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Authors: Nikita Jacob, Luke Munford, Nigel Rice, Jennifer Roberts

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Nikita Jacob [a] Luke Munford [b] Nigel Rice [c,†] Jennifer Roberts [d]

[a] *Centre for Health Economics, University of York, UK*

[b] *School of Health Sciences, University of Manchester, UK*

[c] *Centre for Health Economics & Department of Economics and Related Studies, University of York, YO10 5DD, UK*

[d] *Department of Economics, University of Sheffield, UK*

Abstract

Governments around the world are encouraging people to switch away from sedentary modes of travel towards more active modes, including walking and cycling. The aim of these schemes is to improve population health and to reduce emissions. There is considerable evidence on the latter, yet relatively little on the former. This paper investigates the impact of mode choice on measures of physical and mental health as well as satisfaction with health. Using data from the UK Household Longitudinal Study from 2009-2016, our empirical strategy exploits changes in the mode of commute to identify health outcome responses. Individuals who change modes are matched with those whose mode remains constant. Overall we find that mode switches affect both physical and mental health. Specifically we find an increase in physical health for women and an increase in mental health for both genders, when switching from car to active travel. In contrast, both men and women who switch from active travel to car are shown to experience a significant reduction in their physical health and health satisfaction, and a decline in their mental health when they change from active to public transport.

JEL classification: C1; I1

Keywords: Commuting mode; health; panel data econometrics

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†Corresponding author: *Tel.:* +44 1904 321438; *E-mail address:* nigel.rice@york.ac.uk.

1 Introduction

Governments around the world are encouraging people to switch away from cars and towards more active modes of travel, including walking and cycling. For example, in the UK in 2017 the government announced an investment of £1.2 bn in a scheme to encourage walking and cycling.[1] The aims of such schemes are usually two-fold: (1) to improve population health by encouraging physical activity and (2) to reduce emissions and hence lower pollution levels. There is considerable evidence on the effectiveness of the latter of these aims (Rabl and deNazelle, 2012). There is also evidence on the benefits to health of more active models of travel. However, the majority of existing evidence has relied on cross-sectional data (Flint et al., 2014; Flint and Cummins, 2016) which precludes causal interpretation. Although these cross-sectional associations are important, they do not allow the study of the health effects brought about - or caused - by a change in commuting mode. As well as being promoted by governments, active travel (commuting by walking or cycling) is strongly recommended by the UK National Institute for Health and Care Excellence (NICE, 2012) as a feasible way of incorporating greater levels of physical activity into daily life.

In order to estimate meaningful effects of the impact of mode of transport, we need to address issues of unobserved preferences and changes in mode choices occurring due to health related reasons. In this paper we aim to tackle these important gaps in the literature by providing evidence of the effects of changes in commuting mode on health for adults in employment in the United Kingdom. Commuting is the most regular and frequent reason for travel for working age individuals and is an important modern phenomenon. The average commuter in the UK spends nearly an hour a day travelling and this is increasing over time (Department for Transport, 2017).

Taking advantage of the UK Household Longitudinal Study (UKHLS) which has a large sample size, a longitudinal dimension and a broad range of survey modules covering

[1] https://www.gov.uk/government/news/government-publishes-12-billion-plan-to-increase-cycling-and-walking

health and labour market experiences, we analyse the effect of changes to commuting mode on physical and mental health across working individuals. A key feature of the data that we are able to exploit is that there are a sufficient number of individuals who are observed to change their mode of commute (we refer to these as treated individuals) and we have an extensive pool of potential controls for whom commuting mode remains constant across waves of observation. This permits us to exploit matching methods (via entropy balancing[2]), such that we are able to obtain a close balance on confounding covariates, that in part determine both health outcomes and commuting mode choice, across treated and control individuals. This allows us to derive estimates of average treatment effects on the treated (ATTs). Following Ho et al. (2007), we do this by preprocessing the data via matching prior to undertaking parametric modelling. This 'doubly robust' approach has the advantage of being robust to either misspecification in the parametric model but complete covariate balance via matching, or incomplete balance through matching but correct specification of the regression model. This can be viewed as a way to achieve balance in covariates with the objective of reducing model dependence in the subsequent regressions to extract the ATTs (Abadie and Imbens, 2011).

We follow individuals over time until they experience a change in their mode of commute, and compare their health responses to that observed in a matched control group. We match on socio-demographic characteristics observed pre-treatment, including initial mode and duration of commute and initial health status. Using regression methods we then compare health outcomes between treated individual's (who experience a change in commuting mode) and their matched controls. Conditional on the validity of selection on observables, the approach identifies a causal effect of a change in commuting mode on health outcomes. Our main outcomes of interest are summary measures of mental and physical health derived from the SF-12 and a self-reported measure of satisfaction with health. Our findings show that adopting active means of travel improves health, for both men and women. Changing from an active mode to either public transport or car travel

[2]Hainmueller (2012); Hainmueller and Xu (2013).

has an expected negative impact on health. Further analyses, comparing outcomes in the short and intermediate term, confirm our main results.

2 Related literature

A number of studies have looked at the relationship between mode of commuting and health/well-being of individuals. The general consensus in these literatures is that active commuting has positive effects on an individual's physical, mental and overall general health. In what follows, we briefly set out the main findings from these studies.

Evidence from the UK has largely relied on the use of the British Household Panel Survey (BHPS), its successor the UKHLS and more recently the UK Biobank data. This has consistently suggested that levels of physical activity involved in active modes of commuting, such as walking or cycling, translate into greater health benefits for individuals. These benefits include lower BMI and percentage of body fat, enhanced mood, increases in mental health and physical well-being for individuals engaged in active modes of travel compared to users of motor transport.[3] For example, Laverty et al. (2013), using data from the first wave of the UKHLS, consider the association between active travel and cardiovascular risk factors. They find that participants living in London were more likely to engage in active travel. In comparison to the use of private means of transport, the use of public transport, as well as walking or cycling to work was associated with a lower likelihood of being overweight. Individuals who walked or cycled to work had a lower likelihood of having diabetes, and individuals who walked had a lower likelihood of having hypertension than those who used private means of transport.

The mental health benefits of active travel arise from the fact that it is perceived to be both more relaxing and exciting than other modes of transport (Scheepers et al., 2014). It also promotes higher life satisfaction (Morris, 2015) and is found to be associated with a lower rate of mental and emotional distress. MacDonald et al. (2010) and Frank

[3] Flint et al. (2014); Flint and Cummins (2015, 2016); Martin et al. (2014); Humphreys et al. (2013); Yang et al. (2012); Ettema and Smajic (2015).

et al. (2004) suggest that spending more time in cars is associated with increases in both obesity and blood pressure, perhaps due to the frustrations of commuting traffic congestion (Stokols et al., 1978). Other studies have also concluded that car commuting is stressful and leads to negative mood among drivers[4], since car users perceive their journey as requiring greater effort and being more unpredictable than users of public transport (Wener and Evans, 2011). Contrasting evidence, however, by Anable and Gatersleben (2005) and Eriksson et al. (2013) has shown that driving to work provides individuals a positive feeling through greater control and flexibility over their commute. As commonly expected, active travel also has positive effects on the environment since it reduces air pollution (Rabl and deNazelle, 2012), which in turn reduces the risk of cancer (Litman, 2010) and cardiovascular diseases (Litman, 2010; Hamer and Chida, 2008; Genter et al., 2008; Scheepers et al., 2014).

Studies outside the UK report similar evidence on the relationship between commuting mode and well-being. In terms of commuter satisfaction, Turcotte (2005), Turcotte (2011), and Páez and Whalen (2010) using Canadian data and Friman et al. (2013) using Swedish data, find that active travel commuters tend to report higher satisfaction than users of other means of travel. Cyclists display the highest level of satisfaction, followed by pedestrians. Public transport users were least satisfied compared to other modes of transport including car users.[5] Moreover, Turcotte (2011) found that users of public transport were less satisfied than car drivers over short commutes, but with longer commutes, a large proportion of public transit users reported being satisfied with their travel time. This indicates that public transport users may have a higher tolerance for longer commutes than car drivers (St-Louis et al., 2014). However, in terms of the effects on health, several studies have concluded that public transport users tend to be physically healthier than car commuters since they meet the recommended level of physical activity more often, as they tend to walk to reach bus or train terminals (MacDonald

[4]Wener and Evans (2011); Bellet et al. (1969); Ferenchak and Katirai (2015); Gatersleben and Uzzell (2007); Künn-Nelen (2015); Rissel et al. (2014).

[5]Friman et al. (2013); Gatersleben and Uzzell (2007); Páez and Whalen (2010); Turcotte (2005); Eriksson et al. (2013).

et al., 2010; Wener and Evans, 2007). Other studies suggest that using public transport causes travellers to experience lower levels of stress since they do not experience traffic congestion especially when they use train or light rail transit (Wener and Evans, 2011).

