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# Which activities do those with long commutes forego, and should we care? 

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#### Abstract

Commuting imposes opportunity costs on travelers since those with long commutes have less time to participate in other activities. This paper examines how commute duration is associated with activity patterns. It utilizes a twoday time use survey administered in the United Kingdom in 2014 and 2015. Focusing on full-time employees and controlling for socio-demographic characteristics, we regress time spent engaging in 22 different activities on commute duration using OLS and Cragg two-part hurdle modeling. We separately test the effects of commute duration on activity participation for men versus women and for single persons versus persons in couples. We also report the subjective well-being (SWB), specifically the hedonic affect, associated with these activities as determined by using fixed-effects panel regression. The estimations suggest that commutes are associated with time constraints and entail trade-offs, with longer commutes being associated with significantly less time engaging in most of our activities including sleep, cooking, housework, shopping/accessing services, arts/entertainment activities, TV/music time, computer games and other computer use, visiting with others, sports/exercise/outdoor activities, hobbies, volunteering, and non-work travel. Those with longer commutes are found to tend to engage in more of two activities: work and eating out. The activities those with longer commutes tend to forego run the gamut from high-SWB to low-SWB. Given that the lowest-SWB activity in our sample is commuting itself, it appears as if the substitution of nearly any activity for commuting may bring emotional benefits. In all, the results suggest that longer commutes are associated with significant emotional costs.


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## 1. Introduction

The journey to work, or "commute," comprised only about 14.6\% of trips in the U.K. (the setting of this paper) in 2018 (Department for Transport, 2019). But commutes are costly to travelers, particularly since they tend to be disproportionately long in distance and duration (in the U.K. they account for almost $20 \%$ of passenger miles (Department for Transport, 2019)). Commutes involve considerable monetary expense, for example in terms of fuel, vehicle maintenance and depreciation, parking, tolls, and transit fares. Moreover, commutes may impose emotional costs during and even after the trip, including feelings of stress, frustration, or boredom. These emotional costs have been extensively studied (Clark et al., 2019; Ettema et al., 2012; Evans and Wener, 2006; Gatersleben and Uzzell, 2007; Gottholmseder et al., 2009; Higgins et al., 2018; Kahneman and Krueger, 2006; Koslowsky et al., 1996; Morris and Guerra, 2015a, 2015b; Morris and Zhou, 2018; Olsson et al., 2013; Sposato et al., 2012; Stokols et al., 1978; White and Dolan, 2009). Finally, commutes may involve danger, for example due to vehicle crashes.

[^0]However, prior research on what is perhaps the most significant cost of commuting - the opportunity cost of time - is limited in terms of both scale and scope (see the literature review below). Long commutes take away time that might be put to other purposes, with possible deleterious impacts on commuters' psychological, social, and economic lives. In addition to reducing commuters' happiness, or "subjective well-being" (SWB), this time loss may affect the well-being of others, such as commuters' families and friends, and might even harm society if the foregone activities have broader social benefits. However, whether this lost time actually represents a meaningful cost depends in large part on what those foregone activities are, and how important they are to the lives of commuters, those they interact with, and society.

This paper is among the first to address this question, and it advances prior work in several novel ways. For example, we observe much more finely disaggregated activity classifications than has been done in the past; we examine time use over multiple days; and we are, to the best of our knowledge, the first to marry data on how commutes affect time use with data on the SWB associated with activities to see if long-duration commuters are foregoing activities with high (or low) SWB. Since there were roughly 11.4 billion commuting trips in the U.K. alone in 2019 (authors' calculation based on Department for Transport (2019)), the import of gauging the emotional costs of the commute is not merely academic.

The next section of this paper features a literature review that covers prior research on the SWB associated with travel, the more limited body of research on the trade-offs between travel and activity participation, and the larger body of research on SWB and activity participation. We next describe our data set, the United Kingdom Time Use Survey conducted in 2014-2015. We proceed to outline our methods, describing the Cragg hurdle modeling we use to study time use, the generation of predicted unconditional activity times, and the fixed-effects panel model we use to gauge SWB during activities. We then present our empirical results, both for the time use models which show how commute duration is associated with participation in other activities (including a special investigation of how this may change based on couple status and gender), and then models which show the SWB associated with those activities. We conclude with a discussion section which reflects on the possible causes, results, and import of our findings, and a conclusion which discusses shortcomings in our research, potential ideas for future research, and the implications of our findings for policy.

## 2. Literature review

### 2.1. The SWB associated with commuting

Numerous studies have found that commutes, particularly long commutes, may result in poor mood, or "affect," during travel. Commutes may be stressful, tiring, frustrating and/or dull (Ettema et al., 2012; Evans and Wener, 2006; Gatersleben and Uzzell, 2007; Gottholmseder et al., 2009; Higgins et al., 2018; Kahneman and Krueger, 2006; Koslowsky et al., 1996; Morris and Guerra, 2015a, 2015b; Sposato et al., 2012; Stokols et al., 1978; White and Dolan, 2009). On the other hand, some research suggests these impacts may be more limited than might be supposed, or even that commutes might have positive emotional benefits (Mokhtarian and Salomon, 2001; Olsson et al., 2013; Ory et al., 2004; Redmond and Mokhtarian, 2001; Wener and Evans, 2011). This may be the case because useful or pleasant activities can be performed during the trip, or because commutes provide a psychological buffer between home and work (Ettema et al., 2012; Lyons et al., 2013; Ory et al., 2004). Some researchers have moved beyond affect during and immediately after travel and have investigated whether long commutes detract from commuters' overall satisfaction with their lives. Results are mixed, with some studies finding long commutes do indeed detract from life satisfaction (Choi et al., 2013; Hilbrecht et al., 2014; Morris, 2011; Stutzer and Frey, 2008; Wheatley, 2014) but others failing to find this association (Dickerson et al., 2014; Kroesen, 2014; Morris and Zhou, 2018; Munford, 2014). The studies also differ in terms of the assumed mechanisms by which commute duration influences well-being. While Stutzer and Frey (2008) find that commutes may reduce life satisfaction through their impact on household interactions, through subdomains of life such as health and family life, and through the commuter's psychological makeup, little work has investigated whether the effect of commute duration on SWB is mediated by time use effects. Hilbrecht et al. (2014) find that longer commutes are associated with less time spent on physically active leisure, which in turn may result in lower life satisfaction. Little other research we have identified has investigated this question.

