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Michael Simora and Colin Vance[1]

Travel Mode and Tour Complexity: The Roles of Fuel Price and Built Environment

Abstract

Despite steady increases in fuel economy, CO2 emissions from road transportation in Germany are on the rise, increasing by nearly 4% since 2009. This study analyzes the impact of different policy levers for bucking this trend, focusing specifically on the role of fuel prices and features of the built environment. We estimate two multinomial logit models, one addressing work-related tours and the other non-work related tours. Both models consider two interrelated dimensions of travel on the extensive margin: mode choice and tour complexity. We use the model estimates to predict outcome probabilities for different levels of our policy variables. Our results suggest significant effects of the built environment – measured by bike path density, urbanization, and proximity to public transit – in discouraging car use and increasing tour complexity. Fuel prices, by contrast, appear to have little bearing on these choices.

JEL Classification: D10, R48, R42

Keywords: Activity-based approach; travel mode choice; tour complexity; multinomial logit; predicted probabilities

September 2017

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1 Introduction

The transportation sector has emerged as a seemingly intractable obstacle to Germany's success in reducing CO_2 emissions. While the country's overall CO_2 emissions decreased by 27% between 1990 and 2014, emissions in transportation are on the rise. To buck this trend, legislation was introduced by the European Commission in 2009 that limits the average emissions of new cars to 130g CO_2/kilometer by 2015 and 95g CO_2/kilometer by 2020 (European Commission, 2009). On its face, the legislation has been effective: Between 2009 and 2014, the per kilometer CO_2 discharge of new cars in Germany decreased by about 14%, from 154.0 to 132.5g CO_2 /kilometer (European Environment Agency, 2017). Over the same interval, however, overall emissions from road transportation in Germany increased by nearly 4%, from approximately 156 to 162 million tons (Umweltbundesamt, 2016).

One explanation for these opposing trends is a rising travel demand. Between 2005 and 2014, the mileage of German drivers steadily increased from 875.7 to 935 billion kilometers (Bundesministerium für Verkehr und digitale Infrastruktur, 2016). Various factors have contributed to this increase, one being that the real per kilometer costs of driving decreased due to improved fuel economy and a stagnation in the level of the ecotax on fuel, which has been set at 0.65 cent per liter for petrol and 0.45 cents per liter for diesel since 2003. Higher fuel taxes is therefore one of the debated policy options to decrease emissions, as taxes directly confront motorists with the costs of driving. Several studies by Frondel and colleagues (Frondel and Vance, 2009, 2014, 2017) using household data from Germany support this tact, estimating fuel price elasticities for German drivers to be on the order of 60%. Other studies, however, have found substantially lower responsiveness to the cost of driving, calling into question the effectiveness of fuel taxation as an instrument to reduce emissions (De Borger et al., 2016; Gillingham et al., 2016; Goodwin et al., 2004; Ritter et al., 2016; Small and Van Dender, 2007).

These discrepancies raise the question of what policy levers can be availed to discourage automobile dependency. Drawing on data set stemming from 16 years of individual travel data in Germany, the present paper addresses this issue by presenting results from two multinomial logit models, one addressing work-related tours and the other non-work related tours. Both models consider two interrelated dimensions of travel on the extensive margin: mode choice and tour complexity. Specifically, the models distinguish four distinct combinations of tour choices according to whether the car is used and whether the tour is simple or complex, with simple tours being those without intermediate stops. The model includes a rich array of explanatory variables, many of which, including fuel prices, the accessibility of public transit and bike path density, have immediate relevance for policy, but have rarely been parametrized using household data. In a second step, we move beyond the standard focus on the magnitude and significance of the parameter estimates to consider their implications for predicted outcomes. To this end, we employ a Monte Carlo simulation technique proposed by King et al. (2000) to explore the predictions of the model and the associated degrees of uncertainty.

Among our main results, we find significant effects of the built environment – measured by bike path density, urbanization, and proximity to public transit – in discouraging car use and increasing tour complexity. Fuel prices, by contrast, appear to have little bearing on these discrete choices, notwithstanding the high fuel price elasticities that have been estimated for German drivers (Keller and Vance, 2013; Frondel and Vance, 2017). Taken together, these results suggest that the extension of transit infrastructure and increased building density hold promise for discouraging car use.

