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The relation between bicycle commuting and non-work cycling: results from a mobility panel

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Abstract This study aims to establish whether or not bicycle commuting and cycling for other purposes (e.g. shopping, visiting friends) are related over time. Using previously gathered panel data (the Dutch mobility panel) these relationships are revealed by (1) a series of conditional change models and (2) a latent transition model. The conditional change models indicate that, with a lag of 1 year and controlling for a range of background characteristics, bicycle commuting and non-work cycling (in number of weekly trips) have a positive reciprocal influence on each other. The models show that work-related factors, such as the distance to work or whether a person receives a travel allowance, affect not only bicycle commuting but also non-work cycling. The latent transition model indicates that people can be clustered into four groups: non-cyclists, non-work cyclists, all-around cyclists and commuter cyclists. This model shows that people with a consistent propensity to not cycle at all (non-cyclists) or to cycle for both work and non-work purposes (all-around cyclists) are most stable in their travel behavior. Non-work cyclists and commuter cyclists are less stable in travel behavior. The model also shows that all-around cyclists are not (significantly) affected by a change in the distance to work. The article concludes with several directions for future research.

Keywords Bicycle commuting · Non-work cycling · Panel data · Poisson model · Latent transition model

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Introduction

Cycling is a cheap, quiet, emission-free, congestion-reducing, and health-promoting form of transportation. Because of these benefits, cities around the world are increasingly committing resources to stimulating cycling (Pucher and Buehler 2012). Efforts include infrastructure and service improvements as well as promotional programs (Pucher et al. 2010). Of growing popularity are “ciclovias,” events where streets are temporarily closed to motor traffic, usually on weekends (Sarmiento et al. 2010). One of the goals of such events is to get people who never or rarely cycle to give it a try, in the hope that the experience will lead to more regular cycling. Evidence suggests that participating in ciclovias is associated with cycling for transport (Gomez et al. 2005), though it is not clear whether participation causes an increase in cycling. This possibility points to an important but understudied question more generally: does cycling for one purpose lead to an increase in cycling for other purposes?

In this paper we focus on the relationship between bicycle commuting and cycling for other purposes (leisure, shopping, social visits, etc.). In several previous studies researchers have posited the idea that non-work cycling may have a positive effect on commuter cycling (Gardner 1998; Lee et al. 2012; Park et al. 2011; Stinson and Bhat 2004; Xing et al. 2010). To some extent this idea is supported by empirical evidence. For example, among a sample of British cyclists Gardner (1998) found that many people who currently cycle for utility purposes claim that leisure cycling encouraged them to cycle to work. Among a sample of Korean cyclists, Park et al. (2011) found that 57 % of commuter-cyclists began as leisure-cyclists. In a general sample of Americans, Stinson and Bhat (2004) found a positive relationship between cycling for other purposes and the propensity to commute by bicycle. Finally, in a study of cycling in small U.S. cities, Xing et al. (2010) found that while over one-quarter of cyclists only cycled for recreation, only 10 % cycled only for transportation and the majority cycled for a mix of recreational and transportation purposes, suggesting a significant connection between the two.

While this evidence suggests that non-work cycling positively influences bicycle commuting, the direction of causation remains uncertain. It is possible, for example, that bicycle commuting influences non-work cycling instead of the other way around. Alternatively, there may be factors omitted from prior studies that influence both outcomes. Establishing the direction of causation and assessing the strengths of the effects in either direction (from bicycle commuting to non-work cycling and vice versa) is important to answering the question of whether (government) policy should focus on stimulating work cycling, non-work cycling, or both.

In this study we aim to address the issue of causality by testing the reciprocal relationships between cycling for non-work purposes (leisure, shopping, social visits, etc.) and bicycle commuting. To this end, previously gathered panel data (the Dutch mobility panel) are analyzed. Two different statistical models are applied to these data, namely a (series of) conditional change model(s) and a latent class transition model. Each model is associated with a different conceptual framework, thus providing different substantive insights on the relationship between non-work cycling and bicycle commuting.

Additionally, whereas previous studies considered utility-versus-leisure cycling (Gardner 1998) or commuter-versus-leisure cycling (Park et al. 2011), we focus on non-work cycling versus bicycle commuting[1] (similar to Stinson and Bhat (2004)). This choice

[1] Bicycle trips for employers’ business which represent a very small portion of all bicycle trips in the Netherlands (0.3 % in our sample), were not considered in the analysis.

is principally motivated by the fact that leisure cycling was not measured as a separate category in the survey (it fell under the 'other purpose' category instead). The use of these categories also provides the opportunity, however, to test the idea that certain work-related factors, namely distance to work and whether a person receives a travel allowance, may indirectly impact non-work cycling through its effect on bicycling commuting. Should this be the case, non-work as well as commute cycling may be stimulated by such factors, an interesting possibility to explore.

Theoretical background and research focus

The present study focuses on the (reciprocal) effects over time between bicycle commuting and cycling for other purposes. Various theoretical notions can be identified that support these reciprocal relationships. Stinson and Bhat (2004), for example, note that people who cycle for non-work purposes are more experienced and may therefore enjoy more comfort in their bicycle commute. In particular, they may be more comfortable riding with motorized traffic or carrying cargo (Stinson and Bhat 2004).

Since experience makes cycling more comfortable, it may also make cycling more fun. This notion is indirectly supported by empirical evidence showing that active modes like walking and cycling are considered most relaxing and exciting compared to other modes like the car and public transport (Gatersleben and Uzzell 2007). In this context, Paez and Whalen (2010) also show that active travellers have less desire to reduce their commute time in comparison to car and public transport users. If cycling frequency indeed increases satisfaction with cycling, bicycle commuting and non-work cycling may be expected to reinforce each other for this reason.

The concept of habit provides a third explanation. Verplanken and Aarts (1999, p. 104) have defined habits as 'learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end states'. Hence, although the regularity of past behavior is considered an important feature of habits, Verplanken and Aarts (1999) emphasize that habits arise when a specific cue (e.g. I need to go to work) is satisfactorily paired with the execution of a behavioral act (e.g. I will use the car). If a mode is successfully used for a certain cue (e.g. work), it is plausible to assume that it will also (unconsciously) be considered for other purposes (e.g. shopping).

These notions suggest positive effects between bicycle commuting and non-work cycling in either or both directions. Hence, if a person commutes by bicycle, he or she can be expected to cycle more for non-work purposes and vice versa. It should be noted, however, that the marginal utility of cycling might also decline with increased levels of cycling. For example, those who already cycle for their commute might derive less satisfaction from non-work (e.g. recreational) cycling compared to those who do not cycle to work. This would imply a negative relationship between bicycle commuting and non-work cycling. Hence, while most theoretical notions suggest a positive link between bicycle commuting and non-work cycling, a negative relationship is also theoretically plausible.

