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Mobile phones and telecommuting

Effects on trips and tours of Londoners

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Abstract: This study contributes to the existing literature on the travel behavioral effects of mobile phone possession and telecommuting by investigating the effects of both and looking at average trips and tours per day as well as tour complexity. In contrast to other studies, we investigate the effects of "informal telecommuting," defined as working from home on a personal computer. The data used in this study is taken from the London Area Travel Survey 2001, providing us with a large sample size of 27 634 individuals. The results of our descriptive and multivariate regression analysis imply that mobile phone possession significantly and positively affects total trips made, but does not necessarily affect tour complexity. Our study provides good evidence that mobile phone possession is clearly associated to total tours made. Though telecommuting does decrease the number of work trips, trips for other purposes (such as shopping or leisure) are likely to increase. We provide further evidence that it is the simple home-work-home tours that decrease through telecommuting and are replaced by other tour types, keeping the total tour numbers fairly constant. The effects are particularly pronounced for the part-time working population. Controlling for geographic characteristics, we further find that population density has an effect on the number of leisure trips and on tour complexity but not on the number of work or shopping trips.

Keywords: Travel behavior; Mobile phones; Telecommuting; London

1 Introduction

Through mobile phones, people can connect with their families, friends and colleagues almost everywhere and at any time. Household members might call during a journey to ask for a favor that obliges the traveler to make another trip. Similarly, there are times when friends might call a person out of their home to arrange a short meeting, dinner or a joint activity, which could change the planned trip or tour pattern. In summary, mobile phones are often used for short-notice coordination and organization of schedules for various purposes (Pica and Kakihara 2003). In other instances, trips can be avoided by using mobile phones. For example, a sudden change or cancellation of a business meeting can be arranged even if the person is not in the office or at home. Taking these two effects together, it is therefore not clear whether the possession of mobile phones reduces or increases the total number of trips.

Work trips might be influenced by information technologies in further ways. Increasingly, work can be done at home without the need to commute to a workplace daily. Telecommuting is generally defined as working at home or at an alternate location and communicating with the usual place of work using electronic or other means instead of physically traveling to a more distant work site (Mokhtarian 1991). This implies that those who adopt telecommuting might reduce their daily work trips or change their tour patterns. However, a reduction in the number of work trips might be counterbalanced by an increase in other trips, such as leisure or shopping trips. Because telecommuting reduces commuting time, people who adopt it might have more time for household chores or family errands.

The main objective of this study is to explore the effect of information and communications technology (ICT) on daily weekday trips. In particular, this research focuses on the effects of mobile phone possession and "informal telecommuting" on the frequency of daily trips as well as on different types of tours. In contrast to previous studies, we define every respondent who uses their personal computer for work from

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home as a telecommuter. Therefore, an "informal telecommuter" as defined here might not necessarily replace their work trips, but, finish remaining work tasks in the evening from home. In line with this assumption, this study also seeks to understand how much time spent working from home is needed to cause a shift in travel patterns.

The rest of the paper is arranged as follows. Section 2 reviews related research regarding the effects of mobile phones and telecommuting on travel behavior and states our hypotheses on the impacts of mobile phone possession and telecommuting on travel behavior. Section 3 describes the data used in the analysis and presents the results of the descriptive analysis. Section 4 presents the empirical regression results and discusses the effects on trips, tour types and complexity. Section 5 summarizes the findings of this paper and discusses implications.

2 Literature review

Our literature review is further subdivided as follows. After a short general discussion of the effects of ICT on travel behavior, Section 2.1 reviews the complementary and substitutive effects of mobile phones followed by a review of the effects of telecommuting on travel. Based on these findings, Section 2.2 then develops hypotheses that we aim to confirm and extend with our London data.

2.1 Previous studies

Generally, ICT provides alternatives to face-to-face communication and thus has a potential to substitute for physical travel. Wang and Law (2007) define ICT use as utilizing email, internet, video conferencing or video telephony for either business or personal purposes. Using a structural equation model, their study suggests that the use of ICT triggers additional time use for out-of-home recreational activities and tends to increase the frequency of trips. Moreover, a review paper by Golob (2001) forecasts ICT effects on activity and travel and suggests that mobile phones and other portable communication devices will redefine our ability to conduct business and dynamically schedule activities while on travel or at locations away from home or workplace.

Srinivasan and Raghavender (2006) investigate the effects of mobile phones on unplanned activity-chaining and unplanned ride sharing arranged through mobile phones. They find that at any given instant mobile phones can lead to unplanned stops during travel. Also, a study by Hjorthol (2008) used a survey to investigate the relationship between mobile phone use, planning of everyday activities and car usage in families with children. Her results suggest that, aside from the significantly positive relationship between car use and the use of mobile phones, short planning is also positively related to mobile phone use. In addition, Viswanathan and Goulias (2001) investigate the effects of both mobile technology and internet use on travel times and find that mobile technology and travel times are complementary whereas internet use and travel times are substitutive. Bhat *et al.* (2003) study the impact of ICT, particularly of mobile phone adoption, on non-maintenance shopping activity. According to their result, there is a substitution between mobile phone use and shopping travel that is underestimated when the effects of common unobserved attributes affecting mobile phone adoption and shopping travel are not considered. Schmöcker *et al.* (2010) investigate trip chaining among older London residents. Though the focus of their research is not on ICT effects, their results suggest mobile phone possession effects are not limited to certain age groups. They also find that older residents with mobile phones tend to make more complex tours. Alexander *et al.* (2009) conduct a study in the regions of Utrecht, Amersfoort and Hilversum (Netherlands) examining the causal relationship between ICT and fragmentation of paid-work trips. The empirical results of their study show that the frequencies of mobile phone and landline phone calls are highly associated with the temporal as well as the spatial fragmentation of paid work, which increases the number of work-related trips and the time spent on travel. Some studies with aggregate data (e.g. Choo *et al.* 2007; Choo and Mokhtarian 2005) also support the hypothesis that travel and telecommunication have a complementary relationship. Summing up, mobile phone effects—that is, possession of a mobile phone as well as the amount of time a mobile is used—have been found in travel patterns. There appears to be a lack of literature, though, on some specific effects such as whether mobile phones lead to more trip chaining.

