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Does walking and bicycling more mean exercising less? Evidence from the U.S. and the Netherlands

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ABSTRACT

Introduction: Active travel, such as utilitarian walking and bicycling, may address public health challenges, such as obesity and poor cardiovascular health, if increased active travel results in an increase in overall physical activity. However, it is possible that active travel may substitute for other forms of exercise, because time in the day is limited and active travel time may crowd out exercise time, because people who travel actively may see less need to get other forms of exercise for health purposes, or because active travel causes fatigue that discourages other forms of exercise.
Methods: We investigate this question using time use data from the American Time Use Survey and the Dutch Tijdsbestedingsonderzoek. We utilize Cragg two-part hurdle models to explore 1) correlates of time spent on active travel, and 2) correlates of exercise time, with the time spent on active travel as the independent variable of interest.
Results: In both data sets, we find that the likelihood of exercising is actually higher for those who participate in active travel, not lower. It appears that active travel does not substitute for other forms of exercise, but instead adds to total daily physical activity.
Conclusions: Our findings imply significant health benefits could flow from engaging in active travel. Since the relationship between physical activity and positive health outcomes is well-established, we can presume that people who engage in active travel are likely to enjoy health benefits that they would not otherwise experience. Future research should attempt to quantify these benefits.

1. Introduction

Interest in making cities healthier places is growing (Corburn, 2007), especially in response to the waxing epidemic of obesity and other diseases associated with sedentary lifestyles (Bauman et al., 2012; Fisher, 2002; Sugiyama et al., 2010). Since physical activity is an important correlate of overall health (Wilkinson and Marmot, 2003), transportation and land use policies that increase walking and bicycling might improve public health.

One premise for promoting active travel (AT) is that it has health benefits, including better cardiovascular fitness and decreased body weight (Wanner et al., 2012). However, the relationships between physical activity, AT, and obesity are difficult to measure (Nazelleabc et al., 2011). Socioeconomic, environmental, genetic, and cultural factors also influence obesity and physical activity

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(Bauman et al., 2012). Because of these complexities, the impacts of AT may be smaller than assumed, and may even be outweighed by negative impacts of increased AT that may not have been fully investigated.

A clear link between AT and health may have proven elusive because those who walk and bicycle more may compensate by engaging less in other forms of exercise. First, for a given distance AT is usually more time-consuming than car travel, so active travelers may have less time to engage in other exercise. Second, people may believe that, if they walk or bicycle, they have done their daily exercise and that other, potentially more rigorous, types of exercise are unnecessary. Third, AT may leave travelers fatigued so they lack energy to engage in other exercise. If one or more of these are true, and AT substitutes for other exercise, promoting more AT may be less effective for improving health outcomes.

Conversely, it may be possible that physical activity and AT complement each other. It is intuitive that increased AT could contribute to greater overall physical activity since AT is itself a form of physical activity (Sahlqvist et al., 2012). It is also possible that increases in AT may cause people to participate more in other forms of physical exercise; utilitarian walking or bicycling may enable people to make other healthy choices. For example, those who participate in AT may be more physically fit and thus more likely to participate in other exercise because they have the energy and stamina to do so. Alternatively, a positive correlation between AT and exercise might be due to a third, confounding variable, such as more positive attitudes towards engaging in healthy behavior generally.

We evaluate these possibilities by applying Cragg two-part hurdle regression models to data sets from the U.S. and the Netherlands. These models accommodate large numbers of zeros in our data sets' dependent variables (active travel time and exercise time) by separately modeling (1) the propensity to take part in the activity, and (2) conditional time spent on the activity (i.e., how long a person is predicted to take part in the activity once the decision has been made to engage in it). Using the coefficients generated in both parts of the models, we produce predictions for unconditional exercise times for different levels of AT by holding all control variables at their means and multiplying the probabilities of engaging in exercise by predicted conditional exercise times.

The purpose of this research is to determine whether AT substitutes for or complements other physical activity. We do not directly investigate the causal impacts of AT on health. However, given the demonstrated relationship between health and physical activity (Warbuton et al., 2006; Hamer et al., 2009), a finding that AT does not substitute for other physical activity would imply that AT may improve health generally by increasing overall physical activity. More research is needed to confirm whether more AT leads to significant health outcomes.

2. Literature review

2.1. Physical activity, active travel, and health outcomes

Many factors contribute to physical activity participation, including age, sex, health, societal norms, genetics, urbanization, and stage of life (Bauman et al., 2012; Butler et al., 2007; Davis et al., 2011). Physical activity in turn contributes to various positive health outcomes, including reduced risk of cardiovascular disease (Warburton et al., 2006) and other chronic diseases such as diabetes, colon and breast cancer, obesity, osteoporosis, osteoarthritis, and depression (Warburton et al., 2006), as well as psychological distress (Hamer et al., 2009).

The relationships among physical activity, weight, and body mass index (BMI, which is based on height and weight) are complex. Physical activity is one of many factors affecting fitness and health, some of which are difficult to observe and take years to impact BMI (Saunders et al., 2013). Determining causality presents another problem with studying the relationship between BMI and physical activity: obesity could be a result or a cause of limited physical activity, or both. Recent research has suggested that obesity might be a more powerful predictor of activity than vice versa (Ekelund et al., 2008; Metcalf et al., 2011). More research here is needed.

It is also difficult to separate the health effects of AT from those caused by other physical activity. AT has been investigated as a predictor of heart disease (Gordon-Larsen et al., 2009), all-cause mortality, weight/BMI, and diseases like type two diabetes (Bauman et al., 2012). The existing literature often finds weak and/or conflicting associations between AT and health. For example, one review shows that AT does not consistently have significant health benefits (Saunders et al., 2013). Another does not find consistent evidence that overall physical activity, and BMI, are affected by changes in AT (Wanner et al., 2012). In a review of 24 trials and prospective cohort studies from all over the world, Saunders et al. (2013) find that AT is not a reliable predictor of many health outcomes, including obesity, all-cause mortality, and fitness. They do find some evidence that AT may decrease the likelihood of type two diabetes, but ultimately conclude that more research is needed.

2.2. Physical activity and active transportation across age groups

Much of the research on the relationship between AT and physical activity focuses on young people (Cooper et al., 2003; Larouche et al., 2014; Panter et al., 2008; Rissel, 2009; Roth et al., 2012; Santos et al., 2009; Voulgaris et al., 2017). Children often fail to meet recommended amounts of physical activity daily; it is often asserted that more AT may help them reach those benchmarks (Larouche et al., 2014; Panter et al., 2008). However, a review of research by Larouche et al. (2014) finds that there is not high-quality evidence pointing to a significant relationship between biking and walking to school and BMI or fitness.

Some research has found positive links between AT to school and other forms of physical activity. Supporting the hypothesis that AT and exercise might be complements or spuriously related, one study finds that children who walk to school are significantly more active in terms of total daily physical activity than those who travel by car (Panter et al., 2008), and another finds that children who walk to school have greater total activity than those who do not (Cooper et al., 2003). In contrast, Voulgaris et al. (2017) find evidence for a substitution effect; they find that adolescents in their sample who commute to school by AT spend more time commuting and make up for that time by reducing participation in health-promoting activities, including other exercise.

For adults, Wanner et al.'s review (2012) finds that while most studies suggest a positive relationship between AT and overall physical activity, many of these studies are of poor quality due to flaws in research design, data completeness, controls for confounding variables, etc. Studies showing a positive relationship between AT and exercise include Becker and Zimmerman-Stenzel's (2009) analysis of 50- to 70-year-old adults, which shows that people who bicycle or walk for recreation are more likely to engage in other forms of exercise than those who do not, even when controlling for sociodemographic variables. Again, this may be caused by better levels of fitness or the confounding effect of general attitudes towards health. A study of college students finds that those who bike to campus engage in more overall physical activity (Sisson and Tudor-Locke, 2008). One study in the UK finds that adults who travel actively report more physical activity (Sahlqvist et al., 2012). A longitudinal study of adults in the UK finds a significant, positive change in total physical activity by people who increased their AT (Sahlqvist et al., 2013).

2.3. Time use surveys

Time use surveys offer an important source of data to evaluate the relationship between AT and overall physical activity, since these surveys can offer insight on how various factors may or may not influence the degree to which people engage in activities. The use of time use surveys in planning research has increased as transportation scholars have emphasized that a disaggregated activity-based approach to travel demand modeling (in contrast to zonal trip-based approaches) better represents travel demand, as it is derived from the demand for activity participation (Kitamura et al., 1997; Bhat and Koppelman, 1999). Data from time use surveys have been used to evaluate the joint relationship between activities and health outcomes (Adams, 2010), as well as the division of labor and household-serving travel among household members (Taylor et al., 2015; Smart et al., 2017), the relationship between travel and subjective well-being (Morris, 2015), changes in travel and activity patterns over time (Garikapati et al., 2016), and the relationship between increases in commute time and decreases in time spent on other activities (Voulgaris et al., 2017).

In this paper, we build upon this work by using two time use surveys from countries with very different levels of AT participation to investigate factors that influence the likelihood that a person will spend time traveling by active modes, and, further, to investigate the relationship between time spent on AT and time spent on other exercise. In contrast to related work that focuses on young people, our study population includes all age groups except children.