In addition to testing the reciprocal relationship between bicycle commuting and non-work cycling, the present analysis will focus on the effects of two work-related factors, namely distance to work and whether a person receives a travel allowance (offered via employer). Heinen et al. (2012) note that few studies have examined such work-related factors. Their study showed that they are nevertheless quite relevant in the prediction of commute cycling. Among other factors they found that distance to work and financial support for other modes of transport (the provision of a company car or public transport pass) significantly decreased the probability of being a bicycle commuter, whereas financial support for the bicycle (in the form of an employer contribution) increased this probability.

The present study adds to this research in three ways. First, as mentioned in the introduction, we will investigate the possible (indirect) effects of the two work-related factors on cycling for non-work purposes. Second, the analyses, given their longitudinal nature, can show the effects, if any, of changes in the two work-related factors on both bicycle commuting and non-work cycling over time. And third, we will test the possibility that the effect of a change in commuting distance on future commute cycling frequency is dependent on past cycling frequencies. Specifically, we expect that for people who cycle more frequently (for work or non-work purposes) the effect of an increase in commuting distance on the bicycle commuting frequency is less strong than for those who cycle infrequently. These interactions are suggested by the notion that people who cycle more frequently have a stronger propensity to cycle and that their behavior is therefore more 'robust' in response to a change in distance to work.

Model conceptualizations

Panel data can be modeled in various ways. In this paper we will apply and contrast two models, namely the conditional change model and the latent class transition model, for two points in time. The structure of these models, as depicted in Figs. 1 and 2, respectively, suggest different conceptualizations of the relationships between the variables.

Within a conditional change model the dependent variable is regressed on itself and the independent variable under investigation, both measured at a previous point in time. After accounting for the lagged version of the dependent variable (reflecting the variable's stability), the remaining variance in the dependent variable is due to changes in the period between the measurement occasions. The role of the lagged independent variable is to explain this variance while accounting for the initial overlap between the independent and dependent variable at the first measurement occasion. When the effect of the lagged independent variable is significant, it predicts the direction of change in the dependent variable from the first point in time to the second. In contrast to cross-sectional analyses, the conditional change model is therefore able to satisfy the criterion of time-precedence empirically (Finkel 1995). It thus provides a stronger basis for making causal inferences.

In our case, the conceptual model (Fig. 1) includes two conditional change regressions, one in which bicycle commuting is the dependent variable and non-work cycling the independent variable and one in which non-work cycling is the dependent variable and bicycle commuting the independent variable.

Since the estimated lagged effects may be spurious if common omitted variables influence the variables of interest at both points in time, it is important to include relevant control variables in the model. In the present model seven constant background variables are included: sex, age, education level, income, driver license ownership, household size and number of cars in the household. These are 'constant' in that they are assumed to vary little or not all across the two time points.

The two work-related factors are also included as exogenous control variables. In contrast to the background variables, the effects of changes in these factors are explicitly modeled by including the differences between the first and second point in time (i.e. time 2–time 1). Additionally, the difference in commuting distance is interacted with both bicycle commuting and non-work cycling at time 1 in predicting bicycle commuting at time 2, leading to two possible interaction effects. These effects reflect the expectation

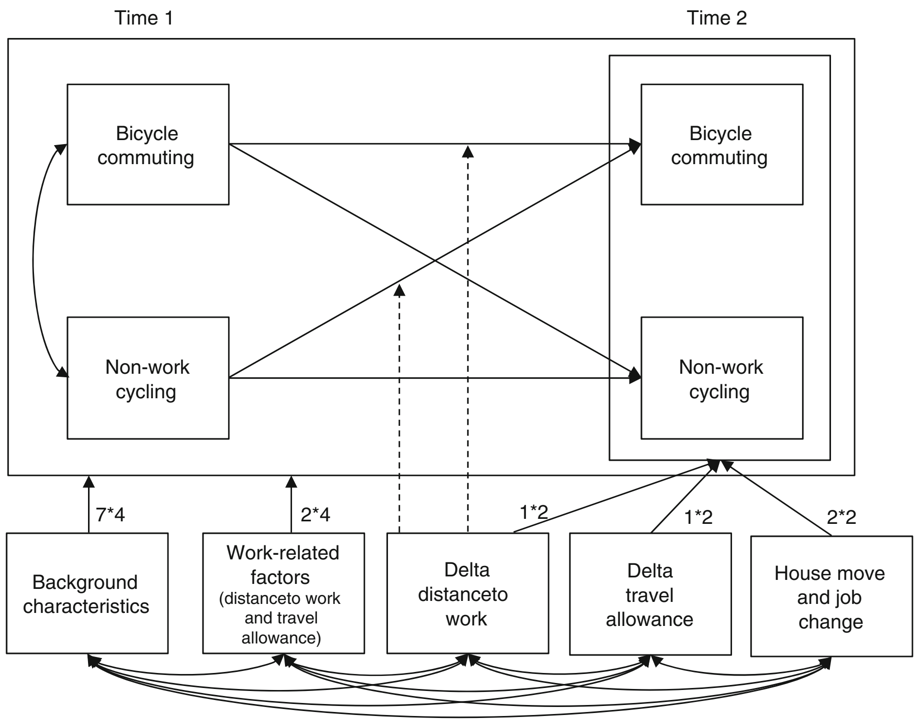

Fig. 1 Conditional change models of bicycle commuting and non-work cycling. *Note*: The multiplications indicate the number of relationships that are estimated (e.g. 7 * 4 indicates that 28 relationships are estimated between the 7 background variables and 4 endogenous variables)

(formulated in the previous section) that people who cycle frequently are less affected by an increase in the distance to work.

Finally, two events are included as well, namely moving house and changing jobs. Because these events may affect changes in distance to work and the travel allowance, as well as cycling frequencies, they too constitute relevant control variables. For example, a house move likely affects the distance to work but may simultaneously pick up changes in neighborhood characteristics (e.g. development density) that, in turn, may affect the (work or non-work) cycling frequency. In contrast to the background and work-related variables, which may affect bicycle commuting and non-work cycling at both points in time, the difference variables and events are assumed to only affect bicycle commuting and non-work cycling at the second point in time.

A second and alternative way of conceptualizing the relationship between bicycle commuting and non-work cycling rests on the idea that both are affected by an underlying categorical factor. This is the main tenet of a latent class model (Magidson and Vermunt 2004; McCutcheon 1987). Within this model, a latent class (i.e. categorical) variable is assumed to explain the association(s) between the included indicators. Hence, in the context of the present study, a set of (latent) behavioral clusters, each related to a different combination of levels of bicycle commuting and non-work cycling, is assumed to account for the association between bicycle commuting and non-work cycling.

