation the higher number of trips by PT, but more attractive local natural recreation reduces trip numbers by PT.

Mobility tools affect trip-generation both in general and for different modes of transport. Car availability increases trips in general and trips by car and decreases trips by all other modes (HPM/PT). If a bicycle is available, car trips will be reduced. Holders of a seasonal PT ticket make less trips by cars and HPM.

Younger people have more trips in general but likewise fewer with cars and more with PT. Low-income households have a higher number of trips using human-powered mobility. Families have more trips in cars in comparison to single-person households.

The ranking of effects is thus MT and SD is stronger than the built environment. The built environment dimension works best for explaining Car and PT travel. In these cases, the quality of public transportation has a stronger effect than the SD dimension.

4.3. Built environment: 95% confidence intervals on predicted impacts based on the Variant 1 models

To compare the effect size of the built environment, 95% confidence intervals on predicted impacts based on Variant 1-models were produced for metric measures and point estimates for categorical variables (public transportation quality). Based on these, the effects of the built environment on travel behavior can be simulated if all other effects from sociodemographics and mobility tool ownership are controlled for.

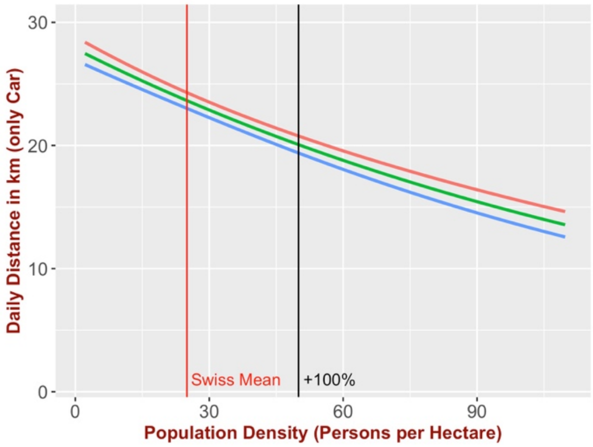
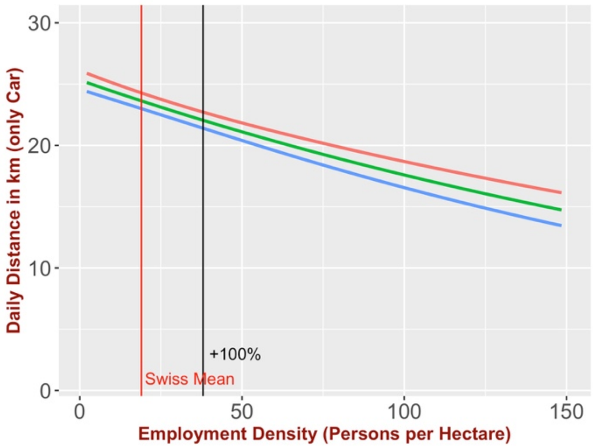
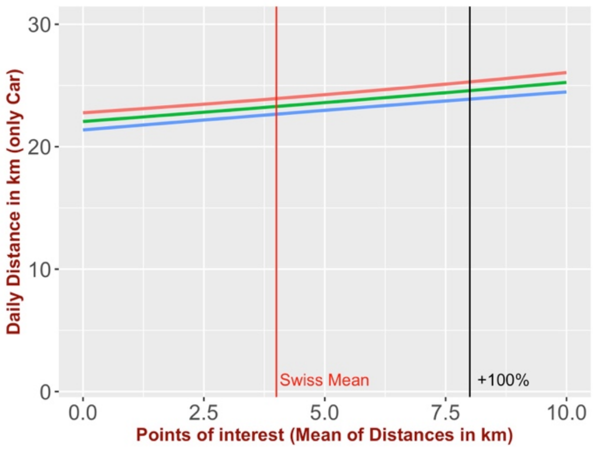
To compute these predicted values, all other explanatory variables in the model are held at their mean values (*ceteris paribus*).