Little research has explored the effects of *changes* in travel mode on health. A recent study by Martin et al. (2014) explores the relationship between active travel and psychological well-being using longitudinal data from the BHPS from 1991-2009. The study relies on fixed effects regression models to investigate how choice of travel mode, commuting time and switching to active travel impact overall psychological well-being as well as specific psychological symptoms reported in the General Health Questionnaire (Goldberg and Williams, 1988). They found evidence to suggest that switching to active travel was associated with an improvement in well-being on the GHQ scale when compared to individuals who always commuted by car or public transport. Extending their study using the same dataset, Martin et al. (2015) examined the effect of switching from private motor transport to active travel or public transport (in the next period) on changes in BMI. They found that those who switched were observed to have a reduction in BMI, even in a short time period of under 2 years.

We advance the above literature by taking into account the potential for selection bias and exploiting methods of matching together with parametric regression, in a panel data setting, to improve identification of the health impacts of commuting mode choice. We only consider individuals for whom household location is fixed but allow job locations to vary; which may be employer or employee induced. A change in job location may lead to a change in commuting mode through either a change in commuting route and/or distance, or a change in job remuneration allowing, via an income effect, greater choice of travel mode.

3 Conceptual framework

We assume that individuals derive utility (or possibly disutility) from commuting, such that $U = U(m, h(m,t), z)$, where m represents mode choice and z represents other consumption from which individuals derive utility. Individuals are also assumed to value any health impacts of their commuting mode choice, which will also be a function of time spent commuting represented by $h(m,t)$. Hence individuals derive utility, both directly and indirectly through their choice of commuting mode. Direct utility may be positive, for example, the enjoyment of driving, the ability to relax or work on public transport, the enjoyment of exercise from walking or cycling to work, or negative, for example, frustration of sitting in heavy traffic, crowded public transport, inclement weather during active commuting. Indirect utility is derived from mode choice through the impact this has on health status; including both physical and/or mental health (Lancee et al. 2017; MacDonald et al. 2010; Wener and Evans 2007; Frank et al. 2004). For example, exposure to exhaust fumes or being seated for long periods of time might impact physical health negatively; the uncertainty of disruption during car travel may affect mental wellbeing; exercise through active travel is likely to impact physical and mental health positively. Accordingly, commuting mode can be seen as being valued for both a consumption property - the direct impact on utility, and an investment property - the indirect health effects (Grossman, 1972). In making choices over mode, individuals are assumed to maximise utility subject to constraints over income and time. Different forms of travel attract different prices and hence cost to the commuter and therefore will be influenced by an individual's income constraint. Individuals also face a time constraint, which, during the working day, consists of choices over time spent on leisure (t_l), work hours (t_w), and commuting (t_c), such that ($t_l + t_w + t_c = 24$hrs). The greater time spent commuting, the less time available for other pursuits, assumed mainly to be leisure for individuals with fixed hours of daily work. In this way, commuting entails an opportunity time cost to the individual and choices over mode will be influenced by this constraint. Under this framework, individuals are assumed to choose the commuting mode that maximises their utility subject to the constraints they face at a particular point in time. Should the value individuals place on the investment and/or consumption properties of mode choice change, or should individuals face changes to their constraints (for example, through a change in job location or road infrastructure affecting commuting time and costs), this may lead to a change in commuting mode.

We are interested in identifying the health effects of commuting mode choice. Our approach considers those individuals who change mode at time t as treated and those who do not change mode as potential controls. By matching controls to treated individuals at time *t-1* we assume that the average utility of the two groups of individuals, prior to treatment is equivalent. Matching is undertaken on a set of potential confounding characteristics thought, a priori, to influence both mode choice and health outcomes. In keeping with the framework described above, this includes initial mode and commuting time, health status, and household income among other factors.[6]

Adopting a potential outcomes framework, the above matching procedure assumes that conditional on the set of confounding covariates, x, selection into treatment, d, is independent of potential outcomes, such that $(h^0, h^1) \perp d|x$. where h^0 and h^1 are potential health outcomes for treated individuals without treatment, h^0, and with treatment, h^1, respectively. This is often termed the conditional independence assumption (for example, see Heckman and Robb (1985)). Where this holds, the average treatment effect on the treated $ATT = E\left(h^1 - h^0|x, d = 1\right) = E\left(h^1|x, d = 1\right) - E\left(h^0|x, d = 1\right)$ can be estimated by replacing the unobserved component $E\left(h^0|x, d = 1\right)$ with its observed counterfactual $E\left(h^0|x, d = 0\right)$. Following matching, we estimate the treatment effect (change in mode) using a regression framework. The latter helps to mitigate bias in the treatment effect resulting from less than perfect matching. Full details of the matching and regression approach is set out in Section 4.

[6]These are measured at time *t-1* to avoid being contaminated by the treatment occurring at time *t*.

4 Empirical approach

Our empirical strategy exploits *changes* to mode of commute observed in the data at time *t*, but occurring somewhere between *t-1* and *t*, to identify the responses on health outcomes at time *t+1*. We compare outcomes for individuals who experience a change to their mode of commute (who we denote as 'treated') with outcomes for observationally identical (as of *t-1*) individuals, who do not experience a change to their commuting mode (who we denote as the 'control group').[7] Prior to the occurrence of the change, observational equivalence is defined by a wide set of potential confounders, including demographic factors such as age, marital status and number of kids; labour market characteristics such as job hours and income as well as baseline health and commuting mode.

Identification relies on the assumption that selection into treatment (change in mode choice) is independent of outcomes, conditional on the set of confounding variables.[8] Our approach follows the principles set out in Ho et al. (2007) to use matching methods to preprocess the data prior to parametric modelling of outcomes. The aim of data preprocessing is to reduce model dependency by using matching to create balance in covariate distributions across treated and control groups. Successful matching renders treatment independent of control variables. Subsequent parametric regression modelling of the preprocessed data is therefore less dependent on specification assumptions and hence more likely to identify consistent causal effects. Where matching proves to be less than perfect, the application of regression techniques conditional on the same set of confounding variables controls for the lack of perfect balance. Ho et al. (2007) describe this two-step procedure as being doubly robust. That is, if matching is correct, but the

[7] We call it a treatment effect but it is not treatment in a strict sense. We do not know histories of individuals prior to changing modes. It maybe that those from the treated or control group may have switched modes in the past. However, we only consider individuals from the time they are first observed in the sample.

[8] An alternative to matching is simply to regress the outcomes on the treatment indicator and the set of confounding variables. However, deriving causal effects from such an approach is highly model dependent, where any alterations to the model specification or parametric assumptions may lead to different inference.

subsequent regression is misspecified, or if matching is incomplete, but the specification of the regression model is correct, treatment effect estimates will be consistent. The approach can be viewed as an extension of the usual matching techniques, which rely on comparisons of means of the matched data. It is straightforward to implement and only requires a preprocessing step prior to undertaking usual parametric analysis.

Matching is undertaken for each of the observed treatments defined by changes in commuting mode: car-public, car-active, public-active and their converse. We then regress outcomes on the set of controls and a treatment effect separately for each of the six matched samples as follows:

$$h_{i,t+1} = \alpha + \beta_d d_{i,t} + X'_{i,t-1}\beta_x + \gamma\lambda_{i,t-1} + \varepsilon_{i,t+1} \qquad (1)$$

where β_d identifies the treatment effect of interest; the change in mode at time t on health outcomes, h_i at time $t+1$. The set of variables used to match controls to treated individuals prior to treatment are represented by $X_{i,t-1}$ (see Table 5 for a list of variables) and their corresponding relationship with outcomes, β_x.[9] $\lambda_{i,t-1}$ are wave indicators to recognise that changes to mode may occur in different calendar years; $\varepsilon_{i,t+1}$ is the usual idiosyncratic error term. Regression weights derived from entropy balancing are applied to Model (1). Models for cardinal outcomes are estimated using ordinary least squares; models of ordered categorical outcomes are estimated with ordered probits. All regressions contain robust standard errors.

We use matching techniques to adjust the covariate distribution of the control group data by reweighting and/or discarding units such that it becomes more similar to the covariate distribution in the treatment group. A number of matching techniques could be employed to preprocess the data in this way. We apply entropy balancing, introduced by Hainmueller (2012), which involves a reweighting scheme that directly incorporates covariate balance into the weight function that is applied to the sample units. This is done by selecting a set of weights for each observation in the control group that minimize an

[9]Note that where perfect balancing is achieved $\beta_x = 0$.

entropy distance metric subject to balance and normalizing constraints. This ensures that the weights are nonnegative and sum to unity. These weights satisfy a set of balancing constraints that involve specifying exact balance on moments of the covariate distributions in the treatment and the reweighted control group. The usual balance constraint is that the sample average of each covariate should be the same in the treatment and control groups, and these can be altered to achieve balance on higher moments such as variance and skewness. We apply exact balance on the mean and variance of the covariate distributions.[10]

All individuals in our sample are considered untreated in the first wave. An individual is assigned only once to the treatment group, when they first change their mode of commute, any subsequent changes in commuting mode are excluded from analysis.[11] Treated individuals never act as potential controls at any other point in time. Potential control individuals are those who never change their mode of commute while they are observed in the UKHLS survey.