The paper is organized as follows. In Section 2 we describe the data set, derive the dependent variable of our model, and introduce the control variables. Section 3 shortly reviews the multinomial logit model. In Section 4 we first show regression results, followed by the prediction of outcome probabilities. Finally, Section 5 summarizes and concludes.

2 Data

The data is drawn from the German Mobility Panel (MOP, 2015) and covers sixteen years, spanning 1999 through 2014. Participating individuals are surveyed upwards of three consecutive years for a period of one week. During this week, they fill out a drivers's logbook documenting their travel behavior, including each trip taken, its purpose, mode, duration, and several other features. In addition, the survey collects sociodemographic information on the individual and household. A total of 13,500 individuals are observed for an average of 16 tours over the three-year survey period, yielding a total sample size of approximately 220,000 observations.

2.1 The dependent variable

Following Ben-Akiva and Bowman (1998) as well as Shiftan et al. (2003), who argue that a tour-based approach is best suited for disaggregate travel demand modeling when analyzing the influence of built environment, we define our dependent variable with reference to home-based tours that occur over the five-day work week. While many studies focus exclusively on work tours (De Palma and Rochat, 1999; Kingham et al., 2001; Krygsman et al., 2007; Rodrìguez and Joo, 2004), we also analyze non-work related travel, since it considerably contributes to traffic and hence, emissions (Bhat, 1997). A tour is considered to be work related as soon as at least one trip of the tour includes the workplace. Hence, work related tours might incorporate several non-work related stops. Conversely, we define non-work tours to include any stops other than work. As work related tours are different from non-work related tours in the sense that they are non-discretionary and repeatedly undertaken, we model these tour types separately using two multinomial logit estimators.

Two dimensions are considered in our models. First, we distinguish the travel mode between car and no car. The latter includes walking, cycling and all modes of public transit, while the former incorporates all modes of private motorized travel, including rides as a passenger. Second, we distinguish between simple and complex tours. Following Strathman and Dueker (1990), we define a tour to be complex if it consists of more than two trips. For example, a tour from home to work and back is considered a simple tour. If the individual adds at least one intermediate stop, the tour becomes complex. Conducting one complex tour instead of several simple ones, i.e. engaging in trip chaining, is an alternative strategy to reduce car usage.

The two dimensions – mode and complexity – result in four distinct options whose shares are presented in Table 1. Note that because we exclude individuals who do not have access to a car as well as individuals who are not working, the presented shares are not intended to be representative of German travel mode choices. Unsurprisingly, complex non-car tours are the least favored option in both cases. It has been found in previous studies that the complexity of tours is negatively correlated with the propensity to use non-car options, since stops would need to be in proximity of each other (Hensher and Reyes, 2000; Krygsman et al., 2007; Strathman and Dueker, 1990).

Table 1: Different tour options and their sample shares

Option	Description	Share (in %)
WCS	Work + Car + Simple	34.8
WCC	Work + Car + Complex	47.0
WNS	Work + NoCar + Simple	11.8
WNC	Work + NoCar + Complex	6.4
	N	123,436

Option	Description	Share (in %)
NCS	NonWork + Car + Simple	46.9
NCC	NonWork + Car + Complex	25.6
NNS	NonWork + NoCar + Simple	23.7
NNC	NonWork + NoCar + Complex	3.8
	N	94,488

2.2 The explanatory variables

In assembling the explanatory variables presented in Table 2, we augmented the MOP with various external data sources to allow investigation of policy-relevant variables like fuel prices and features of the built environment. Fuel prices are obtained from the website of *Aral*, one of Germany's largest gasoline retailers, which publishes nominal fuel prices by month dating back to 1999. The nominal fuel prices are converted into real values using a consumer price index from Germany's Federal Ministry of Statistics.

