Establishing the linkages between online activity and car use: Evidence from a combined travel diary and online-activity pseudo-diary dataset

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Abstract (128 words)

The linkages between online activity and physical mobility are of wide and growing interest to researchers, practitioners and policymakers.

This paper presents results from analysis of Scottish Household Survey microdata, a unique large-scale, nationally-representative dataset that includes both a travel diary instrument and a pseudo-diary of online activity participation.

Multivariate regression models were estimated to relate people's online-activity profiles with their car driving mileage. The models include demographic and spatial characteristics to control for potential confounding effects.

It was found that, net of other effects, Internet usage is associated with a higher level of car use than being a non-user of the Internet. The marginal effect of time spent online was, however, found to be negatively linked with car use. In other words, spending large amounts of time online is *ceteris paribus* associated with less car driving mileage. The paper concludes with a discussion of further research needs to advance this line of enquiry.

Key words

Online activity, Internet, pseudo-diary, car use

1. Introduction

For at least a generation, much scholarly debate has focused on how the opening-up of the online world is affecting people's activity and travel patterns. There is wide interest in both the specific mechanisms by which particular types of activity and travel behaviour are changing, as well as the aggregate impact on traffic levels.

This paper draws on a unique data resource, the Scottish Household Survey (SHS), to contribute to the emerging body of literature relevant to this line of enquiry. The SHS is a large-sample, nationally-representative general social survey that includes a one-day travel diary (1). Crucially, it also includes a pseudo-diary of online activity participation that provides much richer detail in this regard than is typically available in large-scale social surveys.

The rest of this paper is structured as follows. Section 2 presents the conceptual discussion of online/physical-mobility relationships. The data and methods employed in this study are described in Section 3, followed by the discussion of findings in Section 4. Section 5 concludes the paper with a discussion of further lines of research needed to extend from these findings.

2. Background

Mokhtarian (2) presented the seminal taxonomy of relationships between information and communication technologies (ICTs) and physical mobility. *Substitution* effects arise from people performing activities online that otherwise would have been done in-person and hence required physical travel. *Complementarity* effects may be due to people adjusting their activity patterns in response to ICT-availability in ways that result in increased travel, such as learning via an ICT source about desired out-of-home opportunities that are further away than one previously was aware of. These are not the only types of possible impacts; Mokhtarian also points out that the full set in principle includes categories such as *neutrality* (e.g. a routine trip to the grocery store that does not stimulate a phone call) and *modification* (e.g. an e-mail or phone call causing the recipient to leave early, for a trip that they would have otherwise made but at a somewhat later point in time).

In empirical terms, road traffic levels have stagnated in many developed societies in the 2000s (though not in developing countries), following many decades of growth. In developed countries that have experienced stabilisation (or outright decline) in car use, this trend has been led by young men (3, 4). Young men are also amongst the heaviest users of online services (5). One hypothesis is therefore that the ICT/physical-mobility substitution effects described above are dominant empirically, and that therefore the growth in online activity is, in the aggregate, serving to lower traffic levels on a *ceteris paribus* basis (6, 7, 8, 9, 10). There is some evidence to the contrary, however. Taylor et al. (11) report an empirical finding that aggregate mobility (measured in person-miles of travel) is positively linked with self-reported daily web use. Mokhtarian also suggests that in the long-run telecommunications capability is likely to be complementary to physical travel (2).

3. Data and methods

The objective of this analysis was to test whether there is a *ceteris paribus* link, either positive or negative, between online activity participation and car use.

In the present study it was possible to investigate this relationship in some depth due to the richness of the online activity participation descriptors in the dataset we employed, the Scottish Household Survey.

The SHS has been undertaken continuously since 1999 (1); year 2005/6 data are employed in this study (microdata can be accessed publicly via www.data-archive.ac.uk). Limited information is collected about all members of responding households, and the most-detailed information gathered by the SHS is from a single randomly-selected adult (age 16+) respondent in each household.

Only the single randomly-selected adult in each household completes both a one-day travel diary and a pseudo-diary of their online-activity participation. The travel diary instrument records all travel that both begins and ends in Great Britain, by land, air and water, with the exception of short walking journeys (under ¼ mile) (12). The online-activity pseudo-diary consists of binary yes/no responses of whether they have ever performed each of a set of 17 types of online activities, and a separate question of how much time they spend online per week (the full questionnaire is available via [13]).

This analysis therefore draws from the randomly-selected adult SHS data (n=28,261). Data are weighted to represent the Scottish adult population.

Descriptive statistics of the SHS dataset used in this analysis can be found in Table 1.

Multivariate linear regression models of car driving distance (kms/day) are estimated, using both a wide set of demographic and spatial control variables and the online-activity-participation variables that are of direct substantive interest for the purposes of this study. Due to the SHS' sampling protocol, travel diaries are not distributed randomly across days of the week; the models control for this through day-of-week dummy effects.

