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Longitudinal associations of active commuting with wellbeing and sickness absence

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ABSTRACT

Objective. Our aim was to explore longitudinal associations of active commuting (cycling to work and walking to work) with physical wellbeing (PCS-8), mental wellbeing (MCS-8) and sickness absence.

Method. We used data from the Commuting and Health in Cambridge study (2009 to 2012; n = 801) to test associations between: a) maintenance of cycling (or walking) to work over a one year period and indices of wellbeing at the end of that one year period; and b) associations between change in cycling (or walking) to work and change in indices of wellbeing. Linear regression was used for testing associations with PCS-8 and MCS-8, and negative binomial regression for sickness absence.

Results. After adjusting for sociodemographic variables, physical activity and physical limitation, those who maintained cycle commuting reported lower sickness absence (0.46, 95% CI: 0.14–0.80; equivalent to one less day per year) and higher MCS-8 scores (1.50, 0.10–2.10) than those who did not cycle to work. The association for sickness absence persisted after adjustment for baseline sickness absence. No significant associations were observed for PCS-8. Associations between change in cycle commuting and change in indices of wellbeing were not significant. No significant associations were observed for walking.

Conclusions. This work provides some evidence of the value of cycle commuting in improving or maintaining the health and wellbeing of adults of working age. This may be important in engaging employers in the promotion of active travel and communicating the benefits of active travel to employees.

Introduction

Research on the associations between active travel and health has focused on major diseases and mortality(Jarrett et al., 2012; Laverty et al., 2013; Saunders et al., 2013). In contrast relatively little work has explored the associations between active travel and other measures such as sickness absence(Hendriksen et al., 2010) and wellbeing,(Gómez et al., 2013; Humphreys et al., 2013; Martin et al., 2014; Mutrie, 2002) despite the existence of positive associations between overall physical activity and these outcomes(Amlani and Munir, 2014; Bize et al., 2007; Ferrie et al., 2005; Hendriksen et al., 2010; Laaksonen et al., 2009; Lahti et al., 2012; Proper et al., 2006).

These associations are of interest for several reasons. Wellbeing is important to individuals, and is increasingly recognised as important for governments(Boorman, 2009; Office for National Statistics, 2011). Sickness absence is an important measure for employers,(Office for National Statistics, 2014) and is also a good predictor of future disability or death(Kivimäki et al., 2004, Kivimäki et al., 2003; Marmot et al., 1995). If either measure were shown to be associated with active travel, this might strengthen the case for employers investing in its promotion(Black, 2008; National Institute for Health and Clinical Excellence, 2012, 2008). These measures may also be more sensitive to change than disease end points in a relatively healthy population of working age, and therefore may be appropriate outcomes to use in some studies of the effect of active travel on health.

Research in this area has also frequently been limited to cross-sectional studies (Gómez et al., 2013; Hendriksen et al., 2010; Humphreys et al., 2013) which provide a weak basis for inferring causation. Some studies present conflicting findings, particularly concerning the association between active travel and mental well-being (Gómez et al., 2013; Humphreys et al., 2013; Martin et al., 2014; Mutrie, 2002). In this study, we build on previous cross-sectional analysis using data from the Commuting and Health in Cambridge study, which explored the associations between active commuting and wellbeing(Humphreys et al., 2013). With the addition of follow-up data from the same cohort, our aim in this paper is to explore the

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longitudinal associations of active commuting with physical wellbeing, mental wellbeing and sickness absence.

Methods

Study setting and data collection

The analysis used data from the Commuting and Health in Cambridge study, a longitudinal study of commuters working in Cambridge, UK (n = 1431). A full description of this study has been published elsewhere(Ogilvie et al., 2010). Participants completed up to four annual questionnaires (2009–2012) that included information on travel behaviour, physical activity, sociodemographic characteristics and measures of health and wellbeing. Ethical approval was granted by the Hertfordshire Research Ethics Committee and the Cambridge Psychology Research Ethics Committee. All participants gave written informed consent.

Inclusion and exclusion criteria

New participants were recruited during each of the first three years of the study. As only a small number of participants completed three or four waves of the study, we restricted our analysis to those who completed two consecutive waves of the study (n = 866). We further excluded those with missing exposure (n = 25), outcome (n = 5) or covariate data (n = 35), such that we undertook a complete case analysis (n = 801). We defined the baseline questionnaire for each participant as their first questionnaire with complete information on exposure. The follow-up questionnaire for each participant was the questionnaire completed one year after their baseline questionnaire.

Exposure measures

The primary exposures of interest were maintenance of cycling to work and maintenance of walking to work. While these exposures were ascertained at baseline for each participant, we chose to restrict our analysis to those who were confirmed at follow-up to have comparatively stable commuting behaviour. This ensured that estimates of association would not be influenced by the potential misclassification of those who changed their behaviour during the period of observation (e.g. if a participant switched from cycling to work to not cycling to work two weeks after baseline data collection). The secondary exposures of interest were change in weekly time spent cycling to work and change in weekly time spent walking to work.