### 2.2. Associations between commuting, travel time, and time spent on other activities

To determine just which activities longer commutes may replace, some prior researchers have modeled time allocated to activities and travel simultaneously, assuming a general time constraint which implies that time spent on travel reduces participation in other activities (e.g., Chen and Mokhtarian, 2006). Time use research in the context of travel behavior studies confirms the idea that people make trade-offs in time allocation between travel and other activities. Levinson and Krizek (2008) question the validity of the travel time budget theory (see Mokhtarian and Chen (2004)) and propose that reductions in travel time will result in an increase in time
allocated to other activities. Bhat and Misra (1999), using a time-use survey conducted in the Netherlands in 1985, find that individuals who have longdistance commutes are less inclined to participate in out-of-home discretionary activities on weekdays. While these studies provide first insights into the effects of travel in general, and commuting in particular, on time use, they tend to be limited in several ways. For example, they typically use a few very broad activity categories that do not reflect the exact consequences of commuting. In addition, most studies focus on the effects of commute duration on out-of-home activities, ignoring the effects on inhome activities (with the exception of sleeping: see Basner et al. (2007)). Moreover, only the Bhat and Misra paper examines time use over the course of multiple days, which is important for determining whether those with long commutes shift activities to weekend days or forego them entirely.

The effect of travel time on other time uses is theoretically addressed in time allocation frameworks, as initially proposed by Becker (1965), DeSerpa (1971) and Evans (1972), and as extended by Jara-Diaz (2007). In essence, these frameworks assume that individuals optimize the utility derived from activity participation and consumption by adjusting their work hours and time spent on travel given limitations in time and monetary budgets. The relationships established during this optimization can help illustrate the value of travel time savings. Notably, this framework assumes that individuals can freely, and with full knowledge and awareness of the outcomes, choose their amount of work and travel; under these assumptions, people would select travel and activity patterns that optimize utility and well-being. However, various studies (Chatman, 2014; Ettema and Nieuwenhuis, 2017; Stutzer and Frey, 2008) have pointed out that these assumptions may be questionable, given constraints affecting where to live and work and how long to travel, plus the inability of travelers to foresee the daily implications of structural travel choices (Pedersen et al., 2011). As a result, commute durations may be suboptimal, and time use patterns and the experienced utility flowing from them may differ from the theoretical ideal. Consequently, further study of the impact of commute duration on time use and well-being is needed.

### 2.3. Associations between out-of-home activities and SWB

Does time use influence well-being? A body of literature has examined the links between activities and three aspects of SWB. The first is the cognitive judgment of overall life satisfaction. The second and third are manifestations of affect felt during activities. These include hedonic enjoyment, which refers to the pleasure experienced during an activity, and eudaimonia, which emphasizes the deeper meaning people reap during activities in terms of personal progress toward the realization of goals and self-development (Deci and Ryan, 2008; Waterman, 2005; Waterman et al., 2008). Kahneman and Krueger (2006) find that of the 19 daily activities they observed, the morning commute, work, and evening commute are the least enjoyable activities, while intimate relations, socializing, and relaxing are associated with the most positive affect. Anusic et al. (2017) find the highest-affect activities are sports/exercise, intimate relations, socializing, and religious activities, and the lowest are shopping, housework, work, doctors' appointments, and commuting. Bryson and MacKerron (2017) find the highest-affect activities are intimacy, arts/entertainment/ cultural activities, and sports/exercise, and that the lowest-affect activities are caring for adults, working/studying, and being sick in bed. Krueger (2007) finds that the highest-affect activities are playing with children, listening to music, attending sporting events, and outdoor activities; the lowest are homework, medical care, purchasing financial/government services, and home repairs. White and Dolan (2009) disaggregate hedonic and eudaimonic affect, finding that the highest eudaimonic activities are volunteering, work, praying, and caring for children, and the lowesteudaimonic are commuting, self-care, watching TV, and relaxation. They find the highest hedonic activities are outdoor activities, watching TV, praying, and relaxation; the lowest are commuting, shopping, housework, and work. It is noteworthy that many of these studies find commuting is a poor-affect activity.

Ettema et al. (2010) conclude that participation in goal-directed activities promotes the experience of eudaimonia and thus contributes to SWB. Spinney et al. (2009) find significant associations between out-of-home activities and life satisfaction among elderly Canadians, and Morris et al. (2018) find that all discretionary out-of-home activities they observe are associated with elevated affect (both hedonic and eudaimonic). Schwanen and Wang (2014) also find out-of-home activities have a positive effect on affect, but that they have no association with overall life satisfaction. Morris (2015) finds that life satisfaction is positively and significantly associated with involvement in travel in general, and with travel specifically for the purposes of out-of-home eating and drinking, religious activities, volunteering, and playing and watching sports. Taken together, the literature suggests that participation in many types of activities influences SWB, and, consequently, that constraints on activity participation associated with longer commute durations may in turn impact SWB in all three dimensions.

## 3. Data

### 3.1. U.K. time use data

The data for this study were taken from the United Kingdom Time Use Survey, as conducted by the Centre for Time Use Research and as complied by the Multinational Time Use Survey. We accessed the data from the Centre for Time Use Research website (Gershuny and Sullivan, n.d.) as well as the MTUS data aggregation site (Fisher et al., 2019). The survey was conducted in 2014 and 2015 and selected a random sample of U.K. households. There are 8272 valid individuals in the sample. The survey followed the Harmonised European Time Use Survey format. All members of a household aged eight and older completed an activity diary for two 24 -hour periods, one on a weekday and one on a weekend day. The diaries allowed respondents to define in their own words their main activity types, secondary activity types, modes of travel, and location. Separately, participants could report if they were using a cellphone or computer, and with whom the activity was conducted. Time was divided into 10 -minute slots.

The survey also asked most respondents whether they "enjoyed" each activity, which they could rate on a 1-7 scale. It also collected demographic data that are commonly used in social science model specifications, which we employ in the models below as control variables.

We restrict our sample to full-time workers who worked any amount on at least one of the two study days. We do, however, include those who worked but reported zero commute minutes (presumably those who worked at home). This yields a sample of 2052 valid cases in the time use models below.

The U.K survey was chosen for its relative timeliness (2014-2015), and particularly because it includes both a weekday and a weekend day. It would not be surprising to find that many respondents with long commutes give up a substantial amount of other activities on days they commute, but it is possible that they adapt by participating in many of those activities on non-work days; conversely, some activities might be entirely foregone. Thus is it important to jointly consider activities across the course of the week (Astroza et al., 2018). The two-day diaries allow this. We constructed average daily activity times across the week by multiplying weekday activity times by five and weekend activity times by two, summing these, and dividing by seven. While a time use survey that considers all seven days in the week would be preferable in terms of greater precision, surveys conducted over longer timeframes run risks such as respondent attrition and fatigue, and are thus not common. Jara-Díaz and Rosales-Salas (2015) have empirically investigated whether two-day studies are reliable substitutes for weeklong studies by examining time use in a weeklong survey and then randomly sampling one weekday and one weekend day for each respondent and comparing the results with the weeklong data. They find that activity duration means are comparable across the two methods, although variability is higher in two-day studies; overall, their results show that two-day diaries are "sufficient surrogates" for weeklong diaries.