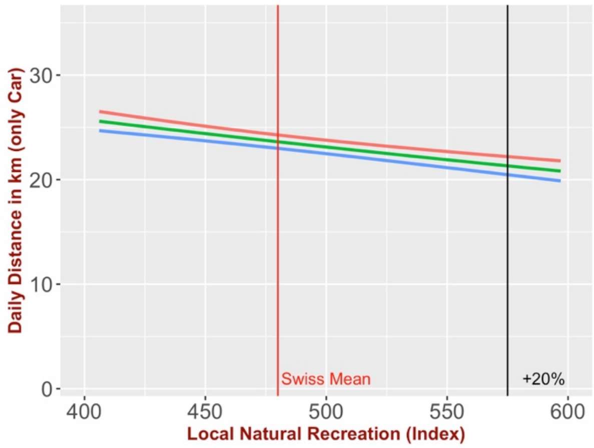
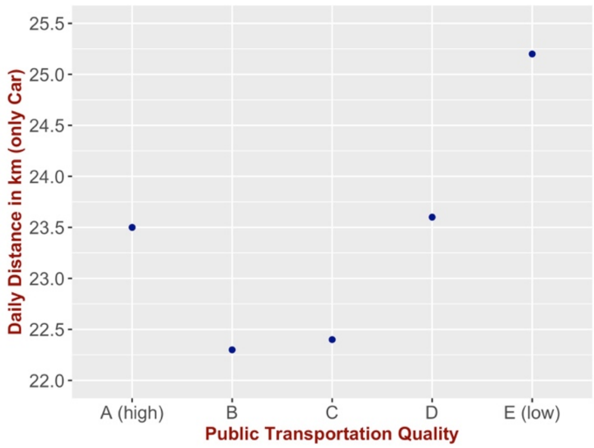
As it was observed that the built environment has the greatest effect in the case of motorized individual travel (car), predicted impacts will be presented for this case. We focus on distance travelled since it has the highest policy implications.

Based on the standardized beta coefficients (see the absolute value in brackets), one can rank the effects of the built environment as following: population density has the strongest effects (.10), followed by employment density (.07), distance to points of interest (.04), local natural recreation index (.028), and finally quality of public transportation (.027 B relative to E).

The influencing variables are ranked in Figure 3 in that order.

Figure 3. Predicted impacts based on variant 1-models of the built environment on daily distances by car (ranked from 1 to 5 according to effect strength)

Rank No.	Predicted impacts
1	
2	
3	

<table>
<tr><td>4</td><td>
</td></tr>
<tr><td>5</td><td>
</td></tr>
</table>

In Figure 3 the following can be observed. The higher the population density the less people travel daily distances by car. For example, if population density is doubled from 25 (the Swiss mean) to 50 persons per hectare, daily distance traveled by car is predicted to decrease by 16%, i.e. from 23.5 to 19.8 km per day.

Likewise, the higher the employment density at the place of residence the less people travel daily distances by car. In fact, if employment density is doubled from 19 (the Swiss mean) to 38 persons per hectare, daily distance traveled by car is predicted to decrease by 7%, i.e. from 23.6 to 22 km per day. The nearer that points of interest (e.g. bars, cinema) can be found (relative to the place of residence), the lower the distance by car a day. For example, if the mean distance to points of interest is doubled from 4 to 8 kilometers, daily distance traveled by car is predicted to increase by 11%, i.e. from 22.2 to 24.6 km per day. Furthermore, if in the near vicinity of the place of residence high-quality natural recreation (parks, forest, see) is provided, residents travel fewer kilometers daily by car. For example, if the index for local natural recreation increases by 20% from 480 (the Swiss mean) to 576, daily distance traveled by car is predicted to decrease by 9.4%, i.e. from 23.5 to 21.3 km per day. Finally, the effect of public transportation quality indicates a reduction in car travel. Lower distances can be found for the quality stages B and C (D is not significantly different from E). Interestingly, the highest public transportation quality A which is found in city centers is associated with higher distances by car than B and C (relative to E).