It was found that Internet-usage varied strongly by age and gender; Figures 1 and 2 show patterns in time-spent-online. In recognition of this empirical finding, a full-sample regression model was run along with six models of the following demographic segments:

- Men aged 17 to 24 (n=889)
- Men aged 25 to 44 (n=3,985)
- Men aged 45+ (n=7,102)
- Women aged 17 to 24 (n=1,153)
- Women aged 25 to 44 (n=5,155)
- Women aged 45+ (n=9,761)

In order to reduce the number of degrees of freedom in the model estimation, a k-means cluster analysis was taken to identify patterns in the high-dimensional online activity participation data. The input to this cluster analysis was the 17 binary variables containing each Internet-using respondent's yes/no responses as to whether they participate in each of the 17 classes of online activity. A four-cluster solution was identified, which leads to a set of five clusters when non-Internet users are added in. Cluster-membership was treated as a categorical variable in the analysis; in each model four separate parameters relating to the four Internet-using-clusters were estimated, with the non-Internet-using segment fixed at zero for identification. Table 2 shows the results of the cluster analysis; for the discussion of this analysis the clusters have been colloquially termed as follows:

- **Non-users** of the Internet (56% of sample)
- **Narrow** Internet users (14% of sample; members perform an average of 3.2 Internet-activity-classes)
- **Moderate** Internet users (12% of sample; members perform an average of 4.8 Internet-activity-classes)
- **Broad (without leisure)** Internet users: (11% of sample; members perform an average of 8.3 Internet-activity-classes)
- **Broad (with leisure)** Internet users: (7% of sample; members perform an average of 10.1 Internet-activity-classes)

Descriptive demographic and travel statistics for each Internet cluster are presented in Table 3. As the models reported in this paper were estimated with purely cross-sectional data, the effects must be interpreted as statistical association rather than evidence of direct causality.

4. Findings

Results from the regression model of driving distance performed by all SHS respondents during their travel diary day can be found in Table 4. The corresponding results from model runs for each of the six demographic segments separately are shown in Table 5 (men) and Table 6 (women).

Goodness of fit for the models varies from r^2=0.10 to 0.31. The effects for the control variables generally either have the *a priori* expected sign or are not statistically significant.

Of the effects associated with Internet-use cluster membership, 10 of the 24 effects from the demographic sub-group models were statistically significant at the $p<0.05$ level. All ten of these effects were positively-signed. The four Internet-usage-cluster-membership effects in the full-sample were also all found to be positive and statistically significant (relative to non-Internet-users). These results imply that some types of Internet-users are likely to drive more mileage than otherwise-identical people that are not Internet users. For other types of Internet users no statistically significant relationship was found.

Of the six estimated effects of time per week spent online (one in each model run for the demographic sub-groups) three were negative and statistically significant at the $p<0.05$ level, and one other was negatively-signed with $p=0.06$. These four segments account for 73% of all Internet users. The two segments for which no significant effect was found are women aged 17-24 and women aged 45+. A negative and statistically-significant relationship was also found in the full-sample model. The implication of these results are that, at the margin, additional time spent online is associated with less car driving mileage.

In order to assess the net linkage between Internet usage and car use, the model estimation results for each demographic segment were applied multiplicatively with the SHS microdata observations in a sample enumeration process. In other words, for each person in the sample the estimated effect of their online activity on their car use is calculated on the basis of their unique internet-use profile and the estimated parameter set.

It was found that for all six demographic segments the average net Internet-usage effect (cluster membership plus time-spent-online) was positive, ranging from a low of 0.77 kms/day (for women aged 17-24) to a high of 4.96 kms/day (for men aged 45+), for an average across all adults of 2.92 kms/day. The net Internet-usage effects for all six demographic segments, along with the percentage of members in each online-activity-based segment are presented in Table 7. It can be seen that the average net effect is larger, for all three age groups, for men than women. Also, the effects rise monotonically with age for both genders.

Table 7 shows the average net effect of online activities on car driving mileage; the distribution of this effect is illustrated for men in Figure 3 and for women in Figure 4. For ease of presentation, on the x-axis the Internet users are sorted from the ones with the smallest simulated-effect of Internet usage on driving mileage on the left hand side to the ones with the largest simulated-effect on the right hand side. The y axis shows the kms/day effect associated with Internet usage as compared to otherwise identical non-Internet-users. For all six demographic sub-groups the distributions include both positive and negative effects, though in the aggregate the positive effects are dominant. Table 7 shows that the *average* effects are positive; Figures 3 and 4 show that the *median* effects (at the 50th percentile) for all six groups are also consistent with an overall positive relationship between online activity and car use. In summary, using the internet is associated with higher levels of car use than not being an internet user, but spending a large amount of time online is associated with less car use than spending a moderate amount of time online.

5. Discussions and conclusions

This paper focused on the linkage between people's patterns of online activity and car use. The analysis is based on a dataset containing both a standard travel diary and a unique pseudo-diary of online-activity participation. Though some travel diary datasets (e.g. the British National Travel Survey and U.S. National Household Travel Survey) have begun to adapt their questionnaires to start collecting data on online activity, the dataset employed in this analysis contains a relatively rich trace of each respondent's profile of online activity participation.