## 4. Methods

Fig. 1 shows a schematic of our research design. Descriptions of each of the parts follows.

### 4.1. Modeling time use and activity participation

As the aim of our study is to investigate the associations between commute duration and activity participation, we use regression models in which average daily time spent performing a particular activity is the dependent variable, and average daily commute duration is the key explanatory variable, together with a set of sociodemographic control variables. Depending on the distribution of the dependent time use variable, we employ different regression methods. Two of the time uses we observe are relatively normally distributed, with little or no censoring at zero. For example, no respondent in the sample reported zero sleep on both days, and sleep time has a relatively normal distribution around 8.2 h per day. Work time has no censoring at zero because we restricted the sample to those who worked during the week. However, many activity times are censored at zero: for example, 853 members of the sample (33\%) reported no shopping or accessing services on the two study days. This renders the use of OLS problematic. Therefore, we employ two-part Cragg hurdle models for the censored variables (Cragg (1971); for the documentation on this technique in Stata (our statistics package) see Stata Press (2017). The Cragg model copes with censoring at zero, and unlike the Tobit model, which is often used for censored data, it produces parameter estimates which reflect real-world behavior in cases where the bound cannot be violated (i.e., in our case it is impossible to participate in an activity for negative minutes). Also, unlike Tobit, it more accurately reflects the separate psychological processes involved in activity participation: these are whether to engage in the activity and how long to engage in the activity if it is engaged in. (Tobit assumes these are both driven by the same underlying mechanism.) For example, one person may choose to go to the movies more frequently than another, but this does not necessarily mean that that person also chooses to go to longer movies. The Cragg method models these decisions separately. We also elected not to use a count model (such as negative binomial) because our time uses are not integers (they are weekly averages we have constructed), and also because time is more properly thought of as a continuous quantity as opposed to a count with each minute being a discrete event.

Part one of the Cragg model is a probit model which identifies which variables affect the propensity to take part in the activity at all during the two study days. Part two is a truncated OLS regression identifying which variables helped determine conditional time use, that is, activity duration assuming an individual took part in the activity. To model conditional activity time, data are only used from those who took part in the activity. The duration of most time uses is skewed to the right; most participants engaged in activities for a relatively short amount of time, with a tail to the right of a small number of people who engaged for a long amount. Thus we take the natural $\log$ of the dependent time use variables in the second parts of the models to produce better fit.

The control variables in the models include demographic characteristics that are typically included in social science model specifications: age, age squared, sex, couple status (married/with partner versus no partner), education level (did not finished secondary school, finished secondary school, post-secondary education), household income (bottom $25 \%$, middle $50 \%$, upper 25\%), physical health (poor, fair, good, very good), number of children, and children*female (which we add since women may perform a disproportionate share of the maintenance activities related to children),

To render the results more interpretable, we also furnish predictions of unconditional average daily activity time. For the time uses which were modeled using the Cragg method, the predictions amalgamate the results of both the probit and the OLS models; they are generated by multiplying the predicted probability of an individual engaging in the activity during the study days by his/her predicted conditional activity time. Predictions presented are for two individuals, one with a 5-minute one-way commute


Fig. 1. Schematic diagram of research design.
and one with a 45-minute one-way commute. These figures were chosen because the mean average daily commute time (including non-commute days) is roughly 33 min with a $31-$ minute standard deviation, so the two selected commute times are approximately one standard deviation below the mean and one standard deviation above. We employ the average marginal effects method to generate the predictions: predictions are generated for each individual in the sample assuming a 5-minute commute and then a 45-minute commute, and these predictions are then averaged across the sample.

It should be noted that these commute times are sensitive to the definition of what constitutes a commute trip, as trip chaining may occur on the journeys to and from work. The survey defines a trip as a "trip to/from work" if the destination is work, or if the origin is work and the destination is home.

We considered estimating a multiple discrete-continuous extreme value (MDCEV) model (Bhat, 2005). This is closed-form model which performs simultaneous estimation of multiple, related discrete-continuous distributions. It has been used to model time use data (Bhat, 2005; Pinjari et al., 2016; Pinjari and Bhat, 2010) as it was designed to reflect trade-offs among all observed activities, and also to reflect the fact that activity participation is bounded by a fixed time budget ( 1440 min in the day) (Dharmowijoyo et al., 2016; Lu and Pas, 1999). The model also allows for correlations in the error terms across related time uses (Bhat, 2005).

Although we have tested the MDCEV model using the Apollo package (Hess and Palma, 2019) in R (R Core Team, 2018), we opt to report the Cragg hurdle model results here for three reasons. First, the simultaneous estimation of 22 time uses plus 14 control variables (as we use in our models below) in an MDCEV model is not feasible; it would involve the
estimation of over 2000 parameters on a data set with only 2052 observations. To reduce the dimensionality and make it possible to estimate the model, an MDCEV model would require a very parsimonious set of time uses and controls, which has been the case when it has been put into practice previously. Since we want a more precise picture of time use, and since many demographic variables are plausibly associated with both commute time and other time uses, we prefer to report models that can handle the full set of time uses and socioeconomic control variables we employ. Second, MDCEV models do not predict actual time uses particularly well. For example, Bhat's (2018) MDCEV model of time use in greater Seattle misestimates the aggregate time spent on six activities by $19 \%$ on average. Our work with the Cragg model has produced smaller errors of prediction. Third, the MDCEV model outputs are difficult to interpret, while the Cragg model consists of two parts that are familiar statistical techniques, and it lends itself to the generation of predictions of unconditional activity times which are quite straightforward.

The main caveat when interpreting the Cragg results is that they do not necessarily precisely reflect how increasing or reducing the commute would change activity patterns for any given individual. This is because they do not consider how changes in each activity time would affect all of the other activity times (and vice versa) due to the way in which all activities are interdependent. Also, Cragg results are not constrained by the limited minutes in the day. However, the Cragg models accurately show the bivariate relationships between commute time and activity time for each activity across the entire aggregated sample.

