Title

Modeling the Adoption of Full-day, Part-day and Overtime Telecommuting: An Investigation of Northern California Workers Using Non-Mean-Centered Factor Scores to Segment on Built Environment Attitudes

Authors

Deng, Huijing
Mokhtarian, Patricia
Circella, Giovanni

Publication Date

2015

Peer reviewed

Modeling the Adoption of Full-day, Part-day and Overtime Telecommuting: An Investigation of Northern California Workers Using Non-Mean-Centered Factor Scores to Segment on Built Environment Attitudes

Huijing Deng
Institute of Transportation Studies
University of California, Davis
One Shields Avenue
Davis, CA 95616, USA
e-mail: hjdeng@ucdavis.edu

Patricia L. Mokhtarian (corresponding author)
School of Civil and Environmental Engineering
Georgia Institute of Technology
790 Atlantic Drive
Atlanta, Georgia 30332, USA
Phone: 1 404 385 1443
e-mail: patmokh@gatech.edu

and

Giovanni Circella
School of Civil and Environmental Engineering
Georgia Institute of Technology
790 Atlantic Drive
Atlanta, Georgia 30332, USA
Phone: 1 530 554 0838
e-mail: giovanni.circella@ce.gatech.edu

Presented at the
94th Annual Meeting of the Transportation Research Board,
Washington, DC, January 2015

ABSTRACT

This paper investigates the impact of several factors on the adoption of telecommuting, using empirical data collected from 1,864 commuters in Northern California. We distinguish three types of telecommuting – full-day, part-day, and overtime – as they might affect travel behavior in very different ways. We develop binary logit models and a trivariate probit model of the adoption of each form of telecommuting, using non-centered factor scores to identify pro-high- vs. pro-low-density workers. We test the hypothesis that the impact of the built environment on the decision to adopt telecommuting differs between those two segments. The results support the hypothesis, with numerous variables significant to one of those segments but not the other; in the case of the binary logit model for overtime telecommuting, employment density in the home area even has opposite influences for pro-high-density (positive) compared to pro-low-density people (negative). Other groups of variables, including personal attitudes and demographic traits, also significantly affect individuals' decisions on whether and how to telecommute, if at all. For example (consistent with other studies), education and household income are strong (positive) predictors of the decision to telecommute. Compared to the separate binary logit models, the trivariate probit model better predicts the joint probabilities of adopting the various forms of telecommuting, and better models the correlated adoption of the three types of telecommuting.

Key words: Telecommuting, Travel Behavior, Personal Attitudes, Built Environment, Non-Centered Factor Analysis, Trivariate Probit Model

1. INTRODUCTION

The journey to work and other work-related travel remain major trip purposes in the developed world. According to data from the United States National Household Travel Survey, in 2009 those purposes constituted about 25% of average annual person-miles traveled (PMT) per household, and 19% of annual person trips. Although the average person trip length for work or work-related purposes shows a decreasing trend since 2001, the average vehicle trip length has actually increased (Summary of Travel Trends, 2009), due to the increased use of private vehicles for these purposes. Accordingly, transportation planners and policymakers continue to investigate potential ways to reduce the number and/or length of work-related trips by private vehicle. Telecommuting has been often proposed as a promising strategy for reducing peak-period commute travel. However, the personal desirability of telecommuting is still being debated. Some studies suggest that telecommuting would improve quality of life, while others argue that telecommuting may not increase overall life satisfaction, given the possible problems of overworking and withdrawal, and unclear boundary setting between work and personal life (Van Sell and Jacobs, 1994; Vitterso et al., 2003; Wilton et al., 2011). In this study, we investigate the factors influencing people's adoption of telecommuting, to help inform evaluations of the (transportation and other) benefits, as well as the disadvantages, associated with that adoption.

Any rigorous study of telecommuting must be clear about the definition being used, in view of the numerous variations that could plausibly merit the label, and the potential very different ramifications of different definitions (Mokhtarian et al., 2005). Here, we distinguish among three distinct forms of telecommuting: *full-day*, meaning working at home for the entire workday and eliminating the commute to a conventional workplace on that day; *part-day,* meaning working at home but also at the usual workplace during different parts of the day, usually time-shifting the normal commute (e.g. working at home for a few hours in the morning to avoid rush hour and then going to work, or conversely in the afternoon); and *overtime,* meaning working at home for part of the day without changing the time of the normal commute (e.g. working at home on evenings or weekends, without affecting the regular commute on workdays). We exclude self-employed home-based business workers, since the influences on their choice to work at home and the transportation impacts of that choice are likely to be very different from those of salaried employees.

From the standpoint of transportation impacts (but from other perspectives as well, such as the employer's willingness to permit it, or the impacts on family life and personal lifestyles), it is clearly important to separate these three forms of telecommuting. The first type has received the most attention in the literature. The second type has received little attention so far, although it may actually be much more common than the first (Haddad et al., 2009; Lyons and Haddad, 2008). Finally, the third form has been the least studied in transportation research, because it usually has little or no direct impact on transportation (Tang et al., 2011). Nevertheless, this type may be the most common of all, and is often (misleadingly) included in aggregate statistics on telecommuting (Mokhtarian et al., 2005). Further, it may be the form that has the most negative impacts on family life.

To help remedy this relative lack of scholarly attention, this paper includes overtime telecommuting in the analysis. This type of telecommuting might be associated with specific attitudes toward work and life, and it is relevant to transportation because it also affects individuals' decisions about activity participation. Analyzing it together with the other two forms of telecommuting allows us to directly compare the factors relevant to the choices of the different forms. Because each of the three forms of telecommuting may be chosen (or not) in any combination, it is natural to use the trivariate probit structure to model the joint choice of the three forms. To our knowledge, this is the first application of trivariate probit to the telecommuting adoption context.

