

Hoe naar het werk vandaag? De dagelijkse keuze om (niet) te fietsen

Eva Heinen
Technische Universiteit Delft
e.heinen@tudelft.nl

Kees Maat
Technische Universiteit Delft
c.maat@tudelft.nl

Bert van Wee
Technische Universiteit Delft
g.p.vanwee@tudelft.nl

**Bijdrage aan het Colloquium Vervoersplanologisch Speurwerk
25 en 26 november 2010, Roermond**

Samenvatting

Hoe naar het werk vandaag? De dagelijkse om (niet) te fietsen

Dit paper onderzoekt de dagelijkse keuze om naar het werk te fietsen gebruikmakend van longitudinale data van 663 parttime woon-werkfietsers. In eerder onderzoek is vervoermiddelkeuze, reisdoel en andere vervoerkeuzes voor slechts één dag onderzocht. Echter, wij kunnen niet aannemen, dat verplaatsingskeuzes niet van dag tot dag verschillen en dat individuen elke dag met hetzelfde vervoermiddel reizen. Wij veronderstellen dat fietsers in het bijzonder geneigd zijn vervoersmiddelen af te wisselen (en dus soms per openbaar vervoer of auto te reizen), aangezien zij meer beïnvloed worden door factoren die van dag tot dag verschillen. In dit paper wordt onderzocht welke aspecten de dagelijkse keuze om te fietsen beïnvloeden. Tevens wordt onderzocht welke verschillen er bestaan tussen verschillende groepen part-time fietsers.

Resultaten geven aan dat de dagelijkse keuzes om te fietsen beïnvloed worden door kenmerken van het werk, kenmerken van de woon-werkreis en weersomstandigheden. Specifieker, werkers die een pak dragen, spullen moeten vervoeren, een auto nodig hebben voor hun werk, een langere woon-werkafstand hebben, in het donker reizen en diegene die reizen op een dag met hardere wind, met meer regen of een langere periode van regen reizen op die dag(en) minder vaak met de fiets. Een positief effect op de keuze om te fietsen is gevonden voor een hogere temperatuur en voor langere periode van zonneschijn. Deze resultaten geven aan dat factoren die van dag tot dag kunnen veranderen voor een groot gedeelte de dagelijkse keuze om te fietsen bepalen.

Onze tweede conclusie is dat er twee groepen part-time fietsers bestaan: incidentele en regelmatige fietsers. Daar waar incidentele fietsen meer beïnvloed worden door positieve weersomstandigheden, zoals een hogere temperatuur en langere periode van zonneschijn, besluiten regelmatige fietsers vaak om een dag niet te fietsen op meer praktische barrières, zoals een sterke wind en een grotere tripcomplexiteit door meerdere werklocaties of stops op de heen- of terugreis.

1. Introduction

This paper uses longitudinal data to investigate day-to-day decisions to commute by bicycle. Commuting enables people to work at locations that are spatially separated from their living locations, but is also associated with transportation and spatial problems, such as traffic jams and parking difficulties. In addition, commuting by car has negative impacts on the environment. Bicycle commuting offers an environmentally friendly, healthy alternative, and it requires less space for parking and for transportation infrastructure. These societal benefits of cycling have attracted policy attention (Pucher et al., 2010). Cycling also provides benefits to individuals, including health advantages due to “the regularity and frequency of physically active commuting” (Hardman, 1999, p. 91) and time savings, especially for short distances.

Previous research has investigated travel choices for one day only, such as mode choice and travel destination. Recent research on bicycle commuting has found effects for the built environment, culture, socio-demographics, slope, weather, work-related factors and attitudes (for an overview, see Heinen et al., 2010). Most of these studies analyze (commute) mode choice in general, but do not investigate day-to-day decisions. They therefore devote only limited consideration to the possibility that commuters alternate transportation modes.

However, we cannot assume that travel choices do not vary between days and that most individuals travel with the same transportation mode(s) every day. On the contrary, the Dutch Ministry of Transport, Public Works, and Water Management and the expertise center for cycling policy (Fietsberaad) have shown that individual commuters do alternate between transportation modes (2009). We assume that cyclists are particularly likely to alternate their mode choices (and commute by car or public transport), as they are more affected by conditions that change from day to day. Increasing the cycling frequency more effectively requires specific knowledge concerning the day-to-day determinants of bicycle commuting.