Two noteworthy effects emerged from this study. First, the marginal effect of the amount of time one spends online was found to be negative – more time spent online is associated, all else equal, with less driving mileage. Second, the net effect of Internet usage was found to be positive (relative to being a non-Internet-user), and this held across all of the six age/gender groups that were studied.

The latter of these findings is consistent with Mokhtarian's hypothesis outlined in (2), that on balance telecommunications and transportation are net complements rather than substitutes. Given the rapid growth in online activity, further research is urgently needed to build on these findings.

The Scottish Household Survey dataset used in this study was collected in 2005/6, and in the years since there have been major changes to both the amount and nature of online activity opportunities. As this set of research questions require empirical analysis to identify the net balance between substitution and complementarity, it will be important to draw on more up-to-date data resources to establish what has changed versus the degree to which these findings are robust across temporal and spatial context.

Randomised field trials with controls of the type frequently undertaken in medical research, in which the 'treatment' subset of study participants would be asked to take part in specific types of online activity and their travel measured, are likely to be infeasible for a number of reasons. It would, for instance, be difficult to credibly apply a stimulus of internet-access to a representative cross-section of people. There are however two other promising avenues for improving the evidence base. First, questionnaire instruments used in regional and national travel surveys should continue to be adapted to take fuller account of people's online activities. This will require further research, as we cannot say on the basis of these results which specific types of online activities are the highest priorities for including in large-scale travel surveys. Second, opportunities should be found to incorporate travel and online-activity diaries into large-scale longitudinal datasets, which would allow researchers to use time-series analytical techniques and move further towards establishing causality (beyond cross-sectional statistical association).

While further research will be needed to deepen our understanding of the links between online activities and physical-world activity/travel (including cross-national comparisons), it is hoped that the findings reported here will be of use in guiding the development of the future research agenda.

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Tables and Figures

Indicator	Mean	Standard deviation
Percentage that use the Internet	53%	50%
Age	49.0	18.3
Income	£22,378	£16,713
Percentage that hold a full car driving licence	65%	48%
Average annual car driving mileage	2,623	6,383
Percentage of women	55%	50%
Percentage living in large urban areas	40%	49%
Percentage living in other urban areas	29%	45%
Percentage living in small accessible towns	9%	29%
Percentage living in small remote towns	4%	20%
Percentage living in accessible rural areas	12%	32%
Percentage living in remote rural areas	6%	32%
Percentage that are self-employed	5%	22%
Percentage that are full-time workers	36%	48%
Percentage that are part-time workers	11%	31%
Percentage that are students	5%	22%
Percentage that are neither employed nor students	42%	49%
Percentage that are managers and other senior officials	6%	25%
Percentage that are professional	7%	25%
Percentage that are associate professional/technical	8%	27%
Percentage that are administrative/secretarial	6%	25%
Percentage that are skilled trades	6%	24%
Percentage that are personal service	5%	23%
Percentage that are sales and customer service	5%	21%
Percentage that are process/plant/machine operatives	4%	20%
Percentage that perform elementary occupations	7%	26%
Percentage that are non-working adults	45%	50%
Percentage that are people with 'good' health	86%	35%

Source: Authors' analysis of SHS microdata

Table 1: Descriptive statistics of the SHS estimation dataset

	Of people within segment, the percentage that indicate they perform the specified activity			
Class of online-activity	Narrow Internet users	Moderate Internet users	Broad (without leisure) Internet users	Broad (with leisure (Internet users)
Buying or ordering tickets and services	0%	100%	91%	85%
Finding information about goods/services	42%	65%	94%	92%
Finding information related to education	22%	27%	69%	79%
General browsing or surfing	62%	69%	91%	96%
Grocery shopping	6%	10%	32%	29%
Looking for work	15%	17%	39%	63%
Non-grocery shopping	17%	24%	87%	73%
Online learning	10%	8%	30%	46%
Paying rent	0%	0%	1%	3%
Personal banking / financial / investment activities	13%	27%	76%	59%
Playing or downloading games	14%	9%	6%	83%
Playing or downloading music	20%	20%	27%	96%
Using chat rooms or sites	9%	5%	5%	43%
Using e-mail	71%	87%	99%	99%
Using or accessing government/official sites	10%	14%	80%	59%
Voting	0%	0%	3%	3%
None of these	4%	0%	0%	0%