Three variables of built environment are used, one of which is derived from a shapefile of bike paths in Germany gathered from *OpenStreetMap.org* (OpenStreetMap, 2017). Using a Geographical Information System (GIS), we intersected this layer with another shapefile of German counties from the year 2005, at which time there were 439 counties having an average size of 814 square kilometers. The resulting intersected shapefile allows us to calculate the total length of bike paths

Table 2: Descriptive statistics of explanatory variables

Variable	Explanation	Mean	Std.Dev.
female	Dummy: 1 if respondent is female	0.526	
age	Age of respondent	44.98	10.18
fulltime	Dummy: 1 if respondent works fulltime	0.656	
numemployed	Number of employed persons in household	1.73	0.59
kids09	Dummy: 1 if kids between 0 and 9 years live in household	0.198	
kids1017	Dummy: 1 if kids between 10 and 17 years live in household	0.280	
middle	Dummy: 1 if middle income household (i.e. 1,500 - 3,500 EUR per month)	0.510	
wealthy	Dummy: 1 if wealthy income household (i.e. ¿ 3,500 EUR per month)	0.423	
lackofcars	Dummy: 1 if number of cars in household is smaller than number of drivers	0.368	
distancework	Distance to work for respondent (in km)	13.03	17.86
rain	Dummy: 1 if rain fell on day of travel	0.495	
temperature	Mean temperature on day of travel	10.59	4.11
petrol	Real petrol price in Cents (monthly average)	134.30	14.64
minutes	Minutes to walk to nearest bus, tram or train station from respondent's home	5.45	4.62
bikepathdens	Bikepath density in respondent's county	0.169	0.161
urbanization	Share of urbanized area in respondent's county	0.195	0.193
1999	Dummy: 1 if year=1999	0.065	
2000	Dummy: 1 if year=2000	0.054	
2001	Dummy: 1 if year=2001	0.072	
2002	Dummy: 1 if year=2002	0.057	
2003	Dummy: 1 if year=2003	0.068	
2004	Dummy: 1 if year=2004	0.060	
2005	Dummy: 1 if year=2005	0.060	
2006	Dummy: 1 if year=2006	0.053	
2007	Dummy: 1 if year=2007	0.053	
2008	Dummy: 1 if year=2008	0.060	
2009	Dummy: 1 if year=2009	0.051	
2010	Dummy: 1 if year=2010	0.055	
2011	Dummy: 1 if year=2011	0.055	
2012	Dummy: 1 if year=2012	0.062	
2013	Dummy: 1 if year=2013	0.086	
2014	Dummy: 1 if year=2014	0.090	

in each county. Dividing this by the total area yields a measure of bike path density. Bhat et al. (2009) find a positive effect of a higher bike path density on opting for non-motorized travel alternatives, though not distinguishing between work and non-work related activities. On the contrary, Kingham et al. (2001) as well as Rodrìguez and Joo (2004) do not detect a significant effect, ascribing their finding to long commute distances precluding an influence of bike paths. However, these two studies focused solely on work commute, leaving open the possibility that more bike paths lead to a more frequent use of this mode for recreational, thus non-work related, travel.

The second metric capturing the built environment measures the extent of urbanized area, which was derived in a similar manner using the Corine Land Cover satellite imagery obtained from the website of the European Environmental Agency. The imagery distinguishes 26 land cover classes in raster format at a resolution of 100 $\times$ 100 meters, and is available for the years 2000 and 2006. We added up the area classified as artificial surfaces (e.g. urban fabric, industrial and transport units) within each county to obtain the square kilometers of urbanized area, and divided this by the total size of the county to obtain the urban share. We assigned the 2000 value of urban area to the years 1999 through 2005, and the 2006 value to the subsequent years. Previous studies have found that a higher degree of urbanization fosters tour complexity (Scheiner and Holz-Rau, 2017; Strathman and Dueker, 1990) as well as non-motorized travel (Frank et al., 2008; Zhang, 2004).

The remaining variable measuring the built environment is directly recorded in the MOP and measures the time in minutes to walk from a respondent's home to the nearest bus, tram or train station. We expect a closer proximity to decrease the probability of those options that include the car as a travel mode.

For the variables of the built environment we might face endogeneity issues, as individuals with less inclination to drive may select into regions with a higher degree of urbanization and better public transit. While endogeneity cannot be completely ruled out, we follow the argumentation of Naess (2014) (p. 75), who notes that this residential self-selection is "unlikely to represent any great source of error ... if traditional demographic and socioeconomic variables have already been accounted for." Consequently, a suite of sociodemographic control variables is incorporated into our analysis. These include the individual's age, gender, and employment status as well as the proximity of the workplace. They also comprise household level dummy variables indicating the presence of (young) children, the income level, and whether the number of licensed drivers is greater than the number of cars. These variables have been shown to significantly influence travel behavior in previous studies (Bhat, 1997; Bhat et al., 2009; Hensher and Reyes, 2000; Kuhnimhof et al., 2006; Scheiner and Holz-Rau, 2017) . Furthermore, we include a measure of the mean temperature on the day of travel and a dummy indicating whether it rained, as De Palma and Rochat (1999) found adverse weather conditions to lead to more car usage. The specification is completed by year dummies to account for changes in travel behavior over time.