This paper aims to answer the question: *Which factors determine the choice of part-time cyclists to cycle or not on a specific day?* We define bicycle commuters as individuals who cycle the entire distance from home to work at least once a year. We assume that day-to-day decisions to commute by bicycle are affected by factors other than those affecting the general decision to commute by bicycle. Mode-alternating bicycle commuters differ from those who commute by bicycle all the time, and their decisions to cycle a specific day are at least partly based on different motives. We also assume that part-time cyclists can be divided in two groups, with different factors affecting their choices regarding bicycle commuting. One group (frequent cyclists) consists of bicycle commuters who choose not to cycle under specific circumstances, such as weather conditions or the need to transport goods. Another group (occasional cyclists) consists of car or public transport commuters who choose to cycle on certain days when conditions are favorable to cycling, such as pleasant weather or not wearing business attire.

To answer this question, we collected longitudinal data in two regions in the Netherlands. Respondents were approached once every two weeks during a period of one year. In contrast to cross-sectional data in which respondents are approached only once, our data-collection method allows us to model the day-to-day decisions of individuals, including factors that vary from day to day.

2 Conceptualization and hypotheses

Using the bicycle as a mode of travelling to work is an option for only a part of all commuters, and the likelihood is determined primarily by distance, but is influenced by a variety of socio-demographic and work characteristics as well. Of all commuters who consider the bicycle as an option, a certain portion still use other travel modes, while another portion use the bicycle on a daily basis. Other commuters who consider the bicycle an option alternate the bicycle with other modes; they belong to the category of part-time bicycle commuters. This paper aims to determine factors influencing day-to-day variations in bicycle mode choice among the latter category: when do part-time bicycle-commuters choose the bicycle? Are there distinctions between groups with regard to frequencies, and is it possible to identify factors that affect cycling for those groups?

We assume that part-time bicycle-commuters can be divided in at least two groups. One category consists of people for whom the bicycle is the preferred mode. These commuters aim to cycle as long as certain conditions are met (or unless certain conditions are not met). Their reasoning follows the form of, "*I cycle, except when*". Another group consists of commuters who prefer other modes, unless conditions are very favorable for cycle. Their reasoning might follow the form of, "*I cycle only if....*". Having assumed that the preferred mode is a point of departure for many commuters, we must acknowledge that we are dealing with a continuum. We also acknowledge the possibility of other categories of bicycle commuters. One example would be individuals whose preferred mode is the bicycle two days a week (e.g., Monday and Tuesday) and the car the rest of the week. They deliberately choose to cycle on certain days and not on others.

Second, we assume a number of factors as determinants. Weather is assumed to be a crucial factor for part-time cyclists for those who prefer to commute by bicycle, as well as for those who prefer other modes. We also assume that the weather characteristics (e.g., temperature, sunshine, rain, wind) have different effects on different commuters; while heavy rain may keep some from cycling, others may be more encouraged by sunshine. In addition to a linear relation between temperature and cycling (i.e., an increase in temperature encourages workers to cycle), we expect that very low and very high temperatures decrease the inclination to cycle. Seasons may play a role as well, due to their close relationship with the weather, but also because differences in hours of daylight. Seasons can thus be seen as long-term weather conditions.

Characteristics related to activity patterns are also assumed to be of influence. Work-related characteristics that could decrease the likelihood of cycling include the need to wear business attire, make business trips, or transport goods. In addition, the need to combine commuting with other destinations (e.g., taking children to school or shopping), which involves trip chaining, may also increase the likelihood of leaving the bicycle at home.

Previous research has related several socio-demographic variables to cycling levels (for an overview, see Heinen et al., 2009). For example, most research shows that men cycle more than women do (e.g., Plaut, 2005). In this research, we control for four socio-demographic variables: gender, age, education, and car ownership.

Although commuting distance does not differ from day to day for most workers, we still expect distance to have an influence. Cyclists who live further away from work are assumed to cycle less frequently, as the trip may be too exhausting to make every day. Conversely, long-distance bicycle commuters may be more dedicated to cycling and consequently be inclined to cycle more often.

In addition to the direct effects of these factors, we expect interactions between these factors to affect the decision to cycle. Commuters who face longer commuting trips are assumed to be more sensitive to the deterrents and less sensitive to the positive factors of their commutes on any given day. We therefore expect long-distance cyclists to be more sensitive to weather conditions. We also assume that female commuters are more inclined than their male counterparts are not to cycle if they would have to commute in the dark. Females are also assumed to be more sensitive to increases in commuting distance and thus to cycle on fewer days. A greater sensitivity to distance is also expected for commuters who travel at night and for those who wear business attire, as they might fear sweating. Commuters who wear business attire are also expected to reconsider commuting by bicycle if it is raining.