Aside from the impact of sociodemographic characteristics and telecommuting- and travel-related attitudes that many telecommuting-adoption studies have emphasized, we also focus, as suggested by Tang et al. (2011) and others, on the possible impact of the built environment (BE) on the eventual choice to telecommute. In fact, as they note, the accessibility and appeal of a particular location – whether workplace or residential neighborhood – are functions of many characteristics of that location. It is reasonable to expect that these characteristics could also affect the choice whether to physically commute or to work from home. In addition, we expect that individuals with different preferences toward some characteristics of the built environment might act differently in terms of the adoption of telecommuting. For example, pro-low-density individuals (those who prefer larger homes and mostly residential neighborhoods) might find highly urban workplaces to be less attractive than their pro-high-density peers do (who prefer denser and more mixed-use neighborhoods), and therefore be more inclined to substitute physical trips to work with telecommuting alternatives. To classify respondents as pro-high-density or pro-low-density, we reintroduce the concept of non-mean-centered factor score computation.

Thus, the contributions of the paper include: (a) distinguishing three quite different types of telecommuting in a study of its adoption, (b) using trivariate probit to model the joint choice of those three types, (c) adding to the hitherto limited literature on the influence of the built environment on telecommuting adoption, and (d) using the rarely-applied concept of non-mean-centered factor score computation to identify people as pro-high- or pro-low-density. The remainder of the paper is organized as follows: Section 2 presents a brief review of the literature on the adoption of telecommuting and its effects on travel behavior. Section 3 discusses the context of the research and the data collection. Section 4 describes the estimation of the discrete choice models. We discuss the results from the study and the impacts of various groups of variables in Section 5. Finally, Section 6 presents some brief conclusions from this study and suggestions for further research.

2. LITERATURE REVIEW

Behavioral frameworks of the employee's choice to adopt telecommuting have long been proposed (Bernardino et al., 1993; Sullivan et al., 1993; Mokhtarian and Salomon, 1996), suggesting that personal attitudes and perceptions, as well as individual and job characteristics, affect an employee's preference for telecommuting. In the ensuing decades, many studies have analyzed the adoption and frequency of telecommuting. For brevity, we refer to the study from Tang et al. (2011) for a more comprehensive general review of empirical studies that have investigated telecommuting adoption and frequency. In the remainder of this section, we focus on the studies most closely related to ours (and we reference others as we discuss our own empirical results in Section 5).

In one of the few studies that separate part-day from whole-day telecommuting among full-time paid employees, Haddad et al. (2009) examined the determinants influencing the desire for and frequency of part-day and whole-day homeworking. Unfortunately, the data analyzed in the study did not specify the time of day at which part-day telecommuting occurred, and thus could not distinguish between telecommuting occurring during normal working hours versus after hours (in contrast, these two options are distinguished in the present study). The authors used data from the third wave of a national longitudinal survey in the UK and estimated ordered probit regressions to model the desire and frequency to telecommute for either part of a day or for the full day, separately. The results showed that being a white collar employee increases the likelihood to both part-day and full-day telecommute. Further, the desire to avoid interruptions from other people at work showed a positive influence on part-day telecommuting but it was not significant in the full-day model. Other factors with a positive influence included appreciation from other household members for working at home, desire to avoid traffic, the cost to travel to/from work, commute distance, and employer's support. Negative factors included conflicts with personal life when working at home.

To date, relatively few studies have investigated the influence of the built environment on the choice to telecommute. To our knowledge, Tang et al. (2011) developed the first disaggregate, revealed preference model that allows built environment characteristics to influence the telecommuting decision. They estimated a multinomial logit model of the work-at-home (telecommuting) frequency using data from a survey of eight neighborhoods in Northern California, and including socioeconomic traits, residential neighborhood preferences and perceptions, objective built environment characteristics, travel attitudes, and behavior as potential explanatory variables. Several built environment factors associated with neo-traditional neighborhoods were found to be linked to the decision to work at home, although several counteracting effects were also observed. Land use and transportation features that are desirable from a sustainability standpoint often resulted in a reduced adoption of work at home. The study focused only on the impact of the built environment features of the residential (home) location; by contrast -- uniquely, to our knowledge -- the present study investigates the impact of built environment characteristics at both the home and work locations.

Khan et al. (2012) also studied the adoption of telecommuting in different built environments, using data collected from a survey distributed in the San Francisco Bay Area of Northern California. They developed a multidimensional, multivariate model that accounts for the adoption of several work arrangements, including the decision to be a *home-based worker*. Home-based workers could be salaried employees (hence, conventional telecommuters) or self-employed; their distinctive characteristic was that home was their fixed workplace (hence, excluding overtime and part-time telecommuting). They found that higher levels of access to recreational activity locations are associated with a greater propensity to work from home. However (as is also true of the present paper), the study could not separate the effects of location on telecommuting (in which individuals who live in these areas are more motivated to work from home so as to enjoy the access to local amenities) from a residential self-selection effect (in which individuals interested in working from home are more likely to relocate to areas that provide higher levels of access to recreational activities).

Using the same data for the San Francisco Bay Area, Singh et al. (2013) adopted a different approach, and focused on workers who are not self-employed, and who have a primary work place that is different from their home. They developed a joint model for the individual availability, choice and frequency of telecommuting. Their results showed that individuals who live closer to non-work and leisure activity locations tend to highly value telecommuting, and are more likely to adopt it.

With respect to the influence of the built environment, several studies (e.g. Mokhtarian et al., 2005; Moos and Skaburskis, 2008) have discussed the issue of causal direction, i.e. whether the decision to telecommute could affect one's job choice and residential location, or if on the contrary the built environments around those locations influence individuals' decisions on whether and how to telecommute. An oft-mentioned scenario is that a prior choice or inclination to telecommute might motivate an individual to move her residence farther from work. Thus telecommuting might act as an enabling factor to move, for instance, to a higher-amenity area. In this study, we first note that among the three types of telecommuting we are studying, full-day telecommuting is the one most likely to affect residential location. Given that full-day telecommuting is often only performed one or two days a week (if at all), and given other factors influencing residential location, we take a position similar to Tang et al. (2011) and consistent with the findings of Ory and Mokhtarian (2006), i.e. that telecommuting probably does not prompt large numbers of people to move, and therefore that the dominant direction of causality is still that of the built environment affecting the adoption of telecommuting.

