

UC Davis

UC Davis Previously Published Works

Title

How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios

Permalink

<https://escholarship.org/uc/item/14n2h736>

Authors

Malokin, Aliaksandr
Circella, Giovanni
Mokhtarian, Patricia L

Publication Date

2019-06-01

DOI

10.1016/j.tra.2018.12.015

Peer reviewed



How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios



Aliaksandr Malokin*, Giovanni Circella, Patricia L. Mokhtarian

School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlantic Drive, Atlanta, GA 30332, USA

ARTICLE INFO

Keywords:

Travel behavior
Multitasking
Activities while traveling
Autonomous vehicles
Mode choice
Attitudes
Value of travel time

ABSTRACT

From early studies of time allocation onward, it has been acknowledged that the “productive” nature of travel could affect its utility. Currently, at the margin an individual may choose transit over a shorter automobile trip, if thereby she is able to use the travel time more productively. On the other hand, recent advancements toward partly/fully automated vehicles are poised to revolutionize the perception and utilization of travel time in cars, and are further blurring the role of travel as a crisp transition between location-based activities. To quantify these effects, we created and administered a survey to measure travel multitasking attitudes and behaviors, together with general attitudes, mode-specific perceptions, and standard socioeconomic traits (N = 2229 Northern California commuters). In this paper, we present a revealed preference mode choice model that accounts for the impact of multitasking attitudes and behavior on the utility of various alternatives. We find that the propensity to engage in productive activities on the commute, operationalized as using a laptop/tablet, significantly influences utility and accounts for a small but non-trivial portion of the current mode shares. For example, the model estimates that commuter rail, transit, and car/vanpool shares would respectively be 0.11, 0.23, and 1.18 percentage points lower, and the drive-alone share 1.49 percentage points higher, if the option to use a laptop or tablet while commuting were not available. Conversely, in a hypothetical autonomous vehicles scenario, where the car would allow a high level of engagement in productive activities, the drive-alone share would increase by 1.48 percentage points. The results empirically demonstrate the potential of a multitasking propensity to reduce the disutility of travel time. Further, the methodology can be generalized to account for other properties of autonomous vehicles, among other applications.

1. Introduction

Multitasking (doing multiple activities “at the same time”) is a common feature of modern life, whether viewed as an annoying distraction, a means of increasing productivity or enjoyment, or both. There is a sizable and growing literature on multitasking in general (e.g., König and Waller, 2010), and in contexts such as work (e.g., Bluedorn and Martin, 2008; Chesley, 2014) or “media multitasking” (e.g., Wallis, 2010) in particular, but the study of activities conducted while traveling is a relatively young area of research (a comprehensive review of travel multitasking studies to date has been conducted by Keseru and Macharis, 2018). Multitasking has been thought to positively affect the (dis)utility of the trip (Mokhtarian and Salomon, 2001; Kenyon and Lyons, 2007;

* Corresponding author.

E-mail addresses: amalokin@gatech.edu (A. Malokin), gcircella@gatech.edu (G. Circella), patmikh@gatech.edu (P.L. Mokhtarian).

<https://doi.org/10.1016/j.tra.2018.12.015>

Received 5 August 2016; Received in revised form 13 December 2018; Accepted 13 December 2018
0965-8564/© 2019 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Wardman and Lyons, 2016) and thence the evaluation of travel time for a trip (a recent International Transport Forum Roundtable was devoted to the subject of “Zero Value of Time”; see <https://www.itf-oecd.org/zero-value-time-roundtable>, accessed November 19, 2018). At the margin, for example, some individuals may choose transit over the automobile for a given trip, even though the transit alternative takes longer, if in so doing they are able to use the travel time more productively.

These effects are expected to become even more relevant in future decades. One promise of partly- and fully-automated vehicles is to reduce the need for drivers to “pay attention to the road”. This, among other effects, will extend to private vehicles the hands-free advantage hitherto enjoyed by public transit, thus potentially allowing motorists to accrue the positive utility of travel-based multitasking (Anderson et al., 2014; Wagner et al., 2014). In this future, time slots that were previously almost exclusively occupied by travel will dissolve into more permeable channels permitting overlapping continuity of activities. In other words, travel will (often) lose its place as a primary activity of its own: activities that were previously possible only at the trip origin or destination (or could take place only when traveling as a passenger rather than a driver), such as relaxing or working with clients, could happen also aboard personal vehicles.

This study investigates the impacts of activities carried out while traveling (travel-based multitasking) on mode choice, specifically in the context of the daily commute. To do this, we created and administered a survey to measure multitasking attitudes and behavior while commuting, together with general attitudes, mode-specific perceptions, and standard socioeconomic traits (N = 2229 Northern California commuters). We used this dataset to estimate a revealed preference (RP) multinomial logit (MNL) mode choice model (Ben-Akiva and Lerman, 1985) that accounts for the impact of multitasking attitudes and behavior on the utility of various alternatives – to our knowledge, the first revealed-preference model to do so. We then used the model to analyze several scenarios highlighting the potential near-term advantage of transit, and longer-term impacts of autonomous vehicles, associated with the ability to conduct activities while traveling.

The paper addresses several research questions: after controlling for the conventionally included mode attributes and socio-demographic traits, as well as other (primarily attitudinal) variables expected to influence mode choice, how and to what extent do the ability and propensity to perform tasks while traveling influence the utility of various travel modes to an individual? What current share of public transit ridership could be attributed to travel-based multitasking? And what potential ridership could be captured by changes in the multitasking conduciveness of these modes? Finally, how would autonomous vehicles affect the mode split if their occupants could fully devote their attention to non-travel activities?

The remainder of the paper is organized as follows. Section 2 briefly reviews the literature, focusing specifically on the impact of travel-based multitasking on travel utility. Section 3 describes the empirical context of the study, including the data collection effort and the sample characteristics. We then present an overview of our methodological approach, and discuss the construction of mode-specific multitasking propensity measures, in Section 4. The mode choice model specification and the discussion of the effects of the explanatory variables are the subject of Section 5. In Section 6, we develop a set of transit-related and autonomous-vehicle-oriented scenarios, showcasing the potential shifts in mode shares attributable to multitasking factors. Finally, Section 7 presents some conclusions and future research directions. Appendices provide additional technical details, including a discussion of issues associated with using a nested logit model instead of the sequential process we adopt, and proof that coefficients in a nested logit model differ when variables in (binary choice) lower nests are associated with different alternatives.

2. Literature review

Within the past few years, growing attention has been paid to the impact of multitasking on travel behavior. For example, Guo et al. (2015) observed and surveyed 3425 students who used the college bus system in Vancouver, British Columbia with respect to their participation in passive/active, information and communication technology (ICT)-based/non-ICT-based, and smart-function/non-smart function (“dumb phone”) activities while riding and waiting. Even though the study focused on a very specific segment of the population (young adults who use public transportation and are often very familiar with ICT devices), the authors pointed to the importance of the temporal dimension (i.e., when and for how long activities are performed) in studying the effects of travel-based multitasking on the travel experience. The authors found that only 30% of the people who owned smartphones used them, despite large shares of riders engaging in non-passive activities while taking the bus (60%) or waiting for it (47%).

Tang et al. (2018) surveyed 901 passengers of high-speed rail (HSR) between Shanghai and Nanjing, and developed quadrivariate probit models of the engagement in four types of activities on the trip (ICT work, ICT non-work, paper work, and non-work paper reading). Nearly three-fifths of the sample engaged in ICT-based work (in contrast to European studies of conventional trains but in keeping with the higher-income clientele of HSR), and more than three-quarters engaged in ICT-based non-work activities. Interestingly, having a laptop along on the trip increased the propensity to conduct ICT-based work only for non-business travelers (signifying an intention to work while traveling for personal reasons), not for business travelers (many of whom may have brought the laptop primarily for activities at the destination).

The link between travel-based multitasking and the value of travel time was hinted at as early as 1965 (Becker), touched on by Mokhtarian and Salomon (2001), and elaborated conceptually by Lyons and Urry (2005). Watts and Urry (2008, p. 860) continued the discussion, arguing that travel time is by no means universally “wasted, dead, or empty”. Accordingly, a number of studies have empirically analyzed the link between multitasking and travel time. For example, Ohmori and Harata (2008) developed a descriptive analysis of activities conducted while traveling among 503 Japanese train riders and discussed the dependence of activity engagement level on travel time (e.g., using ICT for work purposes is more common during long trips). Using a scobit model estimated on a sample of 523 Japanese bus users, Zhang and Timmermans (2010) found that engaging in more activities while traveling decreases the sensitivity to changes in travel time. Thus, travel-based multitasking is likely to partly offset the negative impact of travel time on

the utility of a travel mode. Studying ICT usage among Norwegian train commuters (N = 289) and business travelers (N = 245), [Gripsrud and Hjorthol \(2012\)](#) found that advanced planning and laptop usage increased the probability of getting work done (more so for business travelers) during the trip. Additionally, laptop usage was linked with a more positive subjective valuation of travel time for business travelers.

Several studies ([Ettema et al., 2012](#); [Susilo et al., 2012](#); [Rasouli and Timmermans, 2014](#); [Mokhtarian et al., 2015](#); [Singleton, 2018](#)) have explored the impact of activities conducted while traveling on the subjective evaluation of a trip experience. Among these, [Rasouli and Timmermans \(2014\)](#) found positive associations of working and shopping online, reading, and obtaining travel information, with improved perceptions of the trip experience among 98 Dutch participants in a three-month long GPS-based travel diary study. Similarly, in a study of 400 South Korean travelers, [Rhee et al. \(2013\)](#) included several activities conducted while traveling (e.g., talking on phone, chatting with passengers, and using an ICT device) in models of reported attitudes towards traveling, comparing automobile and public transit users. However, the reported activities were not universally available to users of both transportation modes, which inhibits an adequate side-by-side comparison. For example, while talking to other passengers had the same positive association with feeling happy for both automobile and transit users, social networking through ICT devices was investigated in the study (and was statistically significant and negative) only for automobile users.

At least two studies have estimated a monetary value of travel time savings (VOTTS) in the context of multitasking. [Ettema and Verschuren \(2007\)](#) relied on stated preferences (SP) and found that among 226 Dutch public transit riders, polychronic individuals (i.e., those with a more positive inclination toward multitasking) had lower VOTTS. Concluding, the authors warned about substantial exogenous heterogeneity of travelers' VOTTS. Other stated-preference studies also controlled for the activities conducted while traveling when assessing the demand for Wi-Fi on commuter rail ([Connolly et al., 2009](#)) and mode choice under urgent work tasks during the commute ([van der Waerden et al., 2010](#)). [Varghese and Jana \(2018\)](#), on the other hand, took a revealed preference approach to quantifying the VOTTS while accounting for multitasking. They segmented their sample of motorized trips in Mumbai, India into those on which multitasking occurred (N = 2037) and those where it did not (N = 913), and estimated separate mixed MNL mode choice models for each segment. They found that that the mean VOTTS was 26% lower for the trips on which multitasking occurred.

In a recent paper, [Zheng et al. \(2016\)](#) studied the utility of “laptop stations” on buses and urban trains in Australian cities. In the SP portion of the hybrid (SP/RP) survey, the authors asked more than 6700 respondents whether the availability of a laptop station would influence their mode choice (bus/train/car). The results of the random effects logit model showed that the dummy variable (presence/absence of a laptop station) was significant only in the train utility function: counterintuitively, the normally distributed random coefficient had a negative mean (apparently indicating that the presence of a laptop station *decreased* the utility of train), albeit a large standard deviation (meaning that the coefficient would be positive for a sizable fraction of the sample). Further, the utility of having a laptop station was found to be influenced by the trip purpose being commuting (positively) and by high income (negatively). The heterogeneity among respondents was additionally demonstrated by the willingness to pay for a train laptop station, which fluctuated near zero dollars and was negative for many survey-participants.

In sum, the burgeoning literature on travel-based multitasking exhibits considerable diversity with respect to geographic and cultural context, modes studied, activities examined, dependent variables analyzed, and whether stated or revealed preference formats were used; most studies do not segment the analysis on (or in some cases, even measure) trip purpose. All of this means that while prior research has certainly informed the present study, direct comparisons are problematic. While building upon the accumulating literature (including our own conceptualization of multitasking, in [Circella et al., 2012](#)), the current study is unique in its development of a revealed preference model of primary commute mode choice, incorporating perceptions of the “multitaskability” of each mode and estimated propensities to multitask on each mode, together with conventional measures of travel time and cost, to quantify the influence of travel multitasking on the disaggregate utility, and the resulting aggregate share, of each mode.

3. Empirical context

To keep the scope of the study manageable, and in view of the importance of commuting as a daily anchor at the personal level and a key generator of congestion at the societal level, we chose to focus the transportation context of the study on commute trips. Among short-distance trips, although commuting nominally accounts for only about 15.61% of the personal transportation in the U.S. ([U.S. Department of Transportation, Federal Highway Administration, 2009](#)), many other trips are linked to the commute, it is typically the longest trip made on a frequent basis, and given its temporal peakedness, it is a major source of congestion and thence emissions. With respect to long-distance travel, although in many countries the train is a viable alternative to the car, that is not the case in the U.S. for the most part. The choice between air and car (when there even is such a choice) is made primarily on the basis of travel time and cost, with little room for desired travel multitasking to influence the decision. At the same time, in view of the latter considerations, most public transportation systems in the U.S. offer their best levels of service during commute peak hours. The frequency and length of the trip, together with the relative attractiveness of transit for such trips (compared to many other trip purposes), mean that the opportunities for productive travel multitasking, and the competitive appeal of transit for that reason, are generally highest for the commute trip (among short-distance trips).

Accordingly, our desired population consisted of commuters (including working college students) living in Northern California, with a particular but not exclusive focus on commuters traveling on the Sacramento – San Francisco Bay Area transportation corridor (the study area was chosen for geographic convenience, while the authors were affiliated with the University of California, Davis). Data collection was carried out in fall and winter of 2011–2012, using both paper and online versions of the survey ([Neufeld and Mokhtarian, 2012](#)). The survey was a single questionnaire that was administered once.

Table 1
Selected characteristics of the sample and population.

Characteristic (sample size)	N (%)	Characteristic (sample/pop. size)	N (%)
Gender (2209)		Commute total travel time (2229)	
Female	1370 (61.5)	Less than 15 mins	349 (15.7)
Age (2216)		15 to 30 mins	602 (27.0)
18 to 24	104 (4.7)	31 to 45 mins	437 (19.6)
25 to 40	750 (33.6)	46 mins to 1 h	284 (12.7)
41 to 64	1276 (57.2)	1 to 1½ hours	323 (14.5)
65 to 74	78 (3.5)	1½ to 2 h	142 (6.4)
75 or older	8 (0.4)	More than 2 h	92 (4.1)
Education level (2229)		Sample commute mode shares (2229)	
Some grade/high school	3 (0.1)	Biking	192 (8.6)
High school diploma	64 (2.9)	Commuter rail	176 (7.9)
Some college/technical school	515 (23.1)	Transit ^b	649 (29.1)
4-year college degree	714 (32.0)	Shared ride ^c	355 (15.9)
Some graduate school	241 (10.8)	Driving alone	857 (38.4)
Complete graduate degree(s)	692 (31.0)	Population commute mode shares (4,119,532)^a	
Occupation (2221)		Biking	63,187 (1.5)
Clerical/administrative support	342 (15.3)	Commuter rail	29,508 (0.7)
Homemaker	8 (0.4)	Transit	336,721 (8.2)
Manager/administrator	375 (16.8)	Shared ride	513,277 (12.5)
Production/construction	37 (1.7)	Driving alone	3,176,839 (77.1)
Professional/technical	1114 (50.0)	Characteristic (sample size)	Sample mean
Sales/marketing	79 (3.5)	Household size (2216)	2.69
Service/repair	51 (2.3)	Number of operational household vehicles (2206)	2.08
Student	189 (8.5)		
Other	26 (1.1)		
Annual household income (2142)			
Less than \$25,000	127 (5.7)		
\$25,000 to \$49,999	313 (14.0)		
\$50,000 to \$74,999	436 (19.6)		
\$75,000 to \$99,999	414 (18.6)		
\$100,000 to \$124,999	358 (16.1)		
\$125,000 or more	494 (22.2)		

^a Population commute mode shares for the 16 Northern California counties of the study area were obtained from the Census Transportation Planning Products, available at <http://ctpp.transportation.org/Pages/default.aspx>, based on ACS 2006–2010 data.

^b Includes local bus (current sample share 0.0557), express bus (0.0703) and light rail/subway (0.1783).

^c Includes car/van driving with passengers (current sample share 0.0693), and carpool/vanpool/shuttle passenger (0.0849).

We used a variety of sampling approaches, including choice-based sampling (i.e., contacting people in the process of using their respective commute modes), mailing paper versions of the questionnaires to the addresses of a random sample of study area residents, and distributing links to the online surveys through employers'/ affiliated organizations' email lists and websites. Finally, we used the services of a commercial firm, Survey Analytics (<https://www.surveyanalytics.com>), to circulate the questionnaires to an appropriately filtered subsample of their paid panel members. Our goal was not to achieve a sample that was completely representative of the population of interest. Rather, we needed a sample with “enough” (a few hundred) users of each mode of interest to produce robust statistical results. In fact, the focus of the study lies in investigating the relationship of multitasking to mode choice, and the use of covariates in the estimation of the model – together with the weighting described in Section 5.1 – can largely control for biases due to the non-representativeness of the sample. Although any single sampling method would have been less-than-optimal if used in isolation, the combination of diverse methods helped alleviate the limitations of each, and has produced the desired diversity with respect to commute mode choice and other characteristics in the final sample.

Geographically, origins and destinations of the sampled commuters were unevenly distributed over several dozen Northern California counties. However, we were mainly interested in commutes within major agglomerations in the region. Therefore, only those respondents who commuted within 16 counties were included in the final sample for this study: the nine Metropolitan Transportation Commission counties (Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano and Sonoma), the six Sacramento Area Council of Governments counties (El Dorado, Placer, Sacramento, Sutter, Yolo and Yuba), and San Joaquin County.

The final sample size for this study is 2229, after filtering out apparent mode captives and out-of-region, inconsistent, or frivolous respondents, as well as cases that were severely incomplete on key variables. Because of our sampling strategy, the sample descriptives (Table 1) can differ greatly from those of the general population. In particular, the sample considerably underrepresents drive-alone commuters, and overrepresents users of other modes.

In addition to the socio-economic attributes, the collected data contains responses to various attitudinal statements, which were

Table 2
General attitudinal and mode perception constructs pertinent to the current study.