3 Method

3.1 Data collection

Data were collected through an internet survey conducted among a sample of employees from several large companies and residents of two mid-sized cities in the Netherlands—Delft (population 100,000) and Zwolle (population 115,000)—and two municipalities adjacent to Delft—Midden-Delfland (population 17,000) and Pijnacker-Nootdorp (population 38,000). Respondents were followed from June 2008 until June 2009. Delft is a university town in the western part of the Netherlands, positioned in the southwest section of the Randstad, a polycentric, highly-urbanized area. Zwolle, a city outside this urban conurbation, has a large population of students pursuing higher vocational education. Like many other Dutch cities, Delft and Zwolle have many bicycle facilities, including a separate infrastructure for bicycles.

Respondents were selected from an earlier survey on bicycle commuting, in which participation in subsequent research was requested (for a description, see Heinen et al., 2009). Only commuters who had indicated that they commute by bicycle at least occasionally were included. Every participant was approached by e-mail randomly once every two weeks, in order to reduce the likelihood that respondents would change transportation modes in anticipation of the survey. Participants were therefore approached multiple times on each day of the working week (Monday-Friday), with the days alternating at random. Respondents were asked to answer a short questionnaire (lasting one to two minutes) regarding their commute mode choices on that specific day. Options were provided to indicate working at home or not having worked that day. The chance to win one of forty small prizes worth 12 Euro was offered as an incentive. The specific focus on bicycle use was kept unknown to the respondents, in order to prevent individuals who almost never cycled from stopping their participation and to prevent respondents from cycling more frequently because of their participation in the survey.

We approached 834 part-time cyclists. In total, 20,016 invitations were distributed over the one-year period, and 12,928 questionnaires were completed, resulting in a 65% response rate. We assume that most of the non-response is the result of not working on that day. We excluded a number of respondents for several reasons. First, individuals who moved or changed jobs during the survey were excluded ($n=45$), as they changed their commuting trips, whereas we are interested in variations in mode choice for given origins (residential locations) and destinations (work locations). The effect of the relocation of work or home could also affect the relative position of the bicycle positively or negatively as an option for transportation, thus generating either an increase or decrease in cycling. Second, cases in which respondent did not work or

worked at home the whole day were excluded, as they could provide no relevant commute data. The analyses were thus conducted on 8,680 cases involving 633 participants.

We investigated the responses over time. Because many respondents worked part-time and had holidays, we did not expect that most respondents would participate each time they were approached. The minimum number of useful responses per respondent was 1, and the maximum was 24. Holidays are visible in the response rate: fewer respondents worked and participated in the survey during the summer and in the beginning of May, a period with many public holidays in the Netherlands. We did not survey the respondents in the two weeks around Christmas, as this is also a major holiday period. We also observed a slight reduction in the number of useful responses over time. Although we initially collected more than 400 useful responses per two weeks, the number decreased to around 350 in the second part of the survey period. One reason could be that increased familiarity with the survey could have led respondents to stop participating on non-working days (as they knew no further questions needed to be answered), despite our requests. A second reason could be that some participants did not want to participate for an entire year, despite indicating differently in the previous survey. Finally, some participants faced changes in their personal or working situations, such as the loss of a job, pregnancy, or illness.

To test the differences between the two groups of part-time cyclists (frequent and occasional), we calculated the cycling percentage using the days working out-of-home and the days of commuting by bicycle. We excluded respondents who had made fewer than 10 commuting trips, as their cycling percentage was easily affected by coincidence. There were no distinctive changes in this percentage; the only two real peaks are at 0% and 100%. In our first survey, these respondents had indicated that they commute by bicycle occasionally. Despite the fact that our data do not show their transportation-mode alternation, we have no reason to doubt their previous statements, as we did not approach them every day. Respondents with a cycling percentage of 0% or 100% are therefore included in the models.

To test differences between frequent and occasional cyclists, the part-time cyclists were divided into two groups. "Occasional cyclists" reported cycling 33.3% or less of the time, and "frequent cyclists" 66.6% or more of all their commuting trips. This categorization yielded 232 occasional cyclists and 237 frequent cyclists.

Longitudinal data have been used in the field of transportation research only occasionally, for such purposes as modeling car ownership (e.g., Woldeamanuel, 2009). Their limited application is primarily due to the time and money required for collection. The use of longitudinal data is more common in other fields; for example, they are used in health care and epidemiology to determine the effects of treatments on people's health.