Weekly time spent cycling to work at each time point was estimated by summing the total number of trips to and from work involving any cycling that were reported in a seven day travel record, and multiplying this by the typical duration of cycling per trip (assessed in a separate question) (Panter et al., 2011). Maintenance of cycling to work was defined as weekly cycling time > 0 minutes at both baseline and follow-up. The reference group consisted of those who did not cycle to work at both baseline and follow-up. Consequently participants who stopped cycling to work (e.g. weekly cycling time > 0 minutes at baseline and weekly cycling time = 0 minutes at follow-up) or took up cycling to work were not categorised, and were therefore excluded from analyses that used this exposure measure.

Change in weekly time cycling to work between baseline and follow-up was categorised as either any increase, no change, or any decrease, based on the difference in the estimates of time cycling to work at baseline and follow-up. As small increases or decreases might reflect reporting errors rather than true changes, we also conducted a sensitivity analysis in which only large increases or decreases in cycle commuting time (≥50 min/week) were categorised as 'change', and smaller changes were re-categorised as 'no-change'(Panter et al., 2015).

The same process was followed for walking to work.

Outcome measures

We used three measures (physical wellbeing, mental wellbeing and sickness absence), hereafter collectively referred to as "indices of wellbeing". Physical Component Summary (PCS-8) and Mental Component Summary (MCS-8) scores were derived from responses to the Medical Outcomes Study Short Form questionnaire (SF-8) (see appendix) (Ware et al., 2001). The SF-8 questionnaire comprises eight ordinal response questions concerning participants' wellbeing in the past four weeks, with different weights being applied to each question to derive the scores as described by Ware et al (Ware et al., 2001). In our analysis the two scores were treated as continuous variables and analysed as separate outcomes, as one might expect each measure to have different associations with active travel (Humphreys et al., 2013; Richards et al., 2015). Sickness absence was self-reported as the total number of days absent from work in the past year, using a validated question (Ferrie et al., 2005).

Covariates

Date of birth, date of questionnaire completion, education, sex, height, weight, difficulty walking, limitation of physical activity, home postcode, home to work distance, and physical activity (Recent Physical Activity Questionnaire)(Besson et al., 2010) were assessed by questionnaire. Dates of birth and questionnaire completion were used to calculate age. Weight status (low or healthy weight, overweight, obese) was assigned based on participant's body mass calculated by dividing weight by height squared (World Health Organisation, 2000). Physical activity level (inactive, moderately inactive, moderately active, active) was assigned based on occupation and time spent in recreational activity following the Cambridge Physical Activity Index (Wareham et al., 2003). While the original index incorporated walking and cycling to work, we excluded time spent in these activities when assigning participants. A physical limitation variable (yes/no) was created, with participants being assigned to 'yes' if they either (a) reported difficultly walking for a quarter of a mile on the level or (b) reported that physical health problems limited their ability to do usual physical activities.

Analysis

We used two complementary approaches to testing longitudinal associations.

In the first set of analyses, we modelled the associations between maintenance of cycling (or walking) to work and indices of wellbeing at follow-up. These 'maintenance analyses' were intended to contribute to establishing evidence of a temporal relationship, because the exposure was ascertained before the outcome (Hill, 1965). We used linear regression to test the associations of maintenance of cycling (or walking) to work with PCS-8 and MCS-8. However, sickness absence was positively skewed with a large number of zero counts. Following Zhou et al,(Zhou et al., 2014) we fitted different models (e.g. linear, binomial, negative binomial, zero-inflated) and found our data were fitted best by a negative binomial distribution. Consequently we used negative binomial regression to test the associations with sickness absence. Regression models were adjusted for all covariates (age, sex, education, physical activity, weight status, physical limitation, home-work distance and study year) (model A).

We further conditioned each analysis on the baseline value of the outcome variable in question (i.e. analysis of covariance) (model B). In this context, analysis of covariance addresses whether there is a difference in the change in outcome between cyclists and non-cyclists *who have the same initial value of the outcome*? It is considered the most appropriate approach to test for differences in change between two groups, when there are baseline differences in the outcome of interest between groups (Fitzmaurice, 2001; Twisk and Proper, 2005).

In the second set of analyses, we used linear regression to test the associations between change in cycling (or walking) to work and changes in indices of wellbeing. By focusing on individuals who changed their behaviour, these 'change analyses' were intended to provide a more direct estimate of the effect that might be induced by increasing or reducing a given behaviour. Change in sickness absence had a positive kurtosis, and we truncated outliers (to +/− 30 days) so that residuals were normally distributed. We used the same approaches to adjustment for covariates described above (model A and model B).

In summary we used two analytic approaches ('maintenance' and 'change'), each with two stages of adjustment for covariates (model A and model B), applied to two exposures (cycling and walking to work) and three outcomes (PCS-8, MCS-8 and sickness absence). We also undertook sensitivity analyses adjusting the 'maintenance' analyses for the reciprocal commuting behaviour (e.g. models using cycling to work as the exposure were additionally adjusted for walking to work). All analyses were conducted in Stata v13.

Results

The participants included in analysis were predominantly women (69.7%), educated to degree level or higher (70.2%), of low or healthy bodyweight (65.4%), and slightly more than half reported cycling to