If the same model structure holds for a second point in time, the probability of belonging to a particular class at the second point in time can be conditioned on latent class

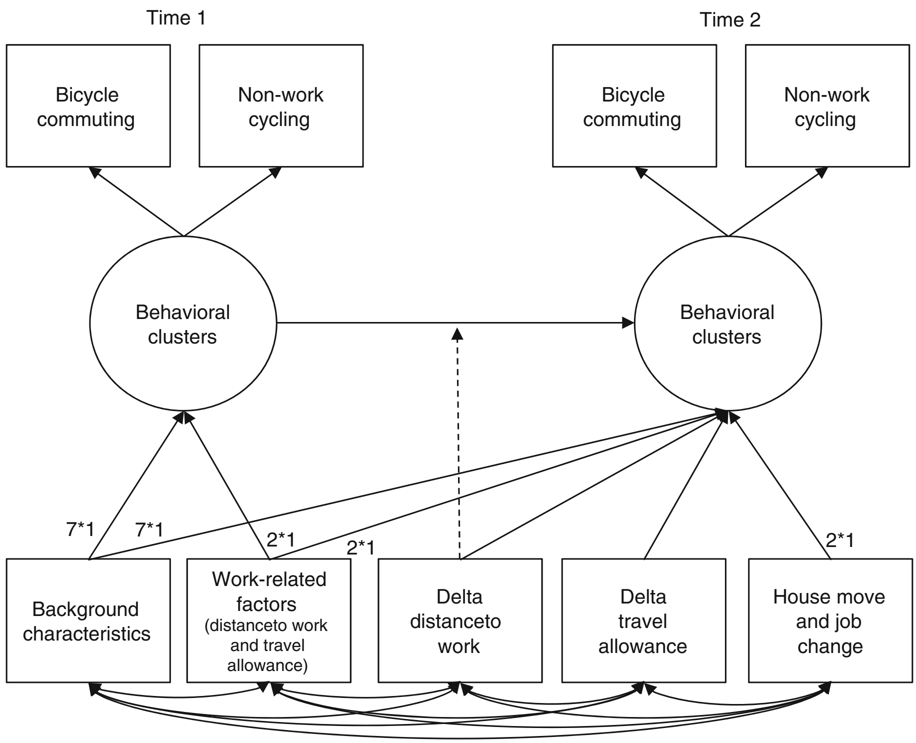

Fig. 2 A latent class transition model. *Note*: The multiplications indicate the number of relationships that are estimated

membership at the first point in time. In effect, transitions can be modeled between the behavioral clusters over time (Collins and Lanza 2009; Nylund 2007). Hence, in contrast to modeling direct effects between bicycle commuting and non-work cycling (Fig. 1), any effects are assumed to be mediated by the latent class variables.

The exogenous control variables can also be added to this model. Again, the background and work-related variables are assumed to influence cluster membership at both points in time, while the difference variables and events are only assumed to affect latent class membership at the second point in time. Finally, an interaction is included between the difference in distance to work and the behavioral clusters at the first point in time. This means that the effect of a change in commuting distance on cluster membership at the second point in time is conditional on cluster membership at the first point in time. Again, we expect that cluster(s) with a high use of the bicycle will be less affected by an increase in the commuting distance than clusters with lower average usage.

Data and methods

The Dutch mobility panel

To estimate the models data were drawn from the Dutch mobility panel. This panel covers a period of 5 years (from 1984 to 1989) and consists of 10 waves (surveys were administered in March and September of each year). The first wave of this panel (March 1984) included 3,863 individuals who were selected using a stratified design based on different community types and life cycle/income groups. In consecutive waves the panel was continuously refreshed using information on the composition of the panel drop-outs. The survey is extensively described in Golob et al. (1985) and Meurs and Van Wissen (1987).

The lag between time points in the models (Figs. 1, 2) should ideally reflect the time it takes for the causal processes to evolve. In the absence of prior research showing how long that is, we therefore (arbitrary) selected the period of 1 year. The behavioral changes that may be expected to occur in this period should be sufficient to test the models. In addition, a 1-year interval excludes the presence of seasonal effects and (in this case) minimizes the amount of panel attrition, given that levels of non-response increase with each successive wave of the panel. The models in the present study were therefore based only on the six March waves of the survey.

We did not model all waves separately but instead pooled the available wave-pairs. In other words, all of the first-wave responses were pooled, regardless of the year in which the wave was conducted, as were all of the second-wave responses. Golob and Van Wissen (1989) previously applied this strategy to minimize the effects of panel attrition bias and to increase the sample size (to study the effects of rare events). Since latent transition analysis generally requires large samples (to sufficiently fill the cells in the transition matrix), this latter benefit is also relevant to our study.

Most respondents participated in more than two waves. For these respondents multiple wave-pairs were therefore available. In these cases, we randomly selected one wave-pair in order to ensure that observations remained independent of each other. In addition, only wave-pairs in which the respondent was employed on both occasions were selected. This strategy led to a sample of 1,969 wave-pairs/respondents in total.

In each wave respondents completed a seven-day travel diary in which they registered their trips and the related characteristics (mode, distance, travel time and purpose). For the present analysis only the frequency of bicycle trips was considered. Two categories were identified: cycling to work (as the primary mode only) and cycling for non-work purposes. The latter included: 'shopping,' 'visiting friends/relatives,' 'bringing or picking up children,' and 'other'.

Table 1 presents the descriptive statistics for the variables included in the analyses, while Fig. 3 presents the response distributions of the dependent variables in the first wave. As shown, these distributions are highly skewed with many zeros: 61.2 % reported zero bicycle commuting trips and 58.9 % reported zero bicycle trips for non-work purposes. For cycling for non-work purposes the frequencies of responses decrease from zero trips onwards, while for commuting trips a second peak can be observed at 5 trips, owing to the fact that people who work full time (5 days per week) and always use the bicycle will report 5 cycling trips to work.