Our longitudinal data collection makes it possible to extend the knowledge on the decision to cycle. It increases the possibility of investigating the relationship between factors that change from one day to the next and day-to-day decisions to cycle, and it enhances the validity of the outcomes, as compared to the collection of one-time (i.e., cross-sectional) measurements. The latter types of data reflect decisions made by different individuals. In our case, we could have approached 8,680 individuals once, but that would have yielded variations in many measured and hidden individual characteristics in addition to those changing from day to day. In the statistical model, however, we can control only for the measured factors. Longitudinal data allow us to

distinguish between events and individuals. By repeatedly measuring the decisions of multiple individuals to cycle in response to factors that vary from day to day (e.g., temperature), we are able to explain the variance within individuals while simultaneously controlling for variations between individuals to a larger extent.

3.2 Variables

We investigated the effect of factors that vary from day to day and factors related to the individual. The individual factors included are commute distance, age (in groups), gender, education level, car ownership, and the municipality. We also included a dummy for the sample sources: inhabitants or employees. The day-to-day factors included are trip characteristics (transporting goods, and trip chaining), work characteristics (working location, amount of working locations, commuting in the dark, needing a car during working hours, needing a bicycle during working hours, clothing style) and weather characteristics (precipitation: amount and length; duration of sunshine, temperature: maximum, minimum, average; visibility: maximum, minimum; wind speed: hourly average, strongest wind of the day, strongest hourly wind).

Weather data from the Royal Netherlands Meteorological Institute (KNMI) were used in the analysis. We used data from two weather stations close to the survey locations: Rotterdam for Delft, Midden-Delfland and Pijnacker-Nootdorp, and Marknesse for Zwolle. Three other weather variables are calculated: (1) rain, a dummy whether it rained that day, (2) freezing, a dummy for whether the temperature was below 0°C and (3) the average temperature of the previous week. We did not include a dummy for heat, as the data showed no decrease in cycling levels in response to increases in heat.

The variable for darkness was calculated using the working hours. For each month, the average sunrise and sunset was determined and rounded down (at the beginning of the working day) and up (at the end of working day) to a full hour. Individuals starting before or ending before sunset and those starting or ending after sunset were coded as commuting in the dark. Density data (number of households per postal code) were derived at the level of four-digit postal codes. A four-digit postal code indicates the district of the city. The population of such a district fluctuates nationally from 0 to 27,030 inhabitants. Finally, we distinguished and controlled for whether respondents had been recruited according to their residence or through their employers.

3.3 Statistical method

The observations of any individual respondent are not independent of each other. Modeling the daily commuting choices thus requires a statistical method that can correct for dependency of observations within one individual and model for a binary dependent variable (bicycle/non-bicycle).

To model longitudinal data, both Generalized Estimating Equations (GEE) and Random Coefficient Analyses (RCA) are suitable methods, as both can correct for dependency of observations within one individual (Twisk, 2004). Also known as multilevel or mixed-effect analysis, RCA is a hierarchical statistic method that can model parameters varying at more than one level. It can be used for longitudinal studies by allowing the regression coefficients to differ between subjects (Twisk, 2007). With GEE, relationships are analyzed at different time-points simultaneously (Twisk, 2007, p62). In this method, a correction for correlation within subjects is made using an a priori selected correlation structure for the repeated measurements of the outcome variable (Twisk, 2007). "Like random coefficient analysis, GEE enables to analysis longitudinal

relationships using all available longitudinal data, without summarizing the longitudinal development of each subject into one value" (Twisk, 2007, p60).

For binary data, GEE is the more suitable method. Compared to RCA, the outcomes of GEE analyses are more conservative and thus more robust for binary dependent variables. With regard to outcomes, the regression coefficients and standard errors of a logistic longitudinal RCA are always higher than those of a GEE. Twisk (2007) advises using GEE analysis for dichotomous outcome variables from longitudinal research "if one is performing a population study and one is interested in the relationship between a dichotomous outcome variable and several other predictor variables," as in our case, as "GEE will probably provide the most 'valid' results" (p.142). In analyses involving the "individual development over time of a dichotomous outcome variable RCA will probably provide the most 'valid' results" (Twisk, 2004, p. 774). Another reason for not choosing RCA is that RCA models for dichotomous dependent variables are not fully developed. Even within one software package, there are multiple estimation options, which often lead to different outcomes (Twisk, 2004). We model daily choice using GEE and RCA in STATA SE 10.

3.3.1 Logistic GEE

Generalized Estimating Equations models are an extension of generalized linear models and are developed to test the influence of factors on binary and other non-normally distributed dependent variables collected within subjects over time (Ballinger, 2004). Models developed according to GEE measure population-averaged effects.

$$U(\beta) = \sum_{i=1}^N \frac{\partial \mu_{ij}}{\partial \beta_k} V_i^{-1} \{Y_i - \mu_i(\beta)\}$$

In this equation, i represents the subject (1,...,N), and N_i represents the choices made by subject i . The symbol $\sum_{i=1}^N$ represents all choices made (i.e., all measurements). The covariance matrix of Y_i is V_i . Y_{ij} represents the j th response of subject i . The vector of choices made by subject i is $Y_i = (Y_{i1}, \dots, Y_{ip})$. The vector of explanatory variables related to Y_{ij} is $X_{ij} = (X_{i1}, \dots, X_{ip})$.