Further, telecommuting allows people to keep away from the hassles of commuting by reducing physical trips. Therefore, encouraging telecommuting is often suggested as one of a series of policy measures to reduce travel demand (e.g. Mokhtarian and Salomon 1997). Telecommuting instead of actual commuting might, however, often reduce travel demand less than hoped for by transport planners. Using time-series data from the national statistics offices in Canada, Norway and Sweden, Harvey and Taylor (2000) reveal that working in isolation at home does not significantly diminish travel. Especially if telecommuting from home, people may become bored with their environment and prefer to spend more time shopping, doing household chores or socializing with friends. Furthermore, a study of the Minneapolis-Saint Paul (USA) region by Douma *et al.* (2004) that focused on work and shopping behavior at the household level reveals that "e-workers" take advantage of ICT to modify their travel patterns without impacting their workday. Instead, ICT is sometimes used before or after work to maintain contact with their offices while leaving for or from work. Similarly, Tilahun and Levinson (2010) mention that organizing or scheduling social meetings is constrained by time and location (home and work). Telecommuting and having a flexible work schedule helps loosen these constraints. Mokhtarian and Salomon (2002) study the effects of working from (nearby) telecommuting centers on macro and micro-scale level. They point out that this kind of telecommuting may also change land use patterns due to changes in travel patterns. Compared to commuting to the (more distant) company office, they find center-based telecommuting to cause a small increase in commute trips on telecommuting days, mostly due to trips home for lunch and back to the center in the afternoon. This conforms to the findings of Balepur *et al.* (1998) who examine the impacts of center-based telecommuting. Their result indicates that on telecommuting days the number of trips for returning home, eating out, shopping, and social/recreational purposes is higher. Finally, the hypothesis of substitution between travel and ICT is supported by Srinivasan and Athuru (2004) using activity-diary data from the San Francisco Bay Area. Their study focuses on the relationship between physical and virtual activity participation in maintenance and discretionary activities.

Nowadays, through laptop computers and powerful personal computers (PCs) at home, telecommuting is taking new forms. Though officially organized off-site working remains a policy tool and is becoming more frequent in many organizations, it is probably "informal telecommuting" that has increased most in recent years. Those with flexible working times often reduce office hours by taking remaining work home or onto journeys. It is this flexibility that might be used for very different or irregular commuting patterns. Work might be completed at home after leisure activities or, for example, a working parent might take over family errands in the afternoon only to finish work later in the evening. The following hypotheses propose that the effects of working from home are similar to the effects attributed to the stricter definition of telecommuting used more commonly in the transport literature (e.g. Balepur *et al.* 1998; Mokhtarian and Salomon 1997, 2002).

2.2 Hypotheses

This study contributes to the growing literature on ICT and travel behavior by analyzing a large sample of London residents. In contrast to previous studies, this study investigates the effect of mobile phones and telecommuting not only on trips and its types but also on the tours a person makes. We consider trips, tour number and tour complexity as our dependent variables. Based on previous literature we formulate three groups of hypotheses: firstly concerning the effects on trip frequency; secondly, concerning the effects on number of tours; and lastly, concerning the effects on tour complexity. For each group, we further establish our hypothesis regarding the effect of mobile phone possession and telecommuting. However, to this point, we find a limited literature regarding the effect of telecommuting on tour numbers. Hence, we develop presumptions based on some rational intuitions (B.1 below). Tours are defined in the following as a chain of trips with home as the anchor point.

A. Trip frequency

A.1. The number of trips per day is hypothesized to be positively associated with mobile phone possession. Our rationale is that the trip-generating effects of mobile phones seem to outweigh the trip-reducing effects in previous literature (e.g. Bhat *et al.* 2003).

A.2. It is reasonable to assume that work trips are reduced through telecommuting, though for example Douma *et al.* (2004) show that using ICT does not necessarily induce a significant change in work patterns.

A.3. We further hypothesize that non-work trips of telecommuters increase, as found by e.g. Harvey and Taylor (2000). When people reduce their work trips, they will have more freedom for leisure or shopping activities.

A.4. Total trip numbers are hypothesized to be unchanged or to increase slightly through telecommuting as suggested by Balepur *et al.* (1998).

B. Number of tours

B.1. Mobile phone possession might have a (weak) negative effect on (home-to-home) tours. This is because the more complex tours of mobile phone users (C.1) might enforce a reduction in total tours due to time and space constraints. Further, as argued above, in some situations mobile phone possession might make additional tours redundant.

B.2. Similarly, telecommuting from home tends to increase the number of tours. This is because it encourages people to make more simple tour chains to relieve their isolation when working from their home PC (Balepur *et al.* 1998).

C. Tour complexity

C.1. Mobile phone possession, generally, is likely to lead to more complex tours as suggested by Schmöcker *et al.* (2010) for a limited sample of those aged over 60. Our rationale is that access to communication during travel might lead to additional unplanned stops.

C.2. On the contrary, tour complexity is likely to decrease for those who telecommute from home. Our presumption is based on the same argument given in B.2.

Our hypotheses are illustrated in Figure 1. Both telecommuting and mobile phone use might lead to shorter trips, but telecommuting and mobile phone use might have an opposing effect on tour complexity.

3 Data structure and descriptive analysis

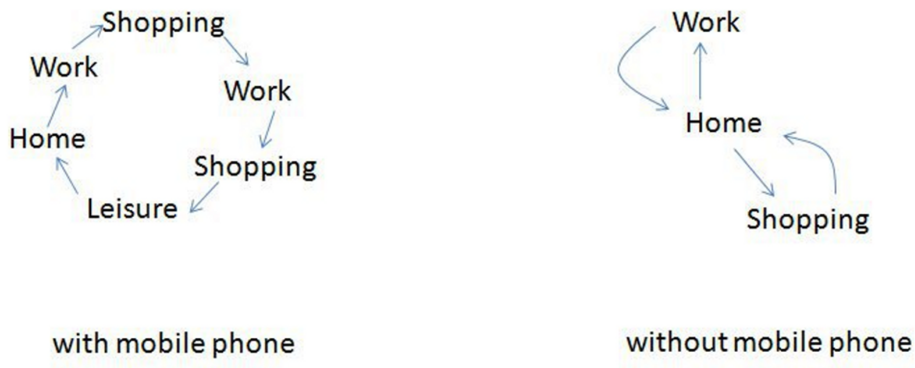
3.1 Data description

Our analysis is based on data from the 2001 London Area Travel Survey (LATS), made available by Transport for London (TfL). The survey collected information on the regular weekday travels of people living in Greater London. All interviews were done on a personal basis, and respondents were asked to fill in a one-day travel survey. In total, 67 252 individuals from 29 973 households were interviewed, which corresponds to a response rate of about one percent. The survey results are made available in four main data tables: household information; information about the individual; trips made by the individual; and information about the vehicles owned by the household. From the first and second tables we extract socio-demographic information, in particular whether the respondent possesses a mobile phone, their working status and how many hours per week the respondent is using their PC to work from home. Unfortunately, this data set does not include any information on how much a respondent uses their mobile phone. Bearing in mind our objectives, we opt to exclude all non-working respondents, which leaves us a with a sample size of 27 634 individuals who made a total of 87 148 trips on the day they were interviewed. The trip information includes the modes chosen, the trip activity duration as well as the type of activities which were carried out at the destination. This information allows us to perform the tour analysis described in subsection 4.4. Note that during 2001, when the survey was conducted, mobile phone possession was still likely to be correlated with income and hence working trips. This is a second reason to focus our analysis on the working population. Further, the analysis that follows controls for income and distinguishes effects of ICT on total trips as well as different trip and tour types.