Source: Authors' analysis of SHS microdata

Table 2: Descriptive statistical results of Internet-usage clusters

Online activity	Non-users	Narrow Internet users	Moderate Internet users	Broad (without leisure Internet users)	Broad (with leisure Internet users)	Weighted average of Internet users
Average number of online activity-types performed	0	3.2	4.8	8.3	10.1	6.0
Average time spent online (hours per week)	0	3.8	3.8	5.5	9.2	5.1
Average age	58	42	43	43	33	41
Average annual driving mileage	1,689	3,296	4,479	5,032	3,448	4,081
Average annual bus mileage	335	329	243	206	374	282
Average annual rail mileage	97	195	326	471	388	332
Percentage with a full car driving licence	49%	70%	83%	90%	72%	79%
Cars per household	0.8	1.3	1.5	1.5	1.4	1.4
Percentage that are women	59%	54%	56%	56%	40%	53%
Average annual household income	£15,795	£21,373	£26,775	£31,268	£27,017	£26,260
Percentage living in large urban areas	43%	34%	36%	39%	45%	38%
Percentage of full- time workers	21%	41%	51%	56%	55%	50%
Percentage of people in each cluster	47%	16%	15%	13%	9%	-
Unweighted sample size	14,623	4,377	3,711	3,450	2,100	-

Source: Authors' analysis of SHS microdata

Table 3: Characteristics and travel patterns of Internet-use clusters

Parameter	r^2=0.14 n=27,206 Mean (standard deviation in brackets) annual car-driving mileage: 2,670 (6,399)	
	Mean parameter	Significance
Constant	-2.835	0.06
Dummy (Holds a full car driving licence)	11.60	<0.01
Age	0.23	<0.01
Age-squared	-0.002	<0.01
Household income (£000s/year)	0.079	<0.01
Dummy (Large Urban Areas)	-10.042	<0.01
Dummy (Other Urban Areas)	-7.344	<0.01
Dummy (Accessible Small Towns)	-4.115	<0.01
Dummy (Remote Small Towns)	-4.758	<0.01
Dummy (Accessible Rural Areas)	-0.360	0.65
Dummy (Remote Rural Areas)	Fixed at zero	-
Dummy (Self-employed)	6.917	<0.01
Dummy (Full-time worker)	3.496	<0.01
Dummy (Part-time worker)	-1.619	0.14
Dummy (Student)	0.426	0.67
Dummy (Neither employed nor student)	Fixed at zero	-
Dummy (Monday)	1.737	<0.01
Dummy (Tuesday)	1,644	<0.01
Dummy (Wednesday)	2.464	<0.01
Dummy (Thursday)	2.453	<0.01
Dummy (Friday)	3.027	<0.01
Dummy (Saturday)	-0.583	0.33
Dummy (Sunday)	Fixed at zero	-
Dummy (Managers and senior officials)	6.548	<0.01
Dummy (Professional occupations)	2.989	0.01
Dummy (Associate professional and technical occupations)	4.304	<0.01
Dummy (Administrative and secretarial occupations)	-0.237	0.84
Dummy (Skilled trades occupations)	4.772	<0.01
Dummy (Personal service occupations)	0.788	0.5
Dummy (Sales and customer service occupations)	0.818	0.47
Dummy (Process, plant and machine operatives)	5.126	<0.01
Dummy (Elementary occupations)	1.860	0.08
Dummy (Non-working adults)	Fixed at zero	-
Dummy (Good health)	0.503	0.31
Dummy (Fairly good/Not good health)	Fixed at zero	-
Dummy – Narrow users	**2.060**	**<0.01**
Dummy – Moderate users	**2.896**	**<0.01**
Dummy – Broad (without leisure) users	**4.367**	**<0.01**
Dummy – Broad (with leisure) users	**3.005**	**<0.01**
Dummy – Time spent online (hour/week)	**-0.155**	**<0.01**

Source: Authors' analysis of SHS microdata

Table 4: Results from linear regression of annual car driving mileage (km/day) with full data sample (men and women of all ages)