We are concerned with three different commuting modes; by car (driver or passenger), public transport (bus, tram and/or underground, or train), or active travel (walking or cycling). We consider the following changes: car to active travel, public transport to active travel, active travel to car, and active travel to public transport. We have additionally considered switches between car and public transport, and vice-versa, but as these do not involve a switch into or out of more active modes, which are often the policy goal, these are not the main focus of our analysis. For each change in mode we match control individuals to treated individuals and then perform regression analysis on the balanced data. Matching is undertaken at $t-1$, mode change is observed at time t and outcomes at $t+1$. We further repeat the analyses (including matching and regression on outcomes) to compare short-run outcomes at time t, and longer term outcomes at $t+2$.[12]

[10] Hainmueller (2012) demonstrates a numerical implementation of the technique and computational methods are presented in Hainmueller and Xu (2013)

[11] That is, observations are dropped if and when a subsequent mode change is observed.

[12] The question on commuting at a given wave is in the present tense: *"How do you usually get to your place of work?"*. It can therefore be assumed that a change of mode took place at some time between waves $t-1$ and t. Accordingly, outcomes at time t can be considered short-run effects.

An important feature of the literature on commuting is the difference in travel behaviour between men and women, with men, on average, undertaking longer commutes. There are a number of possible explanations for the observed differences, arising from the differential domestic and labour market positions of men and women (Hanson and Pratt, 1995). Further, Roberts et al. (2011), find that the wellbeing of women, but not men, is adversely affected by increased commuting times, while Jacob et al. (2019) provide evidence that this is due to the different labour markets in which women and men operate. Accordingly, we undertake heterogeneity analysis by gender and as outlined above, apply entropy balancing and regression analysis within gender for each of the mode changes.

5 Data

5.1 UK Household Longitudinal Study (UKHLS)

Our primary dataset is the UKHLS which is a nationally representative sample of UK households designed as the follow up survey to the BHPS. The survey contains repeated information on around 100,000 individuals in 40,000 households. We use seven waves of data from 2009 to 2016. UKHLS contains a rich set of information on socio-economic, health, and labour market characteristics relating to both individuals and households; this enables us to identify the causal impact of commuting mode on health.

Health is measured using both the physical and mental health component scores derived from the Short Form 12 (SF12) questionnaire. The SF12 uses twelve questions to measure functional health and wellbeing. The responses to these questions are then used to create the Physical Component Summary (SF12-PCS) and the Mental Component Summary (SF12-MCS). The SF12-PCS and SF12-MCS are cardinal representations of underlying health status, designed to lie between 0 (lowest level of health) and 100 (highest level of health). The measures are designed to have a mean of 50 and a standard deviation of 10 for the general population (Ware et al., 2002). As an additional outcome we also use responses to questions on satisfaction with health from the self-completion questionnaire of the UKHLS. This is recorded on a five point ordered categorical scale, where 1 is least satisfied and 5 is most satisfied.[13]

Our measure of commuting mode is taken from the response to the question *"How do you usually get to your place of work?"* which is asked only to people who state they are in employment. The responses to this question are categorised as Car (car drivers and passengers), Public transport (bus, train and undergound) and Active travel (cycle, walk) with Other (taxi, moped, other mode) as an alternative group that we do not consider due to small sample sizes. To control for individual preferences we condition on characteristics typically used in the literature, including age, educational attainment, the number of children in a household, a married/cohabiting identifier, and log equivalised monthly household income (deflated to 2005 prices, and equivalised using the OECD modified scale, detailed in Foster 2009).

Table 1: Information on inclusion criteria and sample size

	Number		Percent	
Criteria	Observations NT	Individuals N	Observations NT	Individuals N
Full UKHLS Sample	333,773	83,287	100%	100%
In at least two waves	315,330	64,844	94%	78%
Employed in all waves	148,218	38,365	44%	46%
No change of house	127,030	35,908	38%	43%
Non-missing Work travel information	119,243	33,620	36%	40%
Non-missing Health indicators	108,292	32,247	32%	39%
Age ≥ 16 and ≤ 65	106,464	31,787	32%	38%
Non-missing education, job hours, other health information	106,195	31,736	32%	38%
Surveyed for ≥ 3 waves	86,519	18,156	26%	22%
Surveyed for ≥ 4 waves	73,715	13,888	22%	17%

Table 1 presents information on the basic inclusion criteria for the sample of UKHLS individuals used to define the estimation sample. The seven waves of the UKHLS sample contains information on $N = 83,287$ individuals who are observed across waves to provide $NT = 333,773$ total observations. We remove individuals who are observed in only a single wave (we are concerned with identifying the effect of *changes* across waves in

[13]In the raw UKHLS, this variable is recorded on a 7 point scale, however, for our analysis we code it on 5 point scale by combining responses 2-3 together and 5-6, respectively.

commuting modes on health); individuals not employed and individuals who change place of residence. Accordingly, our working aged sample (16-65 years of age) sample consists of 31,736 individuals for whom there are a total of 106,195 observations. Descriptive statistics for the estimation sample are provided in Table 2. The mean scores on SF12 PCS (phsyical health) and SF12 MCS (mental health) are 52.90 and 49.94, respectively, while the mean for health satisfaction 3.5. There are slightly more observations on females than males; mean age is 42 years; 45% have a university level qualification, average usual hours of work is 33; and average log equivalised monthly household income is 7.55.[14]

The sample as defined, with $N = 31,736$, represents our starting point for analysis.[15] The criterion of being observed in at least two consecutive waves allows us to consider short-run outcomes at time t following balancing on covariates at time $t-1$.

First, the data are stratified into treated and respective control groups, where the treated are observed to change mode, for example, from car to active travel and the control group never change from car travel. Secondly, for this sub-sample, matching controls to treated individuals through entropy balancing is then undertaken followed by weighted regression of outcomes (here at time t). Exact sample sizes will vary across the four possible mode changes observed. Our main outcome of interest is observed at time $t+1$. Similarly, when considering long-run effects ($t+2$), the initial basic sample is further refined to exclude individuals with less than four waves of data before matching and regression analysis. Resulting sample sizes are reported in the respective tables of results.

Table 3 breaks down the descriptive statistics of commuting time by gender and mode of transport. Males, in general, experience longer commutes (27.83 minutes for a one-way commute compared to 23.62 for women), with the differential between men and women remaining irrespective of the mode of transport. Public transport is associated with the longest commuting times (an average one-way commute of 48 minutes) and

[14]This is equivalent to a monetary value of approximately £1,900 per month.

[15]$N = 31,736$ for analysis of outcomes at time t, consequently, $N = 18,156$ for outcomes at $t+1$ and $N = 13,888$ at $t+2$ (see Table 1).

Table 2: Summary statistics for estimation sample

	Overall					*Women*			*Men*		
	Mean	**Std. Dev.**	**Min**	**Max**	**N**	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
SF12PCS	52.901	8.035	4.64	74.710	106,195	52.773	8.439	58,927	53.059	7.497	47,268
SF12MCS	49.943	8.918	0	77.09	106,195	49.123	9.257	58,927	50.965	8.363	47,268
Satisfaction with own Health	3.495	1.047	1	5	105,952	3.478	1.065	58,783	3.683	0.939	47,268
Male	0.445	0.497	0	1	106,195						
Age	42.072	11.734	16	65	106,195	42.196	11.609	58,927	41.918	11.886	47,268
University level qualification	0.449	0.497	0	1	92,592	0.469	0.499	51,365	0.423	0.494	41,227
College level qualification	0.212	0.409	0	1	92,592	0.197	0.398	51,365	0.231	0.421	41,227
School level qualification	0.201	0.401	0	1	92,592	0.208	0.406	51,365	0.194	0.395	41,227
Household size	3.092	1.345	1	16	106,195	3.049	1.294	58,927	3.146	1.404	47,268
Number of children	0.707	0.979	0	8	106,195	0.681	0.939	58,927	0.739	1.025	47,268
Married/Cohabiting	0.712	0.453	0	1	106,055	0.682	0.466	58,837	0.749	0.434	47,218
Usual hours worked	33.186	10.334	0.1	97.7	106,195	29.614	10.247	58,927	37.638	8.561	47,268
Log household income	7.55	0.537	1.901	9.903	105,986	7.522	0.546	58,777	7.584	0.525	47,209

Our working sample is $NT = 106,195$, based on an unbalanced sample of $N = 31,736$ individuals.

cycling the shortest (16 minutes). The distribution of commuting times for active travel and non-active (users of public transport or car) is provided in the Appendix as Figure A.1. As expected there is a greater concentration of short commute durations for active commuters compared to non-active travel.