Constructs	Statements ^a	Pattern matrix loadings ^b
General attitudes^c		
<i>Pro-technology</i>	I like to be among the first to own new electronic products.	0.755
	I like to track the development of technology.	0.747
	I often introduce new trends to my friends.	0.577
	The internet makes life more interesting.	0.343
	Technology brings at least as many problems as solutions.	-0.305
<i>Pro-active modes</i>	I like the idea of walking (or biking) as a means of transportation.	0.895
	I prefer to walk or bike rather than drive whenever possible.	0.767
	I like the idea of living in a neighborhood where I can walk to the grocery store.	0.420
<i>Pro-transit</i>	I prefer to take transit rather than drive whenever possible.	0.739
	I'd rather drive than travel by any other means.	-0.588
	I like the idea of driving as a means of travel for me.	-0.536
	I like the idea of transit as a means of travel for me.	0.510
<i>Travel is wasted time</i>	I generally enjoy the act of traveling itself.	-0.774
	The act of traveling is boring.	0.710
	Time spent traveling is generally wasted time.	0.592
	The only good thing about traveling is arriving at your destination.	0.567
	I sometimes travel more than I have to, because I want to.	-0.389
	To me, a car is mostly just a way to get from place to place.	0.308
Mode perceptions^d		
<i>Mode convenience</i>	Ability to run errands on the way to/from work	0.897
	Privacy	0.789
	Availability when needed/wanted	0.715
	Ability to carry things with me	0.591
	Door-to-door travel time	0.421
	Reliability	0.411
	Comfort	0.342
	Effect on the environment	-0.308
<i>Mode benefit/cost</i>	Effect on the environment	0.800
	Cost	0.626
	Avoiding congestion	0.583
	Amount of physical activity involved	0.557
	Ability to carry things with me	-0.311
<i>Mode comfort</i>	Safety	0.688
	Traveling in poor weather conditions	0.582
	Comfort	0.532
	Reliability	0.450
	Door-to-door travel time	0.376
	Ability to carry things with me	0.301
<i>Mode multitaskability</i>	Ability to do things I need/want while traveling	standardized single item

^a A statement can load on more than one construct.

^b Represents the degree of association between the statement and the construct. Only loadings greater than 0.3 in magnitude are reported.

^c Items measured on a 5-point Likert-type scale ranging from “Strongly disagree” to “Strongly agree”.

^d Items measured on a 5-point ordinal scale ranging from “Very bad” to “Very good”. Thus, all items are positively oriented. Positive loadings for inherently negative items such as “cost”, or ambiguous items such as “effect on the environment” or “amount of physical activity involved”, should be interpreted as meaning, “viewing [this trait] favorably will contribute to a higher score on the associated factor”.

factor-analyzed to reveal the underlying attitudinal constructs (the constructs appearing in the final models are shown in [Tables 2 and 3](#)). The factor analyses were performed on a cleaned dataset with a larger number of observations (all potentially eligible for future study, e.g., including non-working students; $N \sim 2800$) by using principal axis and maximum likelihood methods for factor extraction, with oblique rotation and Bartlett factor score computation. With respect to the mode perceptions shown in [Table 2](#), respondents were asked to rate multiple modes on parallel sets of attributes such as cost and comfort. For the factor analysis, instead of treating the parallel sets of responses as multiple variables for the same case (person), the variable sets were stacked “mode over mode”, with each person-mode combination constituting a case. This was done so that the same factor structure would be obtained across modes (e.g., so that “comfort” would be associated with the same factor for all modes). One mode perception, namely its multitaskability, did not load onto any factor and was therefore included in the model as a stand-alone variable after being standardized for consistency with the factor scores.

Similarly, with respect to four of the time-use constructs shown in [Table 3](#), parallel statements were presented for whether respondents felt they *must* engage in those behaviors, and whether they *wanted* to do so; these items were also stacked and factor-analyzed to have the same structure across those two variations on the question. The multitasking statements in [Table 3](#) are those

Table 3
Multitasking and time use constructs pertinent to the current study.

Constructs	Statements ^a	Pattern matrix loadings ^b
Multitasking preference^c		
<i>Polychronicity</i>	I prefer to do one thing at a time.	-0.761
	I like to juggle two or more activities at the same time.	0.732
	Doing two or more activities at the same time is the most efficient way to use my time.	0.725
	I am comfortable doing more than one activity at the same time.	0.668
	I typically do two or more activities at the same time.	0.646
	When I work by myself, I usually work on one project at a time.	-0.608
	I believe it is best to complete one task before beginning another.	-0.603
	I would rather complete parts of several projects every day than complete an entire project.	0.566
	I believe people should try to do many things at once.	0.543
	I seldom like to work on more than a single task or assignment at the same time.	-0.538
	I believe people do their best work when they have many tasks to complete.	0.515
	I would rather complete an entire project every day than complete parts of several projects.	-0.492
	I believe it is best for people to be given several tasks and assignments to perform.	0.445
<i>Multitasking is normative</i>	I believe people do their best work when they have many tasks to complete.	0.800
	I believe people should try to do many things at once.	0.504
	I believe it is best for people to be given several tasks and assignments to perform.	0.433
Time use		
<i>Time spent working^d</i>	Amount of time you spend working	0.784
	Amount of time you spend relaxing	-0.452
	Amount of time you spend on the computer/phone/internet for work	0.415
<i>Has to/would like to work on commute^e</i>	Work during your commute	0.513
	Do “nothing” during your commute	-0.339
<i>Has to/would like to do recreation on commute^e</i>	Do recreational activities during your commute	0.641
	Socialize with other people while commuting	0.382
	Constantly be available to friends	0.299
<i>Has to/would like to multitask at work^e</i>	On the job: work on several tasks in the time span of one day	1.022
	On the job: work on several tasks in the time span of one week	0.714
	On the job: work on several tasks in the time span of one hour	0.492
<i>Has to/would like to be available to people^e</i>	Constantly be available to friends	0.678
	Constantly be available to family	0.669
	Constantly be available to co-workers/clients	0.568

^a A statement can load on more than one construct.

^b Represents the degree of association between the statement and the construct. Only loadings greater than 0.3 in magnitude are reported.

^c Items measured on a 5-point Likert-type scale ranging from “Strongly disagree” to “Strongly agree”.

^d Items measured on a 5-point ordinal scale ranging from “Way too little” to “Way too much”.

^e Items measured on a 3-point ordinal scale ranging from “Generally no” to “Generally yes”.

comprising the two main polychronicity scales (batteries of questions designed to measure a person’s inclination to multitask) established in the literature (Bluedorn et al., 1999; Lindquist and Kaufman-Scarborough, 2007). Detailed reports on the factor analyses are available from the authors upon request.

Including the attitudinal variables enhances the estimated models in two ways: (1) it reduces the biases in the estimated coefficients of the *other* variables (notably, but not exclusively, the socio-demographic variables), which would otherwise be partially accounting for the explanatory power of the (missing) attitudes with which those other variables are correlated; and (2) it contributes substantial additional independent explanatory power to the model.

Objective mode attributes, specifically travel time and travel cost (averaged between morning and afternoon commutes), were obtained in post-processing, using fastest routes as suggested by Google Maps, and necessarily involving a number of assumptions as detailed below. Biking incurs a constant cost of \$0 and travel time accounts for topography and accessible infrastructure, assuming an average speed on flat land of about 12 mph. Public transportation alternatives (commuter rail and transit) could be represented by a sequence of private and collective modes (along with walking and waiting episodes). Such alternatives are considered to be available for a commute if the aggregate travel time on collective modes and the associated wait time is over 50% of the total travel time (to exclude these modes from the choice set when lengthy access/egress times by private modes such as walking or car would be required), and if the reported work location can be reached by 9 am within a “reasonable” time (liberally set at 3 h, in view of the geographic expanse of the commute shed for the region). Travel cost for the collective modes is determined by a summation of costs associated with the various modes involved in the trip. Cost minimization, such as a choice of the best pass (single ride, weekly, monthly) based on the reported commuting frequency and inter-agency ticket honoring, is applied. Travel time for driving alone is calculated as an average over several samples of real traffic conditions for AM and PM peaks. Travel cost for driving alone combines

fuel (fuel efficiency is inferred via reported vehicle make and model), tolls, and parking costs. Shared ride travel time computation is similar to that for driving alone except for two details: 5 min were added to account for additional pick-up and drop-off times, and (where available) high-occupancy vehicle lanes were acknowledged through assuming free-flow speed over these segments. Further, shared-ride total travel cost, calculated similarly to that for driving alone, is divided by the average shared-ride occupancy for the region.

4. Methodological approach

With the empirical context and set of available variables in mind, this section describes our methodology in greater detail. [Section 4.1](#) presents the entire process, while [Section 4.2](#) focuses on an important and novel component of the process: the measurement (estimation) of mode-specific propensities to engage in various activities on the commute. Taken together, this section offers a “blueprint” that could be replicated in numerous contexts both similar and dissimilar to the one of this study.

4.1. Overview of the methodology

Narrowly construed, this study offers a methodology for assessing the implications for mode choice of the emergence of new technologies for travel-based multitasking, using a *revealed-preference* discrete choice model. Once the model parameters are estimated, carefully constructed scenarios allow for the evaluation of a “counterfactual present” (i.e., what mode shares *would have been*, *without the new technology*), as well as multiple “hypothetical futures” (i.e., what shares *could be*, *if currently familiar modes become more conducive to the use of the new technology*), all else equal. These applications obviously involve a number of assumptions on how the counterfactual present and hypothetical future *differ* from today’s reality. But because they originate in a representation of actual present-day behavior, pivoting on what the counterfactual present and hypothetical future have *in common* with today’s reality (including the present-day multitaskability of transit and shared-ride modes), we believe they offer a degree of verisimilitude not necessarily present in stated-response models that do not have that degree of commonality, and which require respondents to imagine a rather different world than today’s. Nevertheless, the applicability of this approach will obviously be limited to the extent that future modes evolve into forms relatively *unfamiliar* today.

Furthermore, as applied in this study, the methodology considers primarily a single aspect that is not conventionally considered in a mode choice model: each mode’s multitaskability. Even considering just the context of autonomous vehicles (let alone other transportation alternatives of the future), it is clear that many other aspects of a mode could be important to its adoption: safety perceptions, a “coolness” factor, congruity with self-identity, perceived desirability of sequential or simultaneous sharing of vehicles for that mode, and so on. In principle, the methodology can readily be expanded to incorporate any number of pertinent attitudinal constructs into the model. Survey design considerations, however, will likely limit the number that can practically be included.

Viewed even more broadly, however, a key element of the methodology is its approach to turning observations on *consequences of the chosen mode* (activities conducted on a specific commute, in this case) into *propensities for those consequences to occur if any particular mode were to be chosen*, and then incorporating those propensities into the mode choice model as explanatory variables (as explained in detail in [Section 4.2](#)). In effect, it is a way to capture the influence, on the choice to be made, of the *anticipated consequences* of each of the *possible* alternatives, using only the *observed consequences* of the *actual* choices. This approach could have applications in any number of contexts. For example, suppose we want to model the choice between store and online for a recent shopping activity. We could expect the likelihood of needing to return the item to affect the choice of shopping mode (or “channel”, in marketing research parlance), but what we observe is *whether the item obtained via the chosen channel needed to be returned*. The methodology of this study offers a way to estimate the *likelihood of return for each shopping channel, if it were to be chosen*.

With these observations in mind, then, below we briefly recapitulate the main steps of the methodology. Note, again, that various simplifications, assumptions, and decisions will need to be made at each step. In the present study, for example, we focused on commute trips only, and only the primary commute mode (see [Sections 3, 4.2, and 5](#) for a number of these assumptions etc.). Although such assumptions constitute limitations of the approach, they are consistent with the general character of models as being useful simplifications of reality.

1. Carefully consider the variables expected to influence mode choice in the study context: objective mode attributes, mode-specific perceptions, other attitudes, and sociodemographic variables. Also consider the important *consequences* of mode choice, the *anticipation of which* influence choice.
2. Design a survey to measure the variables identified in Step 1 as being pertinent to the choice process of interest, and administer the survey with attention to obtaining an ample number of cases choosing each mode.
3. As needed and available, supplement the self-reported information from the survey with external data, as we did to obtain travel times and costs for all modes (available to an individual) rather than only for the chosen mode.
4. As needed and appropriate, synthesize responses from individual attitudinal statements into composite, continuous-valued scores on attitudinal factors.
5. Develop mode-specific propensities to experience a given consequence (“use a laptop during the commute”, in the present study; see [Section 4.2](#) for details):
 - a. Using only the choosers of mode j , estimate a model for whether the given consequence is experienced or not, as a function of explanatory variables available for everyone in the sample (both choosers and non-choosers of mode j).
 - b. Using the model estimated for mode j , compute predicted probabilities of experiencing the consequence of interest while using

Table 4
Activities performed during the commute.

Activity (sample size)	Number of engaged commuters (% of mode choosers)				
	Biking	Commuter rail	Transit	Shared ride	Driving alone
Number of choosers:	(186–192)	(168–176)	(625–647)	(343–354)	(836–855)
Technological^b					
Smartphone ^a (2200)	20 (10.6)	122 (70.1)	297 (46.3)	132 (37.8)	241 (28.5)
Internet ^a (2205)	6 (3.2)	86 (49.7)	277 (42.9)	100 (28.6)	94 (11.1)
Reading electronically ^a (2181)	2 (1.1)	90 (52.9)	216 (34.1)	77 (22.4)	54 (6.4)
Gaming electronically ^a (2191)	2 (1.1)	42 (24.9)	147 (23.0)	39 (11.2)	24 (2.8)
Messaging ^a (2206)	14 (7.4)	127 (73.0)	334 (51.7)	140 (40.1)	158 (18.6)
Recreational					
Watching scenery/people (2216)	154 (80.6)	134 (76.1)	479 (74.0)	223 (63.4)	377 (44.4)
Daydreaming (2208)	146 (76.4)	89 (51.7)	387 (59.8)	169 (48.4)	355 (41.8)
Exercising (2207)	185 (96.4)	14 (8.2)	47 (7.3)	5 (1.4)	13 (1.5)
Productive					
Writing electronically ^a (2179)	1 (0.5)	75 (43.6)	65 (10.3)	48 (14.0)	19 (2.2)
Laptop/tablet ^a (2199)	1 (0.5)	82 (47.4)	61 (9.5)	65 (18.6)	31 (3.7)
Thinking/planning ^a (2219)	159 (83.7)	135 (77.1)	475 (73.5)	267 (75.4)	651 (76.2)
Traditional					
Reading from paper ^a (2194)	2 (1.1)	113 (66.1)	347 (53.9)	48 (13.8)	38 (4.5)
Sleeping/resting (2208)	1 (0.5)	100 (58.1)	252 (39.0)	95 (27.1)	16 (1.9)
Talking to strangers ^a (2198)	5 (2.6)	71 (41.3)	168 (26.3)	40 (11.5)	27 (3.2)
Writing on paper ^a (2181)	4 (2.1)	68 (39.5)	99 (15.5)	26 (7.5)	20 (2.4)
Talking to friends ^a (2201)	12 (6.4)	99 (57.2)	277 (43.3)	292 (83.2)	70 (8.2)
Gaming non-electronically ^a (2192)	2 (1.1)	9 (5.3)	24 (3.8)	17 (4.9)	14 (1.6)
Maintenance					
Eating/drinking (2222)	19 (9.9)	122 (69.3)	100 (15.5)	145 (41.0)	424 (49.6)
Audio ^a (2218)	51 (26.8)	101 (51.7)	275 (42.7)	258 (72.9)	813 (95.1)
Grooming (2196)	0 (0.0)	23 (13.7)	35 (5.5)	23 (6.5)	56 (6.6)
Talking on phone ^a (2201)	22 (11.6)	99 (57.6)	213 (33.4)	84 (23.9)	281 (33.1)
Navigating ^a (2162)	5 (2.7)	18 (10.5)	45 (7.2)	46 (13.4)	118 (14.1)
Watching video ^a (2198)	2 (1.1)	37 (21.5)	59 (9.2)	20 (5.7)	27 (3.2)

^a Originally, these activities were reported separately for two purposes: work and leisure/personal. For this analysis the purposes were combined.

^b Categories based on the factor analysis reported in Malokin et al. (2015).

mode j , for all cases who have mode j in their choice set (including both choosers and non-choosers of mode j).

- c. Repeat for each mode. The conclusion of this step will find each mode in a person's choice set to have an estimated "propensity to experience the consequence of interest" associated with it.
6. Develop a mode choice model, including as explanatory variables objective mode attributes, mode perceptions, other attitudes, sociodemographic variables, and the estimated propensity to experience the consequence of interest (Section 5). If choice-based sampling were used in Step 2, the sample should be weighted to properly replicate population mode shares.
7. Compute value of travel time savings and willingness-to-pay measures as desired (Section 5; Malokin et al., 2017).
8. By manipulating the values of selected explanatory variables and/or coefficients, construct various scenarios representing plausible or instructive "hypothetical future" or "alternative present" cases. For a given scenario, use the model estimated in Step 6 (together with the manipulated inputs/parameters) to compute disaggregate predicted probabilities of choosing each mode. Aggregate those probabilities across the (weighted) sample to obtain mode shares associated with the scenario, and compare them to the benchmark shares (Section 6).

4.2. Estimating mode-specific propensities to be engaged in certain (types of) activities while commuting

Multiple measures of multitasking are available in the data. First, respondents' personal orientation toward multitasking in general, i.e., their polychronicity, was measured as described in Section 3. Second, respondents were asked to rate each alternative mode on how well it offered the "ability to do things I need/want while traveling" (*mode-specific perceptions*, Table 2). Third, they indicated which of a number of different activities they performed on a single recent commute (*chosen-mode-based behavior*, Table 4). The mode-specific perception can be included in a model as either generic (with a constant coefficient across modes) or alternative-specific variables. The activities performed on a recent commute, however, are known only after the mode choice being modeled has been made, which makes them endogenous and therefore not directly suitable as explanatory variables influencing choice. Put another way: just as we need to know travel time and cost not only on the chosen mode but also on the alternative modes, so it is not enough solely to know what a commuter *did* on a particular mode; we also need to know *what she could have done* on other modes to know how travel-based multitasking would influence her mode choice.

There are multiple ways to incorporate the effects of mode-based multitasking behavior into a mode choice model. One conceptually elegant way is to view both decisions (which mode, and whether or not to use a laptop) as a multidimensional joint choice problem (Ben-Akiva and Lerman, 1985). Accordingly, one can specify a nested logit model where lower nests would represent the choice between using laptop or not for a given mode, and the upper nest represents the choice of mode. In this way, all parameters of the model are estimated simultaneously, and the use of full information for both choices yields efficient estimators. The inclusive value for each lower nest, representing (loosely speaking) the maximum expected utility of that nest, is fed into the utility function of the associated mode in the upper nest, so that the probability of choosing a given mode is influenced by the benefit the traveler expects to receive from the decision to multitask or not on that mode. The first appendix to the paper (Appendix A) explains the issues associated with this approach, which are why we ultimately chose the alternative approach presented here.