Twisk (2004) offers a more easily interpretable formula, in which $CORR$ is the working correlation matrix, i is the subject, t is time, J is the number of time-dependent predictor variables, and M is the number of time-dependent variables:

$$\text{logit}(Y_{it}) = \beta_0 + \beta_{1t} + \beta_{2j} \sum_{j=1}^J X_{ij} + \beta_{3m} \sum_{m=1}^M X_{im} + \dots + CORR_{it} + \epsilon_{it}$$

To correct for within-subject correlation, GEE uses one of five a priori correlation structures: independent, exchangeable, autoregressive, stationary m-dependent, and unstructured (Twisk, 2007). We expect the sequence of measurements to have no effect; in other words, we assume similar correlations between the measurements. The correlation between the second and third measurements of a given respondent is thus expected to equal the correlation between the third and fourth and between the fourth and fifth measurements. We therefore used an exchangeable structure (see below), as it assumes that correlations between each subsequent measurement are similarly independent of the length of time between intervals. The estimated regression

coefficients form a combined within-subjects and between-subjects relationship, resulting in one regression coefficient for each independent variable.

$$\begin{array}{cccc}
 & t_1 & t_2 & t_3 \\
 t_1 & 1 & \rho & \rho \\
 t_2 & \rho & 1 & \rho \\
 t_3 & \rho & \rho & 1
 \end{array}$$

Twisk (2004) indicates that analyses of an incomplete dataset due to missing data can produce results that differ from those obtained by analyzing a complete dataset. However, imputing data can also produce unpredictable results in longitudinal analysis with a dichotomous dependent variable (Twisk, 2007). To assess the stability/validity of the obtained results, we also ran models for respondents who had at least 10 useful responses. In addition, we compared the results of the GEE model to those of a model based on RCA (random coefficient only, no random slope).

4 Results

We modeled the effect of work-related factors, trip-related factors, and weather conditions on the day-to-day choice to commute by bicycle, controlling for socio-demographic factors, two sample sources, and area of data collection. The dependent binary variable is whether the respondent cycled to work. Only significant variables in the GEE including all cases were included in the final model. All previously discussed variables not included were insignificant. Our discussion is based on the outcomes of the GEE with all observations included (left part of the table). The presented coefficients from the GEE analyses are a combined effect of within-subject and between-subject relationships (Twisk, 2004). The RCA was conducted with a random intercept only.

4.1 Cycling to work

Table 4 shows corresponding with our expectations, that work, trip, and weather characteristics affect the day-to-day decision to cycle. Working somewhere else than the primary location and working at more than one location on a specific day decreases the probability of commuting by bicycle. This is probably a result of both the possible additional distance and the increased trip complexity. Commuters needing a car during working hours, needing to transport goods, or wearing business attire are more likely to leave their bicycles at home. Needing a bicycle during office hours increases the chance of cycling to work.

Each additional kilometer (home-to-work distance) decreases the likelihood of commuting by bicycle. Individuals needing to make stops (trip chaining) during their commute trips are also less likely to cycle to work. An additional analysis (not reflected in the tables) reveals that combined trips made for childcare (picking up/dropping off), work, sport, social activities, cultural activities, and education reduce the likelihood of commuting by bicycle. The combination of commuting with daily errands increases the chances of cycling to work. In contrast to other activities, doing daily errands is apparently easy to combine with commuting by bicycle.

Five weather conditions influence cycling behavior. Both the quantity and the duration of rain affect cycling negatively. In addition, the inclination to cycle decreases in proportion to increases in wind speed. Increases in the duration of sunshine or in

temperature, however, increase the likelihood of commuters to cycle. Commuters thus base their mode choices partly on the weather conditions of a given day.

In contrast to our expectations, only one interaction effect is significant. Women are less likely to cycle to work in the dark, so women are more sensitive to the absence of daylight. No interactions between gender and distance were significant, indicating that male and female respondents are equally sensitive to distance. Moreover, wearing business attire is no stronger as a deterrent for commuters who cycle over longer distances, and cycling in the rain wearing business attire is no more unpleasant than it is when wearing another type of attire. Likewise, there is no effect of clothing style combined with distance. In contrast to our assumptions, several variables have insignificant effects (and therefore are not included in the model), including the following: density, season, temperature the previous week, extreme temperatures (below 0°C), and visibility. The insignificance of season and the previous week's temperature reveals that day-to-day weather conditions explain more of the variation in mode choice than do long-term conditions. Counter to our expectations, extreme temperatures (below 0°C) have no added effects above those of the ratio variable for temperature. In addition, the outcome of the model shows no influence of the respondent's region, and no effect was found for the sample source.