Figure 1 shows the percentage of individuals who use each of the three modes over time. The percentage of people using a car is relatively stable at around 70% in each wave. The percentage of people using public transport drops between waves 1 and 2, but then steadily increases to a similar level in wave 7 as in wave 1. There has been a slight decline in the number of people walking or cycling. Figure 2 shows the associated commuting times. All three modes have experienced a gradual increase in commuting time, but this is largest for walking and cycling.

Table 4 reports the transition probabilities between waves t and $t + 1$. Among car users at time t, 95% will remain so in the following wave, with 2% switching to public transport and 3% switching to walking or cycling. Amongst initial public transport users, 81% remain using public transport whereas 13% switch to car and 6% switch to active modes. Finally, among initially active commuters, 78% remain so, whereas 16% and 5% switch to car and public transport, respectively. So in summary, there is much more resilience to switching away from car than the other two modes.

Table 3: Sample commuting times by gender and mode

	NT	Mean	Std. Dev.	Median
All modes				
Commuting time[a] - full sample	106,195	25.50	20.48	20
Male	47,268	27.83	22.11	20
Female	58,927	23.62	18.86	20
By mode[b]				
Car - all	74,181	23.19	17.81	20
Male	33,120	25.36	19.70	20
Female	41,061	21.43	15.92	20
Public transport - all	14,576	47.88	24.21	45
Male	6,579	50.79	24.89	45
Female	7,997	45.49	23.37	45
Walk or Cycle - all	15,643	15.94	12.60	15
Male	6,402	17.86	14.07	15
Female	9,241	14.61	11.28	10

[a]We winsorize the commuting data, such that any observations above the 99th centile are recoded to be equal to the value at the 99th centile. Without doing this the maximum CT was 740 minutes, which we think unrealistic. This winsorization does not affect our conclusions, and results without this recoding are available on request.

[b] Car is defined as any commuter who uses either a car or van (either as a driver or a passenger) as their main mode of travel to work. Public transport is defined as those who use either a bus, train, or underground/tram, and those who either walk or cycle the whole way are the Walk or Cycle commuters. Note that the sum of Car + Public Transport + Walk or Cycle is not equal to the overall sample size as we do not include people who use a motorcycle, moped or taxi.

Figure 1: Percentage of individuals using each mode across all seven waves

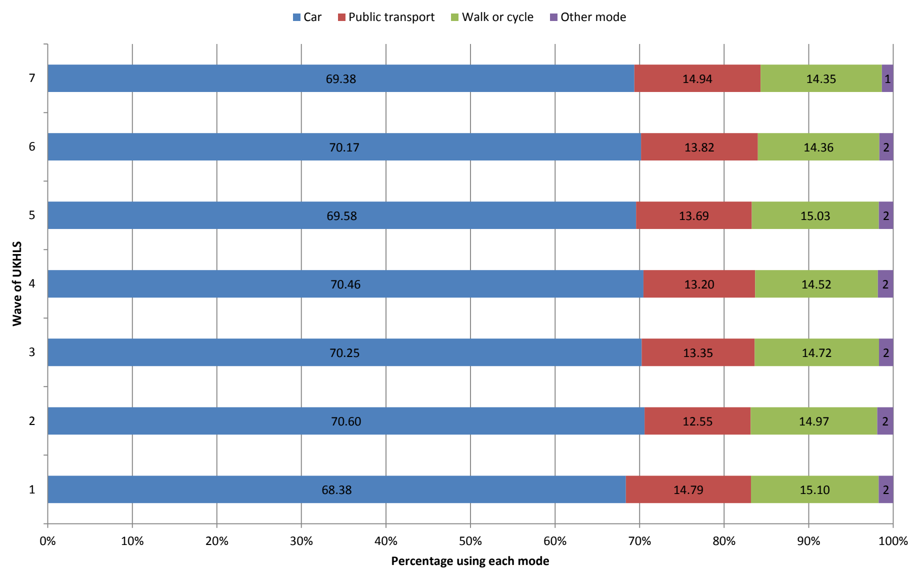


Figure 2: Average commuting time by mode of travel across all seven waves

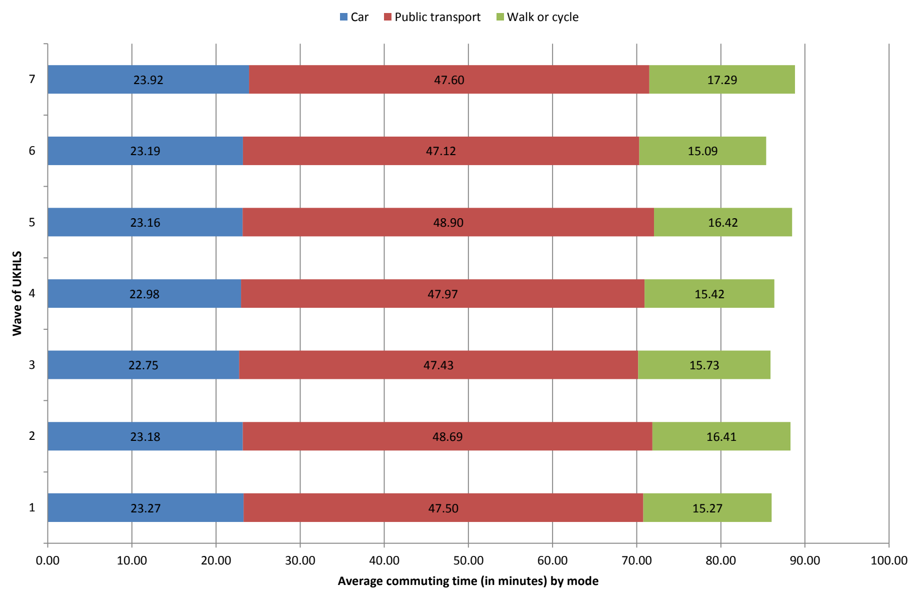


Table 4: Transition probabilities between waves

	$t+1$		
Mode	Car	Public transport	Walk or cycle
Car	0.95	0.02	0.03
Public transport	0.13	0.81	0.06
Walk or cycle	0.16	0.05	0.78

6 Results

The success of any matching strategy is achieved through obtaining close covariate balance and common support between treated and controls.[16] This relies on the availability of an adequate number of potential control individuals. From our analytical sample, 82% (26,177) of individuals report no change in their commuting mode, while 12% (3,654) report having changed mode once across the sample period. The remaining observations are observed to change mode twice (5%) or more. A full breakdown is provided in Table A.1 in Appendix A. We only use information on the first observed mode change for treated individuals and any subsequent changes in mode are dropped. All 26,177 individuals observed not to change mode, form the pool of potential controls.

Table 5 illustrates entropy balancing for a mode change from car to public transport. Matching takes place on covariates measured at time $t-1$. The table shows summary statistics prior and post matching using entropy balancing (EB). Treated individuals undergo the change in mode, control individuals remain as car users. EB equates the moments of the covariate distribution across treated and control groups (via weighting). Successful balancing occurs where the specified moment conditions imposed on EB are met empirically. Table 5 illustrates results for balancing on the first and second moments (mean and variance). As can be seen, following EB the mean and variance of the set of covariates are very similar across treated and control individuals. This is reassuring as it provides support that the conditional independence assumption, $(h^0, h^1) \perp d|x.$, set out in Section 3 holds. EB for other mode changes and for men and women separately, follow a similar pattern. To conserve space we do not present all the results here, but they are available on request.

The set of results in Table 6 exploit changes to commuting mode occurring between *t-1* and *t* to identify health outcomes observed at *t+1*. These results suggest that mode changes from car to public transport and vice versa, do not impact health outcomes.

[16]Common support ensures there exists no treated individual with an observed covariate value outside the range of the distribution in the control group.

Table 5: Mode change: Car to Public, Entropy Balancing Match estimates

		Treated $N = 646$			Control $N = 39636$		
		Mean	Variance	Skewness	Mean	Variance	Skewness
Before balancing	Age	40.10	126.40	-0.14	43.44	109.40	-0.22
	Number of kids	0.75	1.02	1.19	0.75	0.97	1.15
	Job hours	33.61	94.24	-0.80	34.00	89.41	-0.48
	Married	0.67	0.22	-0.75	0.77	0.18	-1.29
	Household Income (log)	7.55	0.34	0.10	7.57	0.25	-0.14
	SF12_PCS	53.49	64.79	-1.66	53.10	61.96	-1.65
	SF12_MCS	49.44	77.44	-1.06	50.19	74.61	-1.18
	CT_5 mins (log)^c	3.23	0.49	-0.19	2.93	0.51	-0.17
	Wave	2.92	2.38	0.39	3.41	2.57	0.08
	Treated wave	4.33	2.51	0.15	4.58	2.57	0.00
After balancing	Age	40.10	126.40	-0.14	40.44	125.90	-0.01
	Number of kids	0.75	1.02	1.19	0.75	1.01	1.24
	Job hours	33.61	94.24	-0.80	33.71	93.81	-0.52
	Married	0.67	0.22	-0.75	0.68	0.22	-0.79
	Household Income (log)	7.55	0.34	0.10	7.54	0.34	-1.23
	SF12_PCS	53.49	64.79	-1.66	53.42	64.58	-1.81
	SF12_MCS	49.44	77.44	-1.06	49.51	77	-1.11
	CT_5 mins (log)	3.23	0.49	-0.19	3.20	0.51	-0.35
	Wave	2.92	2.38	0.39	2.98	2.45	0.38
	Treated wave	4.33	2.51	0.15	4.36	2.53	0.15

Matching using entropy balancing on 1^{st} and 2^{nd} moments of covariate distribution. Note that except treated wave, all are lagged (1) variables. Dependent variable measured at t+1. Sample consists of individuals who are in the survey for at least 3 (or more) waves. ^{c} The log of commuting time in 5 minute bins. We match in small time windows so as to achieve close balance.