3. STUDY CONTEXT AND AVAILABLE DATA

The study uses data collected through an empirical survey distributed to workers in Northern California, as part of an investigation of the transportation impacts of the Fix I-5 project (Ye et al., 2012). Fix I-5 (commonly referred to as "the Fix") was the major reconstruction of an important stretch of Interstate 5 in Sacramento, and involved the alternating closures of all northbound and all southbound lanes for several days at a time during summer 2008. To study the impacts of the project on commuters, three internet-based surveys were conducted, two during the time of the reconstruction project and another one six months later.

This study does not focus on the impacts of the Fix, but we used data collected for that project to investigate the reasons affecting individuals' adoption of telecommuting. In particular, we used data from the third ("Wave 3") survey, which was conducted six months after the reconstruction project, in February 2009, because it collected detailed information on attitudes, as well as on the adoption of telecommuting as a regular lifestyle (thus not necessarily related to the Fix), and detailed geographical information which was geocoded to add important land-use variables to the dataset.

The sample for this study is not necessarily representative of the overall workforce of the Sacramento region, for several reasons. First, for the entire Fix I-5 evaluation, there was no time to draw a rigorous, geographically-based random sample and recruit participants by mail before the beginning of the Fix. Second, specifically for the third wave, participants were recruited from the respondents to the previous surveys who expressed willingness to be surveyed again in the future. Thus, the sample is probably biased toward those who are more altruistic and perhaps those whose travel behavior is more socially desirable. Third, this survey was oriented toward the persistence (or lack thereof) of changes made during the Fix, so those with more commendable behavior (e.g. persistence in environmentally-beneficial travel patterns) may have been more likely to respond or to complete this survey.

Thus, in general we expect this sample to be more pro-environmental than the population as a whole. The model results, however, are expected to be reliable, in that the models include covariates to control for such biases, and represent conditional relationships rather than the unconditional ones of univariate means. In other words, the estimated models should properly portray the impact on telecommuting of having a certain set of characteristics, even if the share of the population having those characteristics is different from that of the sample.

The original database consisted of 2056 cases. After screening out cases with missing data on the telecommuting questions, attitudinal questions and selected sociodemographic traits, the final sample size is 1864.

3.1 Dependent variables

We created three variables, i.e. part-day TC, full-day TC, and overtime TC, from the respective questions about the adoption of these forms of telecommuting in the survey. All three questions had the same introduction – "Considering a typical month, how often do you do each of the following?" – with the relevant options listed as:

- "Work at home and change the time you commute to or from work (for example, work at home in the morning and travel to your regular workplace after the morning rush hour)";
- "Work at home for basically a full day without commuting at all that day (for example, if you're self-employed or telecommute the whole day[1])"; and
- "Work at home for part of the day without changing your normal commute (for example, if you routinely check e-mail at home on Sat. and Sun., that would be at least 2 times a week. Don't forget to count weekday evenings too)".

The choice lists, for each form of telecommuting, comprised the options "Seldom or never", "1-3 times a MONTH", "1-2 times a WEEK", "3-4 times a WEEK", "5 times a WEEK" and "6-7 times a WEEK". Since in this study we analyze the adoption, not the frequency, of telecommuting, all three dependent variables were treated as binary variables, where 0 is associated with the answer "Seldom or never", and 1 with any of the remaining options. Comparing the marginal frequencies of choosing full-day (13.9% yes, 86.1% no), part-day (16.0% yes, 84.0% no), and overtime TC (24.8% yes, 75.2% no) shows that full-day TC is the least often adopted (consistent with Haddad et al., 2009), whereas overtime TC, to which previous studies have paid little attention, has a much larger adoption rate than the other two types (almost twice as high as full-day TC). This again supports the importance of analyzing overtime TC separately, giving it at least the same attention as the other two types of TC.

Using the same marginal frequencies, we computed the expected combination frequencies under the assumption that these three types of TC are independent (uncorrelated), and then compared them with the observed combination frequencies. Table 1 shows the observed and expected frequencies of the eight choice combinations. For example, the expected share of the FP0 combination (i.e. someone who chooses full-day TC and part-day TC, but no overtime TC), under the assumption of independence, is 13.9%*16.0%*75.2% = 1.7%.

The table shows that the three forms of telecommuting are by no means independently adopted. The independence assumption substantially overpredicts the adoption of single forms of telecommuting, and underpredicts the adoption of none of them. In other words, given that one form of telecommuting has been adopted, it becomes more likely that one or both other forms have also been adopted. Using log-linear analysis to conduct the Cochran-Mantel-Haenszel chi-squared test of independence, we find that all interactions among the three binary variables are statistically significant ($p<0.0001$).

[1] Self-employed individuals were identified through a question in the survey that requested information on their current employment/occupation, and were later excluded from the analysis.

TABLE 1 Observed and expected (under independence) distributions of TC adoption combinations

	observed	*(percent)*	*expected*	*(percent)*
F00	52	2.8%	163	8.8%
0P0	67	3.6%	193	10.4%
00T	220	11.8%	334	17.9%
FP0	36	1.9%	31	1.7%
0PT	70	3.8%	64	3.4%
F0T	46	2.5%	54	2.9%
FPT	125	6.7%	10	0.5%
000	1248	66.9%	1015	54.4%
Total	**1864**	**100.00%**	**1864**	**100.00%**

Note: F = adoption of full-day TC, P = adoption of part-day TC, T = adoption of overtime TC, and 0 = the associated form of TC is not chosen.

3.2 Explanatory variables

3.2.1 Socioeconomic and attitude variables

The available socio-demographic variables include gender, age, education, primary job schedule (part-time, conventional, compressed, etc.), job type (manager/administration, professional/ technical, clerical/administrative support, etc.), household information (size, income, number of individuals in each age group), vehicle constraints (number of vehicles, number of driver's licenses), and housing type (single family detached, apartment/condo, etc.).