Statistical models and evaluation procedure

Several different statistical models can be used for estimating the relationships in the conceptual model in Fig. 1. Since the endogenous variables, i.e. the bicycle trip frequencies, represent (highly skewed) count outcomes, a linear model is inappropriate, however, because it assumes that the errors are normally distributed and because it would predict negative and non-integer outcomes. A Poisson model can effectively address these problems and has been successfully applied in the transport literature to various count

Table 1 Descriptive statistics ($N = 1{,}969$)

Endogenous variables		
Bicycle commuting trips (wave 1)	Mean (SD)	1.8 (2.7)
Bicycle trips with other purpose (wave 1)	Mean (SD)	1.4 (2.6)
Bicycle commuting trips (wave 2)	Mean (SD)	1.7 (2.7)
Bicycle trips with other purpose (wave 2)	Mean (SD)	1.4 (2.5)
Constant exogenous variables (wave 1)		
Sex (%)	Male (0)	66.4
	Female (1)	33.6
Age	Mean (SD)	37.0 (10.3)
Education (%)	Secondary education (1)	29.1
	Vocational degree (2)	41.9
	Higher education (3)	29.1
Personal net income (%)	0–17,000 guilders (1)	35.2
	17,000–27,000 guilders (2)	33.9
	>27,000 guilders (3)	30.9
Owns driver's license (%)	No (0)	14.4
	Yes (1)	85.6
Household size	Mean (SD)	3.3 (1.3)
Number of cars in the household (%)	0	13.0
	1	70.5
	2	14.4
	3 or more	2.2
Distance to work (km)	Mean (SD)	12.5 (16.4)
Travel allowance (payment that can be used for any mode) (%)	No (0)	66.1
	Yes (1)	33.9
Non-constant exogenous variables (wave 2–wave 1)		
Delta distance to work (km)	Mean (SD)	0.6 (12.4)
Delta travel allowance (%)	Lost travel allowance (−1)	4.1
	No change (0)	89.7
	Gained travel allowance (1)	6.1
Moved house (%)	No (0)	95.2
	Yes (1)	4.8
Changed jobs (%)	No (0)	91.7
	Yes (1)	8.3

outcomes, such as accident frequencies, activity frequencies, and, similar to the present analysis, trip frequencies.

A Poisson model, however, has no residual term. As a result, this model is unable to account for any correlations between the residual variances of bicycle commuting and non-work cycling at the first and second point in time. Such correlations are typically included in cross-lagged models based on linear equations. However, since a model based on linear equations is inappropriate (for the reasons stated above), we decided to estimate four separate models (one for each dependent variable in the model) instead of simultaneously estimating a single model (in a structural equation framework). A drawback of this

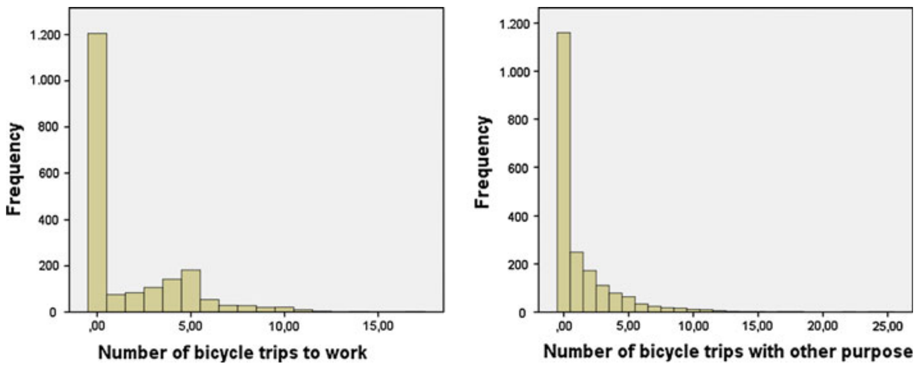

Fig. 3 Distributions of commuting trips (*left*) and trips with other purpose (*right*) by bicycle in the first wave of the selected wave-pairs ($N = 1{,}969$)

approach is that it remains unknown to what extent the residual variances in bicycle commuting and non-work cycling are in fact correlated at the first and second point in time.

A second drawback of the Poisson model lies in its restrictive assumption that the conditional mean is equal to the conditional variance. Often the latter is greater than the former, indicating so-called over-dispersion. Generally there are two causes of over-dispersion, with related methods to address it (Long 1997). The first cause is that explanatory variables have been omitted from the model, the solution to which is the use of a negative binomial (NB) model. Over-dispersion can also be caused by an excess of zeros. In this case it can be assumed that the observed count is the result of a dual-state process: a person can either be located in a perfect state (zero) or in an imperfect state (governed by a Poisson process). As noted by Lord et al. (2005) it is plausible that such a dual-state process underlies trip frequency data. For example, in the case of cycling frequency, it can be argued that for some people the perfect state (zero) applies. They may be committed to other modes of transport or simply not own a bicycle and therefore never use a bicycle. For other people the imperfect state (zero and non-zero) applies. Within a particular time-interval they may use the bicycle to various extents (non-zero) or not use it (zero) for any non-structural reason (e.g. because they have a cold). As a result of this dual-state process, the total count of observed zeros in the data can result in an excess of zeros not explained by a Poisson or negative binomial process. The solution to this form of over-dispersion is to estimate a zero-inflated Poisson (ZIP) model, in which both processes are modeled separately (within a single model): a logit model for the probability of the perfect state and a Poisson model for the mean (λ) of the imperfect state. Explanatory variables can be added to both models (and need not necessarily be the same for both models). Finally, both forms of over-dispersion may be present, in which case a zero-inflated negative binomial (ZINB) would provide the best fit to the data. In the present analysis the above-described models (Poisson, NB, ZIP and ZINB) will be tested against the data. The package Stata 11 is used to estimate the models.

Estimation of the latent transition model (Fig. 2) is more straightforward. Because the distributions of the dependent variables (Fig. 3) can be assumed to be generated by several distinct Poisson distributions, we estimated different Poisson means for the two indicator variables for each (latent) behavioral cluster. We used multinomial logit models to estimate the effects of the behavioral clusters in the first wave on cluster membership in the second wave as well as the effects of the explanatory variables on cluster membership across both waves. To decide what number of latent classes is appropriate, consecutive models with one through seven classes were estimated and compared. These models were estimated without covariates in order to assess only the measurement part of the model. Next, the complete latent transition model (with covariates) is estimated. Mplus 6 was used to estimate the models. We used the parameterization described by Muthén and Asparouhov (2011).

Results

Conditional change models

For the conditional change models (Fig. 1), comparison of the various models (Poisson, NB, ZIP and ZINB) showed that the ZINB-model provided the best fit to the data for non-work cycling and bicycle commuting in the first wave and non-work cycling in the second wave. For bicycle commuting in the second wave the ZIP-model fitted best.

Table 2 presents the parameter estimates of the best-fitting models for the four endogenous variables. In the first wave the frequency of bicycle commuting and non-work cycling is explained by the seven background variables and the two work-related factors. The regressions in the second wave additionally include the two lagged dependent variables, the two change variables, and the two event variables. Finally, two interactions are included in the regression of bicycle commuting in the second wave, between the change in distance to work and bicycle commuting and non-work cycling in the first wave.