Estimated effects are generally small, particularly for a switch from car to public, and do not attain statistical significance. In contrast, when considering a mode change from car to active travel, we observe a large positive effect on mental health, measured by the SF12-MCS. The effect is observed, in similar magnitude, for both men and women (although the statistical significance for women is lower due to smaller sample sizes). There is also an indication that physical health improves for women (SF12-PCS), significant at the 10% level. Interestingly, individuals who switch mode from active travel to car report a significant decrease in physical health. Again these effects are observed overall and also for men and women separately (at reduced significance levels). We also observe a decrease in satisfaction with health for the overall sample (at the 10% significance level). It would appear, therefore, that the effect of a change from car to active travel is felt more strongly through improvements to mental health, whereas the effect of a mode change to car from active travel is felt through decreases to physical health. We do not observe the same effects when considering changes from public transport to active travel and vice-versa. Individuals who switch from public to active forms of travel report increased health satisfaction, predominantly men, but we do not observe significant effects for mental or physical health. However, this may be due to the small sample sizes observed for this mode change. The reverse mode change from active travel to the use of public transport is associated with a reduction in reported mental health, particularly for men.[17] A graphical illustration of these results, for switches to or from active travel across both men and women is shown in Figure 3 below.[18]

Overall, we do not observe effects on health from changes in mode between public transport and car use, or vice-versa, but do observe effects when moving between active forms of travel and vehicular travel (car or public). However, effects appear generally small being typically less than a tenth of a standard deviation. In comparison to other

[17]Ideally we would control for the time spent on physical exercise by individuals to derive the true effect of a switch from active or into active modes of travel. However, questions of physical exercise are only asked in one wave of the dataset.

[18]We also conducted analyses with the SF12 Index as a measure of health. We find increases in women's health at $t + 1$ when switching from car to active travel.

studies that use the SF12 health measure, Ziebarth (2010) shows that the difference in means for the mental health index of the SF12 is 6.2 and physical health is 3.6 (when rescaled between 0 and 100), when comparing health for the lowest income group to the highest group. While the study does not explicitly consider changes in income and instead compares means across groups of individuals the results do provide context to the size of effects found in this paper for observed changes in commuting mode. In general, our findings indicate that changing commuting mode has a notable impact on health. A change of mode from car to active travel for women has an approximate equivalent effect on physical health of one sixth of the effect of moving between the lowest and highest income percentile groups. The corresponding effect on mental health for both men and women is approximately equivalent to one eighth of the effect of changing income percentile groups.

6.1 Immediate and longer run effects

In this section we investigate the possible immediate effects (at time t), as well as longer-run effects (at time $t+2$), of a change in commuting mode (occuring at time t) on health outcomes. Full results are reported in Tables A.2 and A.3 in the Appendix, respectively. Results are broadly similar to those reported in Table 6. Mode changes from car to public transport or vice-versa, do not lead to changes in reported health or health satisfaction (an exception is that women report increased health satisfaction from a change from public to car at time $t + 1$). A shorter run effect of a change from car to active travel is observed for women's mental health and for health satisfaction overall. We also observe a decrease in reported physical health for men in the short-run when switching mode from active travel to car. These results echo those observed for the main results at time $t+1$. We also observe shorter-run effects of a reduction in health satisfaction (at p <10% level). Similarly, mode change from public transport to active travel results in a short-run increase in reported health satisfaction, driven predominantly by men (as with effects observed at time $t + 1$). However, we do not observe significant shorter-run effects from

Table 6: Entropy Balancing by gender for outcomes at time t+1

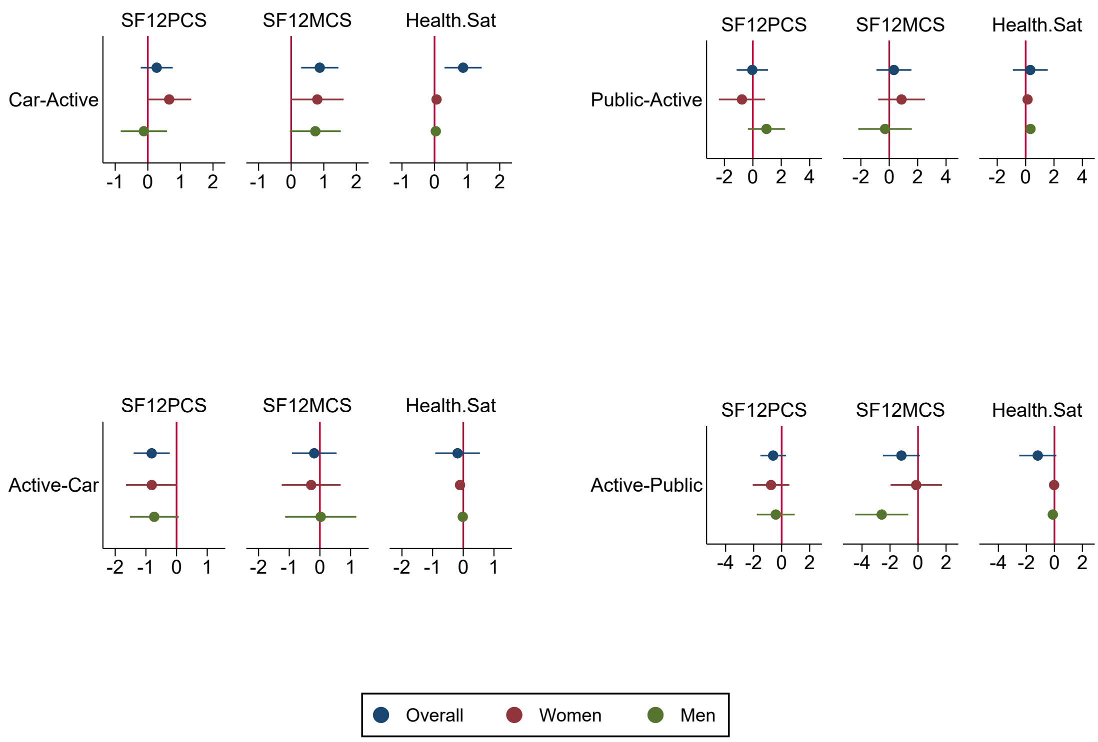
	Overall	Women	Men	Overall	Women	Men	Overall	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	SF12PCS	SF12PCS	SF12PCS	SF12MCS	SF12MCS	SF12MCS	Health.Sat	Health.Sat	Health.Sat
Car->Public	0.022	0.019	0.085	0.013	-0.122	0.124	0.034	0.006	0.093
	(0.350)	(0.492)	(0.491)	(0.391)	(0.538)	(0.563)	(0.056)	(0.075)	(0.084)
N	29,714	16,954	12,760	29,714	16,954	12,760	29,617	16,895	12,722
Treated	646	369	277	646	369	277	644	367	277
Control	39636	22518	17118	39636	22518	17118	39544	22463	17081
Car->Active	0.273	0.656*	-0.121	0.877***	0.802*	0.741*	0.052	0.063	0.039
	(0.250)	(0.345)	(0.362)	(0.291)	(0.411)	(0.399)	(0.042)	(0.056)	(0.062)
N	29,937	17,064	12,873	29,937	17,064	12,873	29,839	17,005	12,834
Treated	909	498	411	909	498	411	906	496	410
Control	39636	22518	17118	39636	22518	17118	39544	22463	17081
Public->Car	-0.070	0.513	-0.692	0.343	0.593	0.111	0.022	0.047	0.021
	(0.358)	(0.510)	(0.486)	(0.433)	(0.614)	(0.609)	(0.059)	(0.077)	(0.091)
N	3,909	2,094	1,815	3,909	2,094	1,815	3,889	2,083	1,806
Treated	707	412	295	707	412	295	706	411	295
Control	4639	2473	2166	4639	2473	2166	4619	2461	2158
Public->Active	-0.039	-0.767	0.960	0.330	0.866	-0.295	0.230***	0.137	0.345***
	(0.563)	(0.829)	(0.669)	(0.627)	(0.840)	(0.963)	(0.083)	(0.108)	(0.129)
N	3,609	1,912	1,697	3,609	1,912	1,697	3,589	1,901	1,688
Treated	330	188	142	330	188	142	329	187	142
Control	4639	2473	2166	4639	2473	2166	4619	2461	2158
Active->Car	-0.810***	-0.808*	-0.727*	-0.186	-0.285	0.027	-0.080*	-0.106	-0.016
	(0.300)	(0.427)	(0.406)	(0.371)	(0.490)	(0.592)	(0.048)	(0.065)	(0.074)
N	4,098	2,542	1,556	4,098	2,542	1,556	4,083	2,533	1,550
Treated	861	487	374	861	487	374	856	483	373
Control	4688	2964	1724	4688	2964	1724	4678	2959	1719
Active->Public	-0.605	-0.756	-0.420	-1.187*	-0.128	-2.591***	-0.068	-0.020	-0.114
	(0.468)	(0.666)	(0.689)	(0.673)	(0.935)	(0.965)	(0.084)	(0.119)	(0.121)
N	3,670	2,305	1,365	3,670	2,305	1,365	3,659	2,299	1,360
Treated	333	196	137	333	196	137	332	195	137
Control	4688	2964	1724	4688	2964	1724	4678	2959	1719