3. Data

3.1. U.S. time use data from the American Time Use Survey

Our data are drawn from two time use surveys. The first is the American Time Use Survey (ATUS), a joint project of the U.S. Census Bureau and the U.S. Bureau of Labor Statistics (Bureau of Labor Statistics, 2016; Hofferth et al., 2018). The ATUS has collected time use data through interviews with roughly 13,500 participants age 15 and older each year since 2003. Each response is from a unique individual and reflects a single day in that person's life. The sample is representative of the non-institutionalized U.S. population age 15 or older.

ATUS respondents are drawn from those who have completed the Census' Current Population Survey (U.S. Census Bureau, 2018). The ATUS conducts interviews in which respondents reconstruct their daily activities on the day prior to the survey. Professional interviewers conduct the interview and facilitate respondent recall. The interviewers then code the activities according to a pre-existing coding schema that includes over 450 activity codes.

We accessed the data using the American Time Use Extract Builder (Hofferth et al., 2018).

3.1.1. Active travel

In the ATUS, utilitarian travel is one activity category, which is further disaggregated by mode, including walking and bicycling. All activities are assigned one activity category; travel supersedes all other categories, so that, for example, socializing while walking is only classified as walking travel. Walking or bicycling to/from a public transit stop or station is coded as walking or bicycling. Thus, in models below, AT includes walking or bicycling to and from transit but not time waiting for the transit vehicle or in the transit vehicle.

3.1.2. Other exercise

The ATUS has a category for "Sports, Exercise and Recreation," which is subcategorized based on the specific activity. The activities shown in Table 1 are aggregated in this paper as "exercise," based on the authors' judgment that these activities involve physical exertion. Admittedly some of these activities are more physically intensive than others; for example, running may be more intense exercise than playing softball. However, it is beyond the scope of this paper to investigate the intensiveness of each form of exercise, making this a limitation for our findings.

3.1.3. Demographic data

The Current Population Survey and the ATUS also collect demographic information, which we have included in our models as control variables. Some variables are significant predictors of AT time and exercise time, as is shown below. We utilize three control

Table 1
ATUS activities classified as "exercise."

Aerobics	Gymnastics	Softball
Baseball	Hiking	Using cardiovascular equipment
Basketball	Hockey	Volleyball
Biking (non-utilitarian)	Martial arts	Walking (non-utilitarian)
Boating	Racquet sports	Water sports
Climbing, spelunking, caving	Rodeo	Weightlifting or strength training
Dancing	Rollerblading	Working out (unspecified)
Dog walking/exercise/playing with animals*	Rugby	Wrestling
Equestrian sports	Running	Yoga
Fencing	Skiing, ice skating, snowboarding	
Football	Soccer	

*Note: dog walking is the only activity not classified as "Sports, Exercise and Recreation"; it is classified as a "Household Activity."

variables in our models that were only collected in certain years: self-reported health, BMI, and mobility disability. We limit our sample to the years for which data on all three of these variables are available: these are 2008 and 2014 through 2016. Even with data from only these four years, our models still contain a sample size of 33,431 respondents.

Survey probability weights provided by the ATUS ensure the results are representative of the U.S. population.

3.2. Dutch time use data from the Tijdsbestedingsonderzoek

We also use data from the Tijdsbestedingsonderzoek Dutch time use surveys (Breedveld and Sociaal en Cultureel Planbureau, 2000; Sociaal en Cultureel Planbureau, 2005). These have been collected by the Multinational Time Use Survey (MTUS) project (Gershuny and Fisher, 2013), which we accessed through the Multinational Time Use Survey Extract Builder website (Fisher et al., 2019).

The Dutch Sociaal en Cultureel Planbureau performed these surveys as part of larger time use study administered every five years between 1975 and 2005. We limit our data to the years 2000 and 2005 to ensure they are relatively timely. The sample has 3921 observations (accounting for some missing data) and includes individuals 12 years and older. The sample is largely representative of the Dutch population, and we also use sampling weights provided by the MTUS site.

We augment the U.S. data with Dutch data for two reasons. First, unlike the ATUS, which asks each respondent about a single day, the Tijdsbestedingsonderzoek covers an entire week. This helps account for substitution of activities across days. For example, if those who participate in AT on the study day in the U.S. data are less likely to engage in other forms of exercise on that day, this may be because they shift exercise to a day with no AT as opposed to foregoing it entirely. Data on a full week would allow us to better rule out this possibility. This does, however, mean the results of the Dutch models must be interpreted differently from the U.S. data, since we examine average daily AT and exercise time use across the week in our Dutch models, not minutes on one survey day.

Although the Tijdsbestedingsonderzoek is a richer data set than the ATUS data since it includes information on an entire week for each survey respondent, in other respects it is a more limited data set because it includes a smaller sample size and a smaller set of demographic variables. In spite of this limitation in the Tijdsbestedingsinderzoek data, the suite of covariates is reasonably comparable between the two surveys, although some characteristics are described and coded differently. The Dutch data is also of interest because Dutch people take part in far more AT than Americans, including walking and bicycling, as Table 2 shows. By examining data from both surveys, we are able to create a more complete picture of the relationship between AT and exercise than we could relying on either survey in isolation. Both the ATUS and the Tijdsbestedingsonderzoek exclude young children from the survey samples, but they include adolescents. Each survey, however, has a different age threshold for inclusion in the sample. The Tijdsbestedingsonderzoek collects data on activity participation by individuals as young as 12, while the ATUS does not collect data from individuals younger than 15. For our analyses of both surveys, we included responses from all survey respondents rather than excluding specific age groups.

The activity definitions used by the MTUS-X data aggregation site (Fisher, Gershuny, Flood, Backman, and Hofferth, 2019) differ from the ATUS categories. To measure exercise in the Dutch data, we use the MTUS-X category of "general sport, exercise, and outdoor activities." This includes exercising, playing sports, and recreational walking and cycling, but may include some non-strenuous sporting activities, such as bowling, and may not include some forms of physical activity that are not recreational, such as dog walking.

Table 2 shows descriptive statistics for the variables of interest. For both the ATUS and Tijdsbestedingsonderszoek data, we have not included AT in the total amount of time spent exercising. Thus, total physical activity can be approximated as the sum of time spent exercising and time spent on AT.

4. Methods

In this paper we model (1) correlates of AT time, and (2) correlates of exercise time, with AT as the independent variable of interest.

In both data sets, both AT and exercise time are censored at zero; many survey respondents did not take part in one or both of

Table 2
Descriptive statistics for AT and exercise times.

	American Time Use Survey			Tijdsbestedingsonderszoek		
	Mean (minutes/ study day)	Standard deviation (minutes/study day)	Sample size	Mean (avg. minutes /day across week)	Standard deviation (avg. minutes/day across week)	Sample size
Unconditional active travel						
Total active travel (bicycle and walk)	2.4	11.8	33,727	25.0	27.5	4017
Walk	2.2	11.1	33,727	7.4	15.8	4017
Bicycle*	0.2	3.9	33,727	17.6	23.1	4017
Transit	2.4	17.6	33,727	9.3	24.0	4017
Conditional active travel (time spent on active travel for those who were active travelers)						
Total active travel (bicycle and walk)*	23.1	29.3	3516	33.1	27.1	3038
Walk	22.3	28.0	3366	16.2	20.1	1824
Bicycle*	36.1	39.0	187	29.0	23.4	2440
Transit	79.6	63.9	1021	36.8	35.5	1025
Unconditional exercise	17.2	45.0	33,727	19.5	31.2	4017
Conditional exercise	74.7	67.1	7761	34.3	35.5	2281
Percent that actively traveled (on the study day in the US sample; during the study week in the Dutch sample)						
Total active travel (bicycle and walk)*	10.4%			75.6%		
Walk	10.0%			45.4%		
Bicycle*	0.6%			60.7%		
Transit	3.0%			25.5%		
Percent that exercised	23.0%			56.8%		

*Note in the Dutch travel data bicycling is included in the category "other physical travel." We assume this overwhelmingly consists of bicycling.

these activities on the study day (in the ATUS data) or during the study week (in the Dutch data). For example, in the ATUS data about 90 percent of our sample did not engage in AT on the study day, and 77 percent did not engage in other exercise. Censoring at zero renders the use of ordinary least squares (OLS) regression problematic due to the potential for biased and inconsistent estimates.

A common method for performing regressions on censored data is the Tobit Type 1 model. We rejected the use of this for two reasons. First, Tobit estimates refer not to actual time use but to latent time use if the censoring did not exist—in our case, this would mean that the Tobit parameter estimates would reflect exercise time if it were possible to exercise for negative minutes, which is clearly not possible. This results in inflated coefficients which do not match real-world behavior.

Second, Tobit Type 1 assumes that an independent variable increases or decreases both the propensity to engage in activity *and* the amount of the activity, provided it takes place. This is too strong of an assumption; just because a person is more likely to bicycle than another, it does not follow that his/her bicycle trips are also longer when he/she does bicycle.

We also elected not to use the Heckman model (Tobit Type 2) as we are not dealing with a sample selection problem. We opted not to use a count model, such as a zero-inflated negative binomial model, for two reasons. First, since we construct average daily activity times using a week for our Dutch data, activity times for that sample are not integers. Second, the amount of time spent doing an activity is a continuous quantity, not a count of discrete events.

Therefore, we employ two-part Cragg hurdle models (Cragg, 1971). The Cragg model was originally developed to model purchasing decisions. The first decision the purchaser makes is the decision on whether to purchase or not. Once a decision has been made to purchase, the second decision is about how much money is to be spent. This mechanism works well when studying how we spend our time as well as how we spend our money. See Wooldridge (2009) and the Stata documentation for the "churdle" command (Stata Press, 2017) for more on this modeling technique.