We included all relevant respondents in the analysis, even those with few useful responses. We assumed that the low number of useful responses was caused by fewer working days or hours, illness, or dismissal and that the commuting styles of these respondents did not differ from those of other respondents. To check for an effect, we repeated the analysis with respondents who provided more than 10 useful responses. Corresponding to our assumptions, we obtained similar results (see Table 1). We also ran a GEE for all cases, but excluding the respondents who reported cycling 100% or 0% of the time (not reported). Identical results were obtained in this case as well. The choice to cycle was analyzed with RCA models, too (not reported). The results are comparable (note that the interaction between darkness and gender is not included in the RCA model), and there are only a few differences in significance. These findings imply that the outcomes are robust.

Table 1 The daily decision to cycle to work

		GEE			GEE, 10 or more valid cases				
		Coef.	Std. Err.	P> z	Coef.	Std. Err.	P> z		
gender	(male)								
	female	-0.248	0.13	0.053	*	-0.188	0.15	0.219	
age	(<40)								
	40-60	0.125	0.14	0.357		-0.008	0.17	0.959	
	60+	-0.241	0.32	0.447		-0.105	0.35	0.761	
education	(high)								
	low	-0.407	0.20	0.042	**	-0.617	0.24	0.011	**
	medium	-0.320	0.15	0.028	**	-0.459	0.18	0.010	**
car ownership	(no)								
	yes	-1.277	0.28	0.000	***	-1.372	0.32	0.000	***
needing a car during office hours	(no)								
	yes	-1.720	0.18	0.000	***	-1.702	0.20	0.000	***
needing a bicycle during office hours	(no)								
	yes	1.267	0.16	0.000	***	1.271	0.17	0.000	***
transporting goods	(no)								

wearing business attire	yes	-1.465	0.12	0.000	***	-1.589	0.15	0.000	***
	(no)								
primary working location	yes	-0.437	0.17	0.011	**	-0.364	0.19	0.053	*
	(primary working location)								
	home	-0.146	0.28	0.606		-0.368	0.35	0.290	
	other location	-1.355	0.17	0.000	***	-1.465	0.19	0.000	***
working at multiple locations	(no)								
	yes	-0.188	0.09	0.042	**	-0.154	0.10	0.131	
precipitation, daily amount (in .1 mm)		-0.002	0.00	0.003	***	-0.002	0.00	0.003	***
precipitation, length (in 0.1 hour)		-0.002	0.00	0.090	*	-0.002	0.00	0.139	
maximum temperature		0.002	0.00	0.000	***	0.003	0.00	0.000	***
sunshine, duration (in 0.1 hour)		0.003	0.00	0.000	***	0.002	0.00	0.005	***
wind speed, daily average (in 0.1 m/s)		-0.005	0.00	0.000	***	-0.005	0.00	0.001	***
distance		-0.085	0.02	0.000	***	-0.091	0.02	0.000	***
darkness while commuting	(no)								
	yes	0.015	0.07	0.834		-0.006	0.08	0.937	
making stops/chaining trips	(no)								
	yes	-0.365	0.07	0.000	***	-0.372	0.07	0.000	***
interaction female-darkness		-0.249	0.12	0.042	**	-0.218	0.14	0.111	
sample source	(inhabitants)								
	employees	0.120	0.14	0.396		0.244	0.16	0.137	
city	(Delft)								
	Zwolle	0.371	0.17	0.029	**	0.559	0.21	0.008	***
	Pijnacker-Nootdorp	0.031	0.18	0.860		0.239	0.21	0.248	
	Midden-Delfland	0.615	0.18	0.001	***	0.777	0.22	0.000	***
cons						0.492	0.40	0.214	
Wald chi2(26)=511.10						Wald chi2(26)=421.21			
*** P<0.01; ** P<0.05; *P<0.1									

4.2 Occasional and frequent cyclists

To test for the differences in factors affecting the daily choices of occasional and frequent cyclists, we estimated two GEE models using the same variables included in the model for all part-time cyclists (Section 4.1). The outcome of the GEE supports our assumption that occasional and frequent cyclists base their decisions to commute by bicycle on different factors (Table 2). Frequent cyclists are mostly influenced by factors that make commuting by bicycle more difficult, whereas occasional cyclists are also affected by factors that make the bicycle trip more pleasant.