Parameter	r^2=0.31 n=889 Age: 17-24		r^2=0.10 n=3,985 Age: 25-44		r^2=0.12 n=7,102 Age: 45+	
	Mean	Significance	Mean	Significance	Mean	Significance
Constant	7.787	0.83	0.261	0.99	6.163	0.65
Dummy (Holds a full car driving licence)	15.66	<0.01	15.10	<0.01	11.76	<0.01
Age	0.36	0.99	0.08	0.95	-0.127	0.77
Age-squared	-0.019	0.83	0.003	0.87	0.000	0.97
Household income (£000s/year)	0.108	<0.01	0.051	0.09	0.157	<0.01
Dummy (Large Urban Areas)	-6.028	<0.01	-14.864	<0.01	-8.836	<0.01
Dummy (Other Urban Areas)	-7.617	<0.01	-9.549	<0.01	-4.609	<0.01
Dummy (Accessible Small Towns)	-5.816	0.02	-5.945	0.03	-1.659	0.41
Dummy (Remote Small Towns)	-3.050	0.27	-4.794	0.19	1.722	0.48
Dummy (Accessible Rural Areas)	6.934	0.13	-1.640	0.56	2.923	0.11
Dummy (Remote Rural Areas)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy (Self-employed)	4.952	0.13	4.947	0.29	17.232	<0.01
Dummy (Full-time worker)	-3.034	0.08	0.148	0.97	13.831	<0.01
Dummy (Part-time worker)	-4.505	0.05	-7.175	0.20	6.292	0.19
Dummy (Student)	-3.503	0.03	-5.300	0.33	4.161	0.71
Dummy (Neither employed nor student)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy (Monday)	0.546	0.71	2.292	0.245	2.110	0.17
Dummy (Tuesday)	-0.493	0.74	0.413	0.83	3.419	0.03
Dummy (Wednesday)	3.186	0.03	2.159	0.28	3.254	0.03
Dummy (Thursday)	-2.428	0.11	3.481	0.08	3.245	0.03
Dummy (Friday)	4.832	<0.01	-1.133	0.58	3.560	0.02
Dummy (Saturday)	-0.132	0.93	-3.909	0.05	-1.026	0.51
Dummy (Sunday)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy (Managers and senior officials)	6.548	<0.01	11.136	0.01	-6.285	0.15
Dummy (Professional occupations)	2.300	0.39	6.786	0.13	-8.782	0.05
Dummy (Assoc. prof'l. and tech. occs.)	1.550	0.41	11.073	0.01	-5.337	0.23
Dummy (Admini. and sec. occupations)	-1.345	0.58	5.402	0.268	-7.411	0.14
Dummy (Skilled trades occupations)	4.118	0.01	7.493	0.09	-7.156	0.10
Dummy (Personal service occupations)	4.894	0.12	11.041	0.04	-5.035	0.33
Dummy (Sales and cust. svc. occupations)	4.040	0.01	8.010	0.11	-0.134	0.98
Dummy (Process, plant and mach. ops.)	7.309	<0.01	6.904	0.12	-5.747	0.20
Dummy (Elementary occupations)	6.298	<0.01	6.449	0.15	-7.749	0.09
Dummy (Non-working adults)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy (Good health)	0.643	0.75	-1.369	0.53	1.616	0.17
Dummy (Fairly good/Not good health)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy – Narrow users	**1.056**	**0.40**	**3.612**	**0.03**	**3.511**	**<0.01**
Dummy – Moderate users	**4.878**	**<0.01**	**1.875**	**0.30**	**4.598**	**<0.01**
Dummy – Broad (without leisure) users	**-2.223**	**0.29**	**3.855**	**0.05**	**7.338**	**<0.01**
Dummy – Broad (with leisure) users	**2.132**	**0.11**	**4.289**	**0.04**	**4.361**	**0.07**
Dummy – Time spent online (hrs/week)	**-0.192**	**<0.01**	**-0.202**	**0.05**	**-0.450**	**<0.01**

Source: Authors' analysis of SHS microdata

Table 5: Results from linear regression of annual car driving mileage (kms/day) for SHS men by age group

Parameter	r^2=0.23 n=1,153 Age: 17-24		r^2=0.15 n=5,155 Age: 25-44		r^2=0.17 n=9,761 Age: 45+	
	Mean	Significance	Mean	Significance	Mean	Significance
Constant	24.889	0.45	12.471	0.37	14.794	0.02
Dummy (Holds a full car driving licence)	12.76	<0.01	11.47	<0.01	8.187	<0.01
Age	-1.040	0.75	-0.063	0.94	-0.409	0.03
Age-squared	0.016	0.84	0.002	0.90	0.003	0.04
Household income (£000s/year)	-0.012	0.64	0.017	0.49	0.076	<0.01
Dummy (Large Urban Areas)	-15.429	<0.01	-18.945	<0.01	-5.726	<0.01
Dummy (Other Urban Areas)	-11.783	<0.01	-16.118	<0.01	-4.954	<0.01
Dummy (Accessible Small Towns)	-7.751	<0.01	-10.118	<0.01	-3.485	<0.01
Dummy (Remote Small Towns)	-10.267	<0.01	-17.292	<0.01	-3.804	<0.01
Dummy (Accessible Rural Areas)	-12.999	<0.01	-7.605	<0.01	1.065	0.25
Dummy (Remote Rural Areas)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy (Self-employed)	-6.026	0.24	0.617	0.82	-1.592	0.55
Dummy (Full-time worker)	1.847	0.23	-0.259	0.91	-0.510	0.83
Dummy (Part-time worker)	0.830	0.62	-3.213	0.16	-1.115	0.65
Dummy (Student)	-0.526	0.69	-1.402	0.60	-5.211	0.19
Dummy (Neither employed nor student)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy (Monday)	-0.125	0.93	0.857	0.49	2.424	<0.01
Dummy (Tuesday)	3.518	<0.01	0.306	0.81	1.716	0.02
Dummy (Wednesday)	1.807	0.15	1.907	0.13	2.293	<0.01
Dummy (Thursday)	0.754	0.56	2.252	0.07	2.064	<0.01
Dummy (Friday)	3.274	0.01	4.570	<0.01	3.685	<0.01
Dummy (Saturday)	-1.255	0.35	0.569	0.66	0.421	0.58
Dummy (Sunday)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy (Managers and senior officials)	0.486	0.86	8.164	<0.01	8.634	<0.01
Dummy (Professional occupations)	1.750	0.50	7.131	<0.01	6.224	0.01
Dummy (Assoc. prof'l. and tech. occs.)	-4.214	0.04	6.415	<0.01	6.755	<0.01
Dummy (Admini. and sec. occupations)	-1.198	0.44	4.559	0.05	1.219	0.63
Dummy (Skilled trades occupations)	-2.024	0.57	10.484	<0.01	-0.258	0.93
Dummy (Personal service occupations)	0.852	0.59	4.635	0.05	0.669	0.79
Dummy (Sales and cust. svc. occupations)	-0.422	0.76	1.334	0.585	0.982	0.70
Dummy (Process, plant and mach. ops.)	-4.766	0.265	1.027	0.77	4.329	0.16
Dummy (Elementary occupations)	-2.211	0.12	3.293	0.18	0.257	0.92
Dummy (Non-working adults)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy (Good health)	1.486	0.32	0.464	0.69	0.474	0.37
Dummy (Fairly good/Not good health)	Fixed at zero	-	Fixed at zero	-	Fixed at zero	-
Dummy – Narrow users	**0.180**	**0.87**	**0.991**	**0.34**	**0.502**	**0.48**
Dummy – Moderate users	**1.389**	**0.26**	**1.553**	**0.16**	**2.959**	**<0.01**
Dummy – Broad (without leisure) users	**2.337**	**0.11**	**3.048**	**<0.01**	**5.820**	**<0.01**
Dummy – Broad (with leisure) users	**-0.096**	**0.94**	**2.197**	**0.13**	**-1.213**	**0.44**
Dummy – Time spent online (hrs/week)	**-0.014**	**0.83**	**-0.151**	**0.06**	**0.003**	**0.974**