5. Discussion, Limitations, and Recommendations for Further Research

At the current state of the art, in order to explain travel behavior transportation research focuses on the following factors: socio-demographics, mobility tool ownership, attitudes and orientations, self-selection processes, and the built environment. The effect sizes of these factors vary from case to case. There is something of a consensus that the impact of the built environment on travel behavior is relatively small compared with the impact of other characteristics. In fact, it is the sociodemographic characteristics that seem to have the strongest effect on travel behavior, followed by attitudes and orientations (unmeasured variables; for an explanation, see van Wee, 2009, Mokhtarian and Cao, 2008), while the impact of the built environment on travel behavior is relatively small and becomes smaller if the self-selection processes are controlled for (Cao, Mokhtarian, and Handy, 2009).

In this strand of research, our study provides an extensive view of the effects of the built environment on travel behavior in the Swiss context by controlling for sociodemographics and mobility tool ownership. The results presented above provide urban planners and decision-makers with statistical evidence to anticipate the desired and unwanted impacts of their planning and policies regarding land use and transport systems on travel behavior. Against this background we can summarize our main findings as follows.

In line with other research, our finding is that sociodemographic and mobility tool ownership variables are the most important in explaining travel behavior in general, including age, household composition, income, gender, and car ownership (Curtis and Perkins, 2006). Based on the comparison of the various models, we observed that subsets modeled with fewer numbers of predictors (excluding the built environment dimension) have a higher explanation of variance. This is the case for three out of eight models that were presented, which are models representing trips and daily distance in total, and for the case of HPM trips.

For all other models, the built environment only plays a central role if the focus lies on mode of transport used. This is especially true for the case of car travel. The key findings reveal that all travel behavior outcomes are primarily influenced by mobility tool ownership and sociodemographic factors and are only secondarily influenced by the built environment. In comparison with previous studies, two of our regression models can explain very high percentages of explained variance in travel behavior outcomes for transportation studies (i.e., daily distance by PT=27% and daily distance by car=20%). The results prove that travel behavior draws multifaceted influences from different dimensions.

This finding incorporates policy implications in the sense that when it comes to changes in the built environment it is the effects on automobile travel that are the strongest. High population and employment density with good public transportation services, low distance to points of interests (bars, cinema, sports) and high-quality local recreation all reduce automobile travel. This result is not surprising but is very prevalent in the data. Thus, these results underpin recent activities in spatial planning by the Swiss government in order to reduce energy consumption triggered by motorized individual travel.

The limitations of the study are as follows.

The statistical analysis could not measure the impacts of residential self-selection for travel behavior because the Swiss National Transport Surveys do not include this information. As mentioned earlier in the literature review, the inconsistent empirical evidence of previous studies creates some doubts about whether the impact of the built environment is large enough to influence travel behavior if residential self-selection is controlled for in statistical analysis (Cao, 2014; Cao et al., 2009; Naess, 2014; Schwanen and Mokhtarian, 2005). In order to find out more about the effects of residential self-selection and the built environment, we suggest that information on residential self-selection should be incorporated into the next planned national surveys in Switzerland. By quantifying these effects, this could create new policy implications that could shift the focus from changes in infrastructure to supporting citizens' interests in an environment that enables a lifestyle (or even a city) of short distances in order to support sustainable mobility lifestyles. Last but not least, such insights could support the development of a combination of hard and soft factors in transport planning in order to reduce car travel.

Finally, it can be concluded that the results of empirical studies have demonstrated the ambivalent relationship between the built environment and travel behavior. Nevertheless, insights from these studies have contributed to the development of sophisticated models to predict travel behavior and behavioral changes in response to changes in the built environment and transport systems (Clifton and Handy, 2003). Likewise, van Wee, Holwerda, and van Baren (2002) indicate that settlement planning measures based on the presented empirical results still make natural sense. This is the case if the impact of the built environment is taken into account in transport policy, regardless of whether residential self-selection is represented in the modeling or not. This is not least because they give people who prefer sustainable means of transport the opportunity to choose their place of residence according to their preferences.