This alternative approach is conceptually similar to the nested logit formulation, in that it allows the prospective benefit of multitasking on a given mode to feed into the utility function for that mode. It differs in that (a) we use a two-stage approach, analogous to the sequential (limited-information) rather than simultaneous (full-information) estimation of nested logit, and (b) the prospective benefit of multitasking on a given mode is reflected by the predicted probability (or *propensity*) of multitasking if that mode were to be chosen, rather than by the inclusive value function. In the latter respect, it is loosely inspired by (though not identical to) the propensity score regression approach to treating endogeneity bias in the context of treatment evaluations¹ (see, e.g., Newgard et al., 2004).

To implement this approach, we estimated the propensity to conduct a particular activity associated with a particular primary commute mode,² as follows. For each mode-activity combination, we formulated a binary logit model using travelers' mode-specific involvement in each activity (=1 if reported, =0 otherwise), as the dependent variable. Individual characteristics such as socioeconomic attributes, multitasking preferences, general attitudes and personality traits, time use expectations and preferences, and attitudes toward waiting were used as observed explanatory variables; although none of these variables differs by mode, their influence on utility (i.e., their coefficients in the models) can. The error term captures the net effect of all unobserved variables on the utility of performing the given activity when using the given mode; those unobserved variables include the intrinsic conduciveness of the mode to performing that activity. The model was calibrated on respondents who chose that mode, and the result was applied to predict the probability of performing that activity *if that mode were to be chosen* for all respondents, regardless of their actual mode choice (for additional information, see Berliner et al., 2015).

The two-stage approach we use here makes the assumption that the model of laptop usage on mode j that is estimated on choosers of j applies equally well to non-choosers of j (i.e. that the estimated *coefficients* are the same for both groups, although we stress that the distributions of the associated *explanatory variables* are allowed to, and almost certainly will, differ by group). The approach also results in a loss of efficiency for the mode choice model estimation (because only information from the choosers of a given mode is used to estimate the propensity to multitask on that mode), and therefore the statistical tests of significance for those parameters should be considered approximate indications. Since for most of our results, however, statistical significance is far stronger than the typical 0.05 threshold, we believe that the essential nature of the estimated mode choice model is sound. Additionally, the two-stage

¹ In treatment evaluation studies, the target variable is an outcome of some kind (such as blood pressure, for medical applications), which is often modeled as a function of the treatment indicator (yes or no), plus a number of pertinent covariates. However, if treatment is not assigned randomly, then characteristics that differ between treated and untreated cases could confound the estimated effects of treatment. One remedy is to estimate a separate model of the probability of being treated or not, and then include that estimated probability of (or propensity for) treatment as another control variable in the outcome model. Doing so means that the remaining coefficients (in particular, that of the treatment indicator) can, in principle, properly capture the effects of the associated variables (particularly, receipt of treatment or not) for people with the same propensity to be treated. In our context, the outcome of interest is mode choice. The “treatment” loosely corresponds to “uses a laptop or not” – but only loosely. In our case the “treatment” clearly occurs after the outcome, which means that it is not causally consistent to have the treatment indicator be a predictor in the outcome model (as would be the case in a conventional treatment evaluation context). In a discrete-outcome context such as ours, the likelihood of “treatment” is also conditional on a specific discrete outcome occurring, which means that the treatment propensity model can only be estimated conditional on a specific outcome occurring (also unlike the conventional situation). Nevertheless (to the extent that the propensity model estimated for the choosers of mode j can be considered transferable to the non-choosers of mode j), we can treat the estimated propensity to use laptop on a given mode as a (counterfactual, for non-choosers of that mode) measure of the benefit the person would receive *if using that mode*, and include it as a statistical control in the utility function for the associated mode (so that the utility, in turn, represents “what the utility would be if that mode were to be used”). Is it reasonable to assume that the propensity model estimated for the choosers of mode j is transferable to the non-choosers of mode j ? Taste heterogeneity between a mode's choosers and non-choosers is quite possible even with an ordinary mode choice model, but a model whose utility function coefficients differ between *choosers* and *non-choosers* of a given alternative (as distinct from one whose coefficients simply differ by alternative, *regardless* of whether that alternative is chosen or not) would not be estimable. Accordingly, *all* mode choice models assume that although the values of *explanatory variables* may differ between choosers and non-choosers of a given mode, the values of the *coefficients* of those variables do not. In the same way, our laptop usage models allow the resulting estimated propensities to differ between choosers and non-choosers (by virtue of the values of the models' explanatory variables differing), while assuming that the coefficients of the models used to estimate the propensities do not.

² We asked about activities conducted while commuting, but to keep the survey burden manageable, for multimodal commutes we do not know the specific mode in use at the time of the activity. Our mode choice model pertains to the *primary* commute mode, defined to the respondents as the mode that was used for the longest portion of the commute trip. Thus, we effectively assume that an activity of interest is being conducted on the primary commute mode, which may be incorrect for some activities. For example, the three respondents reporting using a laptop/tablet, but whose primary mode is “biking”, may have used a tablet on a walk or transit passenger leg of the trip. On the other hand, they could also have been listening to music through earbuds attached to the tablet in their backpack as they cycled to work.

approach allows us to implement weighting only for the mode choice model (see the related discussion in Appendix A), thus more appropriately representing many effects that influence laptop use on the smaller-share collective modes.

Among 23 reported activities, we selected the propensity to use a laptop, netbook, or tablet computer for work or personal purposes (“use a laptop”, hereafter) for inclusion in the mode choice model specification. This decision was based on several reasons. For one thing, conceptually, personal computer usage could be strongly associated with a plethora of productive tasks that commuters would like to undertake to make more valuable use of their travel time (objectively and subjectively). This assumption is corroborated by the data: 61.5% of the respondents who used laptop reported “allows me to get more work done” to be among the benefits of the activities they do while commuting. For another thing, an exploratory factor analysis (Malokin et al., 2015) that we developed on the propensities to engage in activities while traveling showed close association between using a laptop and “writing/editing electronic documents”: together with “thinking/ planning” and “reading electronic documents”, they all load on one factor, i.e., “productive [activities]”. While writing/editing electronic documents could be enabled by a (continuously increasing) variety of technological devices, usually a laptop computer (or a tablet) represents a major gateway for being productive, especially while traveling. From a general perspective, we can view the propensity to use a laptop/ tablet/ netbook during a trip as a *proxy* for the propensity to be productive while commuting on a given mode. More literally, however, we can view it as *only one of various ways* to be productive while commuting, and as such we can expect our results to understate the influence on mode choice of a propensity for productive travel multitasking. Either way, the laptop is merely one current medium of achieving such productivity, which will doubtless be at least partly supplanted by other media over time. To the extent that such new media will also allow for more and better ways to productively travel multitask, our results will be further understated. However, the *methodology* described in this study is robust with respect to advances in technology, and can readily be applied to new and improved media as they emerge.

Although the propensity to use a smartphone, another ICT-based activity which is even more commonly conducted while traveling than using a laptop (31.5% and 6.5% reported using a smartphone and laptop, respectively), was also tested in the mode choice model, it consistently produced coefficients with a negative sign, implying that using a smartphone *decreased* the utility of the given mode. Not only is this counterintuitive, but also, from the conceptual perspective, it seems unlikely that the decision to use a smartphone takes precedence over (and influences) the choice of a commute mode. Rather, it seems more plausible that the opposite direction of causality is indicated, meaning that commuters are more inclined to use smartphones on “lower-utility” modes, to help compensate for the greater disutility of those modes³. This finding and interpretation is consistent with others in the literature (e.g., Ettema et al., 2012; Mokhtarian et al., 2015). Consequently, we chose to exclude the smartphone propensity variable from the model. Keeping in mind that the data were collected in 2011, it is likely that smartphones have become much more prevalent as a productivity tool now than they were at the time (an example of the new media referred to above), so that results obtained with more recent data (potentially including the measurement of additional or alternative attitudinal constructs) may be different. However, it is also possible that during the commute, smartphones are still more often used for entertainment (games, texting, web-browsing) than for productivity – a useful subject for further research.

Model estimation results of the propensity to use a laptop while traveling on each mode are presented in Table 5⁴ (an alternative way of presenting the results of the estimation – as utility function equations – can be found in Appendix B). For economy of presentation we do not interpret the models here, but a full discussion/interpretation of these and other activity propensity models is found in Berliner et al. (2015). All mode-specific final specifications contained exogenous explanatory variables except for the biking model, which, due to the few cyclists reporting using a laptop during their commute, has only a constant term (yielding constant predicted propensities equal to the (low) share of bicycling commuters who use a laptop; see footnote 2). The goodness-of-fit measures, ranging from 38% to 84% of information explained (Hauser, 1978), are high in part because of the unbalanced shares of laptop choosers and non-choosers for most of the modes. Temporarily removing the constants (Mokhtarian, 2016) shows that the explanatory variables account for more than 97% of the explanatory power of the full model for the commuter rail and drive-alone modes, and as low as about 8% for the transit mode. In general, the models exhibit respectable predictive ability, considering their parsimonious nature and the inability of the available variables to fully capture the many factors behind specific multitasking behaviors.

In particular, it is worth pointing out that data were not available on crowdedness, ride bumpiness, and other travel experience variables, which could certainly be expected to influence the propensity to multitask in general, and to use a laptop in particular. However, the net influence (on using laptop) of the level of service and trip conditions experienced by the users of each mode is reflected in the constant terms of the mode-specific models of Table 5. Not surprisingly, the constants (which, of course, also include

³ An alternative argument could be that the result is merely a consequence of the coincidence that the modes with lower market shares – i.e., lower average utility – are also those more conducive to using a smartphone, but the same argument is true for using the laptop, which does not explain why the coefficients of the two variables have opposite signs.

⁴ One point that may deserve mention here, however, is the use of commute distance rather than duration in the model. As a reviewer pointed out, duration is arguably the more relevant of the two measures. However, (1) distance and duration *are* highly correlated (above 0.93 for all modes), and (2) using distance allows us to create laptop propensities even for modes that are not currently in the individual’s choice set (for example, in cases where there is no bus/light rail service that connects residence and workplace locations). Although such modes, by definition, will not come into play in the mode choice model, we considered it useful for our methodology to be able to create the laptop propensity in case those alternatives were to become available to the commuter in the future. For this reason, we chose to use distance as a very good (and always available) proxy for the conceptually more apt (but not always available) duration. The same reason (2) applies to the decision not to use the *mode multitaskability* perception in the binary logit model specifications, as we sacrifice an explanatory variable for the benefit of having a full set of measures of the propensity to use a laptop/tablet.

Table 5
Binary logit models of the mode-specific propensity to use a laptop, netbook, or tablet computer.

Variables	Biking	Commuter rail	Transit	Shared ride	Driving alone
General attitudes^a					
<i>Pro-technology</i>	– ^b	–	0.549 ^{***} (0.120)	–	–
<i>Travel is wasted time</i>	–	–	–	0.564 ^{***} (0.168)	–
Multitasking preference					
<i>Multitasking preference (polychronicity)</i>	–	–	0.241 ^{**} (0.120)	–	–
<i>Multitasking is normative</i>	–	–	–	–	0.401 ^{**} (0.184)
Time use					
<i>Time spent working</i>	–	–	–	–	–0.372 ^{**} (0.185)
<i>Has to work on commute</i>	–	1.148 ^{***} (0.209)	0.368 ^{***} (0.114)	1.262 ^{***} (0.189)	0.770 ^{***} (0.172)
<i>Has to do recreation on commute</i>	–	–	–	–	0.946 ^{***} (0.234)
<i>Would like to do recreation on commute</i>	–	–	–	0.685 ^{***} (0.225)	–0.389 ^c (0.230)
<i>Has to multitask at work</i>	–	–	–	–0.456 ^{**} (0.197)	–
<i>Would like to be available to people</i>	–	–	–	0.486 ^{***} (0.184)	–
<i>Would like to take same route^e</i>	–	–0.543 ^{***} (0.203)	–	–0.383 ^{**} (0.188)	–
Socioeconomic characteristics					
<i>Female</i>	–	–1.360 ^{***} (0.431)	–	–	–
<i>Age</i>	–	–0.049 ^{***} (0.015)	–	–	–
<i>Hourly waged</i> (= 1 if 'yes', = 0 otherwise)	–	–3.276 ^{**} (1.265)	–	–	–
<i>Vehicle age</i>	–	–	–	–	–0.102 ^{**} (0.041)
<i>Annual household</i> <i>per capita income, \$000</i>	–	–	–	–0.021 ^{***} (0.006)	–
<i>Travel distance, mi</i>	–	0.026 ^{***} (0.007)	–	0.029 ^{***} (0.008)	–
Constants					
<i>Constant</i>	–4.470 ^{***} (0.000)	0.313 (0.827)	–2.268 ^{***} (0.135)	–4.408 ^{***} (0.483)	–2.178 ^{***} (0.415)
N (for whom given mode is primary)	265	197	811	389	1001
Choosers (of laptop during commute)	3	95	95	72	37
$\mathcal{L}(0)$	–183.684	–136.550	–562.142	–269.634	–693.840
$\mathcal{L}(c)$	–16.426	–136.426	–292.922	–186.341	–158.328
$\mathcal{L}(\hat{\beta})$ without constants	–183.684	–84.192	–539.375	–191.799	–148.371
$\mathcal{L}(\hat{\beta})$	–16.426	–84.128	–272.025	–113.711	–132.445
$\rho^2(\mathcal{L}(0)$ base) with ASC	0.9106	0.3839	0.5161	0.5783	0.8091
Adjusted ρ^2 ($\mathcal{L}(0)$ base)	0.9051	0.3326	0.5090	0.5449	0.7990
Share of explanatory power due to true variables ^d , %	0.00	99.88	7.85	49.92	97.16

***, ** = significant at 1%, 5%.

^a Effects of the variables are represented by an estimated coefficient and standard error (in parentheses).

^b Dashes indicate coefficients that were constrained to be zero after they were found to have significance > 0.05.

^c This coefficient is significant at the > 0.09 level. It was more significant in preliminary specifications; however, after additional data cleaning to replace missing values, which increased the sample size, the coefficient exceeded the 0.05 threshold. It was maintained in the current specification for its conceptual merit.

^d Defined as the ratio between the ρ^2 for the model without ASC and the ρ^2 for the model with ASC.

^e Standardized response to this single item.

the effects of other unobserved variables) are negative (reflecting a lower propensity to use laptop) for all alternatives other than commuter rail.

The estimated mode-specific propensities given the chosen mode are shown in Fig. 1. The results are indeed interesting, showing, for instance, that the distributions of the laptop propensities for the rail and shared ride modes differ substantially between rail

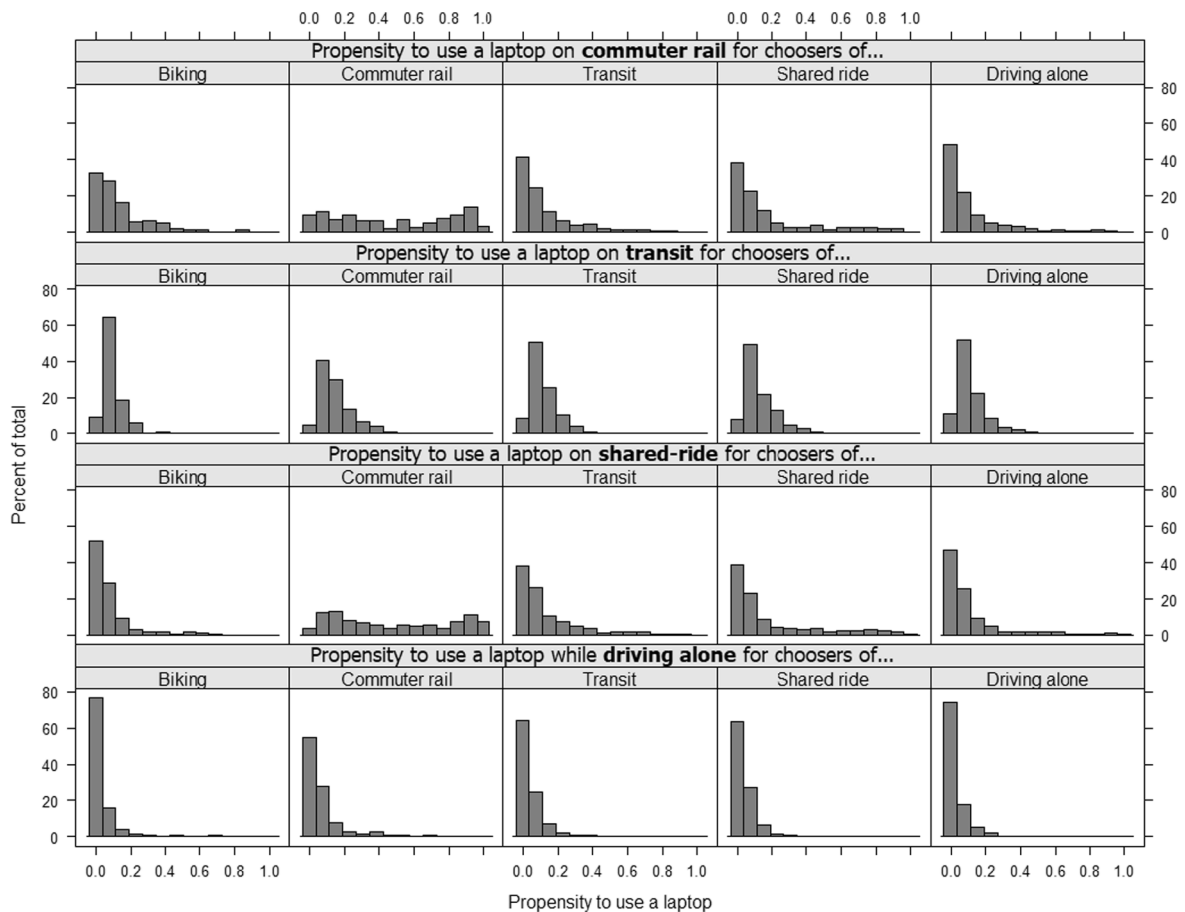


Fig. 1. The estimated mode-specific propensities to use a laptop (row) given the chosen mode (column).

choosers and choosers of the other modes (as a result of differing values on the explanatory variables between rail choosers and others). In these two instances, the distribution for rail choosers has a uniform-like shape while for the remaining cases the distribution has a distinctive exponential decay or gamma-like shape. This signifies that a far greater share of rail choosers has a relatively high propensity to use laptops on the two modes that arguably permit it best (given that crowded conditions, shorter trips, and more frequent transfers on local transit are often not conducive to laptop use), compared to choosers of other modes. In other words, those who are most inclined to use laptops while commuting have been able, to a certain extent, to sort themselves into a mode that allows them to do so, whereas even if choosers of other modes happened to find themselves on commuter rail or sharing a ride, they would still not be highly inclined to use a laptop.