Sample where individuals are present for at least 3 (or more) waves. Dependent variables measured at time $t+1$, and are increasing in good health/satisfaction. Controls are matched to treated individuals using entropy balancing at time $t-1$, prior to regression analysis of outcomes on treatment (at t), conditioning on covariates and wave dummies (at $t-1$). Covariates include age, number of kids, job hours, marital status, household income, commuting time and initial health. Estimates for Health Satisfaction are coefficients from an ordered probit model. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

switches from active travel to public transport.

In the longer-run at time $t + 2$ we find positive and significant effects on health satisfaction from a mode change from public to active travel driven mainly by women, and a corresponding decrease in health satisfaction for changes in the opposite direction (for men only). Mode changes from car to active travel at time t do not affect health at time $t + 2$. This might be due to individuals adapting to the change in travel over the long-run and reporting health relative to recent periods. Oddly, while a mode change from active to car travel leads to a lowering of physical health in the longer run, we also see an improvement in mental health, particularly for women.

Figure 3: Effect of Mode changes on Health at t+1



7 Sensitivity Checks

7.1 The interaction between commuting time and mode

The modelling framework assumes that utility depends on mode choice m, together with health impacts from mode choice and time spent commuting, $h(m, t)$ and other activities z. In order to examine the robustness of our results, we repeat our analysis by including an interaction between commuting time and mode in our sample of individuals who never change residence. These results are reported in Table A.4. We find effects for men when they change from public to active travel and from active to car travel. These effects are larger in magnitude when compared to the main results reported in Table 6.

7.2 Seasonality in mode choices

It is possible that individuals may change their choice of commuting mode depending on weather conditions. Progressing into summer, individuals may increasingly opt to switch to active modes of travel via cycling or walking. Conversely individuals are more likely to switch to car or public transport in winter months. To control for seasonal effects when identifying changes in mode, we include the lag of the month of interview in our balancing and our regression model. Results are reported in Table A.5 and are consistent with the main results. Again, we observe an increase in mental health for both men and women when they switch from car to active travel and a decline in physical health for both groups when they switch from active to car. As before, these effects are observed at reduced significance levels. Similarly, the transition from public to active transport increases health satisfaction for men while the reverse transition decreases their mental health significantly, as previously observed.

7.3 Constant household location and job

So far, our estimation sample consists of individuals who do not change household address but we placed no restriction on their job characteristics. However, changes in commuting mode can also occur if individuals change jobs leading to a greater distance to travel. In a further analysis, we select a subsample of individuals who report no change in household location and job characteristics. These estimates are reported in Table A.6. Once again, these effects confirm our main results, although each of these effects are of a slightly higher magnitude compared to those in Table 6. Again, the main effects are observed for mens' health satisfaction which increases when they change from public to active travel and a significant decline in their mental health when they switch from active to public transport. We observe a decrease in physical health for women when they switch from active to car travel and an increase in physical health (at lower levels of significance) when they move from car to active transport.

8 Concluding Remarks

This paper evaluates the impact of a change in mode of commute on health. There is evidence on the gains to health from active modes of travel. Therefore, schemes to encourage active travel in the form of walking or cycling are being adopted by countries around the world. The majority of this evidence relies on (often dated) cross-sectional data and thus does not examine the effect of *changes* in travel mode on health. Of those few studies that do explore the effect of changes in mode, Martin et al. (2014) use fixed regressions to address the potential for selection bias. In this paper, we improve on the identification of health impacts from commuting mode choice by employing an empirical strategy that combines matching techniques together with regression based analysis, to provide new evidence on the effect of commuting mode change on health.

Using rich data taken from the UKHLS covering 2009-16, we compare health outcomes (at various time periods) for individuals in employment who never change mode throughout the survey, with those who experience a mode change. Our main results indicate a significant increase in physical and mental health for commuters switching from car to active forms of transport, particularly for women. We further observe a decline in physical health for individuals of both sexes who switch from active travel to car. A change in mode from active travel to public transport leads to a decrease in reported mental health, largely for men, but we do not observe significant decreases in physical health. Mode changes in the opposite direction from public transport to active travel are associated with increases in reported satisfaction with health. The lack of an effect on physical health when changing between active and public transport may be due to accessing public transport requiring exercise, often in the form of walking to or from a bus or train station. As this is not the case for switches to and from car travel to active travel the benefits to physical health are more pronounced. Mode changes between car and public transport do not lead to notable affects on physical or mental health outcomes or satisfaction with health. Overall, our results lend support to UK policy initiatives designed to encourage people to move away from car commuting towards more active forms of travel. As well as the individuals health effects estimated here, this trend will also help the UK government to meet its targets for reducing emissions.

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A Appendix

Table A.1: Number of Mode changes in the analytical sample

Criteria	Number		Percent	
	Observations	Individuals	Observations	Individuals
	NT	N	NT	N
Full analytic sample	106,195	31736	100	100
#. of changes				
0	82,213	26177	77%	82%
1	14,193	3654	13%	12%
2	7,168	1452	7%	5%
3	1,936	344	2%	1%
4	572	92	1%	0%
5	106	16	0%	0%
6	7	1	0%	0%

Table A.2: Entropy Balancing by gender for outcomes at time t

	Overall	Women	Men	Overall	Women	Men	Overall	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	SF12PCS	SF12PCS	SF12PCS	SF12MCS	SF12MCS	SF12MCS	Health.Sat	Health.Sat	Health.Sat
Car->Public	-0.238	-0.520	0.156	0.068	0.148	0.014	-0.007	-0.011	-0.004
	(0.279)	(0.393)	(0.381)	(0.316)	(0.434)	(0.460)	(0.046)	(0.061)	(0.068)
N	43,832	24,788	19,044	43,832	24,788	19,044	43,693	24,705	18,988
Treated	764	433	331	764	433	331	761	431	330
Control	43068	24355	18713	43068	24355	18713	42959	24291	18668
Car->Active	0.092	0.206	-0.007	0.654***	1.035***	-0.009	0.079**	0.075	0.083
	(0.225)	(0.310)	(0.325)	(0.243)	(0.343)	(0.340)	(0.035)	(0.048)	(0.054)
N	44,135	24,944	19,191	44,135	24,944	19,191	43,995	24,861	19,134
Treated	1067	589	478	1067	589	478	1061	586	475
Control	43068	24355	18713	43068	24355	18713	42959	24291	18668
Public->Car	0.360	0.474	0.251	-0.010	0.132	-0.167	0.064	0.105	0.010
	(0.280)	(0.399)	(0.396)	(0.348)	(0.517)	(0.481)	(0.048)	(0.065)	(0.071)
N	6,263	3,380	2,883	6,263	3,380	2,883	6,227	3,356	2,871
Treated	853	486	367	853	486	367	851	484	367
Control	5410	2894	2516	5410	2894	2516	5383	2877	2506
Public->Active	0.280	0.406	-0.019	-0.060	-0.172	0.154	0.148**	0.043	0.283***
	(0.375)	(0.449)	(0.624)	(0.465)	(0.642)	(0.683)	(0.066)	(0.086)	(0.103)
N	5,836	3,144	2,692	5,836	3,144	2,692	5,801	3,121	2,680
Treated	426	250	176	426	250	176	425	249	176
Control	5410	2894	2516	5410	2894	2516	5383	2877	2506
Active->Car	-0.396	-0.019	-0.781**	0.332	0.244	0.464	-0.069*	-0.042	-0.112*
	(0.261)	(0.365)	(0.372)	(0.295)	(0.405)	(0.416)	(0.040)	(0.053)	(0.061)
N	6,385	3,946	2,439	6,385	3,946	2,439	6,359	3,931	2,428
Treated	1056	598	458	1056	598	458	1050	593	457
Control	5329	3348	1981	5329	3348	1981	5316	3340	1976
Active->Public	0.424	0.706	-0.190	0.142	0.233	-0.025	-0.029	-0.020	-0.022
	(0.365)	(0.530)	(0.503)	(0.524)	(0.780)	(0.675)	(0.071)	(0.098)	(0.104)
N	5,734	3,583	2,151	5,734	3,583	2,151	5,714	3,572	2,142
Treated	405	235	170	405	235	170	404	234	170
Control	5329	3348	1981	5329	3348	1981	5316	3340	1976