Part one is a probit model which specifies how variables affect the probability of a person engaging in an activity (on the study day in the ATUS data or during the study week in the Dutch data). For the exercise models, this takes the form:

$$\Pr(Y_i > 0) = \Phi(\alpha + \beta_1 A + \beta_2 H + \beta_3 D + \beta_4 G + \beta_5 T + \varepsilon)$$

Where $\Pr(Y_i > 0)$ is the probability of the exercise being participated in at all during the survey day or week, Φ is the cumulative distribution function of the standard normal distribution (i.e., $\Pr(Z \le z)$), α is the intercept, A = the amount of active travel (or a vector of types of active travel) in the day or across the week, H is a vector of variables reflecting the respondent's health, D = a vector of the respondent's demographic characteristics, G = a vector of variables reflecting the respondent's location, T = survey year, and ε is the error term.

Part two is an OLS regression, identifying how variables contribute to conditional activity time (i.e., activity duration provided an individual takes part in the activity). This uses data only from those who took part in the activity. We use an exponential model of the form:

$$H_i^* = \exp(\alpha + \beta_1 A + \beta_2 H + \beta_3 D + \beta_4 G + \beta_5 T + \varepsilon)$$

where H_i^* is the continuous latent time participating in the activity conditional on $Y > 0$, and all other variables are as above. We use the exponential model because, as is the case with most activities, exercise time and active travel time exhibit positive skew; many participants tend to engage for a short amount of time, and a smaller number of participants engage for longer time periods. Taking the log of AT and exercise time thus results in a more normally distributed dependent variable, more accurate predictions, and better model fit.

R^2 is a common goodness-of-fit statistic for OLS regression models which indicates the proportion of variability in the dependent variable that can be explained by variation in the independent variables. Since probit models (like part 1 of a Cragg hurdle model) estimate coefficients through an iterative process rather than to minimize variance, R^2 is not a meaningful statistic. Pseudo-R^2 statistics are commonly used in lieu of R^2 because they tend to have a similar scale (ranging from zero to one) and higher values are associated with better-fitting models. However, pseudo-R^2 values cannot be interpreted as the proportion of variation that is explained by the model and cannot be used for absolute judgments of whether a model fit is good or bad. Rather, pseudo-R^2 statistics can be used to compare the relative goodness-of-fit for alternative models. In our analysis, we use pseudo-R^2 statistics to compare the fit of models predicting active travel and exercise with different sets of control variables as well as our full model.

While different modelers treat modeling time use differently, Wodjao (2007) concludes that two-part models perform better than both Tobit Type 1 and the Heckman selection model (Tobit Type 2) for modeling time use. Further, Stewart (2013) finds the hurdle model superior to Tobit Type 1, and also to OLS if the goal is to model the propensity to engage in activity and conditional activity time separately, as we prefer to do.

To render our results more interpretable, we furnish predicted unconditional exercise times for hypothetical individuals who have representative values for the independent variable of interest, AT. We predict exercise time for an individual with 0, 20, and 60 minutes of AT in the day. The predictions are generated by multiplying the predicted probability of participating in exercise by the predicted conditional time engaging in exercise for individuals with each of those three AT times. Because generating predictions requires an assumption about the values of the covariates, we use the marginal effects at the means method (i.e., the covariates are all held at their mean values).

As we have noted, the U.S. data and the Dutch data must be interpreted differently since the former represent a single-day sample and the latter reflect daily averages over a week. Because the Dutch data is based on daily averages, taking part in an activity for a single minute over the week counts as participation. So, while the coefficient in the probit model for the US data reflects *participation on any given day*, the coefficient for the Dutch model reflects *participation at any point during the week*. Similarly, the conditional OLS coefficients in the US model relate to *activity duration on the day* provided it occurs on that day, while the coefficients in the Dutch model relate to *average daily activity duration across the week* if the activity occurs during the given week.

As a technical matter, taking part in an activity for 1 minute counts as participation. It would be possible to use a more restrictive definition of participation. In practice, however, survey respondents tend to round activity durations to 5- and 10-minute increments, so a threshold greater than 1 minute to count activity participation is unlikely to influence the results of our analysis.

We treat income differently in our American and Dutch data. For the US data we have household income in bins; we take the midpoints of the bins to furnish a numerical household income figure for each respondent. We then normalize income by household size because the material circumstances of a household will vary depending on the number of individuals to be supported. To perform this calculation, we use the modified Organisation for Economic Co-operation and Development (OECD) equivalence scale, which counts the cost of supporting the first adult in the household as 1, the cost of supporting each additional adult in the household as 0.5, and the cost of supporting children as 0.3. Therefore, the cost of supporting a family of four is calculated as roughly the same as the cost of supporting two adults living independently. We divide household income by modified OECD person-equivalents in the household to arrive at our income measure.

The distribution of the income variable in the US data is right-skewed, so we also log-transform it, as is common in social science models. In addition to correcting for skew, this transformation reflects the fact that changes at low levels of income tend to have a bigger effect on behavior than changes at high levels; intuitively, the difference between earning nothing and $20,000 will be more consequential for behavior than the difference between earning $200,000 and $220,000.

In the Dutch model, income is divided into three categories: the bottom quartile of the Dutch income distribution, the middle two quartiles, and the top quartile. We treat this as a categorical variable.

5. Results

5.1. Model of correlates of active travel from ATUS data

Table 3 shows results of a Cragg hurdle model predicting AT participation and conditional AT time based on the American ATUS data. Positive coefficients and t-statistics in the probit model (on the left) indicate that the variable is positively associated with the probably of engaging in AT (and vice versa); positive coefficients and t-statistics in the OLS conditional activity time model to the right indicate that the variable is positively associated with longer durations of AT if it occurs (and vice versa).

As shown, the model has a pseudo-R^2 statistic of 0.046. As we have noted, it is extremely difficult to interpret this statistic, as there are numerous methods that have been proposed for generating pseudo-R^2 statistics for discrete choice models, and, further, pseudo-R^2s "cannot be interpreted as one would interpret an OLS R^2squared, and different pseudo R^2s can arrive at very different values" (UCLA Institute for Digital Research and Education, 2011). However, "while pseudo R-squareds cannot be interpreted independently or compared across data sets, they are valid and useful in evaluating multiple models predicting the same outcome on the same data set. In other words, a pseudo-R-squared statistic without context has little meaning." To provide this context, we ran

Table 3
Cragg hurdle model results predicting AT based on ATUS data.

Independent variable	Model predicting likelihood of participation		Model predicting time spent on activity, given participation	
	Estimated probit coefficient	t-statistic	Estimated log-linear coefficient (ln of AT time)	t-statistic
Individual characteristics				
Physical health (relative to Poor)				
Fair	0.403	0.51	−0.0984	−0.52
Good	0.166*	2.17	−0.193	−1.07
Very good	0.131	1.67	−0.175	−0.94
Excellent	0.174*	2.16	−0.0576	−0.31
Mobility difficulty	−0.0978	−1.34	0.210	1.42
Body mass index	−0.0117***	−4.74	−0.0115*	−2.37
Age	0.00194	−0.42	0.0181*	2.03
Age squared	−0.0000655	−1.38	0.000185*	1.91
Female	−0.0567	−1.86	−0.249***	−4.79
Female with children	.0396	1.63	0.0844	1.79
Education level (relative to Less than 12th *grade)*				
12th grade	−0.116*	−2.66	−0.00341	−0.04
Some college	−0.112*	−2.44	0.1416796	−1.55
Four-year college degree	0.0684	1.46	0.0294	0.32
Beyond four-year degree	0.169***	3.34	0.120	1.21
Race (relative to White)				
Black	0.0431	1.08	0.0672	0.81
Asian	0.0771	1.14	−0.0123	−0.12
Native American	0.133	0.92	0.201	0.68
Other	0.232**	2.61	0.343**	2.65
Hispanic	0.0540	1.32	0.0418	0.55
Non-U.S. citizen	0.0437	0.87	0.211**	2.52
Marital Status (relative to Never married)				
Separated	−0.134	−1.70	−0.0631	−0.44
Divorced	−0.154***	−3.32	−0.169	−1.93
Widowed	−0.093	−1.25	−0.231	−2.06
Married (spouse absent)	−0.170**	−2.68	−0.332	−1.66
Married (spouse present)	−0.271***	−7.24	−0.217**	−3.14
Employment status (relative to Not in labor force)				
Unemployed	0.137*	2.21	0.111	0.97
Employed part-time	0.00633	0.14	0.157	1.77
Employed full-time	0–.0500	−1.16	0.115	1.39
Time use				
Minutes spent at school or work	0.0000691	1.06	−0.000308*	−2.29
Household characteristics				
Ln household income per person equiv.	−0.0681***	−3.87	−0.0893**	−2.77
Number of household children	−0.0191	−0.97	0.0844	−1.79
Residential location				
City (relative to Principal city, large metropolitan area)				
Suburb, large metropolitan area	−0.270***	−8.76	−0.287***	−4.82
Suburb/PC not assigned (small metro area)	−0.169***	−3.78	−0.168	−1.76
Non-metropolitan area	−0.308***	−6.25	−0.461***	4.30
Metropolitan area population (000s)	0.0000219***	6.25	0.0000325***	4.61
Region (relative to Northeast)				
West	−0.137***	−3.49	0.0894	1.22
South	−0.254***	−6.99	−0.389***	−5.61
Midwest	−0.273***	−6.89	−0.138*	-.171
Time of survey				
Survey year (relative to 2008)				
2014	−0.206***	−4.55	0.136	1.63
2015	−0.126***	−2.74	0.0838	0.97