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Appendix

Table 4: Impacts of Built Environment, Mobility Tools and Sociodemography on Daily Distance

		Daily distance (total)			Daily distance by HPM			Daily distance by car			Daily distance by PT		
Variables		Coeff.	SE	t values	Coeff.	SE	t values	Coeff.	SE	t values	Coeff.	SE	t values
Intercept		2.880	0.076	37.665***	0.342	0.064	5.343***	2.186	0.094	23.141***	0.561	0.070	7.986***
Built Environment (BE)													
Population density	When more densely	-0.005	0.0003	-14.451***	0.002	0.0003	5.885***	-0.007	0.0004	-15.426***	-0.001	0.0003	-1.742†
Employment density	When more densely	-0.002	0.0002	-5.413***	0.001	0.0002	6.317***	-0.004	0.0004	-15.426***	-0.0004	0.0002	1.684†
Points of interests	When further away	0.009	0.001	7.155***	-0.003	0.001	-2.794**	0.014	0.002	8.250***	-0.0002	0.001	-0.143
Local natural recreation	When better	-0.001	0.0002	-4.166***	0.0004	0.0001	4.030***	-0.001	0.0002	8.250***	0.0002	0.0001	1.450
Public transportation	A	-0.042	0.022	-1.918†	-0.0001	0.018	-0.007	-0.0712	0.027	-2.632**	0.013	0.020	0.657
Ref.: E	B	-0.062	0.019	-3.265**	0.025	0.016	1.609	-0.124	0.023	-5.307***	0.043	0.017	2.452*
	C	-0.053	0.018	-2.879**	0.036	0.015	2.372*	-0.118	0.022	-5.251***	0.032	0.017	1.893†
	D	-0.020	0.017	-1.147	0.004	0.015	0.297	-0.018	0.022	-0.838	0.010	0.016	0.631
Mobility Tools (MT)													
Car availability	Yes	0.407	0.019	21.191***	-0.322	0.016	-19.963***	1.111	0.024	46.800***	-0.486	0.018	-27.547***
Bicycle availability	Yes	0.093	0.016	5.861***	0.333	0.013	25.167***	-0.185	0.019	-9.471***	0.115	0.015	7.962***
PT season tickets	Yes	0.258	0.014	18.859***	0.316	0.011	27.610***	-0.845	0.017	-49.937***	1.391	0.012	110.688***
Sociodemographic Characteristics (SD)													
Gender	Man	0.246	0.012	20.837***	-0.042	0.009	-4.268***	0.263	0.015	18.011***	0.005	0.011	0.440
Age	Up to 17	0.579	0.069	8.354***	-0.067	0.058	-1.146	0.544	0.086	6.343***	0.357	0.064	5.604***
Ref.: 65+	18-35	0.506	0.033	15.394***	-0.117	0.027	-4.237***	0.432	0.041	10.624***	0.275	0.030	9.114***
	36-64	0.285	0.032	8.996***	-0.031	0.026	-1.165	0.236	0.039	6.037***	0.099	0.029	3.421***
Household (HH) income (CHF)	≤ 4,000	-0.478	0.024	-19.893***	-0.055	0.020	-2.750**	-0.431	0.029	-14.496***	-0.168	0.022	-7.598***
Ref.: above 10,000	> 4,000 to 10,000	-0.213	0.013	-16.234***	-0.035	0.011	-3.194**	-0.153	0.016	-9.457***	-0.128	0.012	-10.662***
HH structure	Family	-0.216	0.017	-13.045***	-0.055	0.014	-3.961	-0.076	0.20	-3.729***	-0.167	0.015	-10.977***
Ref. Single-person HH	Multi-person HH	-0.153	0.018	-8.620***	-0.007	0.015	-0.465	-0.096	0.022	-4.404***	-0.084	0.016	-5.149***
Year 2015, Ref. 2010	Yes	0.001	0.012	0.086	0.012	0.010	1.206	0.064	0.015	4.257	-0.081	0.011	-7.231***
Explained Variance	Total	7.01			5.78			19.66			26.58		
(R^2) in %	Only BE	2.51			1.60			7.10			1.25		
	Only MT and SD	11.25			3.82			18.04			22.72		

Coeff. Coefficient, SE standard error, MT mobility tools, SD socio-demographic, PT Public Transport

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.1$

Table 5: Impacts of Built Environment, Mobility Tools and Sociodemography on Trip Frequency