In addition, the survey contains three blocks of attitudinal statements, which respondents were asked to rate on a five-point Likert-type scale, from "strongly disagree" to "strongly agree". A previously developed (unpublished) factor analysis on these data was used to identify seven *attitude* factors, i.e. pro-transit, utilitarian travel, pro-low-density, travel minimizing, pro-bike/walk, pro-driving, and commute benefit; five *lifestyle* factors, i.e. anti-driving attitude, price sensitivity, variety-seeking, time unpressured, and pro-exercise; and five *belief* factors, i.e. no worries, congestion is a problem, concerned about energy dependence, importance of personal responsibility, and air quality is a problem.

The absence of attitudes toward work, family, technology, and telecommuting is an inevitable limitation of this research in view of the fact that the survey was designed primarily to assess the impacts of a road construction project on travel behavior. Nevertheless, the rich attitudinal and built environment variables that *are* available offer a substantial supplement to the socioeconomic variables customarily measured, with the resulting models exhibiting a respectable goodness of fit as discussed in Section 5.

3.2.2 Built-environment (BE) variables

The BE questions available from the survey measured some simple self-reported characteristics, namely distance to the nearest bus stop or station, and neighborhood type (both through ordinal variables). In addition, the survey asked for intersections near the respondent's home and work. A large amount of additional information was obtained through geocoding those intersections and drawing from Geographic Information System (GIS) databases available for the Sacramento region. Characteristics available from these sources include the areas within a half-mile radius of the intersection that are associated with each land use type (residential, commercial, industrial, etc.), total distance of bike lanes, distance of bus lines and number of stops, distance to the eight nearest amenities (restaurants, coffee shops, groceries etc.), and population and employment densities.

A factor analysis was conducted on the variables measuring the distance to the nearest amenities. Several alternative specifications were tried using the variables associated with work and home locations. Since most of the variables turned out to be grouped in the same way in separate factor analyses, and since it is highly desirable to have the same factor structure for both home and work locations, we ultimately chose a single factor analysis for both sets of variables. In the preferred (two-factor) solution (Table 2), one factor relates to the distance to maintenance activity locations ("maintenance distance"), and the other one to the distance to entertainment activity locations ("entertainment distance"). The final solution used oblique (oblimin) rotation, allowing the factors to be correlated. The resulting correlations of 0.612 for the home location and 0.731 for the work location are moderate to strong, but the large sample size makes the prospect of multicollinearity in the models less worrisome. The total variance explained by the two factors is 78.8%.

TABLE 2 Factors for neighborhood amenities

Factor	Statement	Loading
Distance to maintenance activity locations	Distance to the nearest restaurant	0.945
	Distance to the nearest coffee shop	0.903
	Distance to the nearest grocery	0.705
	Distance to the nearest shopping location	0.617
	Distance to the nearest bank	0.508
Distance to entertainment activity locations	Distance to the nearest bar	0.891
	Distance to the nearest book store or library	0.845
	Distance to the nearest entertainment location	0.689

*Extraction Method: Principal Axis Factoring
*Rotation Method: Oblimin with Kaiser Normalization

3.2.3 Definition of land-use-attitude segments: Use of standardized, non-centered factor scores (NCFSs)

As mentioned in Section 3.2.1, previous factor analyses had been conducted, in which 3 blocks totaling 17 factors had been identified. One of these factors is the *pro-low-density attitude*. Considering the purpose of our study, the pro-low-density attitude is potentially very relevant. The preference for high or low density could influence how people evaluate the characteristics of the built environment in the area where they live, among other considerations. We would expect that pro-high-density individuals would find denser places more attractive, and vice versa for pro-low-density people. This could yield counteracting results when analyzing the influence of some variables on the choice of telecommuting. For example, a workplace with high employment density would be appealing to pro-high-density people, but not to pro-low-density people, thus leading to opposite impacts (negative and positive, respectively) on the propensity to telecommute. The reverse signs would be expected for a home location with high density attributes: more attractive for telecommuting to pro-high-density people, but less so in the case of pro-low-density people.

Given the importance of separating these two opposite types of effects, in this study we decided to segment the sample, to separate the pro-high-density respondents from the pro-low-density ones. However, this raised the issue of the best way to identify the two segments. Conventional computational methods yield mean-centered factor scores, i.e. scores with a mean of zero on each factor. In such cases, using the zero mean as the cutpoint will generally separate the sample into two roughly balanced groups for a given factor. However, using this solution to segment the sample is conceptually unsatisfying because it would classify individuals as pro-low-density or pro-high-density *only relative to the mean of the sample.* For instance, when analyzing the variables most strongly defining the pro-low-density factor (especially items 16 and 20 in Table 3, but also item 5), each of which had possible responses ranging from 1 to 5 (strongly disagree, disagree, neutral, agree, strongly agree), it was observed that the means are not 3 (neutral): instead, the sample tends to be slightly pro-high-density. In such a case, if factor scores are mean-centered, a score of 0 could actually signify "somewhat pro-high-density" (if that is the "average attitude"), and a small positive score, which would be classified as slightly pro-low-density if 0 were the demarcation point, could actually still reflect a pro-high-density attitude (i.e. below a true neutral on a pro-high-density-to-pro-low-density continuum), just not as strongly so as the sample mean. Thus, conventional methods for computing the "pro-low-density" factor score are not satisfactory for identifying the groups who are truly pro-high- or pro-low-density.

Accordingly, in this study we decided to compute *standardized, non-centered factor scores* (NCFSs, Thompson, 1993). Rather than only expressing factor scores relative to the sample mean, this approach respects the substantive content of the constituent items and preserves a true neutral, regardless of where the sample mean falls relative to that point.

To compute these factor scores, variables are first standardized (i.e. converted to their Z-score form). Then, to retrieve central tendency information, the original variable means are added back onto the Z scores (the result denoted as MZ_i, i=1 to 22). This keeps the transformed variables having unit variances, but shifts their distributions from being centered around 0 to being centered around the original means of the raw variables. Finally, the standardized scores MZ_i are linearly combined using the same factor-score coefficients as for the mean-centered factor (the first column of numbers in Table 3), to create the non-centered factor score.