### 4.2. Modeling affect during activities

As we have noted, in the models of affect below, we capitalize on the fact that the survey asked respondents to record how much they "enjoyed" each activity on a 1-7 scale, from "not at all" to "very much." This allows us to utilize fixed-effects panel regression to estimate the affect associated with our 23 activity types (including the commute itself as an activity). In effect, the estimated coefficients are derived by comparing the affect scores associated with all activities within each individual, and then pooling results across all individuals. Because most individual characteristics (excluding things which may vary on the study day) are the same when all of the observations are taken for each individual, in effect the models control for nearly all individual characteristics, including things like gender or age but also much more difficult-to-observe characteristics such as the intrinsic predisposition to feel happy or not.

It is somewhat ambiguous what facet of affect this "enjoyment" variable measures, as it is up to the individual survey respondents to interpret what is meant by the word "enjoy." However, we interpret this to primarily mean hedonic affect (pleasure during the activity) as opposed to eudaimonic affect (contributing to fulfilling goals and self-realization). First, we interpret the word "enjoy" to connote pleasure more than lasting rewards. Second, this interpretation is confirmed by our comparison of our results with those we have obtained from the American Time Use Survey (U.S. Bureau of Labor Statistics, 2019) and other prior work on the affect associated with activities, as outlined above. For example, work is typically associated with low hedonic affect but higher eudaimonia, and our work with the U.K. data give work a low score on the "enjoy" variable.

## 5. Results

### 5.1. Commute duration and activity participation

The rows in Table 1 below present the results of 22 separate regression models. Column 1 lists the activity that is the dependent variable in each model. The next five columns present results for how the activity times are associated with commute duration. For cases where OLS regression is appropriate, column 2 shows the coefficient and the t-statistic for commute time's association with that activity time. For all other dependents, the coefficient and t-statistic for the Cragg probit selection model (indicating
the propensity to take part in the activity at all) are presented in column 3 , and the coefficient and t-statistic for the conditional time OLS model are presented in column 4. The unconditional time predictions are furnished in columns 5 and 6. Note that we do not present results for all of the control variables for brevity's sake: these variables are listed beneath the table. The online supplementary material contains full results tables for all 22 models, including the estimates for the control variables.

The predictions shown in the two right-hand columns of Table 1 are shown graphically in Figs. 2, 3, and 4. Note we outline the methods for generating these predictions above in Section 4.1.

Longer commutes are associated with a significantly lower likelihood of respondents having participated in shopping/using services, arts/entertainment activities, visiting with others, sports/exercise/outdoor activities, hobbies, computer games, volunteering, and engaging in non-commute travel on the study days. Those with longer commutes who did participate in the activities spent significantly less time sleeping, cooking, doing housework, shopping/using services, watching TV/listening to music, and traveling. However, those with longer commutes are found to be significantly more likely to have eaten out on the study days and to have spent more time working.

Examining the unconditional time predictions, in terms of absolute time the largest reduction is in sleep, with those with a 45-minute oneway commute being predicted to sleep an average of 18 min per day less than those with a five-minute commute. The longer-duration commuter is also predicted to engage in 24 min less non-commute travel and 21 min less TV/music time. However, the longer-duration commuter is predicted to average 43 more minutes per day working. In proportional terms the biggest differences are in 1) hobbies, with those with the longer commute predicted to spend $69 \%$ less time on this activity, 2) arts/entertainment ( $36 \%$ less), 3) shopping/services ( $31 \%$ less), 4) non-commute travel ( $31 \%$ less), and 5) computer games ( $30 \%$ less). Those with the longer commute time are predicted to work 9\% more.

We would note that the predictions, plus commute time, sum nearly to the 1440 min that compose a day: a total of 1425 min for the short-duration commuter and 1416 min for the longer-duration commuter. The fact that our predictions sum to slightly below 1440 is likely due in part to the fact that we exclude certain low-duration activities like adult care.

The small size of the discrepancy lends credibility to our results and suggests that not having the 1440 min in the day as a constraint is not a significant problem.

### 5.2. Activities and subjective well-being

Next, in Table 2 we use fixed-effects panel modeling to analyze the subjective well-being associated with these activities. As we have noted, we examine the "enjoyment" associated with these activities. The activities which those with longer commutes do significantly less of (they were negative and significant in one or both parts of the Cragg model) are shaded in yellow. The activities those with longer commutes do significantly more of are shaded in blue. The omitted category is the relatively small number of activities we do not observe (such as care of adults). The activities are sorted from the highestenjoyment activities to the lowest enjoyment (top to bottom and left to right).

As can be seen, the results for the enjoyment associated with activities are quite intuitive, with discretionary activities scoring high and mandatory chores scoring low. Six of the 13 activities that are negatively associated with commute time are associated with quite high enjoyment. These are arts/entertainment, sleep, visiting with others, computer games, hobbies, and exercise/sports/outdoors. Two are associated with medium enjoyment (TV/music and volunteer work), while four are associated with low enjoyment (non-commute travel, cooking, shopping/services, and housework). The two activities which those with long commutes are predicted to do more of are associated with very low enjoyment (work and commute travel itself).

Table 1
OLS and Cragg hurdle models of commute time regressed on activity times.