(*continued on next page*)

Table 3 (*continued*)

Independent variable	Model predicting likelihood of participation		Model predicting time spent on activity, given participation	
	Estimated probit coefficient	t-statistic	Estimated log-linear coefficient (ln of AT time)	t-statistic
2016	−0.0853	−1.81	0.0158	0.18
Weekend survey day	−0.0800**	−2.86	0.103	−1.90
Constant	0.308	1.40	3.829***	9.16

(***) indicates significance at a 99.9-percent confidence level.
(**) indicates significance at a 99-percent confidence level.
(*) indicates significance at a 95-percent confidence level.
Pseudo-R^2 = 0.046.
N = 33,431.
Ln household income per person equivalent takes the natural log of annual household income in dollars divided by the number of person equivalents in the household using the modified OECD scale. We do this to better reflect actual living standards. The scale assumes that cost of supporting a second adult in a household is one half the cost of supporting the first adult, and that each child costs 0.3 compared with the first adult. Thus, the cost of supporting a family of four is estimated to be about the same as the cost of supporting two single adults living independently.
We include the quadratic term age squared because many age-related phenomena, such as income, are not monotonically related to age but have peaks or troughs in the middle of life.

our model without all variables related to physical characteristics (age, health, disability, gender and BMI). This reduced the pseudo-R^2 to only 0.0417, suggesting that geography and income go much further towards explaining AT than physical energy and fitness do.

Several variables have a significant relationship with the likelihood of being an active traveler on a given day, and/or with the amount of time those who engage in AT participate in the activity. People who consider themselves to be in better health are more likely to travel actively, although self-reported health is not significantly related to the conditional amount of time spent on AT. There may be two-way causality here since being in good health might allow a person to be active, and active travel may cause a person to become healthier. More education is a significant predictor of the likelihood of AT, but not of the conditional amount. People with lower BMI, unmarried people, unemployed people, people who live in the Northeast Census region, and people who live in principal cities and in larger metropolitan statistical areas are also more likely to travel actively. Lower-income people are both more likely to travel actively and more likely to spend more time traveling actively if they do so; this is unsurprising in light of prior evidence which shows more active travel by those with low incomes. This undoubtedly has much to do with more constrained vehicle access among those with low incomes which results in the substitution of some walking and bicycling trips for auto trips (Renne and Bennett, 2014).

Those who spend more time participating in AT, if they do participate in it, are those with lower BMI, older people, non-citizens, people who have never been married, lower-income people, people who do not live in the South, people who do not live in the suburbs, people who spent less time working or at school on the study day, and people who live in larger MSAs.

Women are no less likely to travel actively than men, but spend less time doing it if they do travel this way. This may be because women make shorter commute trips than men (Crane, 2007), and because women spend more time on household maintenance than men (Bittman et al., 2003) and thus have less time available to travel by slower modes.

5.2. *Model of correlates of exercise from ATUS data*

Table 4 shows results of a Cragg hurdle model predicting exercise participation and conditional exercise time based on the American ATUS data, with minutes of active travel as the independent variable of interest.

The model predicting exercise has a pseudo-R^2 statistic of 0.030. For comparison purposes, we also estimated a model predicting exercise with all of the independent variables shown in Table 4 except time spent on active travel. The comparison model also had a pseudo-R^2 statistic of 0.030, which indicates that inclusion of active travel in the model does not improve model fit. This suggests that the total amount of exercise a person participates in can be predicted just as well without information about a person's use of active modes as it can with that information. We estimated an additional model without active travel and physical characteristics (age, health, disability, BMI, and gender); this yielded a pseudo-R^2 of 0.0220, indicating that, taken together, physical characteristics do contribute importantly to predicting how much people exercise.

People in better health are significantly more likely to exercise, and among those who exercise, those in better health also spend more time exercising. Those with a higher BMI are less likely to exercise. Older people and women are less likely to exercise and are likely to spend less time exercising when they do exercise. Those with more education are more likely to exercise and are more likely to spend more time exercising if they do exercise; those with higher incomes are more likely to exercise but spend less conditional time exercising. Those living in the Western U.S. are more likely to exercise and to spend more conditional time exercising. Those in more populous MSAs are more likely to exercise. People identifying as black are less likely to exercise than those identifying as white. People who are employed are less likely to exercise than those who are not. Those with more children in the household are less likely to exercise and tend to spend less conditional time exercising. More time spent at school or work on the study day is associated with a lower likelihood of exercising.

Table 4
Cragg hurdle model results predicting exercise based on ATUS data.

Independent variable	Model predicting likelihood of participation		Model predicting time spent on activity, given participation	
	Estimated probit coefficient	t-statistic	Estimated log-linear coefficient (ln of exercise time)	t-statistic
Time use				
Minutes of active travel	0.00175*	1.97	0.000166	−0.24
Minutes spent at school or work	−0.000416***	−7.55	−0.000659***	−9.89
Individual characteristics				
Physical health (relative to Poor)				
Fair	.0156*	2.18	0.0338	0.40
Good	0.251***	3.65	0.141	1.82
Very good	0.413***	5.96	0.271***	3.49
Excellent	0.627***	8.79	0.365**	4.07
Mobility difficulty	−0.2618**	−4.11	−0.259**	−2.61
Body mass index	−0.0127*	−6.41	−0.000613	−0.25
Age	0.00205	0.53	0.0115**	−2.61
Age squared	−0.0000795*	−2.00	0.0000427	0.94
Female	−0.0732**	−2.91	−0.147***	−5.35
Female with children	−0.0428*	−2.00	0.00831	0.36
Education level (relative to Less than 12th *grade)*				
12th grade	−0.0814	−2.18	−0.179***	−3.81
Some college	0.0524	1.30	−0.164***	−3.56
Four-year college degree	0.216***	5.31	−0.127**	−2.64
Beyond four-year degree	0.311***	7.27	−0.102*	−2.12
Race (relative to White)				
Black	−0.201***	−5.63	0.0688	1.53
Asian	−0.0296	−0.53	−0.0135	−0.25
Native American	−0.134	−0.94	−0.240	−1.31
Other	0.154	−1.81	−0.0606	−0.55
Hispanic	0.0384	1.04	0.00870	0.22
Non-US citizen	−0.0705	−1.50	0.0668	1.36
Marital Status (relative to Never married)				
Separated	0.0263	0.37	0.109	1.23
Divorced	0.0223	0.54	0.0750	1.63
Widowed	0.0724	1.46	−0.0512	−0.91
Married (spouse absent)	.00470	0.05	0.211*	2.38
Married (spouse present)	0.0312	0.91	−0.00492	−0.12
Employment status (relative to Not in labor force)				
Unemployed	−0.00182	0.03	0.00428	0.07
Employed part-time	0.110**	−2.95	0–.00927	−0.22
Employed full-time	−0.171***	−4.95	0.00936	−0.24
Household characteristics				
Ln household income per person equiv.	0.0671***	4.20	−0.0435***	−2.70
Number of household children	0.1116***	−6.45	−0.0468*	−2.51
Residential location				
City (relative to Principal city, large metropolitan area)				
Suburb, large metropolitan area	0.00944	0.35	.00197	0.70
Suburb/PC not assigned (small metro area)	0.0305	−0.81	0.0131	1.31
Non-metropolitan area	0.09777*	−2.45	−0.0422	−0.97
Metropolitan area population (000s)	0.0000103**	3.19	−5.25e-07	−0.16
Region (relative to Northeast)				
West	0.0848*	2.41	0.075851*	2.09
South	−0.0887**	−2.72	−0.0285	−0.84
Midwest	0.0403	−1.15	0.0136	0.37
Time of survey				
Survey year (relative to 2008)				
2014	0.135***	3.39	0.0478	1.00
2015	0.179***	4.45	−0.00514	−0.11

(*continued on next page*)

Table 4 (*continued*)

Independent variable	Model predicting likelihood of participation		Model predicting time spent on activity, given participation	
	Estimated probit coefficient	t-statistic	Estimated log-linear coefficient (ln of exercise time)	t-statistic
2016	0.185***	4.57	0.0189	0.39
Weekend survey day	−0.165***	−7.34	0.0162	0.59
Constant	−0.263**	−21.4	4.033*	18.55

(***) indicates significance at a 99.9-percent confidence level.
(**) indicates significance at a 99-percent confidence level.
(*) indicates significance at a 95-percent confidence level.
Pseudo-R^2 = 0.030.
N = 33,431.
Ln household income per person equivalent takes the natural log of annual household income in dollars divided by the number of person equivalents in the household using the modified OECD scale. We do this to better reflect actual living standards. The scale assumes that cost of supporting a second adult in a household is one half the cost of supporting the first adult, and that each child costs 0.3 compared with the first adult. Thus, the cost of supporting a family of four is estimated to be about the same as the cost of supporting two single adults living independently.
We include the quadratic term age squared because many age-related phenomena, such as income, are not monotonically related to age but have peaks or troughs in the middle of life).