		Trip frequency (total)			**Trip frequency by HPM**			**Trip frequency by car**			**Trip frequency by PT**		
Variables		Coeff.	SE	t values	Coeff.	SE	t values	Coeff.	SE	t values	Coeff.	SE	t values
Intercept		1.039	3.134	33.160***	2.093	3.233	6.474***	6.736	3.658	18.415***	2.374	1.863	12.741***
Built Environment (BE)													
Population density	When more densely	4.699	1.411	3.332***	5.309	1.455	0.365	-3.978	1.646	-0.242	1.276	8.386	1.521
Employment density	When more densely	1.403	1.142	1.229	1.014	1.178	8.610***	-8.427	1.333	-6.321***	7.396	6.791	1.089
Points of interest	When further away	7.298	5.434	1.34	1.945	5.606	0.347	-6.818	6.343	-1.075	7.991	3.231	0.247
Local natural recreation	When better	2.233	5.378	4.152***	3.879	5.547	6.993***	-1.186	6.277	-1.890†	-1.641	3.197	-5.133***
Public transportation	A	6.262	8.891	0.070	1.060	9.264	11.439***	-1.755	1.048	-16.741***	7.073	5.340	13.244***
Ref.: E	B	3.761	7.753	0.485	7.090	7.997	8.866***	-1.115	9.050	-12.326***	4.822	4.610	10.461***
	C	-3.859	7.476	-0.516	5.378	7.711	6.974***	-7.777	8.726	-8.913***	2.610	4.445	5.872***
	D	-3.561	7.248	-0.491	2.883	7.476	3.857***	-3.780	8.460	-4.469***	4.765	4.309	1.106
Mobility Tools (MT)													
Car availability	Yes	8.821	7.877	11.198***	-8.924	8.125	-10.983***	2.455	9.194	26.706***	-8.183	4.683	-17.473***
Bicycle availability	Yes	5.946	6.471	9.188***	5.194	6.675	7.780***	-2.160	7.554	-2.860**	5.741	3.848	0.149
PT season tickets	Yes	-4.188	5.608	-7.468***	-2.341	5.785	-4.047***	-1.864	6.546	-28.473***	1.711	3.335	51.319***
Sociodemographic Characteristics (SD)													
Gender	Man	-5.071	4.839	-1.048	-2.561	4.991	-5.131***	3.676	5.648	6.509***	-6.458	2.877	-2.244*
Age	Up to 17	1.398	2.843	4.919***	4.414	2.932	1.505	-5.545	3.318	-1.671†	1.629	1.690	9.638***
Ref.: 65+	18-35	3.157	1.348	2.342*	-4.219	1.390	-3.034**	4.655	1.573	2.959**	2.035	8.015	2.540*
	36-64	1.581	1.298	1.217	-2.001	1.339	-1.494	3.540	1.516	2.336*	4.489	7.720	0.581
Household (HH) income	≤ 4,000	-4.768	9.854	-4.839***	2.035	1.016	2.002*	-4.306	1.150	-3.744***	-9.734	5.859	-1.661†
(CHF)	> 4,000 to 10,000	-8.051	5.377	-1.497	8.592	5.546	1.549	-6.525	6.276	-1.040	-5.250	3.197	-1.642
Ref.: above 10,000													
HH structure	Family	9.660	6.800	1.421	-1.467	7.014	-0.209	2.951	7.937	3.718***	-1.955	4.043	-4.835***
Ref.: Single-person HH	Multi-person HH	-4.839	7.258	-6.667***	-1.705	7.486	-2.227*	-1.303	8.472	-0.154	-1.710	4.315	-3.963***
Year 2015, Ref: 2010	Yes	-2.592	4.978	-5.207***	-2.038	5.134	-3.968***	-1.850	5.810	-31.846***	-3.031	2.960	-10.242***
Explained Variance	Total	1.10			1.87			8.74			9.58		
(R^2) in %	Only spatial structure	0.09			1.30			3.98			1.81		
	Only MT and SD	3.20			2.59			7.45			7.92		

Coeff. Coefficient, SE standard error, MT mobility tools, SD socio-demographic, PT Public Transport

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.1$