3 Methodology

As our dependent variable is nominal without natural ordering, we make use of the multinomial logit model (MNLM). This section shortly reviews this approach.[1]

Let $J = \{1, ..., 4\}$ denote the set of tour options individuals can choose from. Assuming a standard random utility model (RUM), the utility for individual i from option $j \in J$ is given by:

$$U_{ij} = V_{ij} + \epsilon_{ij}. \tag{1}$$

Here, ϵ_{ij} is the unobserved error term and V_{ij} is the observed indirect utility, for which

[1] For more details see Long & Freese (2006) for estimation implementation. Furthermore, note that using a nested logit approach is precluded due to a lack of option specific variables such as travel cost or time.

we assume a linear functional form depending on observed characteristics x_i:

$$V_{ij} = \beta_j^T x_i. \tag{2}$$

x_i comprises fuel price, the variables measuring built environment, sociodemographic and household characteristics, and year dummies. β_j are the coefficients to be estimated with superscript T denoting the transposition of a vector. As individual i chooses option j if its utility is highest from this option, the probability of choosing option j can be written as:

$$P_{ij} = Pr(U_{ij} > U_{ik}) = Pr(\epsilon_{ik} - \epsilon_{ij} < V_{ij} - V_{ik}),\ \forall k = 1, ..., 4,\ k \neq j \tag{3}$$

If we further assume that the differences in the error terms $(\epsilon_{ik} - \epsilon_{ij})$ follow a logistic distribution, we derive the *multinomial logit model* by rewriting equation 3 as:

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_{k=1}^{4} e^{V_{ik}}} = \frac{e^{\beta_j^T x_i}}{\sum_{k=1}^{4} e^{\beta_k^T x_i}}. \tag{4}$$

From equation 4 it directly follows that the odds between two options just depend on the parameters of these two options:

$$\frac{P_{ij}}{P_{ik}} = e^{(\beta_j - \beta_k)^T x_i}, \tag{5}$$

which poses a potential shortcoming of the model, known as the independence of irrelevant alternatives (IIA) assumption. That is, the choice between two alternative outcomes is unaffected by what other choices are available. While the IIA assumption is in some contexts restrictive, particularly when relevant options have been omitted from the definition of the choice set, there are two reasons why it is deemed to be relatively innocuous for the current application. First, as advocated by McFadden

(1973) and reiterated by Long and Freese (2006), the multinomal logit model is appropriate when the choice categories are clearly distinct and not substitutes for one another, a condition that can reasonably be said to apply to the choice between our different travel options. Second, verification is provided by a Hausman testas well as a Small-Hsiao test, both support the IIA assumption for our data.

To facilitate the interpretation of selected results from the model, the predicted probabilities and associated 95% confidence intervals for particular variables of interest are plotted, using a statistical simulation method described in King et al. (2000) and Tomz et al. (2003). Recognizing that the parameter estimates from a maximum likelihood model are asymptotically normal, the method uses a sampling procedure akin to Monte Carlo simulation in which a large number of values – say 1,000 – of each estimated parameter are drawn from a multivariate normal distribution. Taking the vector of coefficient estimates from the model as the mean of the normal distribution and the variance-covariance matrix as the variance, the simulated parameter estimates can be used to calculate predicted values and the associated degree of uncertainty. In generating the predictions, all explanatory variables except the one of interest are held constant at their sample mean while the value of the variable under scrutiny is varied.

4 Results

4.1 Estimates

Table 3 illustrates the effects of our variables of interest on travel behavior for work related tours while Table 4 presents key results for non-work related tours. Results for the further controls can be found in Tables X and Y in the Appendix. Note that during a given day an individual might conduct several tours, which leads to nonindependent observations. To account for this, we cluster standard errors on the person level.

To ease interpretation, the discussion focuses on odds ratios for the different combinations of options. Broadly speaking, an odds ratio bigger than one indicates a preference for the first of the compared options if the independent variable under scrutiny increases. Correspondingly, an odds ratio smaller than one indicates a preference for the second option.