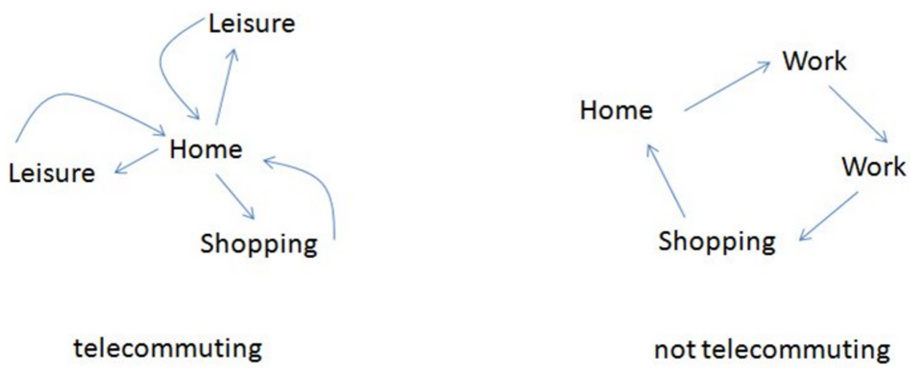
3.2 Descriptive analysis of mobile phone impact

As shown in Table 1, approximately 44 percent of respondents in the sample state that they possess a mobile phone. By comparing this to the statistics of the UK Office of Telecommunications (Office for National Statistics – UK 2004), we find a significant difference. To identify the reasons, additional information is presented in Table 2 from other agencies that collected information on mobile phone penetration. EUROSTAT data are based on subscriptions or sales data, while data from OFTEL, the Office of National Statistics (Office for National Statistics – UK 2010) and LATS are based on individual surveys. ONS and LATS mobile penetration rates are fairly similar, whereas the rates given in EUROSTAT (2001) and Office for National Statistics – UK (2010) differ significantly. OFTEL data are, however, only partly comparable as these are data on "possesses or uses" a mobile phone. Note also that in OFTEL the percentage of those using their mobile phone as main mode of telephony is significantly lower (15%). Both LATS and ONS rates are based on surveys interviewing individuals. We therefore suspect that the difference in statistics is partly due to differences between mobile phone possession statistics based on sales data and those based on individual responses. Data based on sales figures might overestimate possession of actively used mobile phones due to multiple ownership of phones, whereas data based on individual responses might underestimate possession of mobile phones due to respondents omitting to report the possession of mobiles that are seldom used.

We therefore presume that respondents who use mobile phones as their primary phone connection might have answered affirmatively to the interviewer's question on mobile possession. Respondents who only occasionally use their mobile phone might have answered negatively in order to avoid being asked for their mobile phone numbers. A "yes" answer for the previous question on landline possession is followed by a question asking if the respondent is willing to provide their number. In conclusion, though we keep our term "mobile phone owner" in line with the survey question, those who



(a) Hypothesized effects of mobile phone possession.



(b) Hypothesized effects of telecommuting.

Figure 1: Illustration of hypotheses. (a) shows the hypothesis of the effect of mobile phones on trips, tour number and tour complexity as stated in A.1, B.1 and C.1 (b) represents the hypothesis of the effect of telecommuting on trips, tour numbers and tour complexity as discussed in A.2, A.3, A.4, B.2 and C.2.

affirmed having a mobile phone might more accurately be referred to as "heavy" users and those who answered in the negative might be more appropriately called "occasional or not" mobile phone users.

Tables 3 to 5 discuss some socio-demographic characteristics of mobile phone users in our LATS sample. Firstly, we note that the extracted working population sample has a slightly higher penetration than the total LATS sample (a total of 53 020 respondents that includes the unemployed). This is, however, expected due to income effects on mobile ownership as shown in Table 3. The difference, compared to all LATS as well as OFTEL data, is fairly constant among younger age groups but decreases for those near retirement age. One might speculate that this is because middle-aged and older persons are less likely to omit the reporting of their mobiles. (Though especially for the 75+ age group our sample size is, as expected, very small—61 out of 27 634 aged 75+).

Table 4 further illustrates that the difference in penetration rate between ONS-UK data (2001) and the LATS 2001 sample varies across income groups. Compared to the ONS-UK data, LATS reports lower ownership rates in higher-income groups and higher ownership rates in lower-income groups. The reasons for this are not fully understood. One might argue that this effect is partly specific to London where, among employed respondents, income might not be as strong a determinant for mobile ownership as in other parts of the UK where average incomes are lower. Table 5 groups ownership by those employment types also subsequently distinguished in this paper. Those with blue collar jobs have lower ownership rates, as one would expect according to their income. Our sample of self-employed people is too small to conclude that the difference is significant.

Finally, note that in general we would expect to see higher mobile phone ownership rates in our sample compared to the other data sources used in this section, which are based on samples from across the entire UK. As discussed, ownership is related to employment and income, which are higher in London than in other part of the UK. Further factors likely to fa-

Table 1: Mobile phone and personal computer information.

	Frequency	Percentage
Mobile phone possession		
Have	12144	43.95
Don't have	15490	56.05
Personal computer possession		
Have	18520	67.02
Don't have	9114	32.98
Work type and telecommuting		
Full-time workers:		
Does not use PC for work (never)	17095	61.86
Uses PC for work 1–9 hours/week (light)	4655	16.85
Uses PC for work $\geq$ 10 hours/week (heavy)	1147	4.15
Part-time workers:		
Does not use PC for work (never)	3773	13.65
Uses PC for work 1–3 hours/week (light)	609	13.65
Uses PC for work $\geq$ 4 hours/week (heavy)	354	1.28

Table 2: Mobile phone penetration rate by data source.

EUROSTAT 2001	OFTEL 2001	ONS-UK 2000–2001	LATS 2001 SAMPLE (N =27 634)	LATS 2001 ALL (N =53 020)
76	67*	47	44	35

Note: * = own or use; 15% use mobile phone as main means of telephony.

vor higher ownership rates in London are network availability, more dispersed travel patterns and family structures. It should be further kept in mind that the surveys were carried out in 2001, when mobile phone usage was rapidly increasing.

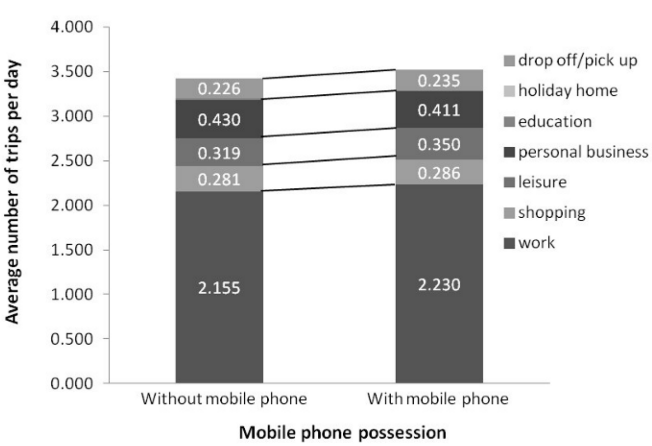


Figure 2: Effects of mobile phone possession on trip frequency (for each type of trip).