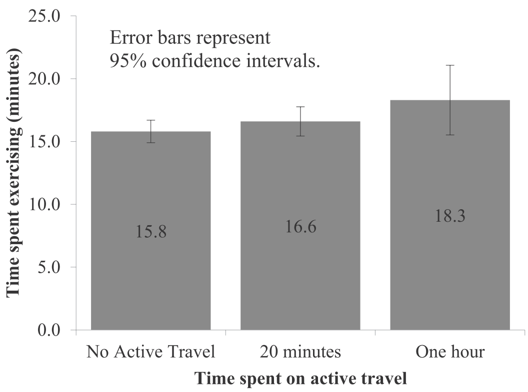

Fig. 1. Predictions of time spent exercising based on varying time spent on AT, holding all other variables at mean values (ATUS data),
Note that the overlapping confidence intervals show that although the association is positive, the unconditional time predictions do not significantly differ from each other. Hence interpreting the overall findings from this model is nuanced.

The amount of time spent engaging in AT is significantly associated with a higher probability of exercising recreationally, though not with more/less conditional exercise time. Fig. 1 shows the predicted unconditional amounts of time spent exercising for those with 0, 20, and 60 min of AT, with all control variables held at their means.

We also constructed an alternative model that disaggregates AT time by mode, and we also include transit use (bus/train) to test whether transit time substitutes for exercise time. Model coefficients for time spent traveling by bicycle, walking, and transit are summarized in Table 5, and the relationships between exercise and travel by each active mode are illustrated in Fig. 2. As shown, disaggregating AT time by mode slightly reduces model fit, with a resulting pseudo-R^2 statistic of 0.025. The results for the control variables are omitted to conserve space, but these variables, which are identical to those used above, are listed below the table.

We find that time spent on utilitarian walking is borderline-significantly positively associated with a higher probability of exercising on the study day, though it is not significantly related to conditional exercise time. The other two modes were not significantly associated with exercise time in either part of the model. It is thus unsurprising that the unconditional time predictions, though substantial in proportional terms, do not significantly differ from one another.

Table 5
Abridged results of alternative Cragg hurdle model predicting exercise based on ATUS data.

Independent variable	Model predicting likelihood of participation		Model predicting time spent on activity, given participation	
	Estimated probit coefficient	t-statistic	Estimated log-linear coefficient (ln of exercise time)	t-statistic
Minutes spent on active travel				
Walking	.00171*	1.96	-.0000178	−0.02
Bicycle	.00271	0.79	.000800	0.59
Transit	-.000776	−1.17	.0000686	−0.11

(***) indicates significance at a 99.9-percent confidence level.
(**) indicates significance at a 99-percent confidence level.
(*) indicates significance at a 95-percent confidence level.
N = 33,341.
Pseudo-R^2 = 0.030.
Control variables with estimates omitted for space include physical health, mobility difficulty, BMI, age and age squared (we include the quadratic term because many age-related phenomena, such as income, are not monotonically related to age but have peaks or troughs in the middle of life), gender, education, race and ethnicity, marital status, presence of children, sex, citizenship, employment status, ln of household income normalized by mod. OECD person-equivalents in household, intraurban location, metropolitan area population, geographic region, work or school minutes on the study day, weekend or weekday, and year.

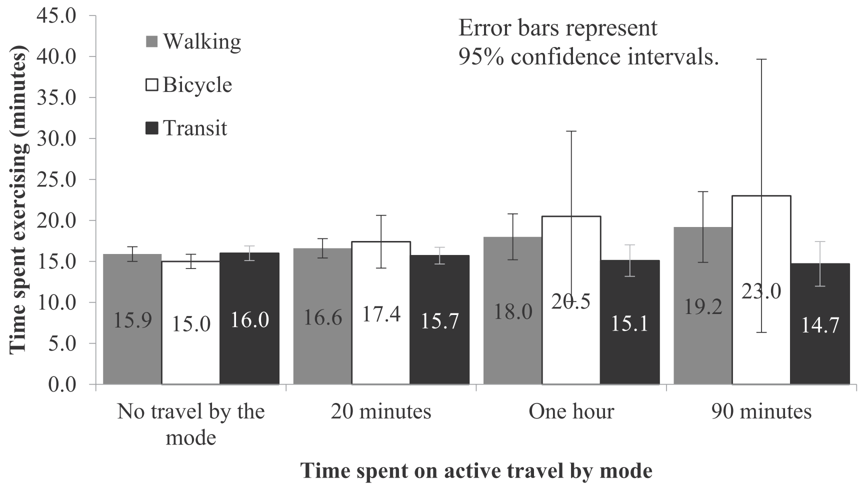

Fig. 2. Predictions of unconditional time spent exercising based on varying time spent on travel by each active mode, holding all other variables to mean values (ATUS data).

5.3. Model of correlates of active travel from Tijdsbestedingsonderzoek data

The results of Cragg models with the Dutch data, similar to those we presented for the U.S. data above, are summarized in Table 6.

The full model for the Dutch data has a pseudo-R^2 statistic of 0.027. Omitting physical characteristics (age, gender, health and disability) produces a model with a pseudo-R^2 of 0.022, suggesting these combined characteristics do contribute to predicting the degree to which people engage in AT.

As with the ATUS data, self-rated health is positively related to the likelihood that a person will engage in AT, but not the conditional amount of time she will spend on AT; those in “very good” or “good” health are significantly more likely to participate in AT than those in “poor” health. Those with disabilities are less likely to participate in AT. Women are more likely than men to travel by active modes, and although women without children are predicted to spend less conditional time actively traveling, women with at least two children spend more conditional time doing so. Women with children may spend more time on AT trips because they are accompanying children who walk more slowly than adults do (Grieve and Greer, 1966), or because physical health facilitates active travel and increases the likelihood of successful pregnancy and childbirth (Balen et al., 2007). Those with higher education are more likely to be active travelers, as are those who live in urban areas. Being employed full-time is associated with both less likelihood of, and less conditional time spent on, AT. Those in couples are less likely to be active travelers and also spend less conditional time traveling actively. Those with low incomes are more likely to travel actively and to spend more conditional time traveling actively, as may be expected since their vehicle ownership may be constrained.

Table 6
Cragg hurdle model results predicting AT based on Tijdsbestedingsonderzoek data.

Independent variable	Model predicting likelihood of participation		Model predicting time spent on activity, given participation	
	Estimated probit coefficient[1]	t-statistic	Estimated log-linear coefficient (ln of AT time)	t-statistic
Individual characteristics				
Physical health (relative to Poor)				
Fair	0.326	1.64	0.146	−0.66
Good	0.524**	2.57	0.189	0.84
Very good	0.490*	2.35	0.215	0.95
Disability	−0.294**	−2.60	−0.127	−1.21
Age	−0.00332	−0.40	−0.0108	−1.67
Age squared	−0.0000351	−0.38	0.0000678	0.93
Female	0.197***	3.44	−0.0930*	−2.00
Female with children	0.0869	1.91	0.0975003***	3.30
Education level (relative to Unfinished secondary education)				
Finished secondary education	−0.000815	0.01	−0.0626	−1.36
Post-secondary education	0.232***	3.48	−0.00264	−0.05
Marital Status (relative to Non-couple)				
Couple	−0.229***	−3.73	−0.230**	−4.79
Employment status (relative to Not in labor force)				
Employed full-time	−0.534***	−7.43	−0.243***	−5.00
Employed part-time	−0.0770	−0.98	−0.0767	−1.39
Unknown	0.361	0.64	0.401 *	2.23
Household characteristics				
Household income (relative to Income in bottom quartile)				
Middle two quartiles	−0.146	−1.77	−0.167**	−2.91
Top quartile	−0.213*	−2.19	−0.219**	−2.92
Income missing	−0.164*	−2.08	−0.101	−1.95
Number of household children	0.0524	1.56	0.0385	1.55
Residential location				
Urban area	0.254***	4.53	0.200***	4.36
Time of survey				
2005 (relative to 2000)	0.130**	2.66	0.0667	1.78
Constant	0.476	1.78	3.389***	12.98

(***) indicates significance at a 99.9-percent confidence level.
(**) indicates significance at a 99-percent confidence level.
(*) indicates significance at a 95-percent confidence level.
Pseudo-R^2 = 0.027.
N = 3,928.
We include the quadratic term age squared because many age-related phenomena, such as income, are not monotonically related to age but have peaks or troughs in the middle of life.
[1]Note that unlike US data, Dutch data are averages for the week. Hence the selection model shows the correlates of taking part in AT at any point in the week, not just a single day.

5.4. Model of correlates of exercise from Tijdsbestedingsonderzoek data

The results of the model predicting exercise from the Dutch Tijdsbestedingsonderzoek, with AT as the independent variable of interest, are summarized in Table 7.

The model has a pseudo-R^2 statistic of 0.021, versus 0.020 for a model predicting exercise with all of the independent variables shown in Table 7 except time spent on active travel. This indicates that inclusion of active travel in the model improves model fit and predictive power, but only very slightly. Omitting AT and physical characteristics (age, gender, disability, and health) does reduce fit substantially, with the pseudo-R^2 dropping to 0.0133, indicating that, as in the U.S. model, physical characteristics are related to how much we exercise.

Those with a disability are significantly less likely to exercise during the study week. Provided that they exercise, those in the middle of life (reaching a trough around age 40) are likely to spend more time doing so. Women are more likely to exercise, unless they have children, and they are predicted to exercise for less time than men if they do exercise. Those with more education are more likely to exercise. Those in a partnership exercise less if they do exercise. People who are employed are less likely to exercise, but those with higher incomes are both more likely to exercise and spend more conditional time exercising. Those in urban areas are less likely to exercise than rural residents.

In terms of our variable of interest, time spent on AT is positively and significantly associated with a higher probability of exercising, although not more time conditional time exercising. Fig. 3 further illustrates the relationship between exercise and AT by

Table 7
Cragg hurdle model results predicting exercise based on Tijdsbestedingsonderzoek data.