Sample where individuals are present for at least 2 (or more) waves. Dependent variables measured at time t, and are increasing in good health/satisfaction. Controls are matched to treated individuals using entropy balancing at time $t-1$, prior to regression analysis of outcomes on treatment (at t), conditioning on covariates and wave dummies (at $t-1$). Covariates include age, number of kids, job hours, marital status, household income, commuting time and initial health. Estimates for Health Satisfaction are coefficients from an ordered probit model. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.3: Entropy Balancing by gender for outcomes at time t+2

	SF12 Indicators at t+2						**Other Indicators at t+2**		
	Overall	Women	Men	Overall	Women	Men	Overall	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	SF12PCS	SF12PCS	SF12PCS	SF12MCS	SF12MCS	SF12MCS	Health.Sat	Health.Sat	Health.Sat
Car->Public	-0.435	-1.211	0.691	-0.388	-0.580	-0.440	-0.040	-0.136	0.084
	(0.508)	(0.771)	(0.594)	(0.559)	(0.808)	(0.749)	(0.073)	(0.094)	(0.112)
N	19,095	10,994	8,101	19,095	10,994	8,101	19,026	10,949	8,077
Treated	521	297	224	521	297	224	519	295	224
Control	34922	20024	14898	34922	20024	14898	34850	19981	14869
Car->Active	0.292	0.187	0.375	0.133	0.100	0.065	0.044	0.073	-0.006
	(0.325)	(0.466)	(0.438)	(0.389)	(0.539)	(0.544)	(0.053)	(0.072)	(0.076)
N	19,262	11,079	8,183	19,262	11,079	8,183	19,192	11,034	8,158
Treated	738	407	331	738	407	331	735	405	330
Control	34922	20024	14898	34922	20024	14898	34850	19981	14869
Public->Car	0.249	0.969	-0.622	-0.167	-0.956	0.715	0.090	0.173*	0.010
	(0.469)	(0.643)	(0.670)	(0.552)	(0.759)	(0.758)	(0.077)	(0.101)	(0.121)
N	2,381	1,258	1,123	2,381	1,258	1,123	2,367	1,249	1,118
Treated	535	314	221	535	314	221	534	313	221
Control	3894	2023	1871	3894	2023	1871	3880	2015	1865
Public->Active	0.132	0.352	0.127	-0.326	0.561	-1.462	0.256**	0.350**	0.040
	(0.642)	(0.858)	(0.991)	(0.845)	(0.967)	(1.543)	(0.107)	(0.140)	(0.173)
N	2,194	1,143	1,051	2,194	1,143	1,051	2,180	1,134	1,046
Treated	253	152	101	253	152	101	252	151	101
Control	3894	2023	1871	3894	2023	1871	3880	2015	1865
Active->Car	-0.950**	-0.763	-0.878	0.833*	1.568**	-0.056	-0.109*	-0.066	-0.116
	(0.418)	(0.556)	(0.639)	(0.477)	(0.662)	(0.714)	(0.063)	(0.081)	(0.101)
N	2,564	1,580	984	2,564	1,580	984	2,554	1,575	979
Treated	679	380	299	679	380	299	675	377	298
Control	3931	2471	1460	3931	2471	1460	3925	2469	1456
Active->Public	-0.901	-0.457	-1.514	0.240	0.217	0.797	-0.163	-0.021	-0.305*
	(0.675)	(0.946)	(0.943)	(0.812)	(1.313)	(1.029)	(0.111)	(0.150)	(0.162)
N	2,268	1,417	851	2,268	1,417	851	2,261	1,414	847
Treated	245	143	102	245	143	102	244	142	102
Control	3931	2471	1460	3931	2471	1460	3925	2469	1456

Sample where individuals are present for at least 4 (or more) waves. Dependent variables measured at time $t+2$, and are increasing in good health/satisfaction. Controls are matched to treated individuals using entropy balancing at time $t-1$, prior to regression analysis of outcomes on treatment (at t), conditioning on covariates and wave dummies (at $t-1$). Covariates include age, number of kids, job hours, marital status, household income, commuting time and initial health. Estimates for Health Satisfaction are coefficients from an ordered probit model. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure A.1: Commuting time for Active vs Non-Active travel

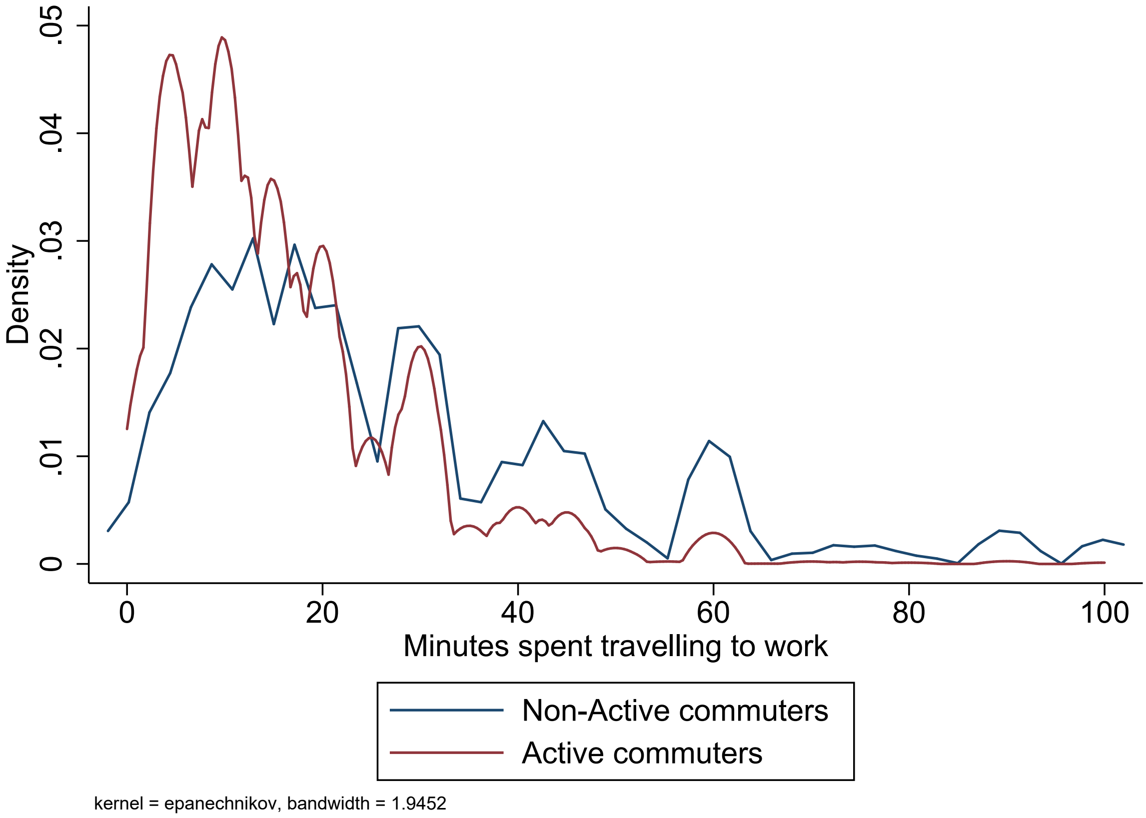

Table A.4: Robustness check 1: with CT*Mode, Outcome at t+1.

	Overall	Women	Men	Overall	Women	Men	Overall	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	SF12PCS	SF12PCS	SF12PCS	SF12MCS	SF12MCS	SF12MCS	Health.Sat	Health.Sat	Health.Sat
Car->Active	0.015	0.219	-0.341	1.076**	0.941	0.971	-0.006	-0.103	0.043
	(0.418)	(0.576)	(0.613)	(0.519)	(0.699)	(0.738)	(0.074)	(0.100)	(0.109)
N	29,937	17,064	12,873	29,937	17,064	12,873	29,839	17,005	12,834
Treated	909	498	411	909	498	411	906	496	410
Control	39636	22518	17118	39636	22518	17118	39544	22463	17081
Public->Active	0.310	-0.235	1.035	0.220	0.946	-0.295	0.244*	0.013	0.530***
	(0.925)	(1.528)	(1.094)	(1.062)	(1.564)	(1.513)	(0.136)	(0.190)	(0.201)
N	3,609	1,912	1,697	3,609	1,912	1,697	3,589	1,901	1,688
Treated	330	188	142	330	188	142	329	187	142
Control	4639	2473	2166	4639	2473	2166	4619	2461	2158
Active->Car	-0.997**	-0.397	-1.474**	-0.222	-0.418	0.117	-0.086	-0.215*	0.074
	(0.489)	(0.676)	(0.721)	(0.608)	(0.834)	(0.973)	(0.082)	(0.110)	(0.123)
N	4,098	2,542	1,556	4,098	2,542	1,556	4,083	2,533	1,550
Treated	861	487	374	861	487	374	856	483	373
Control	4688	2964	1724	4688	2964	1724	4678	2959	1719
Active->Public	-0.843	-1.424	-0.087	0.766	2.161	-1.845	-0.125	-0.094	-0.235
	(0.846)	(1.186)	(1.208)	(1.364)	(1.917)	(1.724)	(0.148)	(0.210)	(0.216)
N	3,670	2,305	1,365	3,670	2,305	1,365	3,659	2,299	1,360
Treated	333	196	137	333	196	137	332	195	137
Control	4688	2964	1724	4688	2964	1724	4678	2959	1719