Figure 2 illustrates that those in possession of a mobile phones make slightly more trips than those without mobile phones (3.522 compared to 3.424 trips per day). The average number of trips for each trip purpose might vary slightly between those with mobile phones and those without. The unpaired t-test analysis confirms that this difference is statistically significant ($N = 27634, t = 4.58, p < 0.001$); however, this and the following t-test results should be viewed with some caution, as our large sample size of two independent samples will easily lead to significant t-values. Numbers of work trips are higher for those having a mobile phone ($N = 27634, t = 5.10, p < 0.001$) but small increases can be seen for leisure and personal business trips as well. However, especially in regards to the relationship between work trips and mobile phone possession, the causal relationship between the two is not as clear as it may appear from the findings presented above. While there might be a similar mixed causal relationship for leisure and shopping trips, it is more likely that mobile phone possession affects these trip numbers than vice

Table 3: Mobile phone penetration rate by age.

Age group	OFTEL 2001	LATS 2001 SAMPLE	LATS 2001 ALL	Difference between OFTEL and LATS 2001 SAMPLE
15–24	83	48*	40*	35
25–34	84	48	44	36
35–44	78	45	42	33
45–54	70	41	37	29
55–64	59	36	29	23
65–74	41	29	16	12
75 and over	13	21	8	-8

Note: * = age 16–24.

Table 4: Mobile phone penetration by income quintile.

Income bracket	ONS-UK 2000–01	LATS 2001 SAMPLE
Top fifth	66	52
Next fifth	60	49
Middle fifth	52	43
Next fifth	34	40
Bottom fifth	23	36

Table 5: Penetration rate by employment type (LATS 2001 SAMPLE).

Employment type (sample size)	Penetration rate
White collar (4503)	49.25
Administrative (2971)	40.98
Health care (3071)	43.65
Blue collar (4464)	39.81
Transport-related (494)	44.62
Self-employed (41)	32.79

versa. Therefore the significant increase ($N = 27634, t = 3.75, p < 0.001$) in leisure trips suggests that mobile phone possession might be associated with additional activities as hypothesized in A.1. Shopping trips exhibit no significant difference. In order to separate income, age and effects of mobile phone possession, a regression analysis is performed and described in Section 4.

3.3 Descriptive analysis of the impact of using home PC for work

From Table 1, it can be seen that approximately 67 percent of respondents have a personal computer at home. According to how many hours per week respondents use their PC to work from home, we further classify respondents as heavy, light or never telecommuting. For full-time workers, we define those using their PC for work from home as more than one full working day (≥10 hours) as "heavy telecommuting." "Light telecommuting" (1–9 hours) might therefore also include employees or employers who usually work from the office but take some remaining work home. For part-time workers, we set our threshold to ≥4 hours to reflect the overall reduced working time.

As shown in Table 1, those who work full-time but never telecommute comprise of about 62 percent of the total respondents. Approximately 17 percent are full-time workers who do light telecommuting and only four percent are full-time workers who do heavy telecommuting. Almost 17 percent of our sample are part-time workers. Out of these, 21 percent do at least some telecommuting using their PC work from home.

As illustrated in Figure 3, among those who telecommute, more time spent using a PC to work from home is generally associated with fewer daily trips. The average number of daily trips for those not telecommuting (at all) from home is similar to those using their computer 35–50 hours per week. As argued before, the observation that those who use a PC to work at home for at least one hour make more trips than those who do not work from home using a PC likely reflects work-related trips made by the former group. A second possible explanation is that those performing jobs that demand more work trips, such as business trips or visits to customers, would also be more likely to use computers at home at least sometimes in the evening, for example to check email and to arrange their schedule for the following work day.

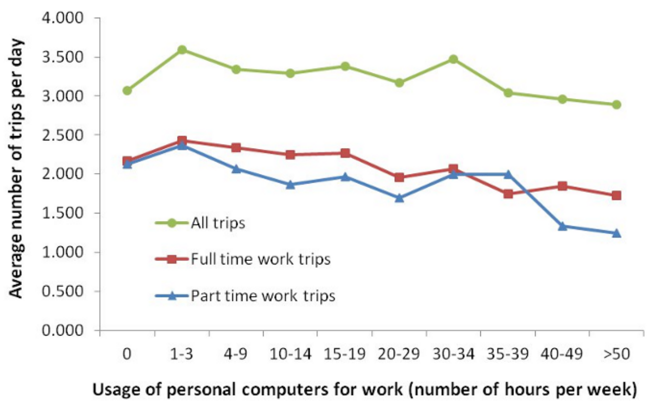


Figure 3: Average number of trips and the duration of personal computer use to work from home.

As expected, the more a person works from home, the more the number of work trips is reduced. However, comparing this to total trips we can see that the number of non-work trips increases, suggesting that the freedom gained through working from home will be used for additional activities. This is further investigated with the cross tabulation of average trips per day by trip purpose and by work/telecommuting status in Table 6. Trip destination purposes are divided into seven groups: (1) work, (2) shopping, (3) leisure, (4) personal business, (5) education, (6) holiday home and (7) drop-off or pick-up. Work and telecommuting status is classified into six groups, as also presented.

Table 6 makes it possible to determine which trip purposes increase and which decrease depending on work status. Using the analysis of variance (ANOVA) among the three groups of full-time working respondents, we find that there is a statistically significant difference between these three groups (F = 13795.61, d.f. = 2). Those who never telecommute make the fewest trips in total, but those who do light telecommuting make more work-related trips than those who telecommute heavily, possibly because of the job type effects previously described. Further, our analysis confirms that there is a complementary effect towards more leisure trips among those who do heavy telecommuting. The more a person works from home, the more freedom they appear to have to undertake additional leisure trips. There is also an increase in personal business trips when doing heavy telecommuting, but this does not appear to be statistically significant.

A similar ANOVA test is performed among the part-time working sample (F = 2506.19, d.f. = 2). The result indicates that those who do light telecommuting make the most work-related trips, followed by those who never telecommute at all, with those who do heavy telecommuting making the fewest work-related trips. Once again, we suspect that the significant increase in work-related trips for those who do light telecommuting might be due to the nature of their work, which allows (or requires) them to use their PCs at home for work but not necessarily reduce the need to make trips for work. Hence, we control for work type and telecommuting status in our regression analysis. The trends described for the other trip purposes follow the trends described for full-time workers, albeit on a generally higher level of average trips per day. The significantly higher number of drop-off/pick-up trips further supports our expectation that it is in general the part-time working parent who will take over these responsibilities. Full-time and part-time workers, regardless of their telecommuting status, make similar numbers of trips for personal business.

4 Regression analyses

4.1 Model specification

The ordered probit regression is most suitable for modeling with a dependent variable that takes more than two values, where these values have a natural ordering. In contrast to a linear regression model, it does not assume cardinality. We further consider count data analysis (e.g. Jang 2005) but find worse model fits and unexpected signs for our coefficients. Further, compared to count data analysis, ordered probit models are more in line with behavioral theory as argued by Roorda *et al.* (2010). In the ordered probit model, the dependent variable is latent and expressed as:

$$y_i^* = \mathbf{x_i}\beta + \varepsilon_i, \tag{1}$$

where y_i^* is the latent variable measuring the number of daily trips (number of stops per tour) for individual i ($i = 1, \cdots, N$) and N is the sample size; $\mathbf{x_i}$ is a $(K \times 1)$ vector of independent (observed) nonrandom explanatory variables; β is a $(K \times 1)$ vector of unknown (coefficients) parameters; and ε_i is the random error term, which is assumed to be normally distributed with zero mean and unit variance.