The estimates show that the probability of a 'certain zero' for commute trips in the first wave increases with income, the number of cars in the household and the distance to work and also for those who receive a travel allowance; it decreases with education and household size. The frequency of bicycle commuting is positively influenced by income and household size and negatively by distance to work. The different effects of the explanatory variables in the regressions are notable. For example, the number of cars in the household and getting a travel allowance influence only the probability of making no bicycle commute trips and not the frequency of bicycle commuting. Personal income decreases the probability of commuting by bicycle, but when people with higher incomes do cycle to work they travel more frequently than those with lower incomes.

For non-work cycling in the first wave, many of the estimates are similar, with notable exceptions. For example, in contrast to commuting trips, the effect of income on non-work trip frequency is negative. Second, in contrast to commuting trips, the number of cars in the household negatively affects the frequency of non-work trips. Similar to the results for commuting trips, however, distance to work positively affects the probability of not cycling and negatively affects the frequency of non-work cycling trips. This apparent direct effect of distance to work on non-work cycling trips may, in fact, be indicative of an indirect effect via previous levels of bicycle commuting. Only age has no significant effect on bicycle commuting trips or non-work cycling trips. This is probably due to the fact that only people with a job are included in the sample, resulting in a limited range for age.

The results of the second wave show that bicycle commuting in the first wave strongly affects both whether a person cycles to work in the second wave and how often. Controlling for the initial overlap between bicycle commuting and non-work cycling, non-work cycling also positively affects bicycle commuting. However, it does so only by decreasing the probability of not bicycle commuting and not by increasing the frequency of bicycle commuting.

Table 2 Parameter estimates of the ZIP and ZINB models

Wave 1	Bicycle commuting trips (ZINB)				Bicycle trips with another purpose (ZINB)			
	Logit ($p = 0$)		Poisson		Logit ($p = 0$)		Poisson	
	Est.	t	Est.	t	Est.	t	Est.	t
Sex (female)	0.181	1.30	−0.095	−1.80	−0.182	−0.89	**0.354**	3.82
Age	**0.011**	1.96	−0.002	−0.69	0.006	0.66	−0.006	−1.39
Education = medium (ref. = low)	−0.026	−0.19	0.002	0.04	0.010	0.05	**0.305**	2.92
Education = high (ref. = low)	**−0.778**	−5.01	0.096	1.69	−0.453	−1.86	**0.532**	4.62
Personal net income = medium (ref. = low)	0.215	1.47	**0.168**	3.02	0.400	1.79	**−0.295**	−2.89
Personal net income = high (ref. = low)	**0.407**	2.40	**0.132**	1.99	**0.655**	2.57	**−0.287**	−2.33
Owns driver's license	**0.387**	2.33	−0.013	−0.24	**1.218**	2.42	0.017	0.17
Household size	**−0.218**	−4.86	**0.045**	2.75	−0.115	−1.75	**0.159**	5.08
Number of cars in the household	**1.118**	9.72	−0.024	−0.56	**0.877**	5.90	**−0.419**	−6.19
Distance to work	**0.086**	10.90	**−0.015**	−4.96	**0.015**	2.66	**−0.009**	−2.72
Travel allowance	**0.493**	3.71	−0.083	−1.41	0.093	0.48	−0.081	−0.80
Intercept	**−2.062**	−5.24	**1.490**	10.45	**−2.479**	−3.08	0.377	1.44
Alpha	**0.094**	5.10			**0.800**	6.99		

Wave 2	Bicycle commuting trips (ZIP)				Bicycle trips with other purpose (ZINB)			
	Logit ($p = 0$)		Poisson		Logit ($p = 0$)		Poisson	
	Est.	t	Est.	t	Est.	t	Est.	t
Bicycle commuting trips (wave 1)	**−0.542**	−15.64	**0.082**	13.85	**−0.180**	−3.40	**0.023**	1.90
Bicycle trips with other purpose (wave 1)	**−0.167**	−4.99	−0.003	−0.48	**−1.427**	−5.90	**0.123**	10.66
Sex (female)	−0.089	−0.54	**−0.148**	−3.11	**−0.529**	−2.24	0.076	0.91
Age	−0.001	−0.19	−0.002	−0.81	**0.029**	3.15	**0.008**	2.13
Education = medium (ref. = low)	−0.185	−1.12	0.063	1.31	0.040	0.18	0.100	1.10

Table 2 continued

Wave 1	Bicycle commuting trips (ZINB)				Bicycle trips with another purpose (ZINB)			
	Logit ($p = 0$)		Poisson		Logit ($p = 0$)		Poisson	
	Est.	t	Est.	t	Est.	t	Est.	t
Education = high (ref. = low)	**−0.376**	−2.01	0.066	1.26	−0.231	−0.89	**0.231**	2.35
Personal net income = medium (ref. = low)	0.133	0.75	**0.111**	2.25	0.126	0.51	**−0.231**	−2.56
Personal net income = high (ref. = low)	−0.138	−0.69	0.096	1.68	0.008	0.03	−0.186	−1.79
Owns driver's license	−0.301	−1.55	**−0.100**	−2.06	−0.331	−1.08	0.043	0.49
Household size	0.016	0.30	0.001	0.07	**−0.196**	−2.66	−0.023	−0.88
Number of cars in the household	**0.602**	4.39	−0.023	−0.62	0.332	1.92	**−0.309**	−4.87
Distance to work	**0.058**	6.37	**−0.016**	−4.60	**0.016**	2.45	0.000	−0.01
Travel allowance	**0.511**	2.99	−0.057	−0.95	−0.241	−1.14	−0.077	−0.87
Delta distance to work	**0.068**	5.31	**−0.024**	−4.69	0.015	1.73	**−0.007**	−2.06
Delta travel allowance = lost (ref. = no change)	−0.602	−1.68	0.099	0.91	**0.942**	2.16	**0.442**	2.20
Delta travel allowance = gained (ref. = no change)	0.418	1.41	−0.100	−1.04	−0.133	−0.31	−0.085	−0.53
Moved house	−0.089	−0.30	−0.086	−0.99	−0.030	−0.07	−0.092	−0.59
Changed jobs	0.362	1.40	0.135	1.86	0.582	1.58	−0.127	−0.98
Bicycle commuting trips (wave 1) * delta distance to work	0.002	0.57	**0.002**	2.33	–	–	–	–
Bicycle trips with other purpose (wave 1) * delta distance to work	−0.001	−0.44	0.001	1.13	–	–	–	–
Intercept	0.809	1.70	**1.466**	10.99	0.810	1.16	0.357	1.46
Alpha	–	–			**0.515**	8.64		

Estimates in bold are significant at $p < 0.05$

Other exogenous variables also influence bicycle commuting in the second wave. Again, number of cars in the household and the distance to work are most influential. The difference in distance to work is also significant, indicating that people are more likely to not cycle at all or will cycle less if the distance to work increases. Finally, the interaction between change in distance to work and commuting trips in the first wave positively influences bicycle commuting in the second wave, indicating that the effect of a change in distance to work is smaller for those who previously cycled more frequently to work.