Sample where individuals are present for at least 3 (or more) waves. Dependent variables measured at time $t+1$, and are increasing in good health/satisfaction. Controls are matched to treated individuals using entropy balancing at time $t-1$, prior to regression analysis of outcomes on treatment (at t), conditioning on covariates and wave dummies (at $t-1$). Covariates include age, number of kids, job hours, marital status, household income, commuting time, initial health and an interaction term between commuting time and mode. Estimates for Health Satisfaction are coefficients from an ordered probit model. Heath Satisfaction 1-5, completely dissatisfied to completely satisfied, i.e poor to good. Entropy Balancing at 1st and 2nd moment. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Robustness check 2: with lag of month, Outcome at t+1.

	Overall	Women	Men	Overall	Women	Men	Overall	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	SF12PCS	SF12PCS	SF12PCS	SF12MCS	SF12MCS	SF12MCS	Health.Sat	Health.Sat	Health.Sat
Car->Public	-0.005	-0.001	0.069	0.045	-0.081	0.066	0.034	0.003	0.095
	(0.350)	(0.491)	(0.491)	(0.394)	(0.535)	(0.573)	(0.056)	(0.075)	(0.084)
N	29,714	16,954	12,760	29,714	16,954	12,760	29,617	16,895	12,722
Treated	646	369	277	646	369	277	644	367	277
Control	39636	22518	17118	39636	22518	17118	39544	22463	17081
Car->Active	0.271	0.655*	-0.126	0.883***	0.803*	0.755*	0.052	0.064	0.038
	(0.250)	(0.344)	(0.363)	(0.291)	(0.411)	(0.397)	(0.042)	(0.056)	(0.062)
N	29,937	17,064	12,873	29,937	17,064	12,873	29,839	17,005	12,834
Treated	909	498	411	909	498	411	906	496	410
Control	39636	22518	17118	39636	22518	17118	39544	22463	17081
Public->Car	-0.069	0.442	-0.733	0.356	0.661	0.131	0.023	0.045	0.015
	(0.358)	(0.516)	(0.480)	(0.435)	(0.620)	(0.608)	(0.059)	(0.077)	(0.091)
N	3,909	2,094	1,815	3,909	2,094	1,815	3,889	2,083	1,806
Treated	707	412	295	707	412	295	706	411	295
Control	4639	2473	2166	4639	2473	2166	4619	2461	2158
Public->Active	-0.031	-0.771	0.970	0.325	0.760	-0.287	0.228***	0.140	0.342***
	(0.561)	(0.824)	(0.671)	(0.640)	(0.839)	(0.958)	(0.083)	(0.108)	(0.129)
N	3,609	1,912	1,697	3,609	1,912	1,697	3,589	1,901	1,688
Treated	330	188	142	330	188	142	329	187	142
Control	4639	2473	2166	4639	2473	2166	4619	2461	2158
Active->Car	-0.801***	-0.767*	-0.741*	-0.198	-0.310	0.016	-0.081*	-0.102	-0.017
	(0.300)	(0.429)	(0.405)	(0.370)	(0.489)	(0.591)	(0.049)	(0.065)	(0.074)
N	4,098	2,542	1,556	4,098	2,542	1,556	4,083	2,533	1,550
Treated	861	487	374	861	487	374	856	483	373
Control	4688	2964	1724	4688	2964	1724	4678	2959	1719
Active->Public	-0.591	-0.723	-0.455	-1.221*	-0.229	-2.648***	-0.067	-0.022	-0.112
	(0.469)	(0.668)	(0.696)	(0.670)	(0.923)	(0.952)	(0.083)	(0.118)	(0.120)
N	3,670	2,305	1,365	3,670	2,305	1,365	3,659	2,299	1,360
Treated	333	196	137	333	196	137	332	195	137
Control	4688	2964	1724	4688	2964	1724	4678	2959	1719

Sample where individuals are present for at least 3 (or more) waves. Dependent variables measured at time $t+1$, and are increasing in good health/satisfaction. Controls are matched to treated individuals using entropy balancing at time $t-1$, prior to regression analysis of outcomes on treatment (at t), conditioning on covariates and wave and month dummies (at $t-1$). Covariates include age, number of kids, job hours, marital status, household income, commuting time and initial health. Estimates for Health Satisfaction are coefficients from an ordered probit model. Heath Satisfaction 1-5, completely dissatisfied to completely satisfied, i.e poor to good. Entropy Balancing at 1st and 2nd moment. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Robustness check 3: Constant HH and Job, Outcome at t+1.

	Overall	Women	Men	Overall	Women	Men	Overall	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	SF12PCS	SF12PCS	SF12PCS	SF12MCS	SF12MCS	SF12MCS	Health.Sat	Health.Sat	Health.Sat
Car->Public	-0.130	0.231	-0.593	0.553	0.186	0.993*	-0.034	-0.030	-0.043
	(0.445)	(0.613)	(0.632)	(0.456)	(0.654)	(0.595)	(0.070)	(0.090)	(0.108)
N	23,423	13,404	10,019	23,423	13,404	10,019	23,338	13,352	9,986
Treated	448	256	192	448	256	192	445	254	191
Control	31953	18228	13725	31953	18228	13725	31872	18180	13692
Car->Active	0.568*	0.730*	0.401	0.390	0.486	0.092	0.030	0.030	0.030
	(0.293)	(0.426)	(0.397)	(0.347)	(0.506)	(0.468)	(0.049)	(0.067)	(0.072)
N	23,596	13,481	10,115	23,596	13,481	10,115	23,512	13,429	10,083
Treated	670	358	312	670	358	312	668	356	312
Control	31953	18228	13725	31953	18228	13725	31872	18180	13692
Public->Car	-0.516	-0.223	-0.920	0.360	1.198	-0.504	-0.047	-0.012	-0.078
	(0.452)	(0.668)	(0.566)	(0.543)	(0.812)	(0.777)	(0.070)	(0.095)	(0.107)
N	2,991	1,613	1,378	2,991	1,613	1,378	2,973	1,601	1,372
Treated	478	287	191	478	287	191	477	286	191
Control	3680	1960	1720	3680	1960	1720	3662	1948	1714
Public->Active	-0.517	-0.985	0.102	0.554	1.427	-0.737	0.270**	0.233	0.331**
	(0.722)	(1.133)	(0.765)	(0.807)	(1.007)	(1.296)	(0.112)	(0.147)	(0.162)
N	2,782	1,480	1,302	2,782	1,480	1,302	2,764	1,468	1,296
Treated	219	121	98	219	121	98	218	120	98
Control	3680	1960	1720	3680	1960	1720	3662	1948	1714
Active->Car	-0.926**	-1.142**	-0.637	-0.648	-0.391	-1.007	-0.098*	-0.061	-0.108
	(0.368)	(0.507)	(0.506)	(0.460)	(0.590)	(0.721)	(0.057)	(0.072)	(0.091)
N	3,443	2,172	1,271	3,443	2,172	1,271	3,430	2,164	1,266
Treated	620	362	258	620	362	258	616	359	257
Control	4084	2597	1487	4084	2597	1487	4075	2592	1483
Active->Public	-1.105*	-1.387	-1.113	-1.538*	0.245	-3.763***	-0.221**	-0.240	-0.189
	(0.634)	(0.914)	(0.939)	(0.851)	(1.223)	(1.143)	(0.107)	(0.150)	(0.149)
N	3,097	1,968	1,129	3,097	1,968	1,129	3,088	1,963	1,125
Treated	202	122	80	202	122	80	202	122	80
Control	4084	2597	1487	4084	2597	1487	4075	2592	1483

Sample where individuals are present for at least 3 (or more) waves. In this sample, we hold household location and job characteristics constant. Dependent variables measured at time $t+1$, and are increasing in good health/satisfaction. Controls are matched to treated individuals using entropy balancing at time $t-1$, prior to regression analysis of outcomes on treatment (at t), conditioning on covariates and wave dummies (at $t-1$). Covariates include age, number of kids, job hours, marital status, household income, commuting time and initial health. Estimates for Health Satisfaction are coefficients from an ordered probit model. Heath Satisfaction 1-5, completely dissatisfied to completely satisfied, i.e poor to good. Entropy Balancing at 1st and 2nd moment. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1