5. MNL mode choice model estimation and interpretation

5.1. Dependent and explanatory variables

In this paper, we model the choice of the “primary” commute mode. Respondents selected their primary mode from a list of 13 alternatives in the survey. However, some of these alternatives were not chosen by many; others were conceptually rather similar. Accordingly, for the purposes of this study, we grouped the 13 alternatives into five broader categories: (a) driving alone, (b) shared ride (including carpooling, vanpooling and taking an employer shuttle), whether as driver or passenger, (c) local transit (bus, light rail, subway) – referred to as “transit” hereafter, (d) intercity/commuter rail, and (e) biking. Each respondent was asked to report perceptions for four of those five mode categories. Everyone was presented with categories (a), (b) and (c)⁵; in addition, online respondents whose one-way commute distance was less than 10 miles were asked to report mode perceptions for category (e), and

⁵ For each of categories (b) and (c), respondents were instructed to choose a specific mode to rate, as follows: “Please answer with respect to **ONE** of the following means of transportation: the one you **actually use most**, if applicable, or else the one **most realistic for your current commute circumstances**. **EVEN** if you seldom or never use this means of travel, your responses will help us understand **WHY** you don’t use it. **Please check the box indicating which means of transportation you have in mind when answering these questions.**”

everyone else (including all paper survey respondents) was presented with category (d). Although we allowed people to report walking as a primary commute mode and provide their perceptions for it, only 40 respondents in the full sample chose this mode. For this reason, we simplified the universal choice set by excluding those cases from the working dataset.

A respondent was assigned (for example) a transit alternative in his choice set if travel time and cost could be obtained, and if self-reported mode perceptions for bus, light rail or subway were present. A total of 45 respondents were excluded from the working sample because they reported perceptions for only one mode; the remaining cases had 2–4 modes in their choice set.

As discussed in [Section 3](#), the explanatory variables available for this study include the following:

- general attitudes, personality traits, and attitudes toward waiting;
- scores on the time use and preference factors shown in [Table 3](#);
- perceptions of four modes, as shown in the “mode perceptions” block of [Table 2](#), which were condensed into the three factors plus single item shown there;
- travel time and cost, which were externally obtained for each feasible mode using online tools including Google Maps and other sources (as described in [Section 3](#)), as well as headways for the transit and rail modes, using the same sources;
- the propensity to use a laptop while traveling, which was computed for each case using mode-specific binary logit models (as described in [Section 4.2](#)); and
- socio-demographic variables.

The mode perceptions, travel time (with the exception of in-vehicle travel time, which was allowed to have a different coefficient for biking), travel cost, and the propensity to use a laptop (travel multitasking) are generic variables (following [Hensher and Johnson, 1981](#), we use “generic” to describe a variable that can take on different values for each alternative for a given person). The remaining variables are individual-specific, and they were given alternative-specific coefficients in the model estimation (with driving alone as the base alternative).

To reproduce population mode shares ([Table 1](#)) and remove the bias in coefficient estimators that would otherwise be associated with our essentially choice-based sampling strategy, each case was weighted (by the ratio of population to sample market shares for the alternative chosen by that person) in the calculation of the log likelihood function and resulting probabilities ([Ben-Akiva and Lerman, 1985](#)).

5.2. Model results

[Table 6](#) presents the summary statistics for the final mode choice model (estimated with NLOGIT 6) and its benchmarks. An alternative way of presenting the results of the estimation – as utility function equations – can be found in Appendix B. The final model explains 58% of the information in the data, of which 90% is accounted for by the variables *other* than the alternative-specific constants in the model. This is considered quite good for a five-alternative revealed preference mode choice model. Consistency with the Independence of Irrelevant Alternatives (IIA) assumption was investigated by conducting Hausman-McFadden tests, and by evaluating a number of alternative model structures, including several nested logit and cross-nested logit specifications. All of these tests failed to reject the null hypothesis that IIA holds in this case. Since some of the modes would be considered “similar” to each other (notably commuter rail and transit; drive alone and shared ride; and shared ride and transit), this is a useful illustration of the point that IIA is a property that a given model specification may or may not have, and not a property inherent to a set of alternatives ([Train, 2009](#)). A well-specified model can capture among its *observed* variables the characteristics common to multiple modes, leaving its *unobserved* variables uncorrelated as is required for IIA to hold.

Coefficients for all the core generic variables have the expected signs and are strongly significant in the model. In the subsections below, we discuss key results for each group of variables in turn.

5.2.1. Socio-demographic variables and objective commute mode attributes

Several socio-demographic variables are significant in the model, all with expected signs. Except for *limitation on walking*, which is a standardized score (created from the 3-point ordinal responses to the item “Do you have any physical conditions or anxieties which prevent or limit you from walking?”), the rest of the socio-demographic traits are measured with dummy variables (= 1 if an attribute is present, and 0 otherwise). The possession of a driver’s license noticeably lowers respondents’ utility for transit as a commute mode. This means that to target drivers, public transit must outweigh that effect through superiority on other characteristics (e.g., including the ability to multitask). Gender differences appear only with regard to shared rides: females are more likely than males to carpool/vanpool or to take a shuttle. These results are consistent with others in the travel behavior literature. For example, [Rosenbloom and Burns \(1994\)](#), citing several national and international studies, point out that women are more likely both to carpool and to drive alone to work. These choices are often determined by family obligations, types of jobs available to females, household and work locations, prevailing income levels, single parenthood, etc. The more recent study by [DeLoach and Tiemann \(2012\)](#) corroborates this finding, specifically for fampooling (sharing a ride with a family member).

Respondents who identified themselves as white have higher utilities for public transit modes. This is a somewhat counterintuitive finding, because whites are the least represented race group among public transportation riders nationally (cf. [AASHTO, 2015](#)). The effect is probably associated with the local conditions in the study region of Northern California, where areas intensively covered by transit networks often overlap with areas having a higher prevalence of affluent white residents. Various types of physical and mental limitations are measured through the standardized variable *limitations on walking* (with a higher value corresponding to greater

Table 6
Multinomial logit commute mode choice model (weighted sample).

Variables	Biking	Commuter rail	Transit	Shared ride	Driving alone
Socioeconomic characteristics^a					
<i>Driver's license</i>	– ^b	–	–1.890** (0.8231)	–	base
<i>Female</i>	–	–	–	0.393*** (0.1510)	base
<i>Race: white</i>	–	–	0.532** (0.2167)	–	base
<i>Limitation on walking</i>	–	–	–	0.166*** (0.0559)	base
Objective mode attributes					
<i>In-vehicle travel time, min</i>	–0.163*** (0.0592)	· · · · ·	· · · · ·	–0.016*** (0.0056)	· · · · ·
<i>Out-of-vehicle travel time, min</i>	· · · · ·	· · · · ·	· · · · ·	–0.048*** (0.0089)	· · · · ·
<i>One-way commute cost, ln(\$)</i>	· · · · ·	· · · · ·	· · · · ·	–1.175*** (0.1375)	· · · · ·
General attitudes					
<i>Pro-active modes</i>	2.088*** (0.4029)	–	–	–	base
<i>Pro-transit</i>	–	0.954*** (0.2931)	0.825*** (0.1150)	0.201*** (0.0818)	base
Multitasking preference					
<i>Polychronicity</i>	–	–	–	0.191*** (0.0693)	base
Mode perceptions					
<i>Mode convenience</i>	· · · · ·	· · · · ·	· · · · ·	0.455*** (0.0616)	· · · · ·
<i>Mode benefit /cost</i>	· · · · ·	· · · · ·	· · · · ·	0.368*** (0.0679)	· · · · ·
<i>Mode comfort</i>	· · · · ·	· · · · ·	· · · · ·	0.405*** (0.0563)	· · · · ·
<i>Mode multitaskability</i>	· · · · ·	· · · · ·	· · · · ·	0.098** (0.0431)	· · · · ·
Propensity for productive travel multitasking					
<i>Propensity to use a laptop/ tablet/ netbook</i>	· · · · ·	· · · · ·	· · · · ·	1.240*** (0.3036)	· · · · ·
Constants					
<i>Constant</i>	–5.327*** (1.0289)	–2.959*** (0.3607)	0.785 (0.8272)	–2.752*** (0.2227)	base
Number of observations	2229		$\mathcal{L}(\hat{\beta})$	–1127.247	
$\mathcal{L}(\mathbf{0})$ (varying choice sets ^d)	–2655.817		$-2(\mathcal{L}(\mathbf{0}) - \mathcal{L}(\hat{\beta}))$	3057.140	
$\mathcal{L}(\mathbf{c})$ (varying choice sets)	–1555.064		ρ^2	0.5756	
$\mathcal{L}(\hat{\beta})$ without constants	–1272.557		Adjusted ρ^2	0.5673	

***, ** = significant at 1%, 5%.

^aEffects of the variables are represented by an estimated coefficient and standard error (in parentheses).

^bDashes indicate coefficients that were constrained to be zero after they were found to have significance > 0.05.

^cCentered coefficients preceded and followed by dots represent generic coefficients (i.e., constrained to be equal across the alternatives indicated by the dots).

^dNote that when choice sets differ by individual, the unweighted equally-likely log-likelihood is not $-N \ln J$ as it is when all N cases have the same J alternatives, but rather $-\sum_n \ln J_n$, where $J_n \leq J$ is the number of alternatives in person n 's choice set. This number will be larger (less negative) than $-N \ln J$, reflecting the information contained in the assumption that some alternatives have a zero probability of being selected rather than $\frac{1}{J}$ (a similar comment applies to the market-share log-likelihood, $\mathcal{L}(\mathbf{c})$). For comparison, the unweighted equally-likely log-likelihood corresponding to equal choice sets is $-2229 * \ln 5 = -3587.437$, so the difference is considerable. The *weighted* equally-likely log-likelihood for individual-specific choice sets is equal to $-\sum_n w_{j(n)} \ln J_n$, where $j(n)$ is the alternative chosen by person n and $w_{j(n)}$ (defined as the population share of $j(n)$ divided by the sample share of $j(n)$) is the weight for someone choosing alternative j . In the special case of equal choice sets, the unweighted and weighted equally-likely log-likelihoods are equal.

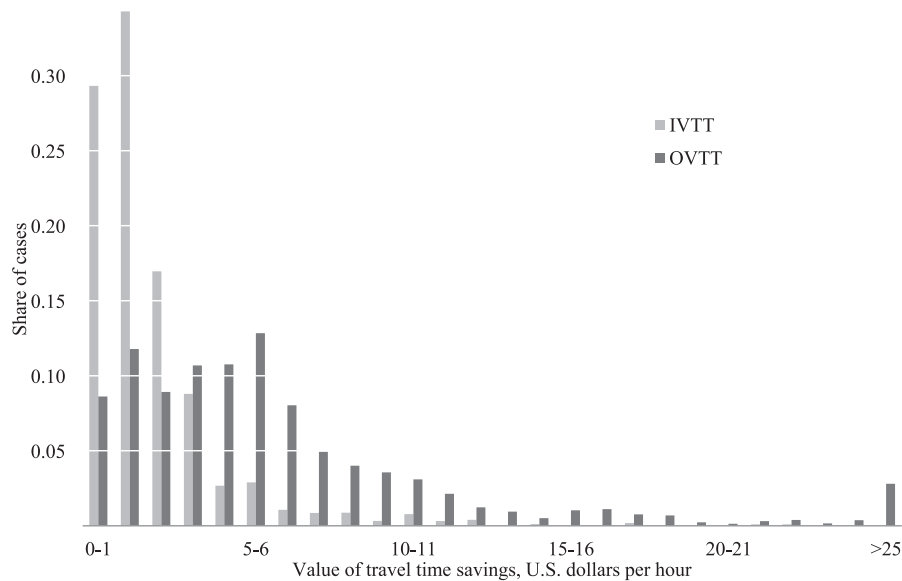


Fig. 2. Distribution of the weighted value of travel time savings (IVTT and OVTT) for non-bikers in the sample (N = 2037).

limitations). This variable is significant with a positive coefficient for shared ride. In other words, commuters who have stronger limitations on walking have a higher probability of sharing a ride with others than do those with weaker or nonexistent limitations.

The coefficients for in-vehicle and out-of-vehicle travel time (IVTT and OVTT) and for the natural logarithm of travel cost are negative, which is consistent with conventional wisdom. In the final model specification, we estimated two different IVTT coefficients, respectively for the biking alternative only and for all other modes. The estimated IVTT coefficient for biking is more than ten times larger in magnitude than the one for the other modes. In other words, according to the model results, the typical commuter in our sample would prefer 10.23 min commuting inside a vehicle over each minute on a bicycle, for example as an effect of the greater physical effort required by biking, or the effects of unpleasant traffic conditions, adverse weather, and topography. As the differences among the other alternative-specific coefficients for IVTT were not statistically significant, we constrained those coefficients to be equal across alternatives, for the sake of parsimony. OVTT, which is the sum of walking and waiting time for commuter rail and public transit alternatives, is perceived as three times more onerous than non-biking IVTT, a finding which is consistent with the dominant literature: public transportation users perceive access and waiting times as more inconvenient than in-vehicle travel time.

We tested multiple model specifications with different transformations of the one-way commuting cost variable. Allowing alternative-specific coefficients for this variable resulted in a counterintuitively insignificant coefficient for commuter rail, and having a non-log-transformed generic coefficient for the travel cost variable caused the generic coefficient of the propensity to use a laptop variable to become insignificant. However, besides resulting in strongly significant generic coefficients for the cost and propensity variables, a logarithmic transformation of the travel cost variable, a standard practice, produced a better fit to the data, and thus, it was selected as the final specification.

Monetizing the utility of saving travel time (via a VOTTS computation) has long been an important subject for transportation research and planning, and as indicated in Section 2, there has been considerable speculation about the impacts of travel-based multitasking on VOTTS. Accordingly, it is of interest to examine the VOTTS implications of the present model, to position it relative to more conventional mode choice models in the literature. We reserve a more in-depth investigation of the impact of multitasking on VOTTS for a separate paper (Malokin et al., 2017).

The log-transformation of travel cost causes the value of travel time savings (VOTTS) to vary across individuals. Fig. 2 summarizes the distribution of the VOTTS, respectively for IVTT and OVTT, among the commuters in the sample. The weighted mean VOTTS for non-bikers is 2.15 U.S. dollars per hour (\$/hr) for IVTT and \$6.45/hr for OVTT, respectively. The weighted median VOTTS of IVTT and OVTT for non-bikers is respectively \$1.63/hr and \$4.90/hr. At first glance, these estimates are substantially lower than the simple ballpark values suggested by U.S. DOT (35–60% and 80–120% of the hourly wage for IVTT and OVTT, respectively) (Trottenberg, 2011). According to the results of the model estimation, only 1.89% and 3.08% (respectively for IVTT and OVTT) of respondents have a weighted individual value of travel time savings that falls into the aforementioned ranges. However, Hensher and Wang (2016) showed that correcting for productive and leisure time while traveling for business purposes reduces VOTTS by 35%, 59%, and 42% for car, train, and bus respectively, supporting the expectation that conventional VOTTS numbers are inflated by the neglect of this factor. Furthermore, the literature identifies several sources that affect empirically-derived VOTTS in specific samples (in contrast to the simplified and policy-influenced guidelines set by government agencies): trip purpose, trip mode, distance traveled, travelers' income, etc. Applying the results of previous meta-analysis studies (Shires and de Jong, 2009; Abrantes and Wardman, 2011) to our context, the VOTTS modeled as a function of these factors would yield a mean of \$3.78/h for IVTT and \$4.81/h for OVTT, after correcting for historical currency exchange rates and inflation. Thus, our results are largely in line with those in the

academic literature. However, the model specification, namely including attitudinal and multitasking variables, also influences the computed VOTTS: these factors may lower the estimated VOTTS in our sample. For a more detailed discussion of VOTTS variability in this study, refer to Malokin et al. (2017).

5.2.2. General attitudes

Among the attitudinal variables that have a significant impact on mode choice, the *pro-transit* factor is positively associated with the choice of commuter rail, public transit, and shared ride modes. The *pro-transit* factor has a double connotation of conveying respondents' preferences both to take transit and to avoid driving as often as possible: with "driving alone" as the base, a positive factor score adds to the utility of the affected modes, to a greater extent for commuter rail, followed by transit and shared ride. This is a plausible result, given that commuter rail is likely to have a higher concentration of choice riders while local transit usually draws more captive riders (e.g., Giuliano, 2005; Taniguchi, 2012). The effect on shared ride users could be due to the half-way nature of this mode, with characteristics falling between those of the driving alone and public transportation modes.

Another "lifestyle" factor has significant effects on mode choice: the *pro-active* (non-motorized) mode attitude manifests people's desire to walk or bike instead of driving whenever possible. Not surprisingly, this factor is strongly significant for the bike alternative, with a large positive coefficient.

5.2.3. Mode perceptions, multitasking preference, and multitasking propensity

All four mode perceptions have positive coefficients, meaning that the more favorably a given mode is perceived on various attributes, the greater the probability that it will be chosen. Since all four perceptions are standardized, by comparing the coefficient magnitudes we can note their order of importance to mode choice. *Convenience* has the greatest impact among them, followed respectively by *comfort*, *benefit/cost*, and the *ability to multitask*. Judging by the magnitude of the coefficients, it appears that a mode's convenience and comfort are respectively more than four and three times as important, in terms of effect on the perceived mode utility, as its multitasking conduciveness. However, given that the ability to multitask is measured as a standardized single item (rating of each mode on "ability to do things I need/want while traveling") while the remaining three perceptions are factor scores based on several items, it is reasonable to speculate that the multitasking variable has greater measurement error, and therefore that its coefficient will have a greater attenuation bias than the others (e.g., Cameron and Trivedi, 2005, Chapter 26). In any case, it is probably fair to say that although the ability to perform activities while traveling has a significant effect, it is not a dominant criterion in mode choice considerations. Both facets of this result are quite consistent with expectations. Further, given that the mean rating of the drive-alone mode on this item is higher than the mean ratings for other modes (both overall, and specifically for choosers of shared ride and bicycling as well as driving alone), it is also possible that a sizable share of respondents interpreted the item in a way differently than we intended,⁶ which could have additionally attenuated the variable's influence.