Independent variable	Model predicting likelihood of participation		Model predicting time spent on activity, given participation	
	Estimated probit coefficient[1]	t-statistic	Estimated log-linear coefficient (ln of exercise time)	t-statistic
Time Use				
Minutes of active travel	0.00496***	5.85	−0.000277	−0.39
Individual characteristics				
Physical health (relative to Poor)				
Fair	−0.0341	−0.18	−0.240	−1.09
Good	0.182	0.94	−0.144	−0.66
Very good	0.264	1.34	−0.00718	−0.03
Disability	−0.252*	−2.37	−0.0653	−0.59
Age	0–.00975	−1.32	−0.0179*	−2.44
Age squared	0.0000399	0.49	0.000223**	2.68
Female	0.119*	2.22	−0.268***	−5.57
Female with children	−0.163***	−4.23	−0.0369	−1.13
Education level (relative to Unfinished secondary education)				
Finished secondary education	0.0784	1.46	0.0637	1.26
Post-secondary education	0.295***	4.91	0.0662	1.24
Marital status (relative to Non-couple)				
Couple	0.0534	0.96	−0.147**	−2.97
Employment status (relative to Not in labor force)				
Employed full-time	−0.195**	−2.99	−0.103	−1.77
Employed part-time	−0.141*	−2.13	0.0494	0.82
Unknown	-.486	−1.10	0.148	0.74
Household characteristics				
Household income (relative to Bottom quartile)				
Middle two quartiles	0.0906	1.28	0.0277	0.43
Top quartile	0.330***	3.78	0.0277*	2.45
Income missing	0.277***	4.16	0.132*	2.18
Number of household children	0.0365	1.19	−0.00747	−0.29
Residential location				
Urban area	−0.223***	−4.16	−0.0553	−1.20
Time of survey				
2005 (relative to 2000)	0.288***	6.53	0.158***	3.98
Constant	−0.0176	0.07	3.656***	13.63

(***) indicates significance at a 99.9-percent confidence level.
(**) indicates significance at a 99-percent confidence level.
(*) indicates significance at a 95-percent confidence level.
Pseudo-R^2 = 0.021.
N = 3,928.
We include the quadratic term age squared because many age-related phenomena, such as income, are not monotonically related to age but have peaks or troughs in the middle of life.
[1]Note unlike U,S. data, Dutch data are averages for the week. Hence the selection model shows the correlates of taking part in exercise at any point in the week, not just on a single day.

showing the predicted amounts of average daily unconditional time spent exercising for those who engage in 0, 20, and 60 minutes of average daily AT, with all control variables held at their means. The predicted amount of non-travel exercise that would be associated with 20 minutes per day of active travel is not significantly different from the amount of exercise that would be associated with no active travel. However, a statistically significant (albeit small) difference does arise for long periods of active travel. Those who spent an average of one hour per day on active travel during the survey week are predicted to have participated in about three more average minutes per day of non-travel exercise than those who did not travel by active modes.

As with the ATUS data, we constructed a model disaggregating active modes. Model coefficients for time spent traveling by walking, transit, and "other active travel" (which we assume overwhelmingly means bicycling, particularly as the data come from the Netherlands) are summarized in Table 8, and are illustrated in Fig. 4. More time spent on utilitarian biking has a significant positive relationship with the likelihood of participating in other forms of exercise. Among those who exercise, time spent riding transit is associated with less conditional time spent exercising.

As shown in Fig. 4, holding all other variables at their average values, varying the amount of time spent on utilitarian walking between 0

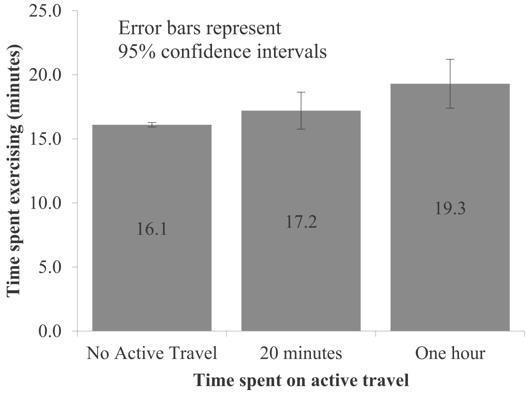

Fig. 3. Predictions of unconditional time spent exercising based on varying time spent on AT, holding all other variables at means values (Tijdsbestedingsonderzoek data).

Table 8
Abridged results of alternative Cragg Hurdle model predicting exercise based on Tijdsbestedingsonderzoek data.

Independent variable	Selection model		Conditional model	
	Estimated probit coefficient[1]	t-statistic	Estimated log-linear coefficient (ln of exercise time)	t-statistic
Minutes spent on active travel				
Walking	0.000550	0.41	−0.000807	−0.62
Bicycle	0.00748***	6.99	0.000186	0.23
Transit	−0.00122	−1.35	−0.00170*	−2.03

(***) indicates significance at a 99.9-percent confidence level.
(**) indicates significance at a 99-percent confidence level.
(*) indicates significance at a 95-percent confidence level.
Pseudo-R^2 = 0.023.
N = 3.928.
Control variables with estimates omitted for space include physical health, disability, age and age squared (we include the quadratic term because many age-related phenomena, such as income, are not monotonically related to age but have peaks or troughs in the middle of life), female, number of children, female*number of children, education, couple status, employment status, household income, and year.
Bicycling is classed as "other physical travel" in the Dutch data; we presume that bicycling constitutes a very large proportion of such travel.
[1]Note unlike the U.S. data, Dutch data are averages for the week. Hence the selection model shows the correlates of taking part in exercise at any point in the week, not just a single day.

and 90 minutes is not associated with any significant change in the amount of time spent on other exercise. The same can be said of riding transit, since decreases in time spent on other exercise are not statistically significant for transit commutes ranging from 0 to 90 minutes. A person who travels by bicycle for 60 minutes per day is predicted to participate in about 5 more average minutes of daily non-travel exercise than a person who does not travel by bicycle, and this difference is statistically significant at a 95-percent confidence level.

6. Discussion

Based on our results, Americans who spend more time on AT are significantly more likely to exercise than those who do not. Similarly, data from the Tijdsbestedingsonderzoek show that, in the Netherlands, AT is positively and significantly associated with a higher likelihood of engaging in exercise. Our results imply that people do not tend to substitute AT for other exercise, and that it is possible that AT either complements exercise or that there is a spurious relationship between them. In the case of a spurious relationship, the confounding third variable could be something like attitude toward leading a healthy lifestyle. Moreover, because there is no apparent substitution between AT and exercise, our findings suggest that AT adds to overall physical activity (since it is a form of physical activity).

Our analysis of both Dutch data and American data reaches similar findings regarding the relationships between time spent on AT and self-rated health, education, marital status, and level of urbanization. There are also some differences between the results of our analysis of the Dutch data and the American data; in the ATUS data we fail to find significant results for the relationships between AT and gender, employment, income, and disability. This disagreement between the two samples may be because of the dramatic difference in the amount of AT across the two countries, which in turn has many causes.

There are some similarities between the Dutch and American correlates of exercise. For example, those with higher education and higher incomes are more likely to exercise in both data sets, although those who are employed are less likely to exercise. The results

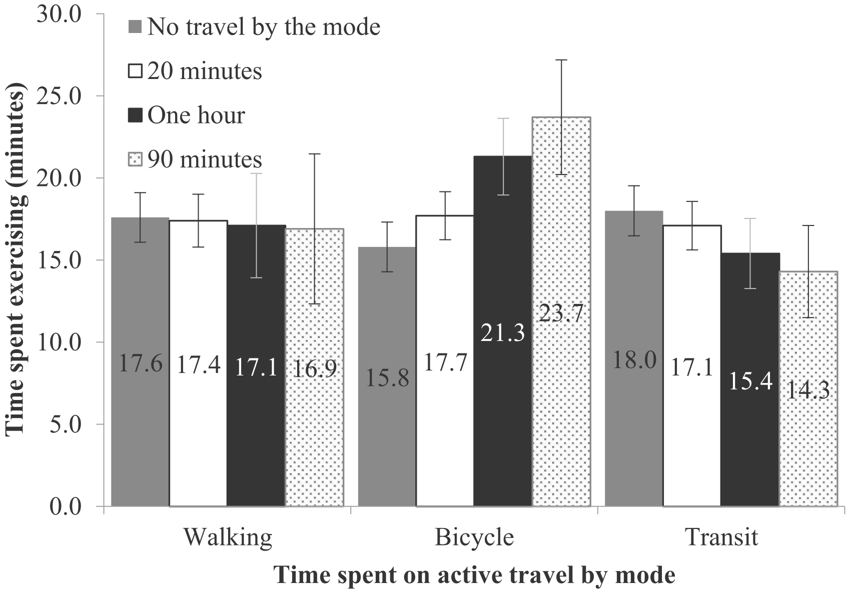

Fig. 4. Predictions of unconditional time spent exercising based on varying time spent on travel by each active mode, holding all other variables at means values, (Tijdsbestedingsonderzoek data).

are nuanced, but both data sets suggest that women exercise less than men. However, there are also noteworthy differences. For example, our Dutch results show that people in rural areas are more likely to exercise, while the American data shows those who live in larger, more urbanized places are more likely to exercise. In the U.S. data, better physical health is associated with a higher probability of exercising and more conditional exercise time, while we do not find this in the Dutch data (although the Dutch data do show that those with disabilities are less likely to exercise).