Table 3: Option odds from MNLM for work related tours

	WCS/WCC	WCS/WNS	WCS/WNC	WCC/WNS	WCC/WNC	WNS/WNC
minutes	1.007	1.026**	1.020*	1.019	1.013	0.994
bikepathdens	0.874	0.851**	0.548**	0.974	0.627**	0.644**
urbanization	0.621**	0.457**	0.095**	0.736	0.154**	0.209**
petrol	1.003	0.995	0.983	0.992	0.980	0.988
N	117,038					

WCS=Work+Car+Simple; WCC=Work+Car+Complex; WNS=Work+NoCar+Simple; WNC=Work+NoCar+Complex.
*** and * denote statistical significance at the 1 % and 5 % level, respectively.*
Further controls as well as year dummies are included, though not depicted.

Results reveal that increasing remoteness of the nearest public transit station, measured by *minutes*, increases the odds that an individual conducts simple car tours for work-related travel. The magnitude of the statistically significant estimates for *minutes*, however, are relatively modest. For example, each minute increase in the walking distance to the public transit is seen to increase the odds of using the car for a simple tour relative to some other mode by just 2.6%. A similar magnitude of 2% is seen for the comparison of a simple car tour relative to a complex non-car tour. Thus, a better connection of the respondent's place of residence to the public transit network is associated with a somewhat higher propensity to refrain from car usage for work related tours.

The results further reveal a strong tendency towards non-car travel given a higher density of bike paths in the respondent's county of residence. Both simple as well as complex tours without the car are preferred over simple car tours. Moreover, there seems to be a preference of complex tours conducted with non-car modes in areas with a high density of bike paths. This would suggest that if bike paths were extended, more individuals would refrain from car usage and chain more trips together on their work commute. We also find strong effects of the degree of urbanization: Respondents who live in urban areas are less likely to use their car for work-related tours. Additionally, those individuals more frequently combine trips to complex tours, especially when traveling without car, which might be explained by a higher density of places of interest in urban areas.

Last, we see no evidence that the fuel price has an effect on the discrete travel choices pertaining to work-related tours. We neither find a tendency to refrain from car usage given high fuel prices, nor a tendency to chain trips together. One explanation for this result is the model's focus on work travel, which is typically non-discretionary and hence less responsive to changes in fuel costs.

Table 4: Option odds from MNLM for non-work related tours

	NCS/NCC	NCS/NNS	NCS/NNC	NCC/NNS	NCC/NNC	NNS/NNC
minutes	1.007	1.027**	1.056**	1.019*	1.048**	1.028**
bikepathdens	0.933	0.923**	0.549**	0.989	0.588**	0.594**
urbanization	0.620**	0.391**	0.175**	0.631*	0.282**	0.447**
petrol	0.992	0.996**	1.000	1.004	1.008	1.004
N	76,570					

NCS=NonWork+Car+Simple; NCC=NonWork+Car+Complex; NNS=NonWork+NoCar+Simple; NNC=NonWork+NoCar+Complex.
*** and * denote statistical significance at the 1 % and 5 % level, respectively.*
Further controls as well as year dummies are included, though not depicted.

Table 4 depicts the odds ratios for non-work related tours. Overall, the results portray a similar pattern as that seen for work related travel. The walking distance to the nearest transit stop, bike path density, and urban residency all encourage non-car modes of transportation. In the case of the latter two variables, there is also evidence for increased complexity of travel. One discrepancy relative to work tours is seen for the petrol price, which now registers a significant effect on the odds of car use for simple tours relative to other modes. Nevertheless, the magnitude of the effect is relatively small: each cent increase in the petrol price reduces the odds of using the car by roughly 0.04%.

4.2 Predicted Probabilities

As the proliferation of estimates produced by the MNLM complicates the interpretation of the results, we illustrate the impact of our key variables of interest in this section by showing predicted probabilities for each travel option using the method of King et al. (2000).

Results for work related tours are depicted in Figure 1. We focus on the three variables capturing the built environment. Notwithstanding the statistically significant odds ratios estimated for these variables, their bearing on the predicted probabilities is in many cases marginal. This is especially evident for the case of bike path density, where the curves corresponding to each choice combination are seen to be relatively flat.