We also tested the impact of an individual's general propensity to multitask. This factor is significant only for the shared-ride mode (relative to driving alone). Its coefficient has the expected positive sign, although the magnitude indicates a rather small impact on the mode choice. This suggests that a general orientation toward multitasking is largely unrelated to one's mode choice consideration directly. At first glance, it might be expectable that highly polychronic people would be more likely than others to multitask while traveling; however, it is also plausible that monochronic individuals do not see the routine commute as a real distraction competing for their attention. Rather, a person's commute might be considered a passive background over which an active task can easily be laid (Circella et al., 2012). To the extent that both mechanisms are at work simultaneously, a polychronic orientation will have little to no influence on mode choice, on average. Still, individual propensities for conducting selected activities are a function of various polychronicity measures, as shown for laptop in Section 4.

Finally, the laptop propensity variable was also significant in the model. As described in Section 4, this variable was modeled using the subsamples of mode choosers, where the specifications (including the alternative-specific constants ensuring that mode-specific shares of laptop adoption were replicated) of those mode-specific models already accounted for the differential conduciveness to using a laptop that pertained to each mode. Thus, driving alone and transit tended to have low conduciveness, while commuter rail had high conduciveness. This result is natural: for drivers, the mental and physical resources required for the driving task prevent the individual from efficiently performing complex activities while driving. For transit users, we can speculate that lower comfort on board (including crowding and vibrations) and the potential subdivision of a trip into several shorter legs (thereby increasing the "overhead" time of unpacking and packing one's productivity tools; see, e.g., Watts, 2008) creates an unsupportive environment for productive tasks. In contrast, commuter rail (at least in the area of study) usually offers a seat, tables, electric outlets, internet connectivity (Wi-Fi), and longer (on average) in-vehicle travel time, all of which contribute to increasing the propensity to be productive while traveling.

The estimated positive coefficient for this variable indicates that a propensity to be productive "on the go" while commuting on a

⁶ We deliberately avoided the use of the term "multitasking" in this item, out of concern that not all respondents would be familiar with the term or think of "activities conducted while traveling" as multitasking. We also deliberately placed the item in question ("ability to do things I need/want while traveling") after the item "ability to run errands on the way to/from work" in the block of 14 perceived mode attributes, to minimize possible confounding of the two. However, it is possible that respondents were still prompted to think of the ability to make multiple stops along the way when they encountered the item in question. Alternatively, in the case of choosers of driving alone, it is possible that they subconsciously tailored the things they "need/want" to do while traveling to fit the capabilities of their preferred mode, or also, of course, that they truly did not need or want to do things that were incompatible with driving.

certain mode *increases* the utility of that mode. When model specifications with alternative-specific coefficients for the laptop propensity variable were tested, only commuter rail and shared ride had statistically significant estimated coefficients (positive, as were the insignificant coefficients for drive-alone and transit, with the one for biking set to zero since the variable does not vary within that alternative). However, using alternative-specific coefficients presents a potential conceptual challenge. Although in principle we saw nothing wrong with allowing a unit of propensity to have a different *impact* on the utilities for different modes, in addition to the propensity *itself* already taking on a differential value for different modes (just as travel time might have an alternative-specific *coefficient* as well as an alternative-specific *value*), it seemed unnecessarily cumbersome, conceptually, to do so. For one thing, our propensity variable differs from travel time in that time *does* have an objective measurement, and allowing time to have an alternative-specific coefficient reflects an assumption that the *perception* of the (dis)utility of time could differ by mode. By contrast, the propensity variable, itself a function of the utility of using a laptop, is by nature subjective at the outset, and, as mentioned, by nature already accounts for the mode-specific differences in that utility. For another thing, allowing the coefficient as well as the value of the propensity variable to differ by alternative would complicate the scenario-testing discussed in the next section: to reflect an autonomous vehicles scenario, should the *value* of the propensity variable be manipulated, its *coefficient*, or both? Accordingly, we retained laptop propensity as a generic variable in the model.

6. Role of multitaskability: transit-advantage and autonomous vehicle scenarios

Using the results from the model estimation, we can further investigate the contribution to commute mode choice of the propensity to use a laptop during the trip. We do so by presenting several what-if scenarios in which we estimate the changes in the weighted mode shares associated with different hypothetical values of the propensity to use a laptop and the multitasking ability perception. Table 7 summarizes the results of this analysis.

All scenarios are generated using various values of the *propensity to use a laptop* variable, with some scenarios also having altered *multitaskability mode perceptions* to reflect hypothetical “objective” changes in a mode’s multitaskability. For simplicity, we do not assume any changes in other variables; i.e., essence we adopt the perspective of, “what would happen if laptops were unavailable, or AVs were available, *today*?” Except for the first scenario, they are grouped in pairs and denoted by Roman numerals. The first (“I”) scenario in each pair is the result of manipulations only in the *propensity to use a laptop* variable, whereas the second scenario (“II”) involves simultaneous changes in both the *propensity to use a laptop* and the *multitaskability mode perception* variables.

The first scenario, *laptop unavailability*, simulates the potential mode shifts that would happen if the productive multitasking propensity did not have any effect on the utility functions of the alternatives. Conceptually, this scenario allows evaluating the mode shares that would be observed if laptops were not available (i.e., passengers were not able to carry out productive activities while traveling), or, in other terms, what proportion of mode shares are attributable to the ability to engage in this multitasking behavior.

Table 7
Weighted mode shares under various assumptions on multitasking propensity/mode multitaskability,^a %

Scenario name	Assumptions	Biking	Commuter rail	Transit	Shared ride	Driving alone
Current population shares		1.534	0.716	8.174	12.460	77.117
<i>Laptop unavailability</i>	For each alternative, <i>propensity to use a laptop</i> set to zero.	1.566 0.033	0.609 -0.110	7.940 -0.234	11.282 -1.178	78.605 1.488
<i>Rail dominance I</i>	For commuter rail alternative, <i>propensity to use a laptop</i> set to one.	1.534 0.000	1.444 0.727	8.113 -0.061	12.294 -0.165	76.615 -0.501
<i>Rail dominance II</i>	For commuter rail alternative, <i>propensity to use a laptop</i> set to one and <i>multitaskability perception</i> set to maximum for that alternative.	1.534 0.000	1.589 0.872	8.102 -0.072	12.264 -0.195	76.511 -0.605
<i>Transit improvement I</i>	For transit alternative, <i>propensity to use a laptop</i> set equal to the <i>propensity</i> for commuter rail (if greater).	1.526 -0.008	0.703 -0.013	8.611 0.437	12.347 -0.113	76.813 -0.303
<i>Transit improvement II</i>	For transit alternative, <i>propensity to use a laptop</i> set equal to the <i>propensity</i> for commuter rail (if greater) and <i>multitaskability perception</i> set to the sample maximum for the commuter rail alternative.	1.510 -0.024	0.695 -0.021	9.329 1.155	12.205 -0.255	76.261 -0.855
<i>Autonomous vehicles diffusion (full adoption) I</i>	For shared ride and driving alone alternatives, <i>propensity to use a laptop</i> set equal to the <i>propensity</i> for commuter rail (if greater).	1.475 -0.059	0.594 -0.122	7.707 -0.467	11.829 -0.631	78.395 1.279
<i>Autonomous vehicles diffusion (full adoption) II</i>	For shared ride and driving alone alternatives, <i>propensity to use a laptop</i> set equal to the <i>propensity</i> for commuter rail (if greater) and <i>multitaskability perception</i> set to the sample maximum for the commuter rail alternative.	1.393 -0.141	0.531 -0.185	7.157 -1.016	12.323 -0.137	78.596 1.479

^a The first row in each band displays mode shares expressed as percentages, and the second row presents the change in percentage points from the current shares under each scenario. Note that at the time of this writing, the simulation function of Limdep 10.0 does not account for weights in its calculation of the predicted aggregate alternative shares. The weights have been incorporated into the results shown here.

The second and third scenarios, which both simulate **rail dominance** conditions, identify some possible *upper* bounds for commuter rail, i.e., a “maximum” attractiveness that commuter rail could have among commuters. In these scenarios, for each individual the rail-specific *propensity to use a laptop* is set to one (implying that all rail passengers would use laptops) and (for the II scenario) the *multitaskability commuter rail perception* is set to the highest value that variable takes on across the entire sample. Such universal appeal of productive multitasking will presumably never be achieved; however it is useful to assess such a ceiling: this represents the maximum share that commuter rail could gain, all else equal, based on its laptop usability advantage alone.

The next pair of scenarios, **transit improvement**, looks at changes in mode shares associated with the enhancement of the same set of variables for the transit (local/express bus, light/metro rail) alternative. However, instead of setting the *propensity to use a laptop* on transit and the *multitaskability perception of transit* to the *highest possible* values (1 and the sample maximum, respectively), as in the previous two scenarios, in these scenarios we use the individual’s currently observed variable values for *commuter rail* as a target (if the values for these variables are greater for commuter rail than for transit for that person, which is the case for 34% and 94% in the weighted sample for the propensity and perception variables, respectively). By doing so, we set a more realistic (albeit still ambitious) goal for the transit mode’s conduciveness towards multitasking, considering that commuter rail is, on average, objectively and subjectively superior to transit in this respect (e.g., due to seat availability, and the presence of tables, electric outlets, and internet connectivity). Effectively, these scenarios evaluate how popular transit services could be if they were perceived as offering the same opportunities to use a laptop as commuter rail.

Finally, we assess the changes in commute mode choice associated with the multitasking potential of fully autonomous vehicles (AVs). Among many other revolutionary impacts, AVs (at the final level of automation, as commonly classified by [NHTSA, 2013](#)) can expand the set of activities that can be conducted while operating the vehicle well beyond what is currently feasible while driving cars. Accordingly, in the **autonomous vehicles** scenarios, for each person we assign the drive-alone and shared-ride modes the same levels of travel-based multitasking “conduciveness” as she currently perceives for commuter rail (if the latter is larger⁷). For example, if a person has a propensity of 0.7 to use a laptop on commuter rail, we assign this value to the driving-alone and shared-ride propensities (if they are smaller), simulating an AV-level of multitaskability of the latter modes. Of course, a personal (autonomous) vehicle will not be exactly equivalent to commuter rail, even in its multitaskability. On the one hand, rail may offer a ride less susceptible to motion sickness, and may offer distinctive amenities such as toilets and diverse food options. On the other hand, personal vehicles offer privacy (potentially including portable toilets), greater insulation from “stranger danger”, mobility (no transfers, real-time route adjustment, etc.), and ownership (including the potential for storage of productivity tools, and storage/preparation of food). Considering the pros and cons of each mode, commuter rail arguably provides a reasonable approximation to a travel multitasking environment for personal autonomous vehicles.

In [Table 7](#), the AV scenarios have the implicit qualifier “full availability”. This refers to the assumption that everyone in the sample has AV alternatives in their choice sets. This approach constitutes the most extreme situation, or an upper limit. A more realistic approach would account for a gradual diffusion of AV technologies. In particular, as a simplification we can consider those individuals having the highest propensity to be productive during their commute (i.e., to use a laptop/tablet/netbook) to be among the earliest group to consider AVs, followed at a later time by the less avid technology users. We reflect this assumption by repeating the **autonomous vehicles diffusion I** simulation nine more times, varying the percent of cases having AVs available from 10% to 90%, where cases are first ranked on the basis of their highest propensity to use a laptop on commuter rail (and, therefore, on future AVs), and then, at each stage, the *x* percent of cases assumed to have AVs available to them are the *x* percent highest-laptop-propensity cases. Thus, in [Fig. 3](#), the *x*-axis represents deciles of adopters such that the first quantile (the earliest adopters) in the graph corresponds to the top decile of the individual multitasking propensity in the sample (the most avid laptop users). The *y*-axis shows the relative change in mode shares given the availability stage. According to [Fig. 3](#), the bulk of the mode share shift has happened by the time the 40% of commuters with the greatest multitasking propensities consider AVs.

In the **laptop unavailability** scenario, all modes lose market share to driving alone (which shows an increase of 1.5 percentage points) and, marginally, biking. The most disadvantaged mode is shared ride, which drops by 1.2 percentage points (p.p.), followed by transit (0.2 p.p.) and rail (0.1 p.p.). Reversing the base of this scenario, we can evaluate these market share changes as the effect attributable to the use of a laptop during the commute. In other words, the mode share for driving alone would be greater by 1.5 p.p. if people had no propensity (ability) to use a laptop while traveling. A similar logic applies to the increase in ridership of the collective modes, thus giving a measure of the positive impact that travel-based productive multitasking has had on the popularity of some travel modes.

The **rail dominance** scenarios exhibit increases in the mode share for commuter rail, which would be gained at the expense of all other alternatives (except biking, which is virtually unaffected). Still, while the increased behavioral propensity to multitask on commuter rail is responsible for a substantial increase in mode share (0.7 p.p.), the incremental impact of the improved perceptions was more modest (0.15 p.p.). This could be a sign of the favorable recognition among travelers of this alternative, which is already perceived as very conducive to productive multitasking. Under these conditions, an increased propensity to use a laptop (specifically a scenario in which everybody on board uses a laptop) still has some potential to attract additional riders. It is also of interest to note the substitution patterns across modes in the **rail dominance** scenarios. Namely, the main “donor” of the increased mode share for commuter rail is driving alone, which loses 0.5 and 0.6 p.p. of mode share in the two scenarios, respectively. By contrast, mode shares

⁷ The rail-specific multitasking propensity (target) is greater than the *shared ride*-specific propensity for 48% in the weighted sample, while the sample maximum multitaskability perception (target) is higher than the *shared ride*-specific one for 95% in the weighted sample. Respectively, the targets are larger than the *driving alone*-specific variables for 74% and 65% in the weighted sample.

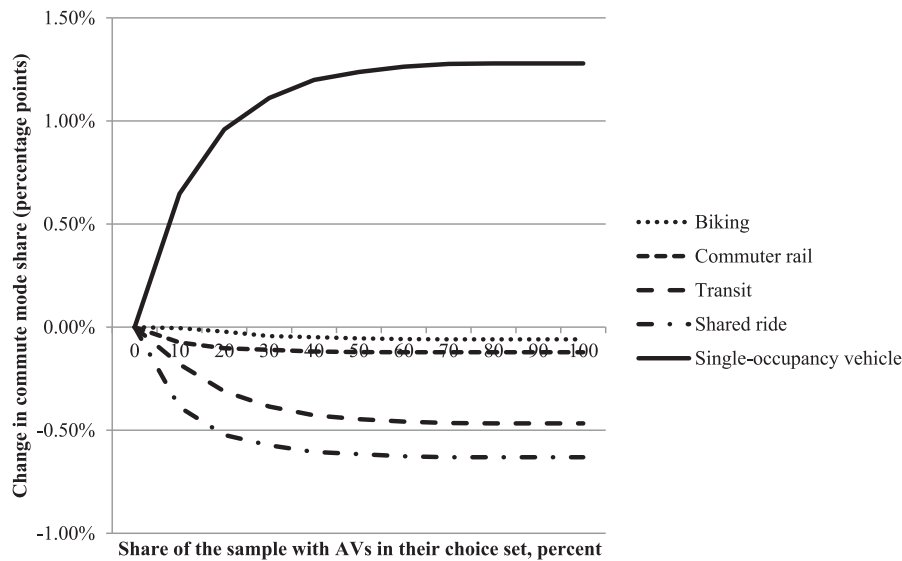


Fig. 3. Mode share changes as a function of AV availability in people's choice (consideration) sets, assuming availability is associated with the propensity to use laptop.

for transit have very modest decreases of 0.06 and 0.07 p.p. This seems to suggest different natures for the ridership bases of these public transportation modes.

The **transit improvement** scenarios have virtually no effect on biking and commuter rail, while an increase is found in the transit mode shares (+0.44 and +1.16 p.p.) at the expense of shared ride (−0.11 and −0.26 p.p.) and, more profoundly, driving alone (−0.30 and −0.86 p.p., respectively). Differently from the **rail dominance** scenarios, an increase in the perception of travel multitasking ability for transit has a substantial impact on its mode share. This could signify the importance for local transit operators of providing an environment that is more favorable towards multitasking if the main priority is to attract new riders.

Finally, according to the **autonomous vehicles diffusion** scenarios, an increase is expected in the mode share for single occupancy autonomous vehicles (SOAVs) (1.28 and 1.48 p.p., respectively, in the two scenarios). Interestingly enough, the shifts in the mode share for shared-ride AVs (SRAVs) do not show the usual compounding effect that was observed in the other scenario pairs, i.e., the magnitude of the change does not further increase in the second scenario (−0.14 p.p.) compared to the first (−0.63 p.p.). Therefore, improving the multitasking perception of SRAV partially mitigates its inferiority to SOAV, but all else equal, SRAVs still have a less multitasking-“friendly” environment compared to SOAVs. The main source of the increased demand for automobile-based modes under the **autonomous vehicles diffusion** scenarios is transit, followed by commuter rail and biking, which reinforces a common notion that automation technology is expected to damage public transportation.⁸ It is worth stressing again that the shifts in mode shares predicted in this study are only associated with some aspects of a given mode, namely its multitasking ability. They are oblivious to the other disruptive effects of automation technology on transportation demand.

A key concern with autonomous vehicles is the potentially great increase in the number of cars on the road, exacerbating traffic congestion and pollutant emissions. The **autonomous vehicles diffusion (full adoption) II** scenario shows that the mode share for driving alone would increase by 1.5 p.p., and the shared ride share would decrease by 0.14 p.p., holding all else constant (e.g., the costs of owning and maintaining a personal vehicle, travel times, etc.). These results translate into almost 59,000 additional vehicles per day on the roads in the study area's commute shed (assuming an average vehicle occupancy of 2.42 people for car/vanpools in the study area), where currently 4.12 million daily car commutes are made (according to the 5-year American Community Survey data, 2006–2010). However, additional changes in vehicle ownership (e.g., increased popularity of carsharing options that involve calling a driverless car only when needed) and intelligent dynamic rideshare matching could be possible solutions, among others, that might at least partially curb the infrastructure load.

7. Conclusions and future research

In this study we investigated the impact of multitasking attitudes and propensities on mode choice and valuation of travel time – to our knowledge, the first revealed preference model developed for this application. Based on a survey of 2229 Northern California commuters, we built an MNL model to predict commute mode choice as a function of objective mode characteristics, socio-economic aspects, individual attitudes and traits, time use, and activities conducted while commuting. Although engagement in activities was

⁸ In this study, we do not model any automation of public collective modes, as the impact of such automation on the ability to multitask while commuting may be negligible.

reported only for the chosen mode and therefore could not be directly used in the MNL model, we circumvented this endogeneity bias by estimating binary logit models of the propensity to conduct each activity while traveling on each mode, and tested the inclusion of the predicted propensities as explanatory variables in the mode choice model. We selected the *propensity to use a laptop/tablet/netbook* as a measure of the inclination to engage in a major type of productive travel-based multitasking, to use in our final mode choice model.