Let y_i denote the number of observed trips per day (stop per tour). To convert the continuous latent variable y_i^* into the discrete observed number of trips (stops per tour), a set of μ $(n \times 1)$ is introduced where n denotes the number of trip

Table 6: Average number of trips per day by destination purpose and work type.

Work type and telecommuting status	Destination purpose: Work	Shopping	Leisure	Personal Business	Education	Holiday Home	Drop-off/ Pick-up
Full-time workers:							
Never	2.170	0.301	0.236	0.417	0.008	0.001	0.159
Light	2.366	0.395	0.269	0.411	0.009	0.002	0.210
Heavy	1.997	0.371	0.335	0.446	0.007	0.000	0.243
Full-time workers:							
Never	2.131	0.349	0.436	0.446	0.026	0.001	0.482
Light	2.248	0.478	0.502	0.417	0.025	0.002	0.634
Heavy	1.822	0.494	0.531	0.427	0.042	0.000	0.480

(stops per tour) categories as shown below:

$$y_i = \begin{cases} 0 & \text{if } -\infty \leq y_i^* \leq \mu_1 \\ 1 & \text{if } \mu_1 \leq y_i^* \leq \mu_2 \\ 2 & \text{if } \mu_2 \leq y_i^* \leq \mu_3 \\ \vdots & \quad \vdots \\ n+1 & \text{if } \mu_n \leq y_i^* \leq \infty \end{cases}, \qquad (2)$$

where the vector of threshold values μ are unknown parameters to be estimated along with the parameter vector β. In subsection 4.3, we specify different models of the number of daily trips for total trips, work trips only, leisure trips only, those making at least one trip. We deal with tour complexity by taking the number of stops per tour as a dependent variable in subsection 4.5.

The parameters are to be estimated so that y_i^* is expected to change by β_k for a unit change in x_{ik}, holding all other variables constant. The maximum likelihood method is employed to estimate the parameters of the model (Long 1997). The predicted probability of the number of trips (stops) m for given $\mathbf{x_i}$ is

$$\Pr(y_i = m \mid \mathbf{x_i}\beta) - F(\mu_{m-1} - \mathbf{x_i}\beta), \qquad (3)$$

where F is the normal cumulative distribution function.

The log likelihood function is the sum of the individual log probabilities as follows:

$$LL = \sum_{i=1}^{N}\sum_{j=0}^{n} Z_{ij} \log((\mu_j - \mathbf{x_i}\beta) - F(\mu_{j-1} - \mathbf{x_i}\beta)) \quad (4)$$

where Z_{ij} is an indicator variable which equals 1 if $y_i = j$ and 0 otherwise.

4.2 Control variables in regression model

The percentage of the various socio-demographic control variables used in this study is tabulated in Table 7 as a separate column for each of the four specified models. After various model testing we group our respondents into seven age categories. Following previous studies with the LATS data on trip frequency of older Londoners by Schmöcker *et al.* (2005), ethnicity is included and grouped as white (almost 80%) and non-white; a more detailed classification was found to be insignificant. Further, several household types are distinguished. Twenty percent of the respondents live alone and five percent are single parents with dependent children. About thirty-five percent of the respondents live with a spouse or partner and approximately twenty-nine percent are married with dependent children. Note that nearly one percent of our respondents state that they are living in an "all pensioner" household; these are presumably older respondents who still have some (part-time) jobs or are still involved in some way in their former work place. Among the respondents, nearly eighty percent have a driver license. We further include car ownership as a continuous variable in the model (78.8% of our sample own a car with an average of 1.12 cars per household). As work type and income are correlated, the interaction effects of these two are dealt with by distinguishing white collar jobs[1], administrative and clerical jobs, health related jobs, blue collar jobs, transport related jobs and being self-employed.

To further control for geographic characteristics, population density data obtained from Census data are matched with the first three digits of the respondents' home-address post

[1] White collar jobs are defined in this paper as managerial positions and professional occupations.

code, available from the LATS data. Tests defining population density as a continuous or categorical variable suggest a better fit for the latter. We define five categories with four percent of the sample living in the least densely populated areas (10 356 persons per km^2 and below) and seventeen percent residing in the most densely populated parts of London (over 64 722 persons per km^2). As areas with low and high population density can be found in both Inner and Outer London, we further include this variable as a separate dummy variable.

Finally, among those who make at least one tour per day, we include two further dummy variables. Firstly, whether the respondent has used public transport on the day surveyed, and secondly a control variable on destination of tour. We distinguish those who have traveled at least once into Central London (since 2003 designated as the Congestion Charging zone). Our reasoning is that trip and tour patterns of those traveling into Central London might be different. Once in Central London, people might tend to make additional trips leading to more trips per day and higher tour complexity. We find that nearly twenty percent of those respondents making at least one tour have traveled into Central London.

4.3 Effects on trips per day

The results of the empirical analysis on trip numbers using the ordered probit analysis are presented in Table 7. We specify four models for trip frequency. The first model includes all respondents, whether they make trips or not. In the second model, work trips only are used as the dependent variable, while in the third model leisure and shopping trips are considered. The fourth model again uses total trips as the dependent variable but excludes those respondents making no trips; this is in order to investigate whether mobile phone possession and telecommuting have the same effect if we consider only those who leave their homes at least once per day. Additionally, our public transport variable and our control variable for those who make at least one trip into Central London are included in the fourth model. These variables are excluded in the first, second and third models for reasons of logical consistency, e.g., those who make no trips will use neither public nor private transport. In all other respects, to allow for a better comparison, the fourth model is a replica of the first model.

The McFadden's R^2 values, which are also presented in Table 7, are found to be small but comparable to other applications of ordered probit analyses in transportation with low R^2 value (e.g. Bhattacharjee *et al.* 1997; Khattak *et al.* 1993; Quddus *et al.* 2002). For this reason, the discussion that follows will focus on explanatory variables that exhibit significant t-values.

Table 7 shows that women tend to make a greater total number of trips and more leisure trips but fewer work trips. Regardless of sex, those aged 35–44 and 65–74 tend to make the most trips in total. Households with children, in particular those made up of married couples with children, tend to make the most trips in all models. Married households with dependent children make more trips overall but fewer work and leisure trips. Presumably, this is because married respondents with dependent children frequently make additional trips for purposes such as dropping off or picking up children. In all models, white people tend to make more trips than non-white people. Furthermore, driver license has a positive effect in all models. All these findings are as expected in light of the existing literature (e.g. Lu and Pas 1999; Schmöcker *et al.* 2010).

Surprisingly, car ownership is negatively associated with the number of leisure trips (Model 3) as well as with making at least one trip (Model 4), but is not significant in the other two models. The effect observed in Model 3 might be due to work day effects, as leisure trips by car are mainly carried out during weekends. Our result in Model 4 is further qualified by the finding that using public transport has the expected (and more significant) negative effect on number of trips.