Across the graphs, the highest probability, at about 0.47, is seen for the option combining car travel with complex tours. Again, however, the flat trajectory of the curve suggests that this is also the option that is least responsive to changes in the explanatory variables. The next most probable option is given by the combination of car use with simple tours. The probability of this option is seen to increase with increasing minutes to the nearest transit stop and to decrease with a higher share of urbanized area in the county of residence.

Non-car modes for work commute are the two least probable options. For complex tours, the probability increases markedly with a higher share of urbanized area, more than doubling from a low of about 0.05 to a high of 0.13 when the urban share reaches

Figure 1: Predicted probabilities for work related tour options depending on variables of the built environment

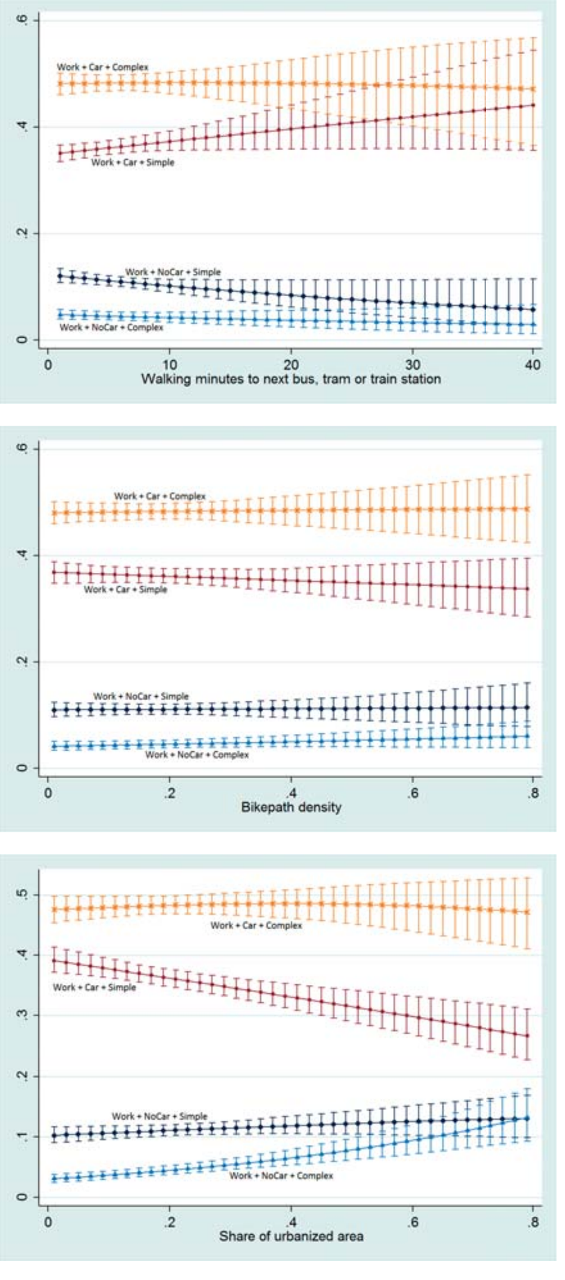
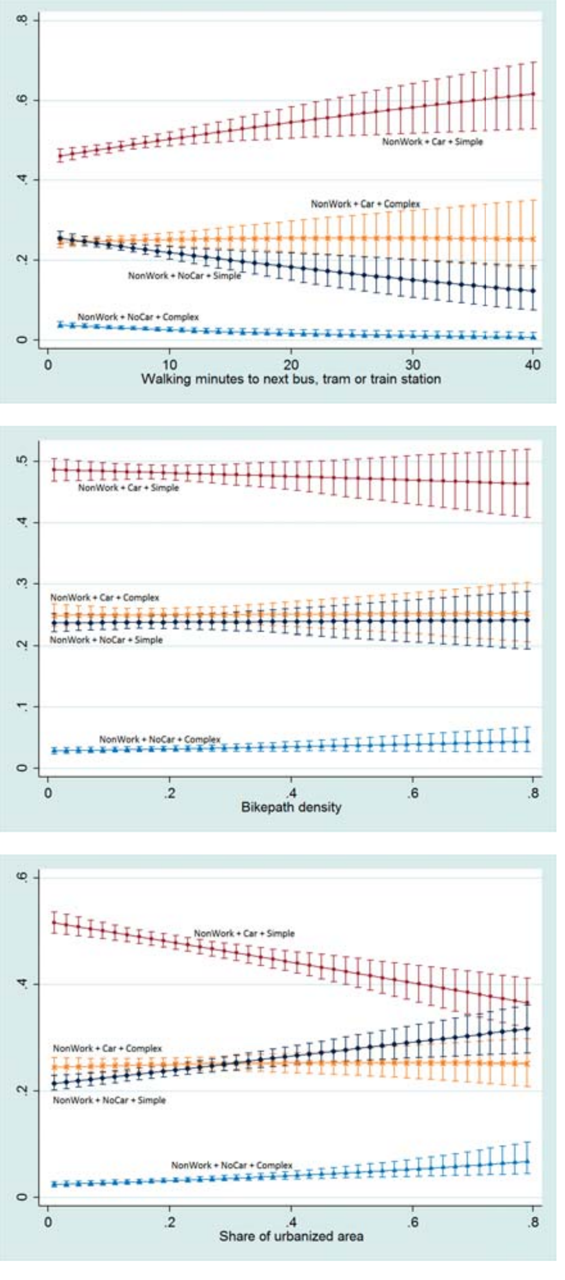