The MNL estimation results show that multitasking is significant to mode choice in three ways. A *generic mode perception* coefficient is positive, indicating that greater perceived multitaskability of a travel mode adds to its utility (and, therefore, to the likelihood that the mode is chosen). The alternative-specific (shared ride) coefficient for the *general preference towards multitasking* (polychronicity) is also positive and strongly significant. And the generic coefficient for the *propensity to use a laptop/ tablet/ notebook* (i.e., propensity for this form of productivity during travel on a given mode) is positive and strongly significant.

We generated a set of scenarios, through manipulating the mode-specific multitaskability perception and propensity to use a laptop while traveling on several modes, to: (a) estimate the effect of the positive utility added by the current level of engagement in productive activities (using laptop); (b) assess the potential of travel-based multitasking to increase the appeal of commuter rail and transit at the expense of other modes; and (c) evaluate the potential impacts attributable to the adoption of autonomous vehicles, when they will offer the same level of multitasking “conduciveness” that commuter rail offers today. In view of the current existence of other ways to be productive while traveling, as well as the continued evolution of technology to permit more and better ways to be productive in the future, the impacts of *propensity to use a laptop/ tablet/ netbook* identified by this study could be viewed as a conservative estimate of the total commute mode choice impacts of productivity-oriented travel multitasking.

Based on the findings of this study, the outlook for public transportation operators is mixed: in the short and medium term, the transit improvement scenarios of Table 7 suggest that public transit modes (here defined as local/express bus and light/metro rail) have the potential to increase their ridership by appealing to the productivity attitudes and behavior of commuters. For example, a recent study (Dong et al., 2015) estimated that introducing free Wi-Fi service increased ridership on Amtrak’s Capitol Corridor (California) intercity train service by 2.7 percentage points. However, in the long term public transportation might be threatened by the diffusion of autonomous vehicle technology, which may ultimately attract commuters by providing superior mobility and accessibility (potentially with reduced costs of ownership and operation achieved through carsharing and/or intelligent rideshare matching), and with increased ability to use travel time productively. This might reinforce the existing tendency towards low-density development, further propagating urban sprawl (e.g., Mokhtarian, 2018).

The laptop propensity and mode choice models were estimated on a diverse commuter cohort which is, we believe, illustrative of urbanized populations in the United States. Clearly the cultural, transportation, and urban form contexts will be different elsewhere in the world, and thus it is unlikely that the specific empirical results of this study will be replicated outside the U.S. The methodology, on the other hand, should be widely transferable – not only to other geographic contexts, but to other dimensions of the commute mode choice context and to different choice contexts altogether. The key features of the methodology include (1) the incorporation of pertinent attitudinal variables as well as more traditional attributes of the alternatives⁹ and socio-economic traits; (2) the existence of a consequence of interest (productive multitasking, in our case) that is only observed conditional on the main choice of interest (primary commute mode, in our case) but (the anticipation of) which is assumed to influence that main choice; (3) the estimation of “consequence adoption” models on choosers of each alternative, followed by the application of those models to the entire sample to generate predicted propensities to experience that consequence if each of the given alternatives were to be chosen; (4) the incorporation of those predicted propensities as explanatory variables in a model of the main choice; and (5) plausible manipulation of those predicted propensities and/or other explanatory variables, applied to the previously-calibrated main choice model to estimate the impacts of various hypothetical scenarios. As an example of a different choice context, this methodology could potentially be applied when the main choice of interest is the adoption of shopping mode or channel (store versus online) and the consequence of interest is whether the item needs to be returned.

Related studies underway or recently completed using this same dataset include investigations of the systematic heterogeneity in the disutility of travel time (Etezady et al., 2019) and of the reported benefits and disadvantages associated with the activities conducted while commuting (Shaw et al., 2018). The early results emerging in the present paper and in these other studies suggest that this will continue to be a worthy subject of investigation for some time to come, with much remaining to be learned as technology continues to alter the landscape of possibilities.

Acknowledgements

A previous version of this paper (Malokin et al., 2015) was presented at the 94th Annual Meeting of the Transportation Research Board (TRB). The thoughtful and constructive comments of five anonymous reviewers have greatly improved the present version. This project was initially funded by the University of California Transportation Center and by the Sustainable Transportation Center of UC Davis, which receive(d) funding from the U.S. Department of Transportation and Caltrans, the California Department of Transportation, through the University Transportation Centers program. Additional financial support was provided by a new faculty grant from the Georgia Institute of Technology and by a partnership with the Capitol Corridor Joint Powers Authority (CCJPA). The authors are immensely grateful to Amanda Neufeld and Zhi Dong, who were deeply involved in the survey design and organized the

⁹ In the present application to mode choice, an additional feature of the methodology is the collection of mode attributes via Google/Bing Maps API.

data collection and cleaning effort. We wish to thank Javier R. Salgado, who helped with descriptive analysis and additional data cleaning. Special gratitude goes to Taha Rashidi, who suggested the multidimensional nested logit modeling of joint choices of mode and laptop usage. Cheng Zhuo, Aurina Lam, Eileen Coletto, Adam Stocker, Valerie Onuoha, Andre Tu, and Kelly Caines provided vital assistance during the data collection and entry. Additionally, we express our gratitude to Chandra Bhat, David van Herick, Hani Mahmassani, Aruna Sivakumar, Laurie Garrow, and William Greene for useful discussions on choice-based sampling and other technical matters.

Appendix A. Investigation of joint choice nested logit models

A.1. Issues associated with nested logit model estimation

The quest for the best specification of the weighted nested logit model for the joint choice of mode and laptop usage (estimated with NLOGIT 6 and shown in Table 8, with the pertinent attitudinal factors defined in Table 9) revealed several issues with this approach. First, estimating the two choices jointly meant that data missing on any explanatory variable in any of the laptop usage models resulted in excluding the associated case from the entire estimation. This led to problems with further unbalancing shares that were already unbalanced. For example, in the stand-alone laptop/tablet usage models of Table 5, there are three bicycle choosers who used a laptop or tablet on their commute (see footnote 2 of the paper for an explanation), whereas in the nested logit model of Table 8, that number has been reduced to zero.¹⁰ Similarly, there are 37 laptop/tablet users among solo drivers in Table 5, but only 29 in Table 8. We speculate that the difficulties we encountered in finding stable specifications of the nested logit model are probably in large measure a result of complete or quasicomplete separation problems arising from the unbalanced shares (Zorn, 2005).

Second, multiple experiments showed that specifying the lower nest models (laptop usage choice) produces different estimates depending on which underlying utility function (for “use laptop” or “do not use laptop”) an explanatory variable is associated with (an analytical proof of this is shown in Section A.2, for the special case in which each lower nest has two alternatives, and all variables are “assigned” to only one or the other of the two alternatives; the empirical evidence for one pair of specifications is presented in Tables 10 and 11). This creates an ambiguity in how to specify each utility equation: for joint choice models with a binary secondary decision, there is little conceptual differentiation between the alternative specifications, which makes the model building process rather arbitrary. In particular, the estimates of the inclusive value (IV) parameter are also affected, and in the pair of models shown in Tables 10 and 11, the different values obtained for that parameter could have led to different conclusions based on the statistical test for equivalency of the nested logit model to MNL (i.e., the t -test of the null hypothesis that the IV parameter is equal to one). In the joint estimation reported in Table 8, for consistency we specified only “use laptop” lower nest functions, leaving their “do not use laptop” counterparts as the base ($V_{\text{notusedlaptop,mode}} = 0$). However, some experimentation showed that a marginal (possibly negligible¹¹) improvement over the current best specification (with respect to the goodness-of-fit measures) could be achieved by switching one or more of the explanatory variables to the “did not use laptop” function.

The third issue is that joint estimation, which applies some parameters such as weighting systematically across the levels, could lead to undesirable effects. The problem of weighting the current nested logit model formulation is two-fold: (a) the true *joint* weights are unknown, and (b) weighting adversely impacts the laptop usage nests for modes with a minor presence in the population. To elaborate: while the regional commute mode shares are known, this is not the case for laptop usage while commuting, let alone the joint distribution of commute mode and laptop usage. To develop our joint models, we circumvented this ignorance by (daringly) assuming that the mode-specific laptop usage shares observed in the sample are representative of the broad population. Setting the issue of unknown weights aside, applying the population mode shares to the lower nest is still undesirable. Since in the region driving alone occupies the lion's share of the commute (77%), the lower nest models are affected proportionally: the significance of the explanatory variables in the laptop usage nests is boosted for those modes with a weight higher than one (driving alone and shared ride), and is hampered for those modes with a weight lower than one (transit, biking, and commuter rail). Consequently, we blur a nuanced view of the explanatory-variables landscape of the travel-multitasking phenomenon, notably, areas of that landscape that are of special interest – those pertaining to collective modes.

Finally, the joint estimation poses additional challenges for constructing “what-if” scenarios (Section 6), which may help in assessing the aggregate effect of travel multitasking on current and future regional commute mode shares. For these reasons, we adopted the alternative approach presented in the main body of the paper.

¹⁰ Even for the stand-alone binary choice model of Table 5, where there were three laptop/tablet choosers out of 268 bicyclists, we used only a constant term to specify the model. That is all the more necessary here, and even so, the constant is (1) large and negative, consistent with there being an essentially zero probability of choosing the associated alternative of laptop-with-bike; and (2) estimated with a large standard error, signifying substantial instability/imprecision (which is logical: there is a very wide range of parameter estimates which would yield an “essentially zero” probability of choice).

¹¹ In one case, moving the single variable *Explorer* (*Driving Alone*-specific) from the laptop to no-laptop branch in the context of the best specification (Table 8) changed the final log likelihood to -1207.262 (compared to -1207.575 for the base model reported in Table 8; here and below the base model estimates are in parentheses). The estimated coefficient for that variable changed to 0.05250 (0.05034). The inclusive value parameter, θ , for *Driving Alone* was 0.11596 (0.11162). The magnitudes for the upper nest estimated coefficients were also noticeably different between the two models (unlike the case in Tables 10 and 11.)

Table 8
Weighted nested logit model for the joint choice of transportation mode and laptop usage.

Variables	Biking	Commuter rail	Transit	Shared ride	Driving alone
TRANSPORTATION MODE CHOICE (upper nest)					
Socioeconomic characteristics^a					
<i>Driver's license</i>	– ^b	–	–2.043** (0.8291)	–	base
<i>Female</i>	–	–	–	0.345** (0.1557)	base
<i>Race: white</i>	–	–	0.601** (0.2352)	–	base
<i>Limitation on walking</i>	–	–	–	0.162*** (0.0599)	base
Objective mode attributes					
<i>In-vehicle travel time, min</i>	–0.149** (0.0591)	· · · · ·	–0.013*** (0.0060)	· · · · ·	· · · · ·
<i>Out-of-vehicle travel time, min</i>	· · · · ·	· · · · ·	–0.046*** (0.0093)	· · · · ·	· · · · ·
<i>One-way commute cost, ln(\$)</i>	· · · · ·	· · · · ·	–1.189*** (0.1476)	· · · · ·	· · · · ·
General attitudes					
<i>Pro-active modes</i>	2.104*** (0.4646)	–	–	–	base
<i>Pro-transit</i>	–	0.906*** (0.3369)	0.804*** (0.1236)	0.205** (0.0858)	base
Multitasking preference					
<i>Polychronicity</i>	–	–	–	0.190** (0.0744)	base
Mode perceptions					
<i>Mode convenience</i>	· · · · ·	· · · · ·	–0.459*** (0.0668)	· · · · ·	· · · · ·
<i>Mode benefit /cost</i>	· · · · ·	· · · · ·	–0.391*** (0.0723)	· · · · ·	· · · · ·
<i>Mode comfort</i>	· · · · ·	· · · · ·	–0.423*** (0.0606)	· · · · ·	· · · · ·
<i>Mode multitaskability</i>	· · · · ·	· · · · ·	–0.118** (0.0455)	· · · · ·	· · · · ·
Constants					
<i>Constant</i>	–5.691*** (1.1365)	–3.286*** (0.4481)	0.853 (0.8314)	–2.648*** (0.2314)	base

(continued on next page)

Table 8 (continued)

Variables	Biking	Commuter rail	Transit	Shared ride	Driving alone
LAPTOP USAGE CHOICE^d (lower nest)					
General attitudes					
<i>Pro-technology</i>	–	–	0.199** (0.1012)	–	0.068*** (0.0187)
<i>Travel is wasted time</i>	–	–	–	0.102*** (0.0370)	–
<i>Pro-active modes</i>	–	–	–	0.095*** (0.0366)	–0.071*** (0.0238)
<i>Pro-transit</i>	–	–	–	–	0.120*** (0.0334)
<i>The only benefit of my job is money to do other things.</i>	–	–	–	–	0.130*** (0.0257)
<i>I'd be willing to give up a day's pay to get a day off.</i>	–	–	–	–	–0.055** (0.0240)
<i>I (would) like to own a car that impresses others.</i>	–	–	–	–	0.048** (0.0207)
Personality traits					
<i>Extraverted</i>	–	–	–	–	0.046** (0.0229)
<i>Leader</i>	–	–	–	–	–0.053*** (0.0171)
<i>Explorer</i>	–	–	–	–	–0.050** (0.0209)
Multitasking preference					
<i>Multitasking preference (polychronicity)</i>	–	–	0.187** (0.0861)	–	–
<i>Multitasking is normative</i>	–	–	–	–	0.111*** (0.0275)
Time use					
<i>Has to work on commute</i>	–	0.879** (0.3416)	–	0.210*** (0.0387)	0.070*** (0.0236)
<i>Has to multitask at work</i>	–	–	–	–0.098*** (0.0366)	–
<i>Would like to do recreation on commute</i>	–	–	–	0.106*** (0.0346)	–0.132*** (0.0268)
<i>Would like to take same route</i>	–	–	–	–0.111*** (0.0382)	–0.080*** (0.0200)
<i>Has to be available to people</i>	–	–	–	0.114*** (0.0412)	–
<i>Time spent working</i>	–	–	–	–0.075*** (0.0273)	–
<i>Time spent for ICT-enabled leisure and social activities^e</i>	–	–	–	0.074*** (0.273)	0.068*** (0.0145)
<i>Has to do recreation on commute</i>	–	–	–	–	0.207*** (0.0393)

(continued on next page)

Table 8 (continued)

Variables	Biking	Commuter rail	Transit	Shared ride	Driving alone
<i>Would like to work on commute</i>	–	–	–	–	0.063*** (0.0227)
<i>Time spent for non-ICT-enabled leisure and social activities</i>	–	–	–	–	–0.066*** (0.0145)
Attitudes toward waiting^f					
<i>Don't mind waiting</i>	–	–	–	–	0.114*** (0.0290)
<i>Don't need to be equipped for a wait event</i>	–	–	–	–	–0.051*** (0.0250)
Socioeconomic characteristics					
<i>Annual household per capita income, \$000</i>	–	–	–	0.005*** (0.0012)	–
<i>Travel distance, mi</i>	–	–	–	0.006*** (0.0016)	–
<i>Race: white</i>	–	–	–	–0.228*** (0.0781)	–
<i>Vehicle age</i>	–	–	–	–	–0.019*** (0.0058)
<i>Vehicle availability^g</i>	–	–	–	–	–0.515*** (0.1264)
<i>Occupation: service</i>	–	–	–	–	0.354*** (0.0994)
<i>Share of time vehicle is available</i>	–	–	–	–	–0.065*** (0.0185)
<i>Race: black</i>	–	–	–	–	0.246*** (0.0661)
Constants					
<i>Constant</i>	–6.548 (82.0408)	–0.819 (0.6498)	–0.757*** (0.1014)	–0.652*** (0.1020)	0.384** (0.1630)
INCLUSIVE VALUE PARAMETERS					
θ	0.151 (1.8922)	0.862*** (0.0237)	0.337*** (0.0394)	0.125*** (0.0160)	0.112*** (0.0109)
<i>SD of ε</i>	0.194 (2.4268)	1.105*** (0.0303)	0.432*** (0.0506)	0.160*** (0.0205)	0.143*** (0.0139)
Number of observations	1948				
$\mathcal{L}(\mathbf{0})$	–4145.429	$-2(\mathcal{L}(\mathbf{0}) - \mathcal{L}(\hat{\beta}))$		5875.708	
$\mathcal{L}(\mathbf{c})$	–1799.691	ρ^2		0.7087	
$\mathcal{L}(\hat{\beta})$	–1207.575	Adjusted ρ^2		0.6918	

***, ** = significant at 1%, 5%.

^aEffects of the variables are represented by an estimated coefficient and standard error (in parentheses).

^bDashes indicate coefficients that were constrained to be zero after they were found to have significance > 0.05.

^cCentered coefficients with dots across the row represent generic parameters (constrained to be equal across alternatives).

^dExplanatory variables were specified only in the “used-laptop” functions in each nest. The “not-used-laptop” functions were the base (i.e., = 0).

^eStandardized responses for this single item.

^fConstructs are defined in Mishra et al. (2015).

^gA ratio between household vehicles and licensed drivers, capped at 1.

Table 9
 Personality traits and time use constructs used in the joint choice model of Table 8.

Constructs	Statements ^a	Pattern matrix loadings ^b
Personality traits^c		
<i>Extraverted</i>	Fun-oriented	0.694
	Spontaneous	0.601
	Variety-seeking	0.537
	Adventurous	0.520
	Like to meet new people	0.439
	Risk-taking	0.308
<i>Leader</i>	Ambitious	0.698
	Work-oriented	0.513
	Like being in charge	0.373
	Efficient	0.318
<i>Explorer</i>	Concerned about the environment	0.751
	Curious	0.494
	Like being outdoors	0.396
Time use^d		
<i>Time spent for non-ICT-enabled leisure and social activities</i>	With friends	0.585
	Doing hobbies	0.427
	Getting exercise	0.379
	With family	0.369
	Volunteering/ doing service	0.320

^a A statement can load on more than one construct.
^b Represents the degree of association between the statement and the construct. Only loadings greater than 0.3 in magnitude are reported.
^c How well the item describes the respondent is measured on a 5-point Likert-type scale ranging from “Hardly at all” to “Almost completely”.
^d Items measured on a 5-point ordinal scale ranging from “Way too little” to “Way too much”.

A.2. Proof that coefficients in a nested logit model differ when variables in (binary choice) lower nests are associated with different alternatives

Let m index the modes in the upper level, $m =$ bicycle (B), rail (R), transit (T), shared ride (S), and drive alone (D).

Let l index the two alternatives in the lower nests, $l =$ laptop used (L), not used (N). In the following discussion, we suppress the subscript denoting the individual case, for simplicity.

Let $V_m = \beta_m'x_m$ be the systematic portion of utility pertaining to mode m (without the inclusive value term from the lower nest), and let $V_l = \gamma_l'z_l$ be the systematic portion of utility pertaining to nest alternative l , where x and z are vectors of explanatory variables, and β and γ the respectively associated vectors of coefficients.