In detail, pleasant weather stimulates cycling among occasional cyclists. Both higher temperature and longer duration of sunshine increase the likelihood to cycle. This indicates that occasional cyclists are specifically encouraged by coincidental positive circumstances. Occasional cyclists do not cycle when wearing business attire, meaning that the clothing style can keep a commuter from cycling. In general, occasional cyclists who live further away from work cycle less frequently.

Frequent cyclists are affected by their working locations. People who need to work at multiple locations on one day, or somewhere other than the primary location are less likely to cycle to work that day. When frequent cyclists combine their commuting trips with trips for other purposes, they cycle less often. These three factors increase trip complexity and possibly distance, which complicates cycling. This indicates that the mode

choices of people who cycle frequently is more affected by changes in their trips, possibly because they decide not to cycle only if they truly cannot cycle. Finally, strong winds discourage frequent cyclists from commuting by bicycle.

For both groups, needing a car during office hours and needing to transport goods decrease the likelihood of cycling to work. Needing a bicycle also encourages both groups of part-time cyclists to commute by bicycle. These findings suggest that these factors have a similar influence on all part-time cyclists.

Table 2 The daily decision to cycle to work; frequent and occasional cyclists

		occasional cyclists			frequent cyclists		
		Coef.	Std. Err.	P> z	Coef.	Std. Err.	P> z
gender	(male)						
	female	0.339	0.20	0.084	-0.060	0.17	0.720
age	(<40)						
	40-60	0.077	0.19	0.678	0.083	0.15	0.589
	60+	0.477	0.32	0.140	0.161	0.46	0.726
education	(high)						
	low	-0.980	0.35	0.005 **	0.266	0.30	0.372
	medium	-0.620	0.20	0.002 **	0.135	0.19	0.478
car ownership	(no)						
	yes	-0.028	0.39	0.942	-0.082	0.23	0.718
needing a car during office hours	(no)						
	yes	-1.566	0.51	0.002 **	-2.283	0.32	0.000 **
needing a bicycle during office hours	(no)						
	yes	2.309	0.36	0.000 **	1.805	0.37	0.000 **
transporting goods	(no)						
	yes	-1.830	0.38	0.000 **	-2.430	0.23	0.000 **
wearing business attire	(no)						
	yes	-1.010	0.42	0.017 *	-0.208	0.30	0.493
primary working location	(primary working location)						
	home	1.051	0.61	0.084	-1.264	0.57	0.026 *
	other location	-0.441	0.39	0.261	-1.832	0.24	0.000 **
work at multiple locations	(no)						
	yes	-0.602	0.33	0.070	-0.513	0.18	0.004 **
precipitation, daily amount (in .1 mm)		-0.002	0.00	0.313	-0.002	0.00	0.250
precipitation, length (in 0.1 hour)		-0.007	0.00	0.073	-0.002	0.00	0.464
maximum temperature		0.005	0.00	0.000 **	0.000	0.00	0.773
sunshine, duration (in 0.1 hour)		0.007	0.00	0.002 **	0.003	0.00	0.136
wind speed, daily average (in 0.1 m/s)		-0.009	0.00	0.072	-0.007	0.00	0.037 *
distance		-0.057	0.02	0.001 **	0.033	0.03	0.211
darkness while commuting	(no)						
	yes	-0.028	0.30	0.925	0.077	0.19	0.687
making stops/chaining trips	(no)						
	yes	-0.309	0.17	0.066	-0.290	0.15	0.046 *
interaction female-darkness		-0.800	0.47	0.087	-0.166	0.31	0.595
sample source	(inhabitants)						
	employees	-0.173	0.23	0.447	0.088	0.18	0.619
city	(Delft)						
	Zwolle	-0.326	0.29	0.265	-0.145	0.21	0.479

	Pijnacker- Nootdorp	0.233	0.24	0.325		-0.390	0.23	0.091
	Midden- Delfland	0.599	0.24	0.014	*	-0.109	0.23	0.640
constant		-3.599	0.66	0.000	**	0.047	0.44	0.915
						Wald chi2(26)=365.14		

Wald chi2(26)=142.54

** P<0.01; * P<0.05

5 Conclusion

This paper provides insight into day-to-day decisions to cycle to work, using longitudinal data from two Dutch regions. The findings add to the existing knowledge in three ways. First, they provide evidence that the mode choices of many cyclists are affected by factors that change from day to day. The GEE results reveal that the day-to-day decision to cycle is largely influenced by short-term conditions, such as weather conditions, work characteristics and trip characteristics.