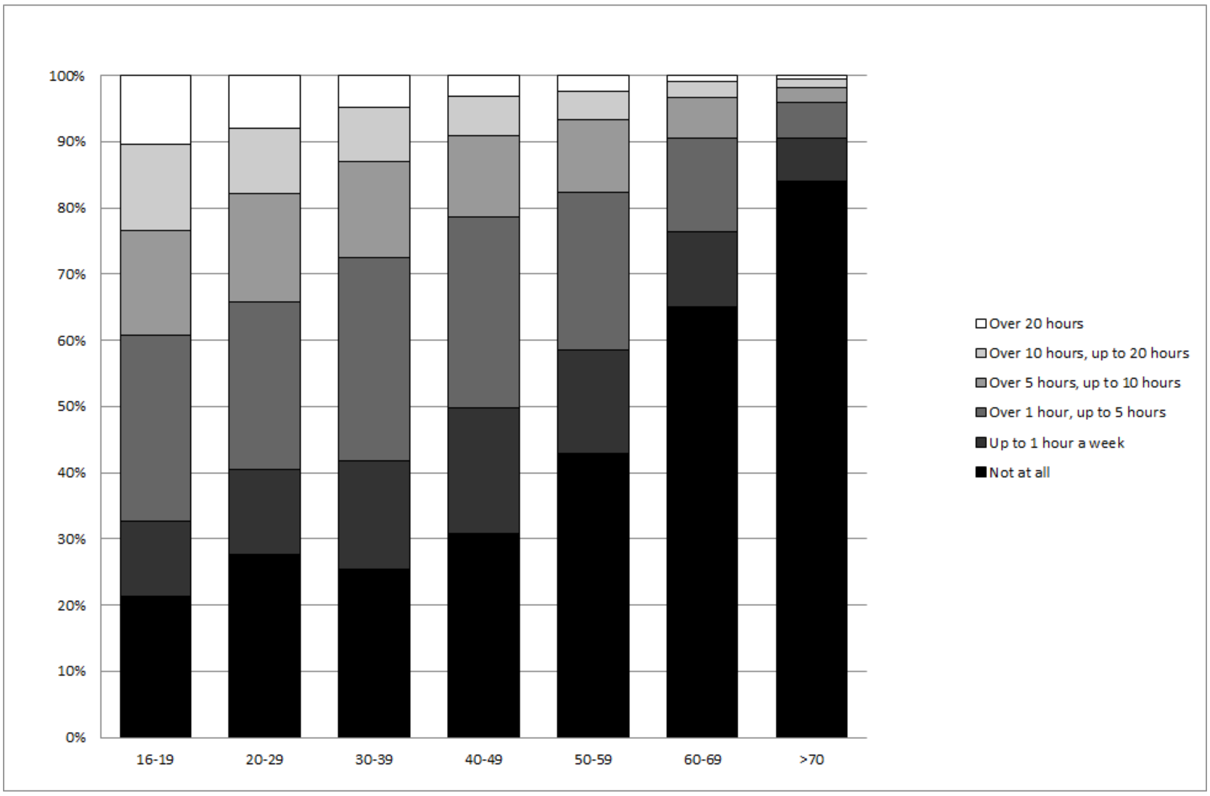
Source: Authors' analysis of SHS microdata

Table 6: Results from linear regression of annual car driving mileage (km/day) for SHS women by age group