If we had only an unnested binary choice between L and N, it would not matter “where the z ’s went”: only differences in utility matter (Train, 2009, p. 19), so for the binary logit model we would have (where θ is the scale parameter of the extreme value distribution):

$$P_L = \frac{e^{V_L/\theta}}{e^{V_L/\theta} + e^{V_N/\theta}} = \frac{e^{\gamma'z_L/\theta}}{e^{\gamma'z_L/\theta} + e^{\gamma'z_N/\theta}} = \frac{1}{1 + e^{-\gamma'(z_L - z_N)/\theta}} = \frac{1}{1 + e^{\gamma'(z_N - z_L)/\theta}}, \tag{1}$$

a function only of $(z_L - z_N)$, and similarly

$$P_N = 1 - P_L = \frac{e^{V_N/\theta}}{e^{V_L/\theta} + e^{V_N/\theta}} = \frac{e^{\gamma'z_N/\theta}}{e^{\gamma'z_L/\theta} + e^{\gamma'z_N/\theta}} = \frac{1}{1 + e^{-\gamma'(z_N - z_L)/\theta}} = \frac{1}{1 + e^{\gamma'(z_L - z_N)/\theta}}. \tag{2}$$

For simplicity and without loss of generality, suppose that $z_L'z_N = 0$, i.e. that if the k^{th} element of z_L is *not* zero then the corresponding k^{th} element of z_N is zero, and similarly for z_N . That is, all explanatory variables in this binary choice model are “assigned” to one alternative or the other (not necessarily all to the *same* alternative), and take on the value 0 for the opposite alternative.

For ease of exposition, we will consider the special case in which all explanatory variables *are* assigned to one alternative or the other – the resulting pair of models could be termed the “stereoisomers” (or “enantiomers”) of binary discrete choice modeling. We also assume (as is the case in our application) that all variables in the binary choice model are individual-specific rather than alternative-specific, so that there is no reason for the sign of a *variable* (as opposed to the *coefficient*) to change if it is assigned to one

Table 10
Weighted nested logit model for the joint choice of transportation mode and laptop usage, with the lower nest variables associated with “not-used-laptop” branch (*Nnon-zero*).

Variables	Commuter rail	Transit	Shared ride	Driving alone
TRANSPORTATION MODE CHOICE (upper nest)				
Socioeconomic characteristics^a				
<i>Driver’s license</i>	– ^b	–2.349** (1.0126)	–	base
<i>Female</i>	–	–	0.280* (0.1513)	base
<i>Race: white</i>	–	0.600** (0.2383)	–	base
<i>Limitation on walking</i>	–	–	0.158*** (0.0590)	base
Objective mode attributes				
<i>In-vehicle travel time, min</i> –0.016*** (0.0058)		
<i>Out-of-vehicle travel time, min</i> –0.049*** (0.0097)		
<i>One-way commute cost, ln(\$)</i> –1.419*** (0.1747)		
General attitudes				
<i>Pro-transit</i>	0.956*** (0.3166)	0.861*** (0.1256)	0.264*** (0.0842)	base
Multitasking preference				
<i>Polychronicity</i>	–	–	0.215*** (0.0717)	base
Mode perceptions				
<i>Mode convenience</i> 0.418*** (0.0662)		
<i>Mode benefit /cost</i> 0.348*** (0.0759)		
<i>Mode comfort</i> 0.413*** (0.0620)		
<i>Mode multitasking</i> 0.110** (0.0462)		
Constants				
<i>Constant</i>	–0.285 (0.5014)	2.119** (1.0426)	–1.174*** (0.3030)	base
LAPTOP USAGE CHOICE^d (lower nest)				
Constants				
<i>Constant</i>	0.102 (0.5159)	2.211*** (0.2589)	1.451*** (0.1582)	3.210** (0.1271)
INCLUSIVE VALUE PARAMETERS				
θ 0.982*** (0.0083)		
<i>SD of ε</i> 1.259*** (0.0107)		
Number of observations	2010	$\mathcal{L}(\hat{\beta})$		–1404.899
$\mathcal{L}(\mathbf{0})$	–3691.503	ρ^2		0.6194

***, **, * = significant at 1%, 5%, and 10%.
^aEffects of the variables are represented by an estimated coefficient and standard error (in parentheses).
^bDashes indicate coefficients that were constrained to be zero after they were found to have significance > 0.05.
^cCentered coefficients with dots across the row represent generic parameters (constrained to be equal across alternatives).
^dExplanatory variables were specified only in the “not used-laptop” functions in each nest. The “used-laptop” functions were the base (i.e., = 0).

Table 11
Weighted nested logit model for the joint choice of transportation mode and laptop usage with the lower nest variables associated with “used-laptop” branch (*Lnon-zero*).

Variables	Commuter rail	Transit	Shared ride	Driving alone
TRANSPORTATION MODE CHOICE (upper nest)				
Socioeconomic characteristics^a				
<i>Driver's license</i>	– ^b	–2.349** (1.0189)	–	base
<i>Female</i>	–	–	0.280* (0.1518)	base
<i>Race: white</i>	–	0.600** (0.2406)	–	base
<i>Limitation on walking</i>	–	–	0.158*** (0.0594)	base
Objective mode attributes				
<i>In-vehicle travel time, min</i>	· · · · ·	· · · · ·	–0.016*** (0.0059)	· · · · ·
<i>Out-of-vehicle travel time, min</i>	· · · · ·	· · · · ·	–0.049*** (0.0110)	· · · · ·
<i>One-way commute cost, ln(\$)</i>	· · · · ·	· · · · ·	–1.419*** (0.2114)	· · · · ·
General attitudes				
<i>Pro-transit</i>	0.956*** (0.3354)	0.861*** (0.1310)	0.264*** (0.0892)	base
Multitasking preference				
<i>Polychronicity</i>	–	–	0.215*** (0.0725)	base
Mode perceptions				
<i>Mode convenience</i>	· · · · ·	· · · · ·	–0.418*** (0.0775)	· · · · ·
<i>Mode benefit /cost</i>	· · · · ·	· · · · ·	–0.348*** (0.0782)	· · · · ·
<i>Mode comfort</i>	· · · · ·	· · · · ·	–0.413*** (0.0622)	· · · · ·
<i>Mode multitasking</i>	· · · · ·	· · · · ·	–0.110** (0.0462)	· · · · ·
Constants				
<i>Constant</i>	–3.273*** (0.5290)	1.132 (1.0168)	–2.900*** (0.3267)	base
LAPTOP USAGE CHOICE^d (lower nest)				
Constants				
<i>Constant</i>	–0.082 (0.4501)	–1.764*** (0.2327)	–1.158*** (0.1325)	–2.561** (0.1185)
INCLUSIVE VALUE PARAMETERS				
θ	· · · · ·	· · · · ·	–0.783*** (0.0502)	· · · · ·
<i>SD of ε</i>	· · · · ·	· · · · ·	–1.005*** (0.0643)	· · · · ·
QUANTITIES TRANSLATING BETWEEN <i>Lnon-zero</i> and <i>Nnon-zero</i> MODELS				
$\Gamma_{m,Lnon-zero}$ (eq. (5))	0.642	0.100	0.205	0.037
$\Gamma_{m,Nnon-zero}$ (eq. (6))	0.747	2.352	1.684	3.307
$-\gamma_L' z / \theta_{mL}$	0.105	2.252	1.479	3.270
$\Gamma_{m,Nnon-zero} - \Gamma_{m,Lnon-zero}$	0.105	2.252	1.479	3.270
unshifted $\beta_{0m,L} + \theta_{mL} \Gamma_{m,Lnon-zero}$	–2.770	1.211	–2.739	0.029
shifted $\beta_{0m,L} + \theta_{mL} \Gamma_{m,Lnon-zero}$	–2.799	1.181	–2.768	0.000
unshifted $\beta_{0m,N} + \theta_{mN} \Gamma_{m,Nnon-zero}$	0.448	4.428	0.479	3.247
shifted $\beta_{0m,N} + \theta_{mN} \Gamma_{m,Nnon-zero}$	–2.799	1.181	–2.768	0.000
Number of observations	2010	$\mathcal{L}(\hat{\beta})$		–1404.899
$\mathcal{L}(\mathbf{0})$	–3691.503	ρ^2		0.6194

***, **, * = significant at 1%, 5%, and 10%.
^aEffects of the variables are represented by an estimated coefficient and standard error (in parentheses).
^bDashes indicate coefficients that were constrained to be zero after they were found to have significance > 0.05.
^cCentered coefficients with dots across the row represent generic parameters (constrained to be equal across alternatives).
^dExplanatory variables were specified only in the “used-laptop” functions in each nest. The “not-used-laptop” functions were the base (i.e., = 0).

alternative rather than the other,¹² in which case we can refer to the single vector of explanatory variables as z . Let γ_L be the vector of parameters that results when z_L is non-zero (i.e., $z = z$) and z_N is zero (in this case, N is technically the base alternative, but to reduce confusion we will refer to this case as “Lnon-zero” and use L subscripts to distinguish it from the other case), and γ_N be the vector of parameters that results when z_N is non-zero (i.e., $z = z$) and z_L is zero (“Nnon-zero”).

Then under this common set of circumstances, when z_L is non-zero and z_N is zero, from Eq. (1) we have:

$$P_{L,Lnon-zero} = \frac{1}{1 + e^{-\gamma'_L z / \theta}},$$

and when z_N is non-zero and z_L is zero we have:

$$P_{L,Nnon-zero} = \frac{1}{1 + e^{\gamma'_N z / \theta}}.$$

Equality of these two probabilities implies that $\gamma_L / \theta = -\gamma_N / \theta$, as would be expected. In other words, in a simple binary choice model, if all the variables are “switched” from one alternative to the other without changing signs, then the estimated coefficients will differ only in that their signs will be reversed.

We turn now to the nested logit model. For simplicity of exposition, we will maintain the special case in which all explanatory variables in the lower nests are individual-specific and all are assigned to the same alternative, whichever that may be. We will demonstrate that switching all variables from one alternative to the other will not result in a simple reversal of signs. This result can be generalized to the more complex case in which only some variables are switched, but the demonstration of the simpler case will suffice for our purposes.

In the nested logit model, for the choice of laptop given mode m we have

$$P_{L|m} = \frac{e^{V_L / \theta_m}}{e^{V_L / \theta_m} + e^{V_N / \theta_m}} = \frac{1}{1 + e^{-\gamma'(z_L - z_N) / \theta_m}}, \quad m = B, R, T, S, D, \tag{3}$$

and for the choice of mode m we have

$$P_m = \frac{e^{V_m + \theta_m \Gamma_m}}{\sum_{m'} e^{V_{m'} + \theta_{m'} \Gamma_{m'}}}, \tag{4}$$

where

$$\Gamma_m = \ln[e^{V_L / \theta_m} + e^{V_N / \theta_m}] = \ln[e^{\gamma' z_L / \theta_m} + e^{\gamma' z_N / \theta_m}].$$

Then for the Lnon-zero case we will have $z_L = z$, $z_N = 0$, and, from Eq. (3),

$$P_{L|m,Lnon-zero} = \frac{1}{1 + e^{-\gamma'_L z / \theta_{mL}}},$$

while for the Nnon-zero case we will have $z_L = 0$, $z_N = z$, and, again from Eq. (3),

$$P_{L|m,Nnon-zero} = \frac{1}{1 + e^{\gamma'_N z / \theta_{mN}}}.$$

Equality of these two probabilities implies that $-\gamma'_L z / \theta_{mL} = \gamma'_N z / \theta_{mN}$, or, on an element-by-element basis of the coefficient vectors, that $-\gamma_L / \theta_{mL} = \gamma_N / \theta_{mN}$.

At the same time, for the Lnon-zero case we have

$$\Gamma_{m,Lnon-zero} = \ln[e^{\gamma'_L z / \theta_{mL}} + e^0] = \ln[1 + e^{\gamma'_L z / \theta_{mL}}], \tag{5}$$

while for the Nnon-zero case we have

$$\Gamma_{m,Nnon-zero} = \ln[e^0 + e^{\gamma'_N z / \theta_{mN}}] = \ln[1 + e^{\gamma'_N z / \theta_{mN}}]. \tag{6}$$

We can express $\Gamma_{m,Nnon-zero}$ as a function of $\Gamma_{m,Lnon-zero}$ by replacing γ_N / θ_{mN} with $-\gamma_L / \theta_{mL}$ in Eq. (6):

¹² On the other hand, if a given variable differed by alternative, for example if the lower level involved access modes, each with its own travel time and cost, then it would be natural for the difference to change sign if it were assigned to the “other” alternative: $(Z_L - Z_N)$ would become $(Z_N - Z_L) = -(Z_L - Z_N)$ if the base alternative changed from N to L (if the travel time on mode L took 10 min longer than on mode N, $TT_L - TT_N = 10$, then the travel time on N is 10 min less than on L: $TT_L - TT_N = -10$). If all variables were like this, then from Eq.(1) we would simply have $P_{L,Lnon-zero} = \frac{1}{1 + e^{-\gamma'_L(z_L - z_N) / \theta}}$ when N is the base alternative and $P_{L,Nnon-zero} = \frac{1}{1 + e^{\gamma'_N(z_N - z_L) / \theta}} = \frac{1}{1 + e^{-\gamma'_N(z_L - z_N) / \theta}}$ when L is the base alternative, which means that for the two probabilities to be equal, the coefficients would be equal: $\gamma_L / \theta = \gamma_N / \theta$. If the z variables are a mixture of individual-specific and alternative-varying, then with a change in the base, the signs of the corresponding γ coefficients would reverse (while the variable would remain the same) or remain the same (while the variable difference would reverse), respectively.

Table 12
Dictionary for model equations.

Abbreviation of variable name in equations	Variable name
Has2workOnCommute	Has to work on commute
Like2takeSameRoute	Would like to take same route
isFemale	Female
Age	Age
isHourlyWaged	Hourly waged
TravelDistance	Travel distance
isProTech	Pro-technology
isPolychronic	Multitasking preference (polychronicity)
ThinksTravelsTimeWasted	Travel is wasted time
Likes2recOnCommute	Would like to do recreation on commute
Has2MTatWork	Has to multitask at work
Likes2beAvailable	Would like to be available to people
HHIncomePerCapita	Annual household per capita income
ThinksMTisNormative	Multitasking is normative
TimeSpentWorking	Time spent working
Has2recOnCommute	Has to do recreation on commute
VehicleAge	Vehicle age
IVTT	In-vehicle travel time
OVTT	Out-of-vehicle travel time
Cost	One-way commute cost
ModeConvenience	Mode convenience
ModeBenefitCost	Mode benefit /cost
ModeComfort	Mode comfort
ModeMultitaskability	Mode multitaskability
Propens2useLaptop	Propensity to use a laptop/ tablet/ netbook
isProTransit	Pro-transit
hasDriverLic	Driver's license
isWhite	Race: white
isProActiveModes	Pro-active modes
LimitsWalking	Limitation on walking

$$\begin{aligned}
 \Gamma_{m,Nnon-zero} &= \ln[1 + e^{\gamma'_N z / \theta_{mN}}] = \ln[1 + e^{-\gamma'_L z / \theta_{mL}}] \\
 &= \ln \left[\left(\frac{e^{\gamma'_L z / \theta_{mL}}}{e^{\gamma'_L z / \theta_{mL}}} \right) (1 + e^{-\gamma'_L z / \theta_{mL}}) \right] = \ln[e^{-\gamma'_L z / \theta_{mL}} (e^{\gamma'_L z / \theta_{mL}} + 1)] \\
 &= \ln(e^{-\gamma'_L z / \theta_{mL}}) + \ln[e^{\gamma'_L z / \theta_{mL}} + 1] = -\gamma'_L z / \theta_{mL} + \Gamma_{m,Lnon-zero}.
 \end{aligned} \tag{7}$$

Thus, $\Gamma_{m,Nnon-zero} \neq \Gamma_{m,Lnon-zero}$; the difference is the term $-\gamma'_L z / \theta_{mL}$. Note that because the Γ_m s are different, the θ_m multiplying the Γ_m in Eq. (4) will (in general) have a different estimated value, which means that the γ / θ_m coefficients of Eq. (3) will also have different estimated values. In other words, the coefficients of the models at both levels will be affected.

This analytically-derived difference is confirmed empirically for the illustrative pair of models shown in Tables 10 and 11, in which the bicycle mode has been removed and the lower level models are specified only with constant terms. Note that in this case, the final log-likelihoods are identical between the two models, and the parameters of the upper-level model differ only in the constant terms (although the standard errors of all parameters differ somewhat). This is as expected, since when the lower level is specified only with constants, $-\gamma'_L z / \theta_{mL}$ is just the constant $-\gamma'_L / \theta_{mL}$, from Eq. (5) $\Gamma_{m,Lnon-zero}$ is also a constant, and in Eq. (4), $\theta_{mL} \Gamma_{m,Lnon-zero}$ is also a constant – and similarly for the Nnon-zero case (see the bottom block of Table 11, in which the quantity $-\gamma'_L z / \theta_{mL}$ is shown to equal the difference in Γ s, per Eq. (7)). The differing values of these constant inclusive value terms between the two cases will simply shift the constant terms of the upper-level model to compensate. Letting $\beta_{0m,L}$ and $\beta_{0m,N}$ be the constant term for mode m corresponding to the Lnon-zero and Nnon-zero cases respectively, it can be confirmed from Tables 10 and 11 that (within round-off error)

$$\beta_{0m,L} + \theta_{mL} \Gamma_{m,Lnon-zero} = \beta_{0m,N} + \theta_{mN} \Gamma_{m,Nnon-zero} \tag{8}$$

after *subsequently* shifting all constants in each model to set the last mode (driving alone) as the base (whose constant is fixed at 0) as is done by default in NLOGIT.

However, as mentioned in Section A.1, the two estimates of the inclusive value parameter (together with their standard errors) could, depending on the conservatism of the analysis, yield different conclusions about whether the nested logit model were statistically equivalent to MNL. For the model of Table 10, the t-statistic of the test is $(0.982 - 1) / 0.0083 = -2.17$ ($p = 0.03$), with the point estimate of 0.982 implying an error correlation (between alternatives in the nest) of $(1 - 0.982^2) = 0.04$, which for all practical purposes indicates independence of the errors. For the model of Table 11, by contrast, the t-statistic is $(0.783 - 1) / 0.0502 = -4.32$ ($p = 0.000016$), with the point estimate of 0.783 implying a (substantial) error correlation of 0.39.