Applying this method, the means of the new pro-low-density factor scores will no longer be zero, but determined by the original means of the variables. The point of neutrality, on the other hand, is the score obtained from original variable values consisting entirely of threes. First, we standardize each 3 (the neutral answer in the original survey) and add that variable's mean to it. For example, the "new (standardized) neutral" for Questions 2 and 5 will be calculated as (3-4.215)/0.953+4.215=2.940 and (3-2.361)/1.057+ 2.361=2.966 separately. Then, by computing the inner product of the factor-score coefficient vector and the vector of new neutral values for each variable, we obtain 1.08 for the neutral point of the non-centered factor scores. We can then consider cases with a non-centered factor score greater than 1.08 as pro-low-density, and the others as pro-high-density.

Since non-centered factor scores have been little-used in previous studies, it is of interest to compare how the sample for this study would be classified under each method of computing the factor scores. As mentioned above, using the non-centered factor scores, a respondent is considered pro-low-density if his /her non-centered factor score is 1.08 or greater and pro-high-density if the score is less than 1.08. By contrast, under the centered factor analysis, the respondent is pro-low-density if his/her centered factor score is 0 or greater, and pro-high-density if the score is less than 0.

TABLE 3 Description of the variables loading on the pro-low-density attitude factor*

m	Description	Factor Score Coeff.	Factor Loading	Mean	Std. Dev.
1	As long as I can do something pleasant or useful while traveling, I often don't really mind how long the trip takes	0.067	0.117	2.967	1.081
2	I'm satisfied with where I'm living right now	0.000	0.046	4.215	0.953
3	I like the idea of walking (or biking) as a means of transportation for me	-0.005	-0.192	3.555	1.197
4	Time spent traveling is generally wasted time	-0.015	-0.085	2.986	1.055
5	Living close to a bus or rail line means I'd be living closer to my neighbors than I'd like	0.239	0.267	2.361	1.057
6	I prefer to take transit rather than drive whenever possible	0.016	0.373	2.836	1.217
7	When I need to buy something, I usually prefer to get it at the closest store possible	-0.007	0.004	3.703	1.017
8	I like the idea of living somewhere with large yards and lots of space between homes	0.236	0.298	3.839	1.035
9	The only good thing about traveling is arriving at your destination	0.055	0.095	2.592	1.003
10	I like the idea of driving as a means of transportation for me	0.001	-0.264	3.392	0.993
11	I often enjoy getting out and going somewhere, even when the trip isn't totally necessary	0.025	-0.118	3.263	1.056
12	The traveling I need to do interferes with doing other things I like	0.074	0.144	2.918	0.975
13	In general, waiting is unpleasant even if I have a way to pass the time	0.021	-0.018	3.116	1.015
14	I like the idea of public transit as a means of transportation for me	-0.048	0.243	3.442	1.135
15	My trips to and from work offer me a useful transition	0.066	0.200	3.393	0.989
16	I like the idea of living in a neighborhood where I can walk to the grocery store	-0.326	-0.437	3.862	0.942
17	I prefer to drive rather than travel by any other means	0.039	-0.155	2.833	1.107
18	I prefer to organize my errands so that I make as few trips as possible	0.020	0.113	4.401	0.611
19	I make productive use of the time I spend going to and from work	0.067	0.214	3.347	1.044
20	I like the idea of having different types of businesses (such as stores, restaurants, offices, library) mixed in with the homes in my neighborhood	-0.298	-0.433	3.822	1.057
21	I prefer to walk or bike rather than drive whenever possible	0.057	-0.076	3.211	1.123
22	My trips to and from work are a real hassle	0.083	0.070	2.701	1.108

*Items with a loading greater than 0.25 in magnitude – i.e. those contributing most to the definition of the factor – are shaded.

The two methods of computing the factor scores return the same segment membership in most cases in the sample, with 988 cases that match on pro-high-density, and 468 cases that match on pro-low-density. However, 408 cases are mismatched: all of them would be counted as pro-low-density in the centered factor analysis method, but they should be considered pro-high-density on the basis of the objective content of their answers in the survey. Based on the non-centered factor score approach, about three-quarters of the sample (1396/1864) is pro-high-density, an orientation completely obscured by the centered factor score approach, which identifies only 53% of the sample (988/1864) as pro-high-density.

4. MODEL ESTIMATION

The built-environment-related hypotheses of the study mainly fall into two groups: 1) built environment variables will influence people's choice of telecommuting – both home and workplace built environment variables will matter, and they should influence people's choices in opposite directions; and 2) respondents holding respectively a pro-low-density attitude or a pro-high-density attitude will show different reactions even to the same influencing variable, not only in magnitude but potentially also in opposite directions.

We propose a number of hypothesized relationships between TC adoption and the available sociodemographic, attitudinal, and built environment variables. In this step we do not distinguish between full-day TC, part-day TC or overtime TC, because we consider it plausible that the direction of impact for a given variable will be the same across all three types of TC, just differing in magnitude (however, this speculation is shown not to be true in every case, as discussed in greater detail in Section 5 on the modeling results). We consider three types of neighborhood characteristics, respectively the *area share by land type*, the *distance to the nearest maintenance activities/entertainment*, and *population/employment density*, as well as *commute distance*. Land types include residential, commercial, and industrial. For example, a lower-density, more residential neighborhood type is expected to be appealing to pro-low-density individuals but not to pro-high-density ones. Accordingly, for pro-low-density individuals, having such a neighborhood at home would be conducive to telecommuting, while having it at work would make the workplace more appealing and thence reduce the motivation to telecommute (and conversely for pro-high-density respondents). We hypothesize no difference between pro-low and pro-high-density people in their attitudes toward commute distance, i.e. the longer the commute, the higher the probability one will choose to telecommute.

Multiple modeling approaches were considered in this study. Logistic regression and probit analysis are appropriate when the response variable takes one of only two possible values, as is the case here. Accordingly, we initially built binary logit models for the adoption of each of the three types of TC. However, although that is a straightforward approach for modeling a single choice with two possible outcomes, it does not allow for dependence among the three choices of interest. The correlations among the adoptions of the three types of TC (shown in the previous section) indicate that a model for simultaneous consideration of all three forms of TC, allowing correlations among the unobserved variables influencing the adoption of each form, would theoretically be better than individual binary logit models. We therefore also estimated a multivariate probit model with three dependent variables, namely the adoption of the three types of telecommuting.