	Of Internet users within each gender and age group, the percentage that falls in each usage category				
	Narrow Internet users	Moderate Internet users	Broad (without leisure) Internet users	Broad (with leisure) Internet users	**Net *ceteris paribus* effect of Internet usage (kms/day)**
Men 17-24	34%	18%	8%	41%	**+1.92**
Men 25-44	27%	24%	24%	24%	**+3.41**
Men 45+	34%	29%	28%	9%	**+4.96**
Women 17-24	35%	26%	16%	23%	**+0.77**
Women 25-44	29%	26%	31%	14%	**+1.95**
Women 45+	37%	33%	24%	5%	**+2.52**
All ages	31%	28%	25%	16%	**+2.92**

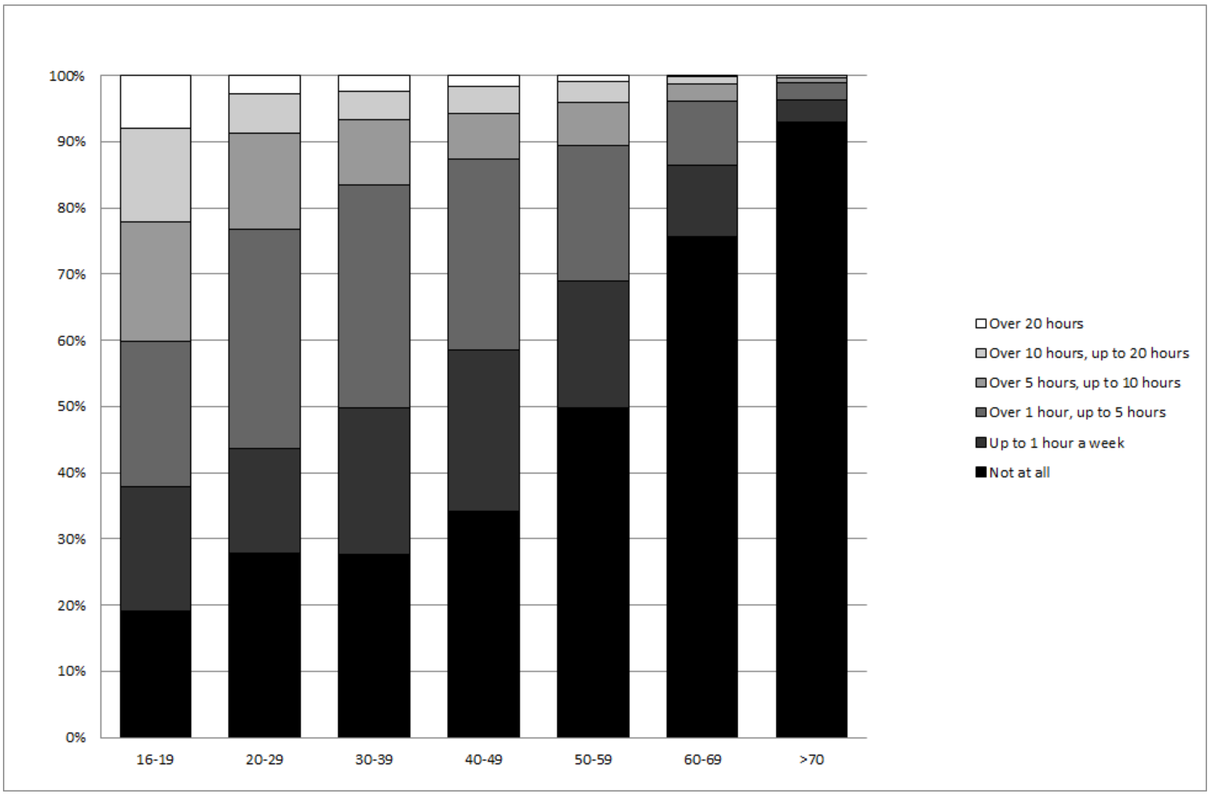
Source: Authors' analysis of SHS microdata