Appendix B. Model equations

Following random utility theory, in a discrete choice problem an individual will choose an alternative that maximizes his or her utility. The utility U that each individual n associates with an alternative i can be decomposed into the deterministic V and stochastic ε parts:

$$U_{i,n} = V_{i,n} + \varepsilon_{i,n}$$

Assuming that the error term has the extreme-value distribution, i.e., $\varepsilon \sim EV(0, \mu)$, the probability of choosing the i^{th} alternative is given by:

$$P_n(i) = \Pr(U_{i,n} \geq U_{j,n} \forall j \in J_n) = \frac{e^{\mu V_{i,n}}}{\sum_{j=1}^{J_n} e^{\mu V_{j,n}}},$$

where j is another alternative from the individual's choice set J_n and μ is the scaling parameter, which conventionally is set to unity.

The rest of this section presents the deterministic parts of the utility equations estimated in Sections 4 and 5 for the five binary logit models of mode-specific propensity to use a laptop, netbook, or tablet computer (Table 5) and the multinomial logit commute mode choice model (Table 6), respectively. In these equations the variable names have been abridged for greater readability. Table 12 provides the correspondence between the abbreviations in the equations and the variable names used in the rest of the paper.

B.1. Binary logit models of mode-specific propensity to use a laptop, netbook, or tablet computer (Table 5)

$$V_{biking} = -4.470$$

$$\begin{aligned} V_{commuterRail} = & -0.313 + 1.148 \\ & * Has2workOnCommute - 0.543 \\ & * Likes2takeSameRoute - 1.36 \\ & * isFemale - 0.049 \\ & * Age - 3.276 \\ & * isHourlyWaged + 0.026 \\ & * TravelDistance \end{aligned}$$

$$V_{transit} = -2.268 + 0.549 * isProTech + 0.241 * isPolychronic + 0.368 * Has2workOnCommute$$

$$\begin{aligned} V_{sharedRide} = & -4.408 + 0.564 \\ & * ThinksTravelsTimeWasted + 1.262 \\ & * Has2workOnCommute + 0.685 \\ & * Likes2recOnCommute - 0.456 \\ & * Has2MTatWork + 0.486 \\ & * Likes2beAvailable - 0.383 \\ & * Likes2takeSameRoute - 0.021 \\ & * HHIncomePerCapita + 0.029 \\ & * TravelDistance \end{aligned}$$

$$\begin{aligned} V_{drivingAlone} = & -2.178 + 0.401 \\ & * ThinksMTisNormative - 0.372 \\ & * TimeSpentWorking + 0.77 \\ & * Has2workOnCommute + 0.946 \\ & * Has2recOnCommute - 0.389 \\ & * Likes2recOnCommute - 0.102 \\ & * VehicleAge \end{aligned}$$

B.2. Multinomial logit commute mode choice model (Table 6)

$$\begin{aligned}
 V_{biking} = & -5.327 - 0.163 \\
 & * IVTT - 0.048 \\
 & * OVTT - 1.175 \\
 & * \ln(Cost) + 2.088 \\
 & * isProActiveModes + 0.455 \\
 & * ModeConvenience + 0.368 \\
 & * ModeBenefitCost + 0.405 \\
 & * ModeComfort + 0.098 \\
 & * ModeMultitaskability + 1.240 \\
 & * Propens2useLaptop
 \end{aligned}$$

$$\begin{aligned}
 V_{commuterRail} = & -2.959 - 0.016 \\
 & * IVTT - 0.048 \\
 & * OVTT - 1.175 \\
 & * \ln(Cost) + 0.954 \\
 & * isProTransit + 0.455 \\
 & * ModeConvenience + 0.368 \\
 & * ModeBenefitCost + 0.405 \\
 & * ModeComfort + 0.098 \\
 & * ModeMultitaskability + 1.240 \\
 & * Propens2useLaptop
 \end{aligned}$$

$$\begin{aligned}
 V_{transit} = & 0.785 - 1.890 \\
 & * hasDriverLic + 0.523 \\
 & * isWhite - 0.016 \\
 & * IVTT - 0.048 \\
 & * OVTT - 1.175 \\
 & * \ln(Cost) + 0.825 \\
 & * isProTransit + 0.455 \\
 & * ModeConvenience + 0.368 \\
 & * ModeBenefitCost + 0.405 \\
 & * ModeComfort + 0.098 \\
 & * ModeMultitaskability + 1.240 \\
 & * Propens2useLaptop
 \end{aligned}$$

$$\begin{aligned}
 V_{sharedRide} = & -2.752 + 0.393 \\
 & * isFemale + 0.166 \\
 & * LimitsWalking - 0.016 \\
 & * IVTT - 0.048 \\
 & * OVTT - 1.175 \\
 & * \ln(Cost) + 0.201 \\
 & * isProTransit + 0.191 \\
 & * isPolychronic + 0.455 \\
 & * ModeConvenience + 0.368 \\
 & * ModeBenefitCost + 0.405 \\
 & * ModeComfort + 0.098 \\
 & * ModeMultitaskability + 1.240 \\
 & * Propens2useLaptop
 \end{aligned}$$

$$\begin{aligned}
 V_{\text{drivingAlone}} &= -0.016 \\
 & * IVTT - 0.048 \\
 & * OVTT - 1.175 \\
 & * \ln(\text{Cost}) + 0.455 \\
 & * \text{ModeConvenience} + 0.368 \\
 & * \text{ModeBenefitCost} + 0.405 \\
 & * \text{ModeComfort} + 0.098 \\
 & * \text{ModeMultitaskability} + 1.240 \\
 & * \text{Propens2useLaptop}
 \end{aligned}$$

Appendix C. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.tra.2018.12.015>.

References

- Abantes, Pedro A.L., Wardman, Mark R., 2011. Meta-analysis of UK values of travel time: an update. *Transport. Res. A* 45, 1–17.
- American Association of State Highway and Transportation Officials (AASHTO), 2015. *Commuting in America 2013*. The National Report on Commuting Patterns and Trends. Washington, DC. Available at <http://traveltrends.transportation.org/Pages/default.aspx>, accessed April 3, 2015.
- Anderson, James M., Nidhi, Kalra, Stanley, Karlyn D., Sorensen, Paul, Samaras, Constantine, Oluwatola, Oluwatobi A., 2014. *Autonomous Vehicle Technology: A Guide for Policymakers*. Santa Monica, California: Rand Corporation. Available at http://www.rand.org/pubs/research_reports/RR443-1.html, accessed July 20, 2014.
- Becker, Gary S., 1965. A theory of the allocation of time. *Econ. J.* 75, 493–517.
- Ben-Akiva, Moshe E., Lerman, Steven R., 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge, Massachusetts.
- Berliner, Rosaria M., Malokin, Aliaksandr, Circella, Giovanni, Mokhtarian, Patricia L., 2015. Travel-based multitasking: modeling the propensity to conduct activities while commuting. Presented at the 94th Transportation Research Board Meeting, Washington, DC.
- Bluedorn, A.C., Kalliath, T.J., Strube, M.J., Martin, G.D., 1999. Polychronicity and the Inventory of Polychronic Values (IPV). *J. Manag. Psychol.* 14 (3/4), 205–230.
- Bluedorn, Allen C., Martin, Gwen, 2008. The time frames of entrepreneurs. *J. Bus. Ventur.* 23 (1), 1–20.
- Cameron, A. Colin, Trivedi, Pravin K., 2005. *Microeconometrics: Methods and Applications*. Cambridge University Press, New York.
- Chesley, Noelle, 2014. Information and communication technology use, work intensification and employee strain and distress. *Work Employ Soc.* 28 (4), 589–610. <https://doi.org/10.1177/0950017013500112>. Available at <http://wes.sagepub.com/content/early/2014/03/10/0950017013500112.abstract>, accessed July 30, 2014.
- Circella, Giovanni, Mokhtarian, Patricia L., Poff, Laura K., 2012. A conceptual typology of multitasking behavior and polychronicity preferences. *Electronic Int. J. Time Use Res.* 9 (1), 59–107.
- Connolly, Dara, Caulfield, Brian, O'Mahony, Margaret, 2009. Rail passengers' preferences for on-board Wi-fi internet access. *Transportation Research Board Paper #09-2618*, Washington, DC, January.
- DeLoach, Stephen B., Tiemann, Thomas K., 2012. Not driving alone? American commuting in the twenty-first century. *Transportation* 39, 521–537.
- Dong, Zhi, Mokhtarian, Patricia L., Circella, Giovanni, Allison, James R., 2015. The estimation of changes in rail ridership through an onboard survey: did free Wi-Fi make a difference to Amtrak's Capitol Corridor service? *Transportation* 42 (1), 123–142.
- Etezady, Ali, Mokhtarian, Patricia L., Circella, Giovanni, Malokin, Aliaksandr, 2019. Not all minutes are created equal: How does the impact of travel time on commute mode choice differ by demographics and propensity to multitask? In: Paper #19-03326 Presented at the 98th Annual Meeting of the Transportation Research Board, Washington, DC, January.
- Ettema, Dick, Verschuren, Laura, 2007. The effect of multitasking on the value of travel time savings. *Transp. Res. Rec.* 2010, 19–25.
- Ettema, Dick, Friman, Margareta, Gärling, Tommy, Olsson, Lars E., Fujii, Satoshi, 2012. How in-vehicle activities affect work commuters' satisfaction with public transport. *J. Transp. Geogr.* 24, 215–222.
- Giuliano, Genevieve, 2005. Low income, public transit, and mobility. *Transp. Res. Rec.* 1927, 63–70.
- Gripsrud, Mattias, Hjorthol, Randi, 2012. Working on the train: from 'dead time' to productive and vital time. *Transportation* 39, 941–956.
- Guo, Zhan, Derian, Alexandra, Zhao, Jinhua, 2015. Smart devices and travel time use by bus passengers in Vancouver, Canada. *Int. J. Sustain. Transport.* 9 (5), 335–347.
- Hauser, John R., 1978. Testing the accuracy, usefulness, and significance of probabilistic choice models: an information-theoretic approach. *Oper. Res.* 26 (3), 406–421.
- Hensher, David A., Johnson, Lester W., 1981. *Applied Discrete-Choice Modelling*. Croon-Helm, London.
- Hensher, David A., Wang, Baojin, 2016. Productivity foregone and leisure time corrections of the value of business travel time savings for land passenger transport in Australia. *Road Transport Res.: A J. Aust. New Zealand Res. Practice* 25 (2), 15–29.
- Kenyon, Susan, Lyons, Glenn, 2007. Introducing multitasking to the study of travel and ICT: examining its extent and assessing its potential importance. *Transport. Res. A* 41 (2), 161–175.
- Keseru, Imre, Macharis, Cathy, 2018. Travel-based multitasking: review of the empirical evidence. *Transport Rev.* 38 (2), 162–183. <https://doi.org/10.1080/01441647.2017.1317048>.
- König, Cornelius J., Waller, Mary J., 2010. Time for reflection: a critical examination of polychronicity. *Human Performance* 23 (2), 173–190.
- Lindquist, J.D., Kaufman-Scarborough, C., 2007. The polychronic – monochronic tendency model: PMTS scale development and validation. *Time Soc.* 16, 253–285.
- Lyons, Glenn, Urry, John, 2005. Travel time in the information age. *Transport. Res. A* 39 (2–3), 257–276.
- Malokin, Aliaksandr, Circella, Giovanni, Mokhtarian, Patricia L., 2015. How do activities conducted while commuting influence mode choice? Testing public transportation advantage and autonomous vehicle scenarios. Presented at the 94th Transportation Research Board Meeting, Washington, DC.
- Malokin, Aliaksandr, Circella, Giovanni, Mokhtarian, Patricia L., 2017. Do multitasking millennials value travel time differently? A revealed preference study of Northern California commuters. Presented at the 96th Transportation Research Board Meeting, Washington, DC. Submitted for peer review; available from the authors.
- Mishra, Gouri S., Mokhtarian, Patricia L., Widaman, Keith F., 2015. An empirical investigation of attitudes toward waiting on the part of Northern California commuters. *Travel Behaviour Soc.* 2 (2), 78–87.
- Mokhtarian, Patricia L., 2016. Discrete choice models' ρ^2 : a reintroduction to an old friend. *J. Choice Modell.* 21, 60–65.
- Mokhtarian, Patricia L., 2018. The times they are a-changin': what do the expanding uses of travel time portend for policy, planning, and life? Thomas B. Deen

- Distinguished Lecture of the Annual Meeting of the Transportation Research Board. *Transp. Res. Rec.* <https://doi.org/10.1177/0361198118798602>.
- Mokhtarian, Patricia L., Salomon, Ilan, 2001. How derived is the demand for travel? Some conceptual and measurement considerations. *Transp. Res. Part A* 35, 695–719.
- Mokhtarian, Patricia L., Papon, Francis, Goulard, Matthieu, Diana, Marco, 2015. What makes travel pleasant and/or tiring? An investigation based on the French National Travel Survey. *Transportation* 42, 1103–1128. <https://doi.org/10.1007/s11116-014-9557-y>.
- Neufeld, Amanda J., Mokhtarian, Patricia L., 2012. A Survey of Multitasking by Northern California Commuters: Description of the Data Collection Process. Institute of Transportation Studies, University of California, Davis, Research Report UCD-ITS-RR-12-32. Available at http://www.its.ucdavis.edu/?page_id=10063&pub_id=1802, accessed Aug. 20, 2013.
- Newgard, Craig D., Hedges, Jerris R., Arthur, Melanie, Mullins, Richard J., 2004. Advanced statistics: the propensity score – a method for estimating treatment effect in observational research. *Acad. Emerg. Med.* 11 (9), 953–961.
- NHTSA, 2013. U.S. Department of Transportation releases policy on automated vehicle development. Available at <http://www.nhtsa.gov/About+NHTSA/Press+Releases/U.S.+Department+of+Transportation+Releases+Policy+on+Automated+Vehicle+Development>, accessed July 6, 2016.
- Ohmori, Nobuaki, Harata, Noboru, 2008. How different are activities while commuting by train? A case in Tokyo. *Tijdschrift voor Economische en Sociale Geografie* 99 (5), 547–561.
- Rasouli, Soora, Timmermans, Harry, 2014. Judgments of travel experiences, activity envelopes, trip features and multi-tasking: a panel effects regression model specification. *Transport. Res. Part A: Policy Practice* 63, 67–75.
- Rhee, Kyoung-Ah, Kim, Joon-Ki, Lee, Back-Jin, Kim, Sungyop, Lee, Young-Ihn, 2013. Analysis of effects of activities while traveling on travelers' sentiment. *Transp. Res. Rec.* 2381, 27–34.
- Rosenbloom, Sandra, Burns, Elizabeth, 1994. Why working women drive alone: implications for travel reduction programs. *Transp. Res. Rec.* 1459, 39–45.
- Shaw, F. Atiyya, Malokin, Aliaksandr, Mokhtarian, Patricia L., Circella, Giovanni, 2018. It's not all fun and games: an investigation of the reported benefits and disadvantages of conducting activities while commuting. Under peer review; available from the authors.
- Shires, Jeremy D., de Jong, Gerard C., 2009. An international meta-analysis of values of travel time savings. *Eval. Program Plann.* 32, 315–325.
- Singleton, Patrick A., 2018. How useful is travel-based multitasking? Evidence from Portland, Oregon commuters. *Transp. Res. Rec.*
- Susilo, Y.O., Lyons, G., Jain, J., Atkins, S., 2012. Rail passengers' time use and utility assessment. *Transp. Res. Rec.* 2323 (1), 99–109.
- Tang, Jia, Zhen, Feng, Cao, Jason, Mokhtarian, Patricia L., 2018. How do passengers use travel time? A case study of Shanghai-Nanjing High Speed Rail. *Transportation* 45 (2), 451–477.
- Taniguchi, Kyle Ken, 2012. Work Trips on Public Transportation: An Analysis of Trends, Select Markets, and Users Using the National Household Travel Survey Series. MS Thesis, Civil and Environmental Engineering, University of South Florida. Available at <http://scholarcommons.usf.edu/etd/4411/>, accessed October 4, 2013.
- Train, Kenneth, 2009. *Discrete Choice Methods with Simulation*, 2nd ed. Cambridge University Press. Available at <https://eml.berkeley.edu/books/choice2.html>, accessed November 16, 2017.
- Trottenberg, Polly. Memorandum to secretarial officers, modal administrators, 2011. Revised Departmental Guidance on Valuation of Travel Time in Economic Analysis, September 28. Available at <http://www.dot.gov/sites/dot.gov/files/docs/Value%20of%20Travel%20Time%20Memorandum.pdf>, accessed April 3, 2015.
- U.S. Department of Transportation, Federal Highway Administration, 2009. National Household Travel Survey. Available at <http://nhts.ornl.gov>, accessed on September 13, 2017.
- van der Waerden, P., Kemperman, A., Timmermans, H., van Hulle, R., 2010. The influence of facilities for multitasking on individual's travel decisions in the context of work trips. Transportation Research Board Paper #10-2459, Washington, DC, January.
- Varghese, Varun, Jana, Arnab, 2018. Impact of ICT on multitasking during travel and the value of travel time savings: empirical evidences from Mumbai, India. *Travel Behaviour Soc.* 12, 11–22.
- Wagner, Jason, Baker, Trey, Goodin, Ginger, John Maddox, 2014. Automated Vehicles: Policy Implications Scoping Study. Texas A&M Transportation Institute, Texas A&M University, Research Report SWUTC/14/600451-00029-1. Available at <http://d2dtl5nnpf0r.cloudfront.net/swutc.tamu.edu/publications/technicalreports/600451-00029-1.pdf>, accessed July 20, 2014.
- Wallis, Claudia, 2010. The impacts of media multitasking on children's learning and development – Report from a research seminar, The Joan Ganz Cooney Center and Stanford University, available at <http://www.joanganzcooneycenter.org/Reports-22.html>, accessed July 23, 2014.
- Wardman, Mark, Lyons, Glenn, 2016. The digital revolution and worthwhile use of travel time: implications for appraisal and forecasting. *Transportation* 43, 507–530.
- Watts, Laura, 2008. The art and craft of train travel. *Soc. Cultural Geogr.* 9 (6), 711–726.
- Watts, Laura, Urry, John, 2008. Moving methods, travelling times. *Environ. Plann. D* 26, 860–874.
- Zhang, Junyi, Timmermans, Harry, 2010. Scobit-based panel analysis of multitasking behavior of public transport users. *Transp. Res. Rec.* 2157, 46–53.
- Zheng, Zuduo, Washington, Simon, Hyland, Paul, Sloan, Keith, Liu, Yulin, 2016. Preference heterogeneity in mode choice based on a nationwide survey with a focus on urban rail. *Transport. Res. Part A: Policy Practice* 91, 178–194.
- Zorn, Christopher, 2005. A solution to separation in binary response models. *Political Anal.* 13 (2), 157–170.