Similar to bicycle commuting, non-work cycling in the second wave is strongly affected by non-work cycling in the first wave, suggesting substantial stability in behavior. In contrast to the effect of non-work cycling on bicycle commuting, however, the effect of bicycle commuting on non-work cycling operates via the probability of not cycling as well as via trip frequency. Hence, controlling for the initial association, frequent bicycle commuting will both decrease the probability of not cycling for non-work purposes and increase the frequency of non-work cycling. Overall, the effects of bicycle commuting on non-work cycling are slightly greater than vice versa.

Other explanatory variables are significant for the second wave as they were for the first (suggesting that these can also explain *changes* in the period between the two points in time). An interesting result is the effect of the change in distance to work, which has a small but significant negative effect on the frequency of non-work trips. Two mechanisms may explain this direct effect. First, the increased distance may mean that people have less time to travel for non-work purposes, as suggested by the notion of fixed travel time budgets (Mokhtarian and Chen 2004). Second, a change in bicycle commuting (after the first wave) may act as a mediator, in which case the change in distance to work affects the frequency of bicycle commuting, in turn affecting the frequency of non-work cycling. This would imply that a synchronous effect between bicycle commuting and non-work cycling exists (possibly for reasons discussed in "Theoretical background and research focus" section). A limitation of the present model is that a direct effect between bicycle commuting and non-work cycling (or the other way around) at the same point in time cannot be estimated because the inclusion of such effects (in addition to the lagged effects) would lead to multicollinearity problems given that bicycle commuting and non-work cycling in the first wave are strongly correlated with their respective counterparts in the second wave.

Overall, the results indicate that bicycle commuting and non-work cycling reciprocally influence each other over time. The finding that distance to work, as a work-related factor, also influences non-work cycling is consistent with this conclusion. Furthermore, the findings indicate that the effect of bicycle commuting on non-work cycling is greater than the other way around. Finally, an increase in distance to work decreases bicycle commuting, but less strongly for people who frequently cycle to work.

Latent transition model

Based on several criteria the four-class model was found to provide the optimal solution in terms of fit and parsimony in each of the two waves. The latent transition model was therefore estimated with four classes at each point in time.

To assess whether the parameters related to the measurement model in each of the waves were equal a likelihood-ratio test was conducted. This test indicated that a restricted model (with the parameters related to the measurement model constrained to be equal in both waves) did not fit significantly worse than an unrestricted model (with freely estimated parameters). Hence, in the final model the parameters relating the latent clusters to the indicators in both waves were constrained to be equal. This, in turn, means that the clusters have the same interpretation in both waves.

Table 3 presents the estimates of the latent transition model. The four clusters can be identified as non-cyclists (51 %), non-work cyclists (11 %), all-around cyclists (12 %) and commuter cyclists (26 %). Through exponentiation of the parameters associated with the indicator variables (bicycle commuting trips and non-work cycling trips) the Poisson means can be derived for each cluster. Non-cyclists cycle very little at all. Non-work cyclists have a mean cycling frequency of 2.8 for non-work purposes and 0.1 for commuting trips. All-around cyclists cycle on average 4.7 times for their commute and 6.5 times for non-work purposes. And commuter cyclists, the reference group in the model, have a mean cycling frequency of 4.5 for commuting trips and 1.0 for non-work trips.

With the exception of age, the exogenous variables all significantly influence latent class membership in the first wave. Men have a higher probability of belonging to the commuter cyclist cluster compared to the other three clusters. Education increases the probability of belonging to the all-around cyclist cluster, while income decreases this probability. Having a driver's license increases the probability of being a non-cyclist, whereas household size decreases this probability. The effect of the number of cars in the household is especially strong, negatively influencing the probability of being an all-around cyclist compared to being a non-cyclist. It should be noted, however, that car ownership among all-around cyclists is still relatively high (63 % has one or more cars in the household). The two work-related factors (distance to work and travel allowance) positively influence the probability of the first two clusters, whose members do not cycle to work (the non-work cyclist and non-cyclist), at the expense of the clusters whose members do cycle to work (the all-around cyclist and commuter cyclist).

Latent class membership in the second wave is strongly influenced by latent class membership in the first wave. In other words, people largely tend to stay in the same behavioral cluster. The all-around cyclist category has an especially large effect on itself, suggesting strong stability in behavior. After controlling for cluster membership in the first wave, several exogenous variables explain changes in cluster membership over time. Again, number of cars in the household, and distance to work are most influential. Whether a person gains or loses a travel allowance also strongly affects the probability of transitioning to the non-work cyclist cluster, probably because a travel allowance encourages the use of more expensive modes like the car and public transport.

Finally, the interaction between the change in distance to work and cluster membership in the first wave also yields several interesting results. For non-work cyclists, non-cyclists, and commuter cyclists, an increase in distance to work increases the probability of transitioning to (or staying in) the non-work cyclist and non-cyclist categories. For commuter cyclists this means that some give up cycling entirely, while others will start to cycle (or increase cycling) for non-work purposes. This latter group may be compensating for the lost opportunity to cycle to work and its role as a means of getting exercising or saving money or saving the environment. This finding indicates that the relationship between non-work cycling and bicycle commuting may not always be positive as was suggested by the conditional change models: a decrease in bicycle commuting may in fact lead to an increase in non-work cycling. Another interesting finding is that the effect of a change in distance to work is not significant for the all-around cyclists. In line with expectations, this behavioral cluster is thus more robust in response to such a change than the other clusters. It should also be noted that the interaction effect is much stronger in this model than in the conditional change models. This difference may arise from the specific combinations of