A number of studies have used the multivariate probit model as a way to analyze correlated binary data (Cappellari and Jenkins, 2003; Song and Lee, 2005). For example, Choo and Mokhtarian (2008) explored the relationships between adoption and consideration of three travel-related strategy bundles. In previous related stages of the Fix I-5 study, Yun et al. (2011) estimated a multivariate probit model to analyze non-work travel behavior changes (route change, location change, time change, day change, and activity change) during the Fix using data from the first two waves of surveys. The method we use here is the same as in Choo and

Mokhtarian (2008), which is based on the study from Chib and Greenberg (1998). The general specification for a trivariate probit model is

$$Y_M^* = \beta_M' X_M + \varepsilon_M, \quad M = 1, 2, 3\,, \tag{1}$$

where Y_M^* is an unobserved variable representing the latent utility of considering type M telecommuting, X_M are the observed variables believed to influence the adoption of M, β_M' is the vector of coefficients to be estimated, and ε_M is normally distributed with mean 0 and variance arbitrarily scaled to equal 1. The variance-covariance matrix of the error terms is

$$\Lambda = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ & 1 & \rho_{23} \\ & & 1 \end{bmatrix}, \tag{2}$$

which identifies the permitted correlations in this model (and which were not allowed in the binary logit specification).

5. MODELING RESULTS

In this section, we present the binary logit (BL) and trivariate probit models of the adoption of each of the three types of telecommuting. We first discuss their goodness of fit, and then interpret both sets of models together. For all models, we tested allowing each variable to have different coefficients for the two density segments (pro-high and pro-low), but constrained coefficients to be equal across segment when the evidence supported doing so. As a result, some coefficients are segment-specific while others are constant across segments.

Table 4 summarizes the estimation results of the binary logit models, and Table 5 presents the trivariate probit model. The ρ^2 (McFadden's R^2) values for the FD, PD and OT binary logit models respectively are 0.516, 0.430 and 0.286. Especially the first two values are considered quite good for disaggregate behavioral models. The third value can also be considered good, given that overtime telecommuting represents a more heterogeneous practice, i.e. a choice open to and made by more diverse kinds of people. For the trivariate probit model the ρ^2 value is 0.474, which is quite strong for a joint model that effectively has eight alternatives (as shown in Table 1).

In our study, we use ρ^2 to measure the goodness of fit of the models. However, when we try to benchmark a model's goodness of fit against the market share model (the model containing only constant terms), the unequal shares across alternatives will give the market-share model alone an apparently strong goodness of fit compared to the equally-likely model. The ρ^2s of the market-share models are 0.442, 0.387, 0.203 for the binary logit models and 0.371 for the trivariate probit model, compared to the final model ρ^2s of 0.516, 0.430, 0.286 and 0.474 respectively. Viewed from this perspective, the variables of interest do not add a great deal of explanatory power.

On the other hand, it is useful to consider the contribution of only the true explanatory variables without the constant terms, rather than looking at the incremental value of the true explanatory variables beyond the constant terms in the model. Thus, we re-estimated the models with only true explanatory variables, which produced ρ^2 values of 0.482, 0.395, and 0.254 for the binary logit models and 0.447 for the trivariate model. Accordingly, we can conclude that the true variables account for most of the explanatory power of each model (89 - 93% for the binary logit models and 94% for the trivariate model). It is also interesting to note that, although the trivariate probit model has a lower final-model ρ^2 value than the best-fitting (full-day TC) binary model, it has the highest percent information explained by true variables among all the models. This confirms the advantages brought by the estimation of this more complex model specification, a finding that is especially impressive in view of the fact that the trivariate probit model predicts the choice among eight alternatives rather than just two.

TABLE 4 Binary logit model estimation results

	Full Day Telecommuting	**Part Day Telecommuting**	**Overtime Telecommuting**
Variables significant for those with pro-high-density attitudes			
Have a part time schedule	0.662 (0.058)		
Distance to maintenance at workplace	0.548 (0.007)		
Share of residential area within 1/2 mile radius of workplace		1.084 (0.030)	
Share of transportation/utilities area within 1/2 mile radius of workplace			-1.753 (0.008)
Share of residential area within 1/2 mile radius of home			0.726 (0.001)
Share of commercial area within 1/2 mile radius of home			-1.789 (0.025)
Share of transportation/utilities area within 1/2 mile radius of home			2.175 (0.063)
Employment density in home area			0.018 (0.057)
Variables significant for those with pro-low-density attitudes			
Household size	-0.201 (0.007)		
Population density at workplace	0.075 (0.022)		
Employment density in home area			-0.249 (0.042)
Variables significant to both segments			
socioeconomic variables			
Gender (1=male; 0=female)		-0.364 (0.014)	
Household income	0.251 (0.001)	0.218 (0.001)	0.296 (0.000)
Education level is college or higher		0.593 (0.001)	0.499 (0.001)
Household size			-0.095 (0.046)
Occupation is clerical	-1.127 (0.002)	-0.981 (0.002)	-0.816 (0.002)
Occupation is manager			0.564 (0.000)
Have a compressed schedule		-0.481 (0.008)	

attitude factors			
Time is unpressured	-0.114 (0.089)		-0.113 (0.032)
Pro-exercise attitude	0.157 (0.018)		-0.136 (0.009)
Concern about air quality	0.185 (0.022)		0.132 (0.027)
Responsibility towards environment		0.138 (0.040)	
No worries about environment	-0.165 (0.017)		
Pro-transit attitude		-0.111 (0.096)	
built environment elements			
Commute distance	0.037 (0.000)	0.016 (0.000)	0.011 (0.004)
Live in an apartment			-0.577 (0.052)
Share of industrial area within 1/2 mile radius of workplace		-0.898 (0.098)	
Share of transportation/utilities area within 1/2 mile radius of workplace	-2.745 (0.001)		
CONSTANT	-3.766 (0.000)	-3.490 (0.000)	-3.290 (0.000)
Sample size	1747	1750	1726
Number of adopters	227	265	416
Log-likelihood for equally-likely model	-1210.928	-1213.008	-1196.372
Log-likelihood with constant only	-674.808	-744.063	-953.188
Log-likelihood without constant	-627.369	-733.434	-891.655
Final log-likelihood	-586.817	-690.210	-854.483

Note: numbers in parentheses report the p-value for each coefficient.