Table 7: Average net effect of Internet usage by age and gender



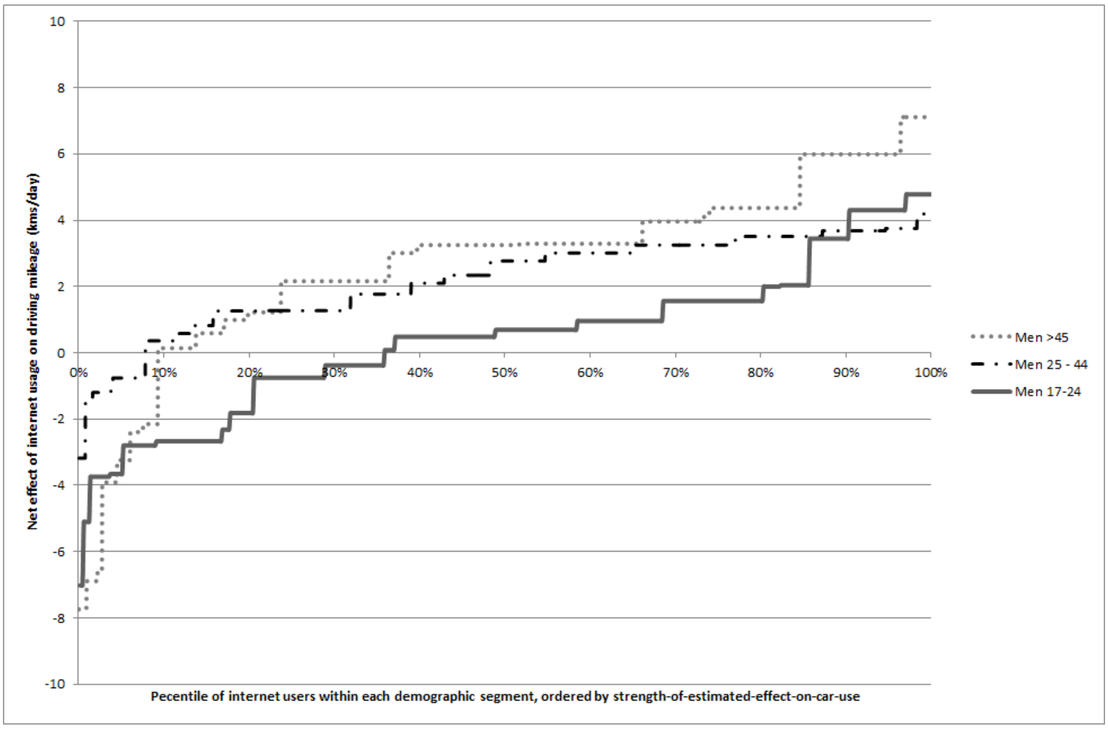
Source: Authors' analysis of SHS microdata

Figure 1: Distribution of men's time spent online, by age group



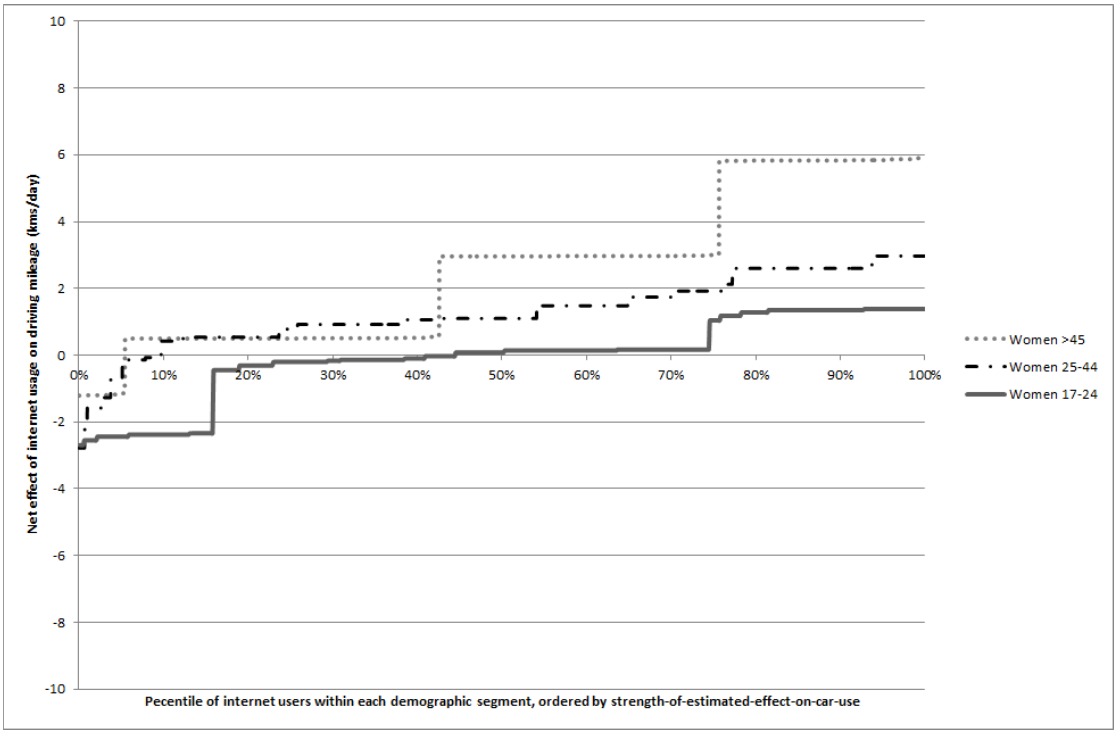
Source: Authors' analysis of SHS microdata

Figure 2: Distribution of women's time spent online, by age group



Source: Authors' analysis of SHS microdata

Figure 3: Distribution of estimated effect (kms/day) on car driving mileage associated with Internet usage, incorporating each male SHS respondent's Internet usage profile, grouped by age



Source: Authors' analysis of SHS microdata

Figure 4: Distribution of estimated net-effect (kms/day) on car driving mileage associated with Internet usage, incorporating each female SHS respondent's Internet usage profile, grouped by age