| Dependent time use variable | OLS coefficient and t-stat <br> Activity duration in min/day | Probit coefficient and t-stat Selection model of probability of taking part in the activity | Truncated OLS coefficient and t-stat Conditional activity duration in $\ln$ (min/day) | 5 min <br> 1-way commute prediction (avg. minutes/day) | 45 min <br> 1-way commute prediction (avg. $\min /$ day) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Sleep | $\begin{array}{r} -0.298 * * * \\ (-4.98) \end{array}$ |  |  | 493.8*** | 476.8*** |
| Groom |  | $\begin{array}{r} 0.00627 \\ (1.55) \end{array}$ | $\begin{array}{r} -0.0000875 \\ (-0.20) \end{array}$ | 56.5 | 56.6 |
| Cook |  | $\begin{array}{r} 0.000591 \\ (-0.57) \end{array}$ | $\begin{array}{r} -0.00194 * * \\ (-2.93) \end{array}$ | 37.2** | 33.0** |
| Housework |  | $\begin{array}{r} -0.00130 \\ (-1.23) \end{array}$ | $\begin{array}{r} -0.00197 * * \\ (-2.95) \end{array}$ | 34.3** | 30.2** |
| Childcare |  | $\begin{array}{r} -0.00154 \\ (-1.18) \end{array}$ | $\begin{array}{r} -0.000569 \\ (-0.44) \end{array}$ | 19.3 | 17.6 |
| Eat in home |  | $\begin{array}{r} 0.000673 \\ (0.36) \end{array}$ | $\begin{array}{r} -0.000497 \\ (-0.97) \end{array}$ | 44.3 | 43.2 |
| Shop |  | $\begin{array}{r} -0.00583^{* * *} \\ (-6.07) \end{array}$ | $\begin{array}{r} -0.00345 * * * \\ (-3.94) \end{array}$ | 27.1*** | 18.6*** |
| Work | $\begin{array}{r} 0.520 * * * \\ (4.76) \end{array}$ |  |  | 343.3*** | 373.0*** |
| Eat out |  | $\begin{array}{r} 0.00223 * \\ (2.15) \end{array}$ | $\begin{array}{r} -0.000276 \\ (-0.40) \end{array}$ | 34.2 | 35.4 |
| Arts and entertainment |  | $\begin{array}{r} -0.00461^{* * * *} \\ (-3.68) \end{array}$ | $\begin{array}{r} -0.00218 \\ (-1.27) \end{array}$ | $12.8{ }^{* * *}$ | 7.7*** |
| TV/music |  | $\begin{array}{r} -0.0000887 \\ (-0.06) \end{array}$ | $\begin{array}{r} -0.0000887 * * * \\ (-3.51) \end{array}$ | 129.5*** | 114.2*** |
| Read |  | $\begin{array}{r} -0.000849 \\ (-0.88) \end{array}$ | $\begin{array}{r} -0.00159 \\ (-1.38) \end{array}$ | 10.8 | 9.4 |
| Visiting others in own or others' homes |  | $\begin{array}{r} -0.00282^{*} * \\ (-3.00) \end{array}$ | $\begin{array}{r} -0.00211 \\ (-1.73) \end{array}$ | 30.4** | 23.9** |
| Conversation |  | $\begin{array}{r} 0.000231 \\ (0.25) \end{array}$ | $\begin{array}{r} -0.000322 \\ (-0.35) \end{array}$ | 10.3 | 10.2 |
| Hobbies |  | $\begin{array}{r} -0.00878^{* * *} \\ (-4.28) \end{array}$ | $\begin{array}{r} -0.00238 \\ (-0.59) \end{array}$ | 5.1*** | 1.6*** |
| Relax |  | $\begin{aligned} & 9.65 \mathrm{e}-06 \\ & (-0.01) \end{aligned}$ | $\begin{array}{r} -0.0000435 \\ (-0.03) \end{array}$ | 7.9 | 7.9 |
| Exercise/sports/outdoors |  | $\begin{array}{r} -0.00186 * \\ (-2.00) \end{array}$ | $\begin{array}{r} -0.00146 \\ (-1.54) \end{array}$ | 30.3* | 25.8* |
| Computer games |  | $\begin{array}{r} -0.00303 * \\ (-2.35) \end{array}$ | $\begin{aligned} & 0.00179 \\ & (-0.71) \end{aligned}$ | 8.0 | 5.6 |
| Other computer |  | $\begin{array}{r} -0.00169 \\ (-1.80) \end{array}$ | $\begin{array}{r} -0.00200 \\ (-1.63) \end{array}$ | 16.4* | 13.5* |
| Religion |  | $\begin{array}{r} -0.00136 \\ (-0.88) \end{array}$ | $\begin{array}{r} 0.00115 \\ (0.24) \end{array}$ | 1.9 | 1.7 |
| Volunteer |  | $\begin{array}{r} -0.00266 * \\ (-2.37) \end{array}$ | $\begin{array}{r} -0.000299 \\ (-0.17) \end{array}$ | 8.5 | 6.8 |
| Travel (non-commute) |  | $\begin{array}{r} -0.00554 * * * \\ (-5.24) \end{array}$ | $\begin{array}{r} -0.00533 * * * \\ (-7.17) \end{array}$ | 56.3*** | 38.6*** |

$N=2052$.
 secondary), household income (bottom $25 \%$, middle $50 \%$, upper $25 \%$ ), physical health (poor, fair, good, very good), number of children, and children $*$ female. Predictions generated using average marginal effects.
 ernment Office Region, household type, tenure, household income grouped, and economic activity.

$$
* p<.05 .
$$

** $p<.01$.
*** $p<.001$.

### 5.3. Commute time, couple status, and activity participation

We investigated whether the impacts of a long commute may differ based on whether the respondent is part of a couple (meaning, for the most part, being married). The presumption was that for those with long commutes some activities might be shifted from the respondent to the respondent's partner in a couple, while a single respondent would have to engage in these activities regardless of commute duration. According to this hypothesis, the expectation would be that "mandatory" maintenance activities such as shopping, cooking and housework would be more elastic with respect to commute time for long commuters in couples than for long commuters who are single.

We do not produce the full results tables for brevity but they are available on request. Table 3.) below is restricted to time uses where the difference in predictions is insignificant for one couple status but significant for the other.

In only two cases was the interaction term significant in at least one part of the model: for housework, couple*commute was negative and significant in the conditional time model, suggesting that for those who engaged in housework, those in couples with longer commutes are likely to engage for a shorter period than those who are single. Second, for volunteering, the interaction term was significant and negative in the selection model, so that those in couples with longer commutes are less likely to participate in this activity, while the same is not true for those not in couples. There


Fig. 2. Predicted activity times for commuters one standard deviation above and below the mean (Part 1). Stars indicate predictions that significantly differ from each other at at least the $p<.05$ level.
were several other variables where neither interaction term was significant but the difference in predictions for commuters with 5-minute commute versus those with the 45-minute commute were significant for one couple status but not the other: this was the case for cooking, arts/entertainment, computer games, and volunteering (which those in couples are predicted to be more likely to forego) and reading and non-game computer use (which those in couples are predicted to be less likely to forego).

### 5.4. Commute time, gender, and activity participation

Finally, similar to the previous section, we examine how the elasticities in time use with respect to commuting vary by sex, on the theory that, due to things like differences in household and childcare responsibilities, men and women might differ in terms of how they adapt to longer commutes. Again, we omit the full results table for brevity and briefly summarize results in Table 4.

There are few significant differences in terms of how men and women adapt to long commutes as reflected by the estimates for the commute time*female interaction term. In two cases the coefficients were statistically significant. Women with longer commutes are more likely to add work time compared with men with longer commutes, and for women who participate in childcare, women with longer commutes are more likely reduce this activity than men (though in general women spend more time on childcare than men do). In addition to these, three time uses do not exhibit significance in either part of the Cragg model, but the differences in predictions differ significantly by gender. One is other computer, with women with long commutes being more likely to curtail this than men with long commutes. For two time uses, the opposite is the case: men with longer commutes are more likely to curtail visiting and exercise/sports/outdoor than women with longer commutes. Still, these results are not of very great magnitude: men and women appear to adapt to long commutes in broadly similar ways.