TABLE 5 Trivariate probit model estimation results

	Full Day Telecommuting	Part Day Telecommuting	Overtime Telecommuting
Variables significant for those with pro-high-density attitudes			
Share of transportation/utilities area within 1/2 mile radius of workplace			-0.693 (0.047)
Share of residential area within 1/2 mile radius of home			0.341 (0.001)
Share of transportation/utilities area within 1/2 mile radius of home			1.319 (0.059)
Variables significant for those with pro-low-density attitudes			
Live in an apartment	0.602 (0.059)		
Population density at workplace	0.040 (0.021)		
Variables significant to both segments			
socioeconomic variables			
Gender (1=male; 0=female)	-0.148 (0.075)	-0.162 (0.036)	
Household income	0.154 (0.000)	0.124 (0.000)	0.179 (0.000)
Education level is college or higher	0.227 (0.043)	0.350 (0.000)	0.315 (0.000)
Household size			-0.056 (0.029)
Occupation is clerical	-0.593 (0.002)	-0.490 (0.002)	-0.378 (0.005)
Occupation is manager			0.331 (0.000)
Have a compressed schedule		-0.193 (0.024)	
attitude factors			
Pro-exercise attitude	0.055 (0.098)		-0.095 (0.001)
Concern about air quality	0.108 (0.003)		0.083 (0.008)
Responsibility towards environment		0.050 (0.081)	
built environment elements			
Commute distance	0.021 (0.000)	0.007 (0.002)	0.006 (0.002)
Live in an apartment			-0.382 (0.008)
Share of transportation/utilities area within 1/2 mile radius of home		1.168 (0.077)	
Share of industrial area within 1/2 mile radius of workplace		-0.609 (0.019)	
Share of transportation/utilities area within 1/2 mile radius of workplace	-1.053 (0.007)		
CONSTANT	-2.449 (0.000)	-1.984 (0.000)	-2.061 (0.000)

Correlation coefficients	
Corr(ε_F,ε_P)	0.740 (0.000)
Corr(ε_F,ε_T)	0.584 (0.000)
Corr(ε_P,ε_T)	0.607 (0.000)
Sample size	1726
Log-likelihood with constant only	-2258.794
Log-likelihood without constant	-1983.224
Final log-likelihood	-1887.326

Note: numbers in parentheses report the p-value for each coefficient.

Many variables significantly affect the adoption of the various types of TC. Most of the estimated coefficients have the expected signs, and they are significant at the 0.1 level or better. When analyzing the impact of attitudinal variables on the adoption of TC, it seems that the individuals who are not under time pressure have less need to save time by telecommuting, and are therefore less inclined to telecommute. Similarly, people who think air quality is a problem seem to be more likely to telecommute (full-days, but also overtime, although the latter may do little to address their air quality concerns), probably because they view telecommuting as a way to reduce emissions or a way to minimize their own contact with poor air quality. Those who feel personal responsibility towards the environment are more likely to telecommute part-days (which might help the environment at least somewhat, if it removes a personal vehicle from one or both peak periods). Not surprisingly, those who are not worried about the environment are less likely to TC full days.

One of the main reasons to engage in part-day TC is to avoid rush hour and save commute time; therefore, it is interesting that having a pro-transit attitude has a negative influence on part-day telecommuting. It is likely that the pain of rush-hour commuting is felt most keenly by car drivers, and that the pro-transit commuter – presumably more often using transit to commute, and thereby (1) able to use the time productively and (2) somewhat insulated from the stress of congestion – might be less motivated to choose part-day telecommuting.

Another interesting finding is associated with the pro-exercise attitude, which increases the chances for full-day telecommuting but decreases them for overtime telecommuting. This violates one of our initial expectations, i.e. that a given variable would have the same sign across all three types of telecommuting. However, we find this result to be quite plausible: full-day telecommuting saves time so that pro-exercise people could spend more time exercising, while overtime telecommuting usually takes extra time for work, reducing the time available for exercising and thus being less appealing to pro-exercise individuals.

Among sociodemographic variables, education and household income have significant influences on people's choice of telecommuting for all three forms of TC and across both sets of models (except that education is not significant to full-day TC in the binary logit model). This is consistent with most previous studies (Mokhtarian and Henderson, 1998; Kuenzi and Reschovsky, 2001; Mahmassani et al., 1993). Higher education levels and incomes probably represent (1) a higher economic value of time and thus more motivation to save commuting time; (2) jobs that are more likely to consist of information work and thus be more telecommutable; and (3) greater autonomy from supervision and thus a greater ability to telecommute. Not surprisingly, household size has a negative influence (the larger the household, the greater the potential distraction if staying at home and the smaller the space available for working at home might be), but, interestingly, only for overtime TC. Thus, household size appears to affect individuals' inclinations to "bring work home" after hours, but not to affect where work is done during normal hours.

Gender has long had an ambiguous influence on telecommuting adoption. While some studies found women to be less likely to adopt TC (Popuri and Bhat, 2003), others found them to be more likely (Sullivan et al, 1993). In our study, being female has a positive influence on the adoption of part-day (in both models) and full-day (in the trivariate probit) TC. Finally, turning to the occupation type of telecommuters, it is well-known that different occupation types have different requirements, which make them less or more suitable for telecommuting. Clerical jobs are often not suitable for telecommuting, as the work tends to require a great deal of face-to-face interaction; not surprisingly, this variable is significant and negative across all three forms of TC, for both sets of models.