Table 3 Parameter estimates of the latent transition model

	Non-cyclist		Non-work cyclist		All-around cyclist		Commuter cyclist (ref.)	
	Est.	t	Est.	t	Est.	t	Est.	t
Cluster indicators (estimates equal across waves)								
Bicycle commuting trips	**−3.703**	16.14	**−2.129**	−5.79	**1.553**	33.39	**1.495**	60.01
Bicycle trips with other purpose	**−2.303**	14.52	**1.020**	12.19	**1.868**	35.58	0.013	0.17
Exp(bicycle commuting trips)	0.0		0.1		4.7		4.5	
Exp(bicycle trips with other purpose)	0.1		2.8		6.5		1.0	
Wave 1								
Class size	0.51		0.11		0.12		0.26	
Prediction of cluster membership in wave 1								
Sex (female)	**0.326**	2.01	**0.888**	3.92	**0.796**	3.34	0	
Age	0.012	1.83	−0.007	−0.68	−0.008	−0.74	0	
Education = medium (ref. = low)	0.105	0.70	0.287	1.19	**0.900**	3.44	0	
Education = high (ref. = low)	**−0.600**	−3.35	0.195	0.69	**1.324**	4.96	0	
Personal net income = medium (ref. = low)	0.191	1.11	−0.311	−1.27	**−0.686**	−2.81	0	
Personal net income = high (ref. = low)	0.350	1.82	−0.556	−1.87	**−0.683**	−2.32	0	
Owns driver's license	**0.483**	2.48	0.134	0.49	−0.062	−0.24	0	
Household size	**−0.238**	−4.69	0.085	1.10	**0.234**	3.21	0	
Number of cars in the household	**0.939**	7.90	0.063	0.31	**−1.194**	−5.33	0	
Distance to work	**0.116**	6.53	**0.116**	6.46	0.012	0.42	0	
Travel allowance	**0.453**	2.80	**0.800**	3.66	0.072	0.25	0	
Intercept	**−2.192**	−4.77	**−3.564**	−5.39	**−1.934**	−2.78	0	
Wave 2								
Class size	0.53		0.11		0.11		0.25	
Prediction of cluster membership in wave 2								
Non-cyclist wave 1 (ref. = commuter cyclist)	**3.611**	16.21	**1.703**	4.56	0.461	0.64	0	
Non-work cyclist wave 1 (ref. = commuter cyclist)	**2.160**	5.21	**3.785**	8.46	**2.720**	3.84	0	
All-around cyclist wave 1 (ref. = commuter cyclist)	1.006	1.77	**1.625**	2.65	**5.123**	7.81	0	
Sex (female)	−0.150	−0.64	**0.720**	2.38	0.331	0.79	0	
Age	−0.001	−0.09	0.010	0.73	0.016	0.82	0	
Education = medium (ref. = low)	−0.131	−0.62	**−0.665**	−2.18	0.450	0.90	0	
Education = high (ref. = low)	−0.131	−0.52	−0.195	−0.55	0.945	1.93	0	
Personal net income = medium (ref. = low)	0.089	0.36	−0.485	−1.50	−0.184	−0.39	0	

Table 3 continued

	Non-cyclist		Non-work cyclist		All-around cyclist		Commuter cyclist (ref.)	
	Est.	t	Est.	t	Est.	t	Est.	t
Personal net income = high (ref. = low)	−0.304	−1.19	−0.740	−1.82	0.009	0.01	0	
Owns driver's license	−0.202	−0.74	0.054	0.15	0.595	1.17	0	
Household size	−0.027	−0.36	0.107	0.96	−0.046	−0.33	0	
Number of cars in the household	0.325	1.84	−0.228	−0.98	**−1.341**	−3.61	0	
Distance to work	**0.097**	4.07	**0.097**	3.98	0.052	1.39	0	
Travel allowance	0.236	0.96	**0.745**	2.38	−0.706	−1.39	0	
Delta travel allowance = lost (ref. = no change)	−0.746	−1.79	**−1.426**	−2.22	0.210	0.19	0	
Delta travel allowance = gained (ref. = no change)	0.550	1.29	0.794	1.45	−0.469	−0.60	0	
Moved house	−0.078	−0.20	−1.046	−1.34	−0.255	−0.43	0	
Changed jobs	0.242	0.57	−0.288	−0.56	0.488	0.61	0	
Intercept	**−1.930**	−2.96	**−4.076**	−4.73	**−4.012**	−3.15	0	
Interaction with delta distance to work								
Non-cyclist (wave 1)	**0.099**	4.36	**0.096**	3.86	0.076	1.81	0	
Non-work cyclist (wave 1)	**0.153**	4.27	**0.152**	4.54	0.064	1.43	0	
All-around cyclist (wave 1)	0.021	0.58	−0.008	−0.23	−0.021	−0.64	0	
Commuter cyclist (wave 1)	**0.281**	3.94	**0.291**	4.05	−0.019	−0.36	0	

Estimates in bold are significant at $p < 0.05$

non-work and work cycling identified in the latent class model in contrast to the past frequencies of each type of behavior separately included in the conditional change models.

Based on the parameter estimates, the transition matrix can be computed (Table 4) (for this purpose the model was re-estimated keeping only the significant parameters). This table is computed by summing over each person the probability that (s)he transitions (or stays in the same class), given his/her cluster membership in the first wave and his/her values for the covariates. Thus, this matrix shows the predicted movement of people between the behavioral clusters over time. The diagonal elements in the matrix indicate the relative stability of each behavioral cluster. For example, all-around cyclists have a probability of 77.6 % of staying in the same behavioral cluster. Commuter cyclists are also relatively stable with a probability of 69.5 %. Non-work cyclists are most instable with a

Table 4 Matrix of transition probabilities

Wave 1	Wave 2			
	NC	NWC	AC	CC
Non-cyclist (NC)	0.872	0.049	0.005	0.074
Non-work cyclist (NWC)	0.259	0.563	0.071	0.107
All-around cyclist (AC)	0.067	0.058	0.776	0.099
Commuter cyclist (CC)	0.190	0.079	0.036	0.695

Table 5 Matrix of transition probabilities for an increase of 3 km in distance to work

Wave 1	Wave 2			
	NC	NWC	AC	CC
Non-cyclist (NC)	0.903	0.049	0.004	0.044
Non-work cyclist (NWC)	0.315	0.586	0.043	0.056
All-around cyclist (AC)	0.126	0.079	0.690	0.106
Commuter cyclist (CC)	0.404	0.153	0.017	0.426

probability of 56.3 % of staying in the same cluster. Finally, non-cyclists are even more stable than all-around cyclists with a probability of 87.2 % of staying in the same cluster.

The off-diagonal elements are also informative from a practical perspective. For example, very few people (0.5 %) transition from the non-cycling cluster to the all-around cycling cluster in the course of 1 year. Thus, non-work cycling and bicycle commuting seem to operate as necessary intermediate clusters to transition from the non-cycling to the all-around cycling profile. The path via bicycle commuting seems more effective, as non-work cyclists have a relatively high probability of transitioning back to the non-cyclist profile (25.9 %).