Fig. 3. Predicted activity times for commuters one standard deviation above and below the mean (Part 2). Stars indicate predictions that significantly differ from each other at at least the $p<.05$ level.


Fig. 4. Predicted activity times for commuters one standard deviation above and below the mean (Part 3). Stars indicate predictions that significantly differ from each other at 6t leistcthssion .05 level.

Table 2
Fixed-effect panel regression with enjoyment regressed on activity participation.

| Activity type | Enjoyed coefficient (t-stat in parentheses) | Activity type | Enjoyed coefficient (t-stat in parentheses) |
| :---: | :---: | :---: | :---: |
| Arts and entertainment | $\begin{array}{r} 0.622 * * * \\ (8.99) \end{array}$ | Eat in home | $\begin{array}{r} 0.0978^{* *} \\ (2.81) \end{array}$ |
| Sleep | $\begin{array}{r} 0.493 * * * \\ (13.22) \end{array}$ | Childcare | (omitted) |
| Visit in own or others' homes | $\begin{array}{r} 0.401 * * * \\ (8.29) \end{array}$ | Other computer | $\begin{array}{r} -0.294^{* * *} \\ (-6.07) \end{array}$ |
| Computer games | $\begin{array}{r} 0.350^{* * *} \\ (5.58) \end{array}$ | Volunteer | $\begin{aligned} & -0.316 \\ & (-1.48) \end{aligned}$ |
| Hobbies | $\begin{array}{r} 0.329 * * * \\ (3.33) \end{array}$ | Groom | $\begin{array}{r} -0.533 * * * \\ (-14.75) \end{array}$ |
| Exercise/sports/outdoor | $\begin{array}{r} 0.305 * * * \\ (6.09) \end{array}$ | Non-commute travel | $\begin{array}{r} -0.536^{* * *} \\ (-14.33) \end{array}$ |
| Conversation | $\begin{array}{r} 0.286 * * * \\ (6.75) \end{array}$ | Cook | $\begin{array}{r} -0.662 * * * \\ (-17.78) \end{array}$ |
| Eat out | $\begin{array}{r} 0.281 * * * \\ (6.79) \end{array}$ | Shop/services | $\begin{array}{r} -0.732 * * * \\ (-15.93) \end{array}$ |
| Read | $\begin{array}{r} 0.233 * * * \\ (5.14) \end{array}$ | Housework | $\begin{array}{r} -0.874 * * * \\ (-21.52) \end{array}$ |
| Religion | $\begin{array}{r} 0.206 * * \\ (2.60) \end{array}$ | Work | $\begin{array}{r} -1.056 * * * \\ (-24.17) \end{array}$ |
| Relax | $\begin{array}{r} 0.167 * * \\ (3.05) \end{array}$ | Commute travel | $\begin{array}{r} -1.185 * * * \\ (-26.12) \end{array}$ |
| TV/music | $\begin{array}{r} 0.123^{* * *} \\ (3.40) \end{array}$ |  |  |
| rho | . 311 |  |  |
| Overall R2 | . 138 |  |  |

* $=p<.05 .{ }^{* *}=p<.01$, ${ }^{* * *}=p<.001$.
$N=2179$ individuals, 130,514 activities.
Cells shaded in yellow are activities that those with long commutes do significantly less of in at least one part of the Cragg model. Cells shaded in blue indicate activities that those with longer commutes do more of probability weights to account for differences between respondents and nonrespondents used. Variables used to produce the weights were age/sex groups, Government Office Region, household type, tenure, household income grouped and economic activity.

Table 3
Time uses that vary for the long and short commute durations based on couple status.

| Time use | Prediction 5-minute commute non-couple | Prediction 45-minute commute non-couple | Prediction 5-minute commute couple | Prediction 45-minute commute couple |
| :---: | :---: | :---: | :---: | :---: |
| Cook | 34.6 | 35.0 | 38.5 | 32.3 |
| Housework ${ }^{\text {a }}$ | 32.3 | 32.2 | 35.3 | 29.4 |
| Arts/entertainment | 11.8 | 9.9 | 13.4 | 6.9 |
| Read | 15.5 | 10.5 | 9.3 | 8.7 |
| Computer games | 7.0 | 6.6 | 8.2 | 5.1 |
| Other computer | 20.9 | 14.6 | 15.0 | 12.8 |
| Volunteer ${ }^{\text {b }}$ | 7.6 | 8.1 | 9.0 | 6.2 |

 secondary), household income (bottom 25\%, middle 50\%, upper 25\%), physical health (poor, fair, good, very good), number of children, and children*female.
Predictions generated using average marginal effects.
${ }^{\text {a }}$ Couple*commute negative and significant in conditional time model.
${ }^{\mathrm{b}}$ Couple*commute negative and significant in selection model.

As might be expected given that there is limited time in the day, we find clear evidence that commutes do result in time constraints and entail trade-offs. In terms of gross minutes, across the sample there is no single activity that is associated with a dramatic reduction when commutes are long; rather, long commutes are on average associated with somewhat less participation in many activities. These include sleeping, shopping/using services, arts/entertainment activities, visiting with others, sports/exercise/ outdoor activities, hobbies, computer games, volunteering, engaging in non-commute travel, cooking, doing housework, and watching TV/listening to music. One interesting and somewhat counterintuitive finding is that there are two activities those with longer commutes are predicted to do more of: work and eating out. We posit that there are plausible explanations for these. Those with longer commutes may tend to eat out more because this economizes on time spent cooking; indeed, we find that those with long commutes do cook less. Hence more eating out may reflect freeing up more time for the commute. In terms of work, it is possible that those with longer commutes work in more remunerative or in other ways rewarding jobs, as reflected by the fact that they are willing to travel farther to reach them. If this is the case, it may be unsurprising that those with longer commutes may spend more time working at these jobs.

In terms of unconditional minutes, as reflected by our predictions the biggest reductions are in sleep, non-commute travel, and TV/music time. This may be explained in part by the fact that these are three activities that our respondents spend considerable amounts of time doing, so that small proportional changes are associated with fairly large absolute changes. In proportional terms there are some large and negative associations, including for hobbies, arts/entertainment, shopping/services, and non-commute travel. The most dramatic of these results is a $69 \%$ predicted
reduction in hobbies time for the 45 -minute commuter as opposed to the 5 minute commuter. Thus our results suggest that hobbies are the most elastic activity with respect to commute time.