Figure 2: Predicted probabilities for non-work related tour options depending on variables of the built environment



0.8. Likewise, simple non-car tours respond strongly to public transit proximity, being more likely when the station is nearby.

Figure 2 depicts predicted probabilities for non-work related tours. The most probable option is now the one combining car travel with simple tours, indicating that trip chaining is less likely when work stops are not part of the tour. This option appears relatively responsive to changes in walking minutes to public transit and the share of urban area, increasing with the former and decreasing with the latter. Likewise, non-car simple tours are responsive to these two variables, in this case decreasing with the former and increasing with the latter. It is also notable that the probability of non-car simple tours, which ranges between nearly 0.2 and 0.3, is roughly twice that of the corresponding probability for work-related travel.

Regarding bike path density, we again observe discrepancies between the statistically significant regression results and a relatively flat pattern of the predicted probabilities (middle chart). Taken together, we conclude that an increase in bike paths has little bearing on travel probabilities relating to work and non-work purposes.

5 Conclusion

Using a large data set stemming from 16 years of a household travel diary panel, this paper has analyzed the roles of the fuel price and the built environment on work and non-work related tours. To this end, we first estimated a multinomial logit model that considered mode and the complexity of travel, two decisions that interrelate with each other and thus should be scrutinized jointly (Bhat, 1997; Feng et al., 2013; Krygsman et al., 2007). In a second step we estimated outcome probabilities for different levels of our policy levers.

Several findings emerge. First, for work related tours, we find no evidence for an effect of fuel prices on the discrete choice pertaining to mode and tour complexity.

This result may be partially explained by the fact that such tours are for the most part non-discretionary and hence less likely to be subject to changes in fuel costs. For non-work travel, we find slight evidence for an effect of the fuel price, decreasing the odds that the car is used for simple tours. Overall there seems to be limited response of individuals to fuel price changes with respect to discrete work-related travel decisions. This may owe to the possibility that individuals react via investing in more fuel efficient vehicles if fuel prices continue to increase (Bhat et al., 2009; Feng et al., 2013; Goodwin et al., 2004).

Regarding features of the built environment, we find a statistically significant but modest effect of a higher bike path density in the respondent's county. Although regression results suggest a tendency towards non-car travel with more bike paths being available, the predicted probabilities reveal little decrease in car usage. Thus, making bike use more practicable seems to foster only a muted effect on non-motorized travel. This might be ascribed to long commute distances or inconveniences in e.g. shopping with bike.

By contrast, we observe a significant impact of public transit proximity on discouraging car use for simple tours. This effect is more pronounced for non-work related travel than for work commute. In line with previous studies, we conclude that extending public transit is the most promising approach to discourage car use (De Palma and Rochat, 1999; Frank et al., 2008; Gärling and Schuitema, 2007; Kingham et al., 2001). Results from Weis et al. (2010) moreover suggest that price elasticities for public transit are higher than for car use, especially for leisure trips. Consequently, subsidizing public transit should lead to stronger reactions than increasing fuel prices. If public transit can compete better with car usage in terms of comfort and price, individuals might switch.