Second, the results show the existence of two groups of part-time cyclists. The decision of frequent cyclists (those who cycle more than 66.6% of their commuting trips) to choose an alternative mode of transportation is affected largely by factors that complicate cycling, such as strong wind and working at multiple locations. In contrast, occasional cyclists (those who cycle for less than 33.3%) are affected by factors that make cycling more pleasant, for example nice weather.

Third, the use of longitudinal data collection allowed us better insight into the decision to cycle than would have been possible with cross-sectional data. Longitudinal data make it possible to investigate a person's decision at multiple moments in time, in contrast to data that reflect only one observation per person (logically from only one day). By repeatedly measuring the decisions of multiple individuals to cycle in response to factors that vary from day to day, we are able to explain variance within individuals while controlling to a large extent for variation between individuals.

The similarities between the outcomes of the models testing for the factors influencing the choice to commute by bicycle (see Section 4.1) indicate that the results are robust. The coefficients of the GEE are indeed lower than those produced by the RCA. The GEE is thus more reserved with reporting the significance of factors. The results from the GEE analysis with all cases are nearly identical to those from the GEE with the cases of individuals providing more than 10 useful responses, indicating that the model including all cases is quite robust despite the missing data.

Efforts to increase the cycling rate should focus primarily on occasional cyclists, as the factors that affect occasional cyclists to cycle are weaker deterrents than are those that affect frequent cyclists. Frequent cyclists are apparently cyclists by conscious choice. The days that they commute by alternative modes also appear to be the result of conscious decisions.

Dutch commuters cycle more than commuters in other countries do. Differences in the built environment, cycling culture, attitudes, norms, and facilities at work could cause the findings of this study to differ from situations in other countries, and the insignificant factors in our analysis may have a significant effect in other countries. First, if cycling is associated with stereotypes, individuals who do not fit this image, such as women, may be less inclined to cycle in certain circumstances. In most countries, men and young adults cycle more (see Heinen et al., 2010), whereas cycling in the Netherlands is relatively gender and age neutral. In other countries, therefore, we could

expect to observe stronger effects of socio-demographics and interaction effects between socio-demographics and other factors. In addition, weather conditions may be more extreme in other countries. The Dutch climate has mild summers and winters, with rain all year. Cycling is therefore usually possible in all seasons. Commuters in countries with periods of colder weather, heat, or strong rainfall may face severe difficulties with cycling on those days. Nevertheless, the factors identified in this study are likely to have similar effects on the decision to commute by bicycle in other countries, given their negative effects in the Netherlands, a cycling-minded country. Reducing the impact and frequency of these factors is thus likely to increase the probability of cycling in any country.

References

- Hardman, A.E. (1999) Accumulation of physical activity for health gains: what is the evidence? *British Journal Sports Medicine* 33(2), pp.87-92.
- Heinen, E., Wee, B. Van, Maat, K. 2010. Commuting by bicycle, an overview of literature. *Transport Reviews* 30(1), 59-96.
- Heinen, E, Maat, K and Wee, B van (2009) The Effect of Work-related Factors on the Bicycle Commute Mode Choice in the Netherlands, IATBR, India 2009.
- Hox, J. (2002) *Multilevel analysis. Techniques and applications*. Lawrence Erlbaum Associates, Inc. Publishers, Mahwah, New Jersey.
- KNMI [Koninklijk Nederlands Meteorologisch Instituut] (Royal Dutch Meteorological Institute) weather data the Netherlands, 2008-2009.
- Ministry of Transport, Public Works and Water Management and Fietsberaad [*Centre of Expertise on Bicycle Policy*] (2009) *Cycling in the Netherlands*. Den Haag, The Netherlands.
- Plaut, P. O. (2005) Non-motorized commuting in the US, *Transportation Research Part D* 10, pp. 347-356.
- Pucher, J., Dill, J. & Handy, S. (2010) [Infrastructure, programs, and policies to increase bicycling: An international review](#). *Preventive Medicine*, 50(Supplement 1): S106-S125.
- Twisk, J.W.R. (2007) *Applied longitudinal data analysis for epidemiology. A practical guide*. Cambridge University press, New York.
- Twisk, J.W.R. (2004) Longitudinal data analysis. A comparison between generalized estimating equations and random coefficient analysis, *European Journal of Epidemiology* 19, pp. 769-776.
- Woldeamanuel, M.G., Cyganski, R., Schulz, A. and Justen, A. (2009) Variation of households' car ownership across time: application of a panel data model. *Transportation Research Board Annual Meeting*, Washington D.C, pp.: 1-16.