Table 7: Ordered probit models for number of weekday trips.

	Model 1: All Trips			Model 2: Work Trips			Model 3: Leisure + Shopping			Model 4: All Trips (Filtered)		
	%	Estimate	*t*-stat	%	Estimate	*t*-stat	%	Estimate	*t*-stat	%	Estimate	*t*-stat
Cut points (All trips, Work trip, Leisure trip)												
0 trips				26.05	0.082	1.352	59.97	0.592	9.812			
1 trip	9.99	−0.904	−15.658	57.29	1.752	30.045	25.7	1.434	23.609	1.91	−1.929	−28.265
2 trips	43.06	−0.797	−13.816	16.66	—	—	14.33	—	—	46.93	0.177	3.198
3 trips	9.29	0.592	10.288							51.17	—	—
4+ trips	37.66	—	—									
Socio-demographic												
Gender:												
Male = 1, Female = 0	54.55	−0.093	−6.065		0.081	5.365		−0.119	−7.448	54.49	−0.126	−7.448
Age:												
Age 16–24 (reference)	8.29	—	—		—	—		—	—	8.23	—	—
Age 25–34	28.98	0.05	1.778		−0.018	−0.627		−0.014	−0.461	28.85	0.042	1.33
Age 35–44	29.42	0.083	2.898		−0.021	−0.739		−0.032	−1.053	29.54	0.062	1.941
Age 45–54	20.58	0.023	0.793		−0.045	−1.521		−0.071	−2.268	20.63	−0.014	−0.416
Age 55–64	10.87	0.065	1.98		−0.025	−0.768		−0.091	−2.595	10.85	0.038	1.039
Age 65–74	1.86	0.262	4.081		−0.068	−1.086		0.207	3.217	1.9	0.21	2.983
Age 75 and above	0.22	0.302	1.9		−0.148	−0.943		0.08	0.513	0.23	0.285	1.647
Race:												
White = 1, Non-white= 0	77.63	0.202	11.724		0.117	6.812		0.276	14.658	78.01	0.202	10.51
Driver's license												
With license = 1, No license = 0	79.65	0.18	9.182		0.048	2.472		0.135	6.451	80.01	0.145	6.604
Car ownership*	1.12	0.004	0.349		−0.003	−0.208		−0.029	−2.203	1.12	−0.036	−2.599
Household structure												
Single	16.64	−0.049	−2.036		0.065	2.744		0.287	11.517	16.57	−0.032	−1.223
Single parent with dependent children	5.15	0.167	4.734		0.069	2.016		0.172	4.782	5.28	0.135	3.502
Married/co-habiting	34.57	−0.309	−8.665		0.036	1.924		0.063	3.206	34.52	−0.161	−7.719
Married w/depend. children (reference)	28.54	—	—		—	—		—	—	28.88	—	—
All pensioners	0.93	−0.199	−3.606		0.032	0.371		0.005	0.06	0.95	−0.426	−4.55
All other households	14.17	0.202	−8.42		0.013	0.553		0.092	3.683	13.8	−0.147	−5.572
Interaction between household income and employment type*												
Household income × White-collar job	44 535.67	0.042	9.946		0.039	9.507		0.048	11.079	44 710.01	0.049	10.616
Household income × Administrative job	35 828.11	0.045	8.254		0.039	7.38		0.057	10.292	35 828.41	0.063	10.207
Household income × Health-related job	37 456.42	0.041	8.007		0.004	0.838		0.067	12.932	37 565.18	0.058	10.152

Continued

Table 7: Ordered probit models for number of weekday trips.

	Model 1: All Trips			Model 2: Work Trips			Model 3: Leisure + Shopping			Model 4: All Trips (Filtered)		
	%	Estimate	t-stat	%	Estimate	t-stat	%	Estimate	t-stat	%	Estimate	t-stat
Household income × Blue collar job	28 438.85	0.018	3.127		−0.005	−0.842		0.039	6.542	28 298.09	0.032	4.993
Household income × Self-employed	32 991.80	−0.144	−3.98		−0.103	−2.727		−0.039	−0.883	31 845.24	−0.037	−0.776
Household inc. × Transport-related job	28 741.59	0.039	3.14		−0.037	−3.053		−0.001	−0.051	29 252.19	0.053	3.922
Public transport use and trip destination												
Public transport user = 1, non-user = 0										32.65	−0.346	−18.382
At least one trip with destination within Central London = 1, otherwise 0										18.77	0.085	3.977
Geographic characteristics												
Area:												
Inner London = 1, Outer London = 0	34.83	−0.063	−3.245		−0.017	−0.877		−0.059	−2.896	34.38	−0.046	−2.118
Population density, pop./km² (pop./sq. mile):												
2589–5178 (1000–2000)	2.19	−0.033	−0.61		−0.053	−1		−0.084	−1.521	2.17	−0.027	−0.444
5178–10 356 (2000–4000)	2	0.028	0.502		0.045	0.827		−0.114	−1.971	2.06	−0.063	−1.025
10 356–25 889 (4000–10 000)	22.73	0.002	0.053		0.033	1.148		−0.077	−2.555	22.93	−0.028	−0.866
25 889–64 722 (10 000–25 000)	56.43	−0.028	−1.23		−0.01	−0.423		−0.083	−3.45	56.51	−0.057	−2.22
Over 64 722 (25 000)	16.65	—	—		—	—		—	—		—	—
Mobile phone possession												
Mobile phone (with mobile phone = 1)	43.95	0.032	2.244		0.018	1.262		0.017	1.17	44.26	0.018	1.112
Telecommuting status												
Full-time workers:												
Do not use PC for work	61.86	0.137	3.865		0.596	16.577		−0.141	−3.852	62.05	0.006	0.152
Uses PC for work 1–9 hours per week	16.85	0.24	6.357		0.636	16.703		−0.037	−0.955	17.04	0.154	3.577
Uses PC for work ≥10 hours per week	4.15	—	—		—	—		—	—	3.92	—	—
Part-time workers:												
Do not use PC for work	13.65	0.322	7.913		0.136	3.32		0.243	5.135	13.59	0.266	5.745
Uses PC for work 1–3 hours per week	2.2	0.453	7.496		0.02	0.344		0.313	5.35	2.21	0.446	6.512
Uses PC for work ≥4 hours per week	1.28	0.198	2.792		−0.616	−8.146		0.315	4.487	1.18	0.387	4.559
Number of observations		27 634			27 634			27 634			25 357	
Log likelihood, intercept only		48 968.65			47 456.63			45 707.55			36 616.44	
Log likelihood, final		47 907.27			45 735.15			44 396.61			35 159.43	
McFadden's R^2		0.02			0.03			0.03			0.04	

Note: * = Value in column % is an average rather than a percentage.