Results for both data sets also show that income is a significant predictor of both exercise and AT. In the Netherlands, poorer people are both more likely to engage in AT and to do so for longer, which follows intuition and is supported in the literature (Renne and Bennett, 2014); traveling actively is significantly less expensive than other modes (Edmonds, 2017), so it may be an appealing mode choice for those with lower incomes. Thus our results suggest that poorer people may engage in more AT not by choice, but by necessity, possibly because of a lack of a personal vehicle or unaffordable/absent transit. Similar findings are also true for women with children, which indicates that AT may increase total activity time for these more vulnerable populations. This may be problematic, since in cases where AT is a requirement even in unsuitable conditions it can degrade quality of life and presumably lead to negative health outcomes (Bostock, 2001).

Another reason for more AT among lower-income individuals may be that living closer to amenities is often more expensive (Diamond, 1980), so it follows that more time may be required for low-income people to walk or bike to destinations. Possible troubling equity implications also arise frorm the fact that, in the Dutch data, wealthier people are more likely to exercise and spend more time exercising when they do so. This may be because poorer people have less discretionary time than wealthier people (Goodin et al., 2005), for example because wealthier people may pay others to do activities such as home maintenance or cleaning, where a poorer person may do these tasks themselves. However, in the U.S. data, results regarding exercise differ; wealthier people are more likely to exercise, although they are likely to spend less conditional time doing so.

The discrepancies between the U.S. and Dutch results might have numerous causes. First, the results may be due to differing cultures, differences in the built environment, differences in transportation infrastructure, etc.; as noted, those in the Netherlands are much more likely to travel actively, particularly by bicycle. There may be other causes. First, time use in the Dutch data set is measured differently; as has been noted, we construct weekly averages as opposed to observing a single study day in our ATUS data. Second, the surveys were administered differently, with a live interviewer for the U.S. data and a paper diary for the Dutch data. Further research would ideally investigate these issues by conducting surveys with more similar methodologies across geographies.

However, our most important finding is that both data sets show a positive relationship between time spent on AT and the likelihood of exercise. The results suggest that AT does not replace recreational exercise; in the aggregate, active travelers participate in this activity in addition to their other exercise, not in lieu of it. This is true both in a country with relatively little AT and in one with a great deal, and on both on days individuals are active travelers and across entire weeks. It further possible that, in the Netherlands, bicycling complements AT, as does walking in the U.S.

If physical activity improves health, as several studies suggest (Hamer et al., 2009; Warburton et al., 2006), our findings would imply that policies to foster AT could promote better health by increasing overall physical activity. Thus, in addition to its environmental, social, and psychological benefits, AT is likely to make us more active, healthy, and fit people.

7. Conclusion

There are several limitations of our study. First, while the data sets complement each other in some ways, we recognize that the Dutch data set is limited both in its depth of control variables and in the fact that the data are not particularly recent (collected in 2000 and 2005). Second, as we have noted, we aggregate different types of physical activity, some of which may be more intensive than others. Also, we do not directly extend our analysis to whether active travel leads to health benefits, as we only observe physical activity, which is only one factor in overall health. Other unobserved factors, like genetics, diet, and pre-existing conditions also contribute to a person's overall health. Further, we treat health and BMI as exogenous and causal in our models of AT and exercise, following research cited above which suggests that obesity is likely more a cause of limited physical activity than an effect of it (Bauman et al., 2012). However, it is likely that the causal relationship flows in both directions and that there is some endogeneity. Further investigation of these relationships is warranted. Finally, since both the American and Dutch surveys provide cross-sectional rather than longitudinal data on the time use of survey participants, our analysis cannot directly determine whether increases in AT cause changes in exercise or total physical activity. Finally, self-selection likely influences our results; it seems possible that people who like to exercise more may also be more likely to engage in active travel, perhaps due to things like a propensity for healthy living. We are not able to control for self-selection with our data sets.

Our study suggests a number of potential avenues for future research. For example, it would be ideal if time use research was conducted in more countries, particularly in diverse places such as the developing world. Further, it would be beneficial for cross-national comparisons if more similar methodologies were adopted for time use study in different countries. It would be particularly interesting if more time use studies covered a weeklong period, or at least a weekday and a weekend day, to allow us to better examine trade-offs in time use over the course of the week.

Most importantly, new approaches are required to examine the relationships between the built environment, active travel, health, and fitness. As has been noted, we have assumed that health and fitness lead to AT and exercise more substantially than the reverse, but clearly the effects work in both directions. New data (such as longitudinal data) and methods are needed to untangle these causality issues. Panel data would also be ideal for helping to determine whether changes in AT cause changes in exercise levels.

Our findings contribute to the literature in that results from previous studies were muddled and often conflicting. It has been unclear how AT contributed to overall health outcomes. We do not directly find that AT leads to positive health outcomes, and it is of course true that any statistical analysis aggregates data from many individuals, and does not reveal universal laws. However, it seems likely that, while there may be individuals who do substitute AT for exercise, on the whole, this is not true across the population. In fact, our results suggest it is possible that AT even complements the likelihood of engaging in exercise, though not conditional exercise time. The former might be what is most important, since the U.S. Department of Health and Human Services recommends spreading the weekly recommended exercise (150 minutes) across multiple days as much as possible (Laskowski, 2019). Further, if AT does not substitute for exercise it is associated with more total physical activity, and prior research has found that physical activity is certainly one factor in improving general health (and arguably BMI).

It follows from these results that encouraging AT is a worthwhile endeavor for transportation planners, policy-makers, and public health advocates. Implementing policies like sidewalk improvement ordinances (which create requirements for expanding and connecting sidewalk networks) and urban design standards that encourage high-quality pedestrian spaces have potential to create positive health impacts. Also, educational and event-based programming focused on imparting the benefits of AT (including health benefits) can also prove useful tools for encouraging it, especially for children and young people. Finally, more elaborate networks of active transportation infrastructure (bicycle lanes, trails, separated bicycle facilities, etc.) would create safer and more comfortable places for bicycling and walking, which would promote AT and, ultimately, may make us healthier people.

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References

Adams, R.J., 2010. Improving health outcomes with better patient understanding and education. Risk Manag. Healthc. Policy 3, 61–72. https://doi.org/10.2147/RMHP.S7500.

Balen, P.A.H., Anderson, R.A., BFS, F.T.P., P.C.O.T., 2007. Impact of obesity on female reproductive health: British fertility society, policy and practice guidelines. Hum. Fertil. 10, 195–206. https://doi.org/10.1080/14647270701731290.

Bauman, A.E., Reis, R.S., Sallis, J.F., Wells, J.C., Loos, R.J., Martin, B.W., Group, L.P.A.S.W., 2012. Correlates of physical activity: why are some people physically active and others not? The Lancet 380, 258–271.

Becker, S., Zimmermann-Stenzel, M., 2009. Physical activity, obesity, and educational attainment in 50- to 70-year-old adults. J. Public Health 17, 145. https://doi.org/10.1007/s10389-008-0222-9.

Bhat, C.R., Koppelman, F.S., 1999. Activity-based modeling of travel demand. In: Hall, R.W. (Ed.), Handbook of Transportation Science, International Series in Operations Research & Management Science. Springer US, Boston, MA, pp. 35–61. https://doi.org/10.1007/978-1-4615-5203-1_3.

Bittman, M., England, P., Sayer, L., Folbre, N., Matheson, G., 2003. When does gender trump money? Bargaining and time in household work. Am. J. Sociol. 109, 186–214. https://doi.org/10.1086/378341.

Bostock, L., 2001. Pathways of disadvantage? Walking as a mode of transport among low- income mothers. Health Soc. Care Community 9, 11. https://doi.org/10.1046/j.1365-2524.2001.00275.x.

(dataset)Breedveld, K., Sociaal en Cultureel Planbureau, 2000. Tijdsbestedingssonderzoek 2000 - TBO 2000. Data Arch. Networked Serv.. https://easy.dans.knaw.nl/ui/datasets/id/easy-dataset:31983 .

(dataset) Bureau of Labor Statistics, 2016. American time use survey home page. http://www.bls.gov/tus/ (accessed 7.24.18).

(dataset)Butler, G.P., Orpana, H.M., Wiens, A.J., 2007. By your own two feet: factors associated with active transportation in Canada. Can. J. Public Health, JSTOR, pp. 259–264.

Cooper, A.R., Foster, L.J., Qahwaji, D., 2003. Commuting to school: are children who walk more physically active? Am. J. Prev. Med. 25, 273–276.

Corburn, J., 2007. Reconnecting with our roots: American urban planning in the twenty-first century. Urban Aff. Rev. 688–713.