It might be assumed that those with long commutes might be less likely to give up "mandatory" maintenance activities like grooming or housework and more likely to give up "discretionary" ones like television watching. However, the evidence here suggests that this is not necessarily the case. Sleeping, shopping/using services, cooking, and doing housework might be considered mandatory activities, and yet our evidence from across the sample suggests that they may in fact be economized on to accommodate a longer commute. On the other hand, we also see evidence of discretionary activities being curtailed in response to long commutes, including arts/entertainment activities, visiting with others, sports/exercise/outdoor activities, hobbies, computer games, volunteering, and watching TV/listening to music. One special case is non-commute travel, which may be thought of as either a mandatory activity (if the destination is a mandatory activity) or a discretionary one (if the destination is a discretionary activity).

Conversely, we also see no clear pattern in terms of the mandatory/discretionary nature of those activities for which we find no evidence of elasticity with respect to commute time. These are grooming and in-home eating (which we would class as mandatory) and religion, reading, conversation, and relaxing (which we would classify as discretionary). We would class non-game computer use as possibly mandatory and possibly discretionary depending on the purpose. In sum, we see no clear evidence that people are more likely to curtail discretionary activities as opposed to mandatory ones in the face of time pressure caused by a long commute

Analysis of the SWB associated with activities that are likely to be foregone by those with long commutes shows that such activities tend to be

Table 4
Time uses that vary for the long and short commute durations based on sex.
$\left.\left.\begin{array}{llll}\hline \text { Time use } & \begin{array}{l}\text { Prediction } \\ \text { 5-minute } \\ \text { commute } \\ \text { male }\end{array} & \begin{array}{l}\text { Prediction } \\ \text { 45-minute } \\ \text { commute } \\ \text { male }\end{array} & \begin{array}{l}\text { Prediction } \\ \text { 5-minute } \\ \text { commute }\end{array} \\ \text { female }\end{array}\right] \begin{array}{l}\text { 45-minute } \\ \text { commute } \\ \text { female }\end{array}\right]$
 secondary), household income (bottom $25 \%$, middle $50 \%$, upper $25 \%$ ), physical health (poor, fair, good, very good), number of children, and children*female. Predictions generated using average marginal effects.
 household type, tenure, household income grouped and economic activity.
${ }^{\text {a }}$ Couple*commute negative and significant in selection model.
${ }^{\mathrm{b}}$ Couple*commute negative and significant in OLS model.
found either at the top of the "enjoyment" ranking (arts/entertainment, sleep, visiting, games, hobbies, and exercise/sports/outdoor activities) or at the bottom (non-commute travel, cooking, housework, and shopping/ accessing services). Only two are "medium-enjoyment" activities (volunteering and TV/music time). Perhaps the most noteworthy finding here is that the commute itself is the lowest-enjoyment activity of any we observe, so that it would appear that substituting any of the other activities we observe for commuting itself would be associated with increased SWB, or at least hedonic affect.

We would also note that some of the activities that those with long commutes do less of may be expected to have effects not only on the commuter but on others, such as commuters' families, employers, and friends, and even society more broadly. It may be a positive thing that long-duration commuters work more and engage in less non-commute travel. However, it is troubling that longer-duration commuters tend to give up volunteering and visiting with others, activities which may have social benefits. Further, those with long commutes spend more time commuting itself, which may contribute to societal problems such as congestion, pollution, energy consumption, and vehicle crashes. We do find that this is somewhat offset by those with longer commutes engaging in less of other sorts of travel. But our predictions suggest that 57 extra average commute minutes/day are associated with 18 min /day less non-commute travel, so that in the net longer commutes appear to increase societal costs resulting from travel. This calls the travel time budget theory (Mokhtarian and Chen, 2004) into question.

For those in couples, the results above suggest there is some transfer of activities from those with long commutes to their partners. As we expected, those with long commutes who have a partner tend to be disproportionately likely to do less cooking and housework, which may reflect a partner with a shorter commute (or no commute) taking on these chores. This may account for the fact that being in a couple appears to allow individuals with long commutes to maintain reading and other computer time, which tend to be foregone by single people with longer commutes. On the other hand, those in couples with longer commutes tend to be more likely to give up arts/entertainment, computer games, and volunteering time, which are discretionary activities.

Men and women have very different activity patterns in many respects, and there is some evidence that the ways in which they adapt to longer commutes differ. Women with longer commutes are somewhat more likely to cut back on childcare and other computer time than men with longer commutes, and are less likely to cut back on visiting with others and exercise/sports/outdoor time. Perhaps the most interesting finding is that women with longer commutes are disproportionately likely to work more. This may be explained by the differing natures of work by gender. Women often work shorter hours in jobs relatively close to their homes in order to combine work with housekeeping and childcare tasks. For some, a more constricted choice set of employers may involve accepting less fulfilling and remunerative work. For women, working more hours per week is often associated with more ambitious career perspectives, which also tend to be jobs people commute longer distances for. Hence it is perhaps unsurprising that women with higher career ambitions and commitment may both commute longer and work more.

## 7. Conclusions

There are a number of shortcomings in this research. First, although the date of the survey (2014-2015) is relatively recent, activity patterns are changing over time. Our data capture life in the era of the personal computer, smartphone, and internet, but still it is possible that patterns of work, shopping, social life, entertainment, and much else are evolving rapidly, particularly due to new technology. For example, "other" computer use (for example online shopping, social media participation, reading, etc.) may be rising. In addition, there may be ongoing changes in terms of the affect associated with activities; for example, TV watching may be resulting in higher hedonic affect due to video-streaming services. As is the case with any study, future research with more recent data would be of value.

Second, the data were collected in the U.K, a developed, Western European nation. This may limit generalizability. In particular, different results in terms of both activity patterns and the affect associated with activities might be found in the U.S., the developed nations of Asia, and, particularly, developing countries. We would note that studies in diverse settings (such as Germany, Italy, and the U.S., in addition to the U.K.) show that the affect associated with activities is similar across cultures; in general, people find things like work unpleasant, find attending arts and entertainment events and socializing pleasant, find volunteering and childcare meaningful, and find television and computer use fairly meaningless (Anusic et al., 2017; Archer et al., 2013; Bergstad et al., 2011; Bryson and MacKerron, 2017; Csikszentmihalyi and Hunter, 2003; Csikszentmihalyi and Wong, 2014; Kahneman and Krueger, 2006; Killingsworth and Gilbert, 2010; Krueger, 2007; Tadic et al., 2013; Weinstein and Mermelstein, 2007; White and Dolan, 2009). However, there still may be important differences across nations, as a result of differences in the spatial organization of activities, transportation systems, the nature of work, national culture, and much else. Thus further study in diverse settings would be welcome.