The number of trips increases for respondents who travel to destinations within Central London, as observed among those who make at least one trip per day (Model 4). Further, those living in Outer London tend to make a greater total number of trips than those living in Inner London (Models 1 and 4). Outer Londoners in particular tend to make leisure and shopping trips (Model 3). This might be because in Outer London there are still more local shopping streets with easy access that invite shoppers to make additional trips. In contrast, those residing in Inner London are possibly more often traveling to larger shopping centers, resulting in fewer leisure and shopping trips. For population density, we find similar effects. Those living in the most densely populated areas, especially in Outer London, tend to make more leisure trips (Model 3) and a greater total number of trips if they leave their homes during the day (Model 4). Population density is not significant in Models 1 and 2. Though the discussion of the effects of our control variable could be extended, we focus our discussion on the effects of our variables of primary interest—mobile phone possession and telecommuting.

We find that mobile phone possession has a positive effect on the total number of trips made, which confirms hypothesis A.1. Among those who work full-time, those who never telecommute or do only light telecommuting tend to make a greater total number of trips than those who telecommute frequently, mainly because of work trips (Models 1 and 2). Interestingly, though, those who do light telecommuting make more trips than those who never telecommute, confirming our observations made in the cross-table analysis. Among the part-time working respondents, we see a similar negative effect of heavy telecommuting on daily trips. The only difference is that those who are not telecommuting make the most trips, followed by those who do light telecommuting, with those who do heavy telecommuting making the fewest total trips.

Our results further indicate that full-time workers who are heavy telecommuters make fewer work trips, which confirms hypothesis A.2. In addition, full-time workers who never telecommute make fewer leisure trips, in correspondence to hypothesis A.3. Generally, part-time workers tend to make more leisure trips, and the effect of telecommuting is not very pronounced. The total number of trips made is slightly increased when doing light telecommuting compared to not telecommuting at all. This result supports hypothesis A.4. However, our hypothesis is not supported when the respondents do heavy telecommuting, as we find that those working full-time and not telecommuting tend to make the fewest trips among all six categories of workers.

The results of our work trip model (Model 2) also reveal that self-employed respondents with higher household incomes are likely to make fewer work trips. According to Table 8, most of the self-employed have relatively high household incomes, particularly those who do light telecommuting. We might therefore presume that many of the self-employed, high-income respondents have their own businesses or are working freelance, both of which might not require them to undertake regular commuting trips.

4.4 Effects on number of different tour types made

A tour may comprise one trip or a series of two or more trips linked together. In the most common tour definition, the tour is anchored at both ends by the home (Kuhnimhof *et al.* 2010; Miller *et al.* 2005). For this study, eight tour types were considered. The first four types are single stop (or simple) tours while the latter four are complex tours comprising at least two stops. Tours with single stops are: home-work-home (HWH); home-shop-home (HSH); home-leisure-home (HLH); and home-any-home (HYH), where "any" is any trip purpose except work, shopping and leisure. The four complex tours are: home-shop-work-home or home-work-shop-home (HSWH/HWSH); a similar combination of work and leisure trips (HLWH/HWLH); tours with two or more stops not including a work trip; and all other complex tours. These latter four tour types are distinguished in order to see whether those who do more telecommuting combine their work trips with other activities.

The effect of mobile phone possession is investigated for each of the tour types mentioned above. As shown in the cross-table analysis in Table 9, those who have mobile phones are likely to make greater numbers of simple tours related to shopping and leisure activities ($N = 33809, t = 2.386, p < 0.001$). This contrasts with our assumption in B.1 regarding tour numbers. However, in support of our hypothesis we also find that those with mobile phones make greater numbers of more complex tours ($N = 33809, t = 3.428, p < 0.001$), in particular complex tours that include work trips, suggesting that mobile phones encourage combining work with other activities along the way.

The effect of working from home on tour types is further investigated in Table 10. We find, as expected, that among full-time workers, those who never telecommute make the most HWH tours, followed by those who do light telecommuting and those who do heavy telecommuting. Further, as hypothesized in B.2, those who do heavy telecommuting make the largest numbers of simple shopping, leisure and other tours

(HSH, HLH, HYH). We find similar effects among the part-time working population.

Overall, the results in the cross-table analysis suggest that those who do heavy telecommuting make fewer tours, which corresponds to our findings regarding trip making. Those who do heavy telecommuting make complex tours less often, in general. However, this is mainly due to making fewer work-related tours, as the number of non-work complex tours increases with telecommuting frequency. In accordance with our hypothesis, we find that the number of non-work-related tours increases among those telecommuting heavily. Our hypothesis B.2 (that telecommuting in general leads to more home-to-home tours) is, however, not supported as the increase in non-work tours does not outweigh the reduction in work-related tours.

4.5 Effects on tour complexity

Finally, we create an ordered probit model to investigate the hypothesized effects C.1 and C.2 on tour complexity, where the number of stops is regarded as the dependent variable (Table 11). For simplicity, we omit the discussion regarding effects of socio-demographic characteristics. However, our results regarding some geographic control variables are noteworthy. The results indicate that more stops per tour are made by those who travel into Central London. The reason behind this might be that workers in Central London are more likely to combine their work-related trips with other trip purposes before returning home. To return home after work only to go out once more is probably less common among those working in Central London (and living in Outer London). Similarly, respondents who reside in Outer London tend to make more stops. This also supports our explanation, mentioned previously, of the difference in shopping behavior between Inner and Outer London. Similarly, people residing in areas with population densities of greater than 64722 persons per km^2 make more stops per tour. Further, the results show that those who use public transport on the day of the survey make less complex tours than those who use others.

The model result also indicates that possession of a mobile phone has no significance for tour complexity. This result does not likely confirm our hypothesis C.1. Full-time workers who do light telecommuting make more stops than those who never telecommute, while those who do heavy telecommuting make fewer stops. This effect holds true also for part-time workers. Those who do light telecommuting make more stops per tour than those who never telecommute, but those who do heavy telecommuting make the fewest complex tours. In summary, our hypothesis C.2 is supported only for those telecommuting frequently, while we observe a contrary effect among those doing light telecommuting.

5 Conclusions

This study investigated the effects of ICT, namely mobile phone possession and telecommuting, on weekday trips of Londoners. Absence of information on how much respondents use their mobiles is clearly a limitation of our study. However, our findings show that distinguishing those with and without mobile phone reveals differences in travel behavior. This suggests that the perceived freedom gained by possessing a mobile phone is reflected in travel patterns, independent of the amount of time the mobile is actually used.

In 2001, when the survey was conducted, the relationship between mobile phone possession and income was probably much stronger than it is today. This could explain why our results show that mobile phone holders make more work trips as well as more work-related tours. Similarly, mobile phone possession tends to increase the number of home-to-home tours made each day. Though one might argue that 2001 data are already slightly outdated, the effects of mobile phones will be more difficult to discern in the analysis of surveys carried out nowadays, when mobile phones have become almost ubiquitous. Some of the effects described in this paper might be general trends in societies where communication is increasingly based on mobile phones. Our results might further be of interest for developing countries where the level of mobile phone possession is currently similar to that in London in 2001.

Our results also confirm that telecommuting affects total trips and tour numbers as well as tour types and the number of stops per tour. The regression analysis suggests that those telecommuting heavily make fewer trips per day. The trip decrease is, however, much less than the reduction in work trips, confirming the substitution effect of telecommuting that has been well described in the literature. Our analysis confirms that these substitutions are likely to involve leisure and shopping trips.