However, certain barriers remain. For commuters, the distance to work still is an important obstacle for refraining from car usage (Gorham et al., 2002; Kingham et al., 2001). Furthermore, for some users driving their own car is still a matter of social status, while there is a stigma associated with the use of public transit (Aarts and Dijksterhuis, 2000; Gärling and Schuitema, 2007; Gorham et al., 2002; Jensen, 1999). Nevertheless, the evidence in this and other studies (Bamberg et al., 2003; Kingham et al., 2001) shows that individuals react to infrastructure improvements making public transit more convenient. In particular, young adults, who have not built up strong travel habits yet, have been found to be willing to change to other modes of transport than car (Kuhnimhof et al., 2012).

Future research should address the impact of neighborhood compacts as well as of information and feedback about the environmental friendliness of travel habits as these have been found to change travel behavior in other studies (Rose and Ampt, 2001; Taylor and Ampt, 2003).

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Appendix

Table A1: Option odds from MNLM for work related tours: Full Model

	WCS/WCC	WCS/WNS	WCS/WNC	WCC/WNS	WCC/WNC	WNS/WNC
minutes	1.007	1.026**	1.020*	1.019	1.013	0.994
bikepathdens	0.874	0.851**	0.548**	0.974	0.627**	0.644**
urbanization	0.621**	0.457**	0.095**	0.736	0.154**	0.209**
petrol	1.003	0.995	0.983	0.992	0.980	0.988
female	0.744**	0.820	0.549**	1.102	0.738**	0.670
age	1.008**	0.997	1.013	0.989	1.005	1.016
fulltime	0.907	1.189**	0.859	1.311**	0.947	0.722**
numemployed	1.173**	1.205*	1.464**	1.028	1.248**	1.215*
kids09	0.735**	0.913	0.732*	1.242*	0.997	0.803
kids1017	1.139*	1.112	1.378**	0.976	1.210	1.239
middle	0.778**	1.019	0.949	1.310*	1.220	0.931
wealthy	0.592**	0.983	0.637**	1.661**	1.075	0.647*
lackofcars	1.189**	0.347**	0.358**	0.292**	0.301**	1.031
distancework	1.007**	1.021	1.058	1.013	1.050	1.036
rain	0.989	0.984	1.072	0.995	1.085	1.090
temperature	0.998	1.006	1.011	1.008	1.012	1.004
N	117,038					

WCS=Work+Car+Simple; WCC=Work+Car+Complex; WNS=Work+NoCar+Simple; WNC=Work+NoCar+Complex.
*** and * denote statistical significance at the 1 % and 5 % level, respectively.*
Year dummies are included, though not depicted.

Table A2: Option odds from MNLM for non-work related tours: Full Model

	NCS/NCC	NCS/NNS	NCS/NNC	NCC/NNS	NCC/NNC	NNS/NNC
minutes	1.007	1.027**	1.056**	1.019*	1.048**	1.028**
bikepathdens	0.933	0.923**	0.549**	0.989	0.588**	0.594**
urbanization	0.620**	0.391**	0.175**	0.631*	0.282**	0.447**
petrol	0.992	0.996**	1.000	1.004	1.008	1.004
female	0.890*	0.902	0.620**	1.013	0.696**	0.687
age	1.016**	0.998	1.016	0.982	1.000	1.018
fulltime	1.301**	1.101**	1.330*	0.847**	1.022	1.208
numemployed	1.097*	1.090	1.077**	0.994	0.982	0.989
kids09	0.800**	0.797**	0.597**	0.996	0.746	0.749*
kids1017	1.269**	1.376**	1.761**	1.084	1.388**	1.280*
middle	1.087	1.064	1.592**	0.978	1.464*	1.497**
wealthy	0.956	1.281*	1.405**	1.341*	1.470*	1.096
lackofcars	1.051	0.741**	0.568**	0.705**	0.540**	0.766
distancework	0.999	1.002	1.004	1.003	1.005	1.002
rain	0.938	1.078	1.087	1.149	1.159	1.009
temperature	1.002	0.994	1.000	0.992	0.997	1.005
N	76,570					

NCS=NonWork+Car+Simple; NCC=NonWork+Car+Complex; NNS=NonWork+NoCar+Simple; NNC=NonWork+NoCar+Complex.
*** and * denote statistical significance at the 1 % and 5 % level, respectively.*
Year dummies are included, though not depicted.