Finally, consistent with expectation, the BE variables are found to have a substantial influence on the adoption of TC. In particular, for pro-high-density individuals, longer distances to maintenance activities at the work location, and a greater share of residential area around the workplace, appear to make the workplace less attractive and thus increase the motivation to telecommute. On the other end of the spectrum, for pro-low-density individuals, higher population density around the workplace appears to reduce its attractiveness and increase the inclination to work from home.

A couple of comparisons within pairs of variables are interesting. In the trivariate model's equation for overtime TC adoption, for pro-high-density individuals the shares of transportation/utilities area within a 1/2-mile radius respectively of work and home have opposite signs (-0.693 and 1.319). This supports our expectation that the same variable in work and home areas (if significant to both) has the opposite influence on the adoption of TC, e.g. an attractive factor in the workplace makes the person more willing to go to the workplace to work and thus less likely to telecommute, while this attractive factor in the home area would make the person more likely to stay at home and telecommute. It should be noted, however, that most built-environment variables are significant for either the home or work location, but not both.

Another comparison of interest is the opposite influence of the same variable for pro-high-density versus pro-low-density people. For example, for the overtime TC binary model, employment density in the home area has the opposite direction of influence for pro-high-density (0.018) compared to pro-low-density people (-0.249). This supports our hypothesis that pro-low and pro-high-density people would be differently influenced by the same variable. High employment density in the home area (signifying greater densities and diversity of land uses) may attract pro-high-density people but not appeal to pro-low-density people.

In the trivariate probit model, all correlation terms are strongly significant, with the expected signs: unobserved characteristics important to choosing full-day TC are positively and very highly correlated with part-day TC (0.74), while unobserved factors are somewhat less, but still strongly, positively correlated between overtime and full-day TC (0.58), and between overtime and part-day TC (0.61). Such unobserved characteristics could include attitudes toward telecommuting, job and managerial constraints, and home/family constraints, which could affect all three TC options in similar ways. These results confirm that the three choices are not independent, and also support the idea that overtime telecommuting has a somewhat different nature compared to full-day and part-day telecommuting, in that the first one is doing "extra" work outside of normal working hours, while the other two involve working during normal hours, just at a different location.

Estimating a trivariate probit model is a time- and effort-consuming process, thus it is reasonable to ask whether the outcome is enough better than what is obtained with binary models (which consider the three choices independently) to justify the effort put into it. To answer this question, Deng (2013) compared the shares predicted by the binary logit models to those obtained from the joint model. The results showed that both types of models do a satisfactory job in recovering the marginal shares; however, the trivariate probit model was much better able to predict the joint probabilities of adopting the various forms of telecommuting, thus confirming its superior behavioral realism.

6. SUMMARY AND DISCUSSION

To our knowledge, this study is the first to classify telecommuting into three types when modeling the adoption of different forms of TC, rather than viewing them together (or combining part-day with overtime TC), through the estimation of three independent binary logit models and a trivariate probit model. The different natures of full-day, part-day and overtime TC strongly motivates the need to separate them in modeling, a decision supported after the fact by the very different specifications of the models for the three types of TC. On the other hand, the descriptive analysis also clearly showed dependence across these three types. The model clarified that this dependence is due to common variables both observed (e.g. household income, being clerical, education level appearing in all three submodels) and unobserved (strong correlations between unobserved variables). Thus, joint estimation is important.

The models contained a rich set of explanatory variables, including socioeconomic variables, attitudinal variables and built-environment variables. In particular, built-environment variables for both the workplace and the home location are significant in the models. Telecommuting is a complex decision which is affected by many factors, including place preferences (for both home and work). We also considered the different attitudes people have towards density. Most of the built environment characteristics available to this study are completely objective (externally-measured, in fact, based on the respondents' self-reported home and work locations), but the way those characteristics are valued by different people is subjective; accordingly, the influence of a given built-environment element on the decision whether and how to telecommute may be totally different for a pro-low-density person compared to a pro-high-density person. Thus, we distinguished the pro-high-density respondents from the pro-low-density ones, in particular using non-centered factor scores to find the true neutral point of our pro-low-density factor, based on the prima facie content of the constituent items. Conventional mean-centered factor scores would have misclassified nearly 30% of the pro-high-density respondents as pro-low-density (because their scores were higher than the mean, although still below the true neutral point), thus illustrating the value of this little-used approach. We then allowed the impact of each built-environment variable to differ between those two groups, finding at least one instance in which the sign reversed between groups (higher employment densities near the home encouraged overtime TC for pro-high-density people but discouraged it for pro-low-density people), and numerous instances in which coefficient magnitudes differed (including being non-zero for one type of TC but zero for another).

Several directions for future research are indicated. For example, it is of interest to investigate the influence of the *difference* between a given home built-environment variable and the corresponding work variable, rather than putting each of them into the model separately. For example, if population density is high in the work area, but even higher in the home area, a pro-low-density person may still commute to work because the work area is "less bad" for him/her. It would also be interesting to compare the behavior of people who state they are interested in telecommuting but are currently not doing it, to that of telecommuters and those not interested at all in telecommuting. For future new data collections, it would be valuable to combine the extensive set of built environment variables available to this study with a richer set of variables characterizing the various telecommuting alternatives, including the respondents' perceptions of their advantages and disadvantages or the extent to which each alternative is feasible and desired.

ACKNOWLEDGMENTS

This project was partly funded by the University of California Transportation Center (UCTC), which receives funding from the U.S. Department of Transportation and the California Department of Transportation (Caltrans). The data collection was funded by the California Environmental Protection Agency (CalEPA). The authors wish to thank David van Herick, who created and shared a rich set of built-environment variables created from the home and work location information collected in the survey. An earlier version of this paper was presented at the 94th Transportation Research Board (TRB) Annual Meeting in Washington DC, January 2015; the comments of those anonymous referees have improved the paper.

REFERENCES

Bernardino, Adriana, and Moshe Ben-Akiva. 1993. Modeling the process of adoption of telecommuting: Comprehensive framework. *Transportation Research Record* 1552: 161-170.

Cappellari, Lorenzo, and Stephen P