Moreover, we find some non-linear effects on number of tours made with regards to the amount of telecommuting. Those who do a small to medium amount of telecommuting tend to make more complex tours and almost the same number of tours compared to those not working from home. Only for those telecommuting frequently we can find the hypothesized effects of an increase in simple home-to-home tours.

Table 8: Average annual household income (in £) by telecommuting status.

Telecommuting status	Employed Respondents		Self-employed Respondents	
	Full-time	Part-time	Full-time	Part-time
Never	35 277	27 503	37 439	14 038
Light	47 162	39 007	55 625	7500
Heavy	44 719	38 001	42 500	22 500

Table 9: Effects of mobile phone possession on the average number of tours for each tour type.

Mobile phone possession	HWH	HSH	HLH	HYH*	HSWH/ HWSH	HLWH/ HWLH	Tour with ≥2 stops with no work trip	Other complex tours	Total
Don't have	0.395	0.075	0.106	0.165	0.017	0.022	0.058	0.146	1.320
Have	0.382	0.084	0.111	0.163	0.014	0.024	0.058	0.160	1.357

* Where Y is anything except work, leisure and shopping.

Table 10: Effects of work type and telecommuting status on the average number of tours for each tour type.

Work type and telecommuting status	HWH	HSH	HLH	HYH*	HSWH/ HWSH	HLWH/ HWLH	Tour with ≥2 stops with no work trip	Other complex tours	Total
Full-time workers:									
Do not use PC for work	0.456	0.061	0.100	0.121	0.015	0.025	0.045	0.161	0.983
Use PC for work 1–9 hrs/week	0.359	0.062	0.114	0.145	0.015	0.027	0.047	0.214	0.983
Use PC for work ≥10 hrs/week	0.263	0.121	0.131	0.224	0.014	0.015	0.079	0.126	0.972
Part-time workers:									
Do not use PC for work	0.273	0.113	0.115	0.282	0.021	0.014	0.092	0.078	0.988
Use PC for work 1–3 hrs/week	0.176	0.106	0.146	0.321	0.010	0.014	0.115	0.106	0.993
Use PC for work ≥4 hrs/week	0.108	0.151	0.155	0.337	0.016	0.010	0.139	0.057	0.971

* Where Y is anything except work, leisure and shopping.

Table 11: Ordered probit model of tour complexity.

	%	Estimate	t-stat
Cut points (Tour)			
0 Stops	2.11	−1.806	−30.715
1 Stops	63.7	0.681	11.889
2+ Stops	34.19	—	—
Socio-demographic			
Gender:			
Male =1, female = 0	47.17	−0.125	−8.406
Age:			
16–24 (reference)		—	—
25–34	22.21	0.098	3.45
35–44	24.56	0.115	3.985
45–54	16.13	0.022	0.756
55–64	11.18	0.062	1.881
65–74	9.12	0.169	2.822
75 and above	5.64	−0.046	−0.316
Race:			
White = 1, Non-white = 0	77.6	0.115	6.652
Driver's license:			
With license = 1, No license = 0	70.44	0.017	0.846
Car ownership	1.16	−0.013	−1.026
Household structure:			
Single	18.34	0.058	2.497
Single parent with dependent children	8.06	0.144	4.513
Married/co-habiting	26.6	−0.08	−4.444
Married with dependent children (reference)	28.52	—	—
All pensioners	6.94	−0.096	−1.186
All other households	11.55	−0.046	−1.937
Interaction between household income and employment type*			
Household income × White collar job	45 116.02	0.031	7.58
Household income × Administrative job	36 530.06	0.03	5.683
Household income × Health-related job	38 179.21	0.023	4.727
Household income × Blue collar job	28 799.07	−0.004	−0.648
Household income × Self employed	32 083.33	−0.076	−1.632
Household income × Transport-related job	29 668.59	0.018	1.514
Public transport and destination in Central London			
Public transport:			
User = 1, non-user = 0	26.67	−0.224	−12.836
Destination within Central London:			
Within Central London = 1, Otherwise 0	12.85	0.287	14.466
Geographic characteristics			
Area:			
Inner London = 1, Outer London = 0	32.82	−0.044	−2.299
Population density, population/km^2 (population/sq. mile):			
2589–5178 (1000–2000)	2.2	−0.001	−0.028
5178–10 356 (2000–4000)	2.23	−0.205	−3.946
10 356–25 889 (4000–10 000)	23.49	−0.008	−0.287

Continued

Table 11: Ordered probit model of tour complexity.

	%	Estimate	t-stat
25 889–64 722 (10 000–25 000)	55.64	−0.048	−2.071
Over 64 722 (25 000) (reference)	16.44	—	—
Mobile phone possession			
Mobile phone			
With mobile phone = 1, otherwise 0	37.62	0.012	0.921
Telecommuting status			
Full-time workers:			
Do not use PC for work	34.98	0.142	4.127
Uses PC for work 1–9 hours per week	10.19	0.244	6.705
Uses PC for work ≥ 10 hours per week	2.56	—	—
Part-time workers:			
Do not use PC for work	9.63	0.14	3.653
Uses PC for work 1–3 hours per week	1.68	0.32	6.144
Uses PC for work ≥ 4 hours per week	0.91	0.001	0.013
Number of observations		33 809	
Log likelihood, intercept only		45 846.84	
Log likelihood, final		44 847.5	
McFadden's R^2		0.02	

Note: * = Value in column % is an average rather than a percentage.

Besides telecommuting, the type of employment clearly has an effect on number of trips made and tour complexity. Those being self-employed make fewer work trips but do not seem to compensate with additional leisure or shopping trips. In particular, they appear to make fewer complex tours.

Trip chaining is often seen as a means to reduce total travel effort. Our results suggest, however, that additional personal freedom gained through telecommuting or self-employment is used to decouple errands into multiple tours. Our findings thus support the argument that trip chaining might be rather a burden as it requires more pre-trip planning. With increasing flexibility about work place and time, one might conclude that planned complex tours will continue to decrease in number but be replaced by more simple tours that may be combined with spontaneous activities organized en-route through ICT.

On the one hand, this might indicate a chance for increased uptake of public transport, as our results confirm the negative association between tour complexity and public transport usage. On the other hand, once travelers have reached an attractive destination (such as Central London) they clearly tend to combine this tour with many side activities. For this, again, having a car appears to be the preferred option.

To manage the trip substitution effects of telecommuting henceforth careful neighborhood design might be of increasing importance. Nearby "corner shops" and cafes within local shopping streets could profit from telecommuting trends since they offer the possibility of additional spontaneous trips—arranged, for example, by mobile phone. Our inclusion of geographic characteristics in our analysis gives some support for such a conclusion. Those living in Outer London, where there are probably still more active independent towns, such as Wimbledon or Kingston, appear to make more complex tours as well as more shopping and leisure trips. These results are, however, speculative, and should be confirmed by further analysis looking at average trip distance and controlling for telecommuting status.

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