One problem facing researchers in terms of both of these issues (acquiring timely data and data from diverse settings) is that most time use surveys of which we are aware do not collect multi-day data. As we have argued above, we view it as essential that a study of the trade-offs between the commute and other activities capture both work and non-work days, to see which activities are moved from commute days to non-commute days and which activities are foregone entirely. Our data do allow us to capture this, but our observation of a single weekday and a single weekend day is inferior to data collected over a seven-day week. As noted above, prior research suggests that results from a two-day survey are reliable (Jara-Díaz and Rosales-Salas, 2015). But to further explore how this may be biasing our results, we ran tests to see if our results were sensitive to whether the weekend day sampled for each respondent was a Saturday or a Sunday, reasoning that activity patterns on these days might differ. We did this by adding a control variable for each respondent for Saturday vs. Sunday survey day; further, to gauge how this might relate to our variable of interest we added an interaction term between Saturday survey day and commute duration. Our results do suggest that some time uses are more intensive on Saturdays (for example, shopping, eating out, and participating in arts/entertainment/watching sports) and others are more intensive on Sundays (sleep and religious observance). However, this has limited import for our findings on the trade-offs between activities and commute time: in only three of the 44 model parts were the interactions significant. Compared to those with shorter commutes, those with longer commutes are more likely to participate in childcare on Saturdays as opposed to Sundays, are less likely to eat out on Saturdays as opposed to Sundays, and are likely to participate for a longer duration in religious activities on Sundays. Although these findings are of little import for our overall conclusions, future research using full-week data would be welcome.

A further shortcoming is that the only affect variable in our survey measures whether users "enjoyed" the activity. As noted above, we interpret this as reflecting hedonic affect. It would be ideal for future researchers to work with data that capture both hedonic and eudaimonic affect. The American Time Use Survey (2019) asks separately whether activities are "happy" and "meaningful," but it is only a one-day survey. Future work with multi-day surveys that ask about both sorts of affect would be edifying.

Also, space limitations preclude us from going into more depth about what kinds of people may give up certain types of activities in response to longer commutes, outside of the analyses of gender and couple status presented above. One area of study which would be of particular interest would be to examine whether high-baseline-SWB individuals reorient their activity patterns differently than people with intrinsically lower SWB, which is not possible given that we do not have a data set with both baseline SWB and weekly time use data. In addition, constraints on space and scope prevent us from examining how various demographic and household characteristics interact with activity type to impact SWB during activities, though we refer the reader to Archer et al. (2013) for an in-depth treatment of this.

Finally, and perhaps most importantly, while we have found clear correlations between commute time and activity times, it is difficult to prove causation. In addition to longer commutes causing people to economize on certain time uses, it is also quite possible that people select shorter (or longer) commutes because they wish to accommodate their desire (or lack of desire) for other activities. With that said, although causality doubtless flows in both directions, the nature of our findings suggests that, overall, causation flows more from the commute to the scheduling of other activities than vice versa. We conclude this for two reasons. First, residential location and the selection of what job one holds are major decisions that are affected by many things. Selection of a home involves very important factors like home prices, the quality of homes, neighborhood aesthetics, crime rates, school quality, and proximity to non-work opportunities such as shopping. The location of one's workplace is largely determined by factors such as jobs' suitability for one's skills, wages, potential job satisfaction, and of course the actual offer of a job. Further, in two-worker households, the need to access a spouse's job may entail accepting a longer commute than would otherwise be optimal. Thus desired activity patterns may play a part in the selection of a commute duration, particularly in terms of a general desire to have more free time, but it unlikely that they fully determine commute duration. Indeed, if this were the case, all workers would live as close to work as possible and would have very short commutes. Second, we find that for those with longer commutes activity time is curtailed across a broad range of activities, some of which individuals might find important enough to select a shorter commute to participate in (for example, exercise/sports/outdoors), but others of which are fairly unlikely to cause workers to choose a job close to work, or vice versa (for example, playing computer games). Thus we hypothesize that the desire for more free time to engage in other activities (at least in general terms if not for specific activities) is likely one factor in selecting a commute time, but not the only or even the decisive one, and that causation likely flows more from commute duration to activity patterns than vice versa.

Still, untangling the directions of causality is certainly a worthwhile direction for future research. However, doing this may prove difficult. An instrumental variables approach might be a possibility, though this raises the issue of finding a suitable instrument for commute time. Probably the best way to address this would be through qualitative research using in-depth interviews to attempt to understand what motivates people to select a commute duration and participate in other activities to attempt to understand what motivates people to select a commute duration

What are the implications of these results for public policy? The finding that commuting is the least-enjoyed activity of any that we observe suggests that the substitution of almost any other time use for commuting would have emotional benefits for the commuter, at least in terms of hedonic affect. This is particularly true for many of the high-affect activities which appear to be traded off for commute time. Further, shorter commutes may benefit not just the commuter but also families, friends, and society as a whole. Thus public policies to reduce commute times would very likely have positive effects on our psychological and social lives.

Many policy interventions have been put forward to reduce commute times. Table 5 lists some of these.

All of these policies do have their difficulties and drawbacks, however. For example, land use is slow to change, increasing road capacity would induce demand, and raising the price of driving is politically unpopular. Thus reducing the duration of the commute will require both ingenuity and strength of will. Still, our evidence suggests that yes, we should care: shorter commutes would result in more active and happier people.

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## CRediT authorship contribution statement

Eric A. Morris: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software,

Table 5
Possible policy interventions to reduce commute durations.

| Improving the efficacy of alternate modes | Raising functional road <br> capacity |
| :--- | :--- |
| Constructing high-capacity, high-speed transit | Building and expanding <br> roads |
| Reducing transit headways | Autonomous vehicles |
| Incentives to carpool such as employer TDM programs or | Congestion <br> pricing/managed lanes |
| HOV lanes | Adaptive traffic signals <br> Adding bicycle lanes and infrastructure <br> Concentrating development in areas well-served by <br> transit and walking |
| Traffic management <br> centers |  |
|  | Freeway service patrols <br> Ramp meters |
| Better enforcement of |  |
| traffic laws |  |
| Raising the gas tax |  |
| Reducing/pricing parking |  |

Adapted in part from Downs (2004).

Supervision, Validation, Visualization, Writing - original draft, Writing - review \& editing. Dick Ettema: Formal analysis, Investigation, Methodology, Writing - original draft, Writing - review \& editing. Ying Zhou: Writing original draft, Writing - review \& editing.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi. org/10.1016/j.trip.2020.100119.

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