The matrix of transition probabilities can also be computed at different values of the covariates. Table 5 presents the matrix if the change in distance to work equals +3 km (holding the other covariates at their mean values). Here the interaction between the change in distance to work and cluster membership in the first wave becomes quite apparent. Whereas bicycle commuters are strongly drawn to the non-cycling profile (40.4 %), all-around cyclists are much less affected and tend to stay in their original profile (69.0 %).

Overall, the latent transition model shows that bicycle commuting and non-work cycling are interrelated, but in a more complex way than the one suggested by the conditional change models. The results indicate that (of the cycling clusters) all-around cyclists are most effective in maintaining their behavior, (in effect) all-around cyclists are also least affected by a change in distance to work. Finally, non-work cycling and bicycle commuting seem to operate as necessary intermediate clusters to transition from the non-cycling to the all-around cycling profile; in other words, people tend to start with one or the other rather than immediately taking up both.

Model comparison

As mentioned in the introduction the conditional change model and latent transition model reflect different conceptual frameworks and therefore provide different substantive insights on the relation between bicycle commuting and non-work cycling. The conditional change models assume that bicycle commuting and non-work cycling should be viewed as interrelated but separate categories. Within this conceptualization the results show that the two types of behavior indeed reciprocally influence each other. The models do not, however, provide insight about the theoretical mechanisms that possibly underlie these effects (i.e. whether they arise from experience, satisfaction, habit, or a combination of these, or other mechanisms).

The latent transition model assumes that bicycle commuting and non-work cycling should be viewed as instances of a single nominal factor, a set of underlying behavioral clusters. The data also support this conceptualization, indicating that a limited set of behavioral clusters can effectively explain the association between bicycle commuting and non-work cycling. It can be argued that this conceptualization is strongly related to the notion of habit. In fact, it closely resembles the response-frequency measure developed by Verplanken et al. (1994) as a measure of habit strength. Their method presents respondents with ten short statements about hypothetical journeys (e.g., "Suppose you go to the beach with some friends") and uses the frequency of opting for a certain mode from a set of six options (i.e., bus, bicycle, cab, car, train, or walking) as a measure of habit strength for that particular mode.

The present operationalization differs in the sense that actual behavior is measured and that only two contexts (work and non-work cycling) are considered. Nevertheless, it can be argued that a consistent choice (or non-choice) for a particular mode (irrespective of the context) reflects an intrinsic habitual (or non) preference for that mode. This idea is consistent with the varying stabilities of the cycling clusters, with all-around cyclists and non-cyclists being most stable compared to non-work cyclists and commuter cyclists, in other words, the "all or nothing" states are more stable than the in-between states. It also provides an explanation why all-around cyclists are most robust in response to a change in the distance to work. Hence, by 'measuring' the latent classes more is revealed than what can be inferred from the measurements of bicycle commuting and non-work cycling separately. This is consistent with the idea that latent variables contain 'surplus' meaning, which is not captured by the individual items (Jarvis et al. 2003).

Another difference between the conditional change models and the latent transition model is that the latter can reveal more complex substitution and complementary patterns. Whereas the conditional change models indicate that bicycle commuting and non-work cycling are strictly complementary (i.e. they positively influence each other), the latent transition model shows that bicycle commuters may in fact switch to the non-work cycling profile when the distance to work increases, indicating mode substitution. Thus, in this model non-work cycling and bicycle commuting may act as substitutes as well as complements of each other (an example of a complementary pattern is when commuter cyclists and non-work cyclists function as intermediate clusters in the transition from the non-cycling to the all-around cycling profile). In this sense, the latent transition model provides a more comprehensive picture of the relationship between non-work cycling and bicycle commuting.

Conclusion

The results of our analysis indicate that, while the effect of bicycle commuting on non-work cycling is somewhat greater than vice versa, both types of cycling positively influence each other over time. Because of this bidirectional relationship, work-related factors, such as the distance to work or whether a person receives a travel allowance, not only affect bicycle commuting but also non-work cycling. Both bicycle commuting and non-work cycling may thus be increased by enhancing work-related cycling conditions. In general, the results imply that any efforts to stimulate cycling in a particular domain may be expected to spill-over to other domains. This "multiplier effect" is important to consider in cycling policy evaluation.

The latent transition model indicates that people can be clustered into four groups: non-cyclists, non-work cyclists, all-around cyclists and commuter cyclists. This model shows that people with a consistent pattern of not cycling at all (non-cyclists) or of cycling for both work and non-work purposes (all-around cyclists) are most stable in their behavior.

Non-work cyclists and commuter cyclists are less stable, and tend to move either toward the non-cyclist or the all-around cyclist category. The model also shows that all-around cyclists are not (significantly) affected by a change in the distance to work, though those in other categories, who may be less dedicated to cycling, are. Stimulating all-around cycling therefore seems worthwhile as it will lead to the most stable cycling patterns.

Given that effect of bicycle commuting on non-work cycling is greater than vice versa and that commuter cyclists are more stable than non-work cyclists, the findings of the present study support policies focused on bicycle commuting. This conclusion should be viewed as tentative, however, given the study's limitations. The two most important limitations are the age of the data (on average $\sim$25 years) and the fact that they come from just one country and in particular from one with an especially high level of cycling. Newer data and data from different countries are needed to address these limitations and establish the generalizability of these results.

Newer data will be available in the future from a panel survey recently launched in the Netherlands. This panel includes roughly 2,000 households and will cover a four-year period (2013–2016) (Van Beek et al. 2011). These data can be used to establish whether the effects identified in this study still hold true for a contemporary population. The new panel survey will also include data on attitudinal and lifestyle measures, thereby providing the opportunity to assess the association of these factors with different cycling patterns and examine their evolution over time. It has been suggested in this respect that affective factors are more important in decisions regarding leisure travel than commuting (Anable and Gatersleben 2005). Panel data are also needed in other countries to assess whether the relationships found in this study also hold for other countries with lower levels of cycling than are found in the Netherlands for both work and non-work purposes. Unfortunately, in the transportation domain, panel data are not often gathered (see Ortuzar et al. (2011) for an overview).

This paper provides an important starting point for future studies by developing and testing the conceptual frameworks and statistical methods for two different approaches to the analysis of panel data. Future analyses of panel data should improve on our work by discriminating between pure recreational cycling and cycling for non-work purposes (such as shopping), as promotional programs like ciclovias are based on the assumption that getting people try cycling for fun will lead not only to an increase in recreational cycling but also an increase in cycling for transport, whether for work or non-work purposes. In addition, future studies should account for factors that may moderate these relationships in important ways, including attitudes and preferences as well as characteristics of the built environment, as suggested by previous cross-sectional studies. Such studies would improve our understanding of the relationship between cycling for different purposes over time and thus would provide a stronger basis for both designing and evaluating promotional programs and other efforts to promote cycling.

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