Cragg, J.G., 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. Econometrica 39, 829–844. https://doi.

org/10.2307/1909582.
Crane, R., 2007. Is there a quiet revolution in women's travel? Revisiting the gender gap in commuting. J. Am. Plan. Assoc. 73, 298–316. https://doi.org/10.1080/01944360708977979.
Davis, M.G., Fox, K.R., Hillsdon, M., Coulson, J.C., Sharp, D.J., Stathi, A., Thompson, J.L., 2011. Getting out and about in older adults: the nature of daily trips and their association with objectively assessed physical activity. Int. J. Behav. Nutr. Phys. Act. 8, 116. https://doi.org/10.1186/1479-5868-8-116.
Diamond, D.B., 1980. The relationship between amenities and urban land prices. Land Econ. 56, 21–32. https://doi.org/10.2307/3145826.
Edmonds, E., 2017. AAA Reveals the True Cost of Vehicle Ownership. ([WWW Document]).
Ekelund, U., Brage, S., Besson, H., Sharp, S., Wareham, N.J., 2008. Time spent being sedentary and weight gain in healthy adults: reverse or bidirectional causality? Am. J. Clin. Nutr. 88, 612–617. https://doi.org/10.1093/ajcn/88.3.612.
Fisher, K., 2002. Chewing the fat: the story time diaries tell about physical activity in the United Kingdom. In: Working Papers of the Institute for Social and Economic Research. paper 2002-13, . https://www.econstor.eu/bitstream/10419/92080/1/2002-13.pdf.
Fisher, K., Gershuny, J., Flood, S.M., Backman, D., Hofferth, S.L., 2019. Multinational Time Use Survey Extract System: Version 1.3. Minneapolis MN: IPUMS. https://www.mtusdata.org/mtus/about.shtml (accessed 8.27.17).
Garikapati, V.M., Pendyala, R.M., Morris, E.A., Mokhtarian, P.L., McDonald, N., 2016. Activity patterns, time use, and travel of millennials: a generation in transition? Transp. Rev. 36, 558–584. https://doi.org/10.1080/01441647.2016.1197337.
Gershuny, J., Fisher, K., 2013. Multinational Time Use Study. Centre for Time Use Research. University of Oxford. https://www.timeuse.org/mtus/reference (accessed 5.5.18).
Goodin, R.E., Rice, J.M., Bittman, M., Saunders, P., 2005. The time-pressure illusion discretionary time vs. free time. Soc. Indic. Res., vol. 73, 43–70. https://doi.org/10.1007/s11205-004-4642-9.
Gordon-Larsen, P., Boone-Heinonen, J., Sidney, S., Sternfeld, B., Jacobs, D.R., Lewis, C.E., 2009. Active commuting and cardiovascular disease risk: the CARDIA study. Arch. Intern. Med. 169, 1216–1223. https://doi.org/10.1001/archinternmed.2009.163.
Grieve, D.W., Gear, R.J., 1966. The relationships between length of stride, step frequency, time of swing and speed of walking for children and adults. Ergonomics 9, 379–399. https://doi.org/10.1080/00140136608964399.
Hamer, M., Stamatakis, E., Steptoe, A., 2009. Dose-response relationship between physical activity and mental health: the Scottish Health Survey. Br. J. Sports Med. 43, 1111–1114. https://doi.org/10.1136/bjsm.2008.046243.
Hofferth, S.L., Flood, S.M., Sobek, M., 2018. American Time Use Survey Data Extract System. IPUMS, College Park, MD and Minneapolis MN.
Kitamura, R., Fujii, S., Pas, E.I., 1997. Time-use data, analysis and modeling: toward the next generation of transportation planning methodologies. Transp. Policy 4, 225–235. https://doi.org/10.1016/S0967-070X(97)00018-8.
Larouche, R., Saunders, T.J., Faulkner, J., Colley, R., Tremblay, M., Edward, G., 2014. Associations between active school transport and physical activity, body composition, and cardiovascular fitness: a systematic review of 68 studies. J. Phys. Act. Health 11, 206–227. https://doi.org/10.1123/jpah.2011-0345.
Laskowski, E.R., 2019. How much should the average adult exercise every day? Mayo Clinic: Healthy Lifestyle: Fitness. https://www.mayoclinic.org/healthy-lifestyle/fitness/expert-answers/exercise/faq-20057916 (accessed 6.18.19).
Metcalf, B.S., Hosking, J., Jeffery, A.N., Voss, L.D., Henley, W., Wilkin, T.J., 2011. Fatness leads to inactivity, but inactivity does not lead to fatness: a longitudinal study in children. Arch. Dis. Child. 96, 942–947. https://doi.org/10.1136/adc.2009.175927.
Morris, E.A., 2015. Should we all just stay home? Travel, out-of-home activities, and life satisfaction. Transp. Res. Part Policy Pract. 78, 519–536. https://doi.org/10.1016/j.tra.2015.06.009.
Nazelleabc, A., Josep, A., Nieuwenhuijsen, M., Brauerd, M., Briggs, D., Braun-Fahrlander, C., Cavill, N., Cooper, A.R., Desqueyroux, H., Fruin, S., Hoek, G., Luc, P., Jannes Michael, N., Michael, J., Zorana, J., Andersen, J., Kempen, E., Kingham, S., Lebret, E., 2011. Improving health through policies that promote active travel: a review of evidence to support integrated health impact assessment. Environ. Int. 37, 766–777. https://doi.org/10.1016/j.envint.2011.02.003.
Panter, J.R., Jones, A.P., van Sluijs, E.M., 2008. Environmental determinants of active travel in youth: a review and framework for future research. Int. J. Behav. Nutr. Phys. Act. 5, 34. https://doi.org/10.1186/1479-5868-5-34.
Renne, J.L., Bennett, P., 2014. Socioeconomics of urban travel: evidence from the 2009 national household travel survey with Implications for sustainability. World Transp. Policy Pract. 7–27.
Rissel, C.E., 2019. Active travel: a climate change mitigation strategy with co-benefits for health. New South Wales. Public Health Bull 20, 10. https://doi.org/10.1071/NB08043.
Roth, M.A., Millett, C.J., Mindell, J.S., 2012. The contribution of active travel (walking and cycling) in children to overall physical activity levels: a national cross-sectional study. Prev. Med. 54, 134–139. https://doi.org/10.1016/j.ypmed.2011.12.004.
Sahlqvist, S., Song, Y., Ogilvie, D., 2012. Is active travel associated with greater physical activity? The contribution of commuting and non-commuting active travel to total physical activity in adults. Prev. Med. 55, 206–211. https://doi.org/10.1016/j.ypmed.2012.06.028.
Sahlqvist, S., Goodman, A., Cooper, A.R., Ogilvie, D., 2013. Change in active travel and changes in recreational and total physical activity in adults: longitudinal findings from the iConnect study. Int. J. Behav. Nutr. Phys. Act. 10, 28. https://doi.org/10.1186/1479-5868-10-28.
Santos, M.P., Oliveira, J., Ribeiro, J.C., Mota, J., 2009. Active travel to school, BMI and participation in organized and non-organized physical activity among Portuguese adolescents. Prev. Med. 49, 497–499. https://doi.org/10.1016/j.ypmed.2009.09.021.
Saunders, L.E., Green, J.M., Petticrew, M.P., Steinbach, R., Roberts, H., 2014. What are the health benefits of active travel? A systematic review of trials and cohort studies. PLoS One 8, e69912. https://doi.org/10.1371/journal.pone.0069912.
Sisson, S.B., Tudor-Locke, C., 2008. Comparison of cyclists' and motorists' utilitarian physical activity at an urban university. Prev. Med. 46, 77–79. https://doi.org/10.1016/j.ypmed.2007.07.004.
Smart, M.J., Brown, A., Taylor, B.D., 2017. Sex or sexuality? Analyzing the division of labor and travel in gay, lesbian, and straight households. Travel Behav. Soc. 6, 75–82. https://doi.org/10.1016/j.tbs.2016.07.001.
Sociaal en Cultureel Planbureau, 2005. Tijdsbestedingsonderzoek 2005 - TBO 2005. Data Arch. Networked Serv.. https://easy.dans.knaw.nl/ui/datasets/id/easy-dataset:44212 (accessed 6.25.17).
Stata Press, 2013. churdle. In: Stata 15 Base Reference Manual. Stata Press, College Station, TX.
Stewart, J., 2013. Tobit or not Tobit? J. Econ. Soc. Meas. 38, 263–290.
Sugiyama, T., Merom, D., Reeves, M., Leslie, E., Owen, N., 2010. Habitual active transport moderates the association of TV viewing time with body mass index. J. Phys. Act. Health 7, 11–16.
Taylor, B.D., Ralph, K., Smart, M., 2015. What explains the gender gap in schlepping? Testing various explanations for gender differences in household-serving travel. Soc. Sci. Q. 96, 1493–1510. https://doi.org/10.1111/ssqu.12203.
UCLA Institute for Digital Research and Education, 2011. FAQ: what are Pseudo-R-Squareds? https://stats.idre.ucla.edu/other/mult-pkg/faq/general/faq-what-are-pseudo-r-squareds/ (accessed 6.16.19).
U.S. Census Bureau, 2018. Current Population Survey (CPS). . https://www.census.gov/programs-surveys/cps.html (accessed 5.15.18).
Voulgaris, C.T., Smart, M., Taylor, B.D., 2017. Tired of commuting? Relationships among journeys to school, sleep, and exercise among american teenagers. J. Plan. Educ. Res. 39-2, 142–154.
Wanner, M., Götschi, T., Martin-Diener, E., Kahlmeier, S., Martin, B.W., 2012. Active transport, physical activity, and body weight in adults: a systematic review. Am. J. Prev. Med. 42, 493–502. https://doi.org/10.1016/j.amepre.2012.01.030.
Warburton, D.E., Nicol, C.W., Bredin, S.S., 2006. Health benefits of physical activity: the evidence. Can. Med. As. J. 174 (6), 801–809.
Wilkinson, R.G., Marmot, M., 2003. Social determinants of health: the solid facts. World Health Organization.
Wodjao, T.B., 2007. A double-hurdle model of computer and internet use in american households.
Wooldridge, J.M., 2009. Hurdle and selection models. http://legacy.iza.org/teaching/wooldridge-course-09/course_html/docs/slides_twopart_5_r1.pdf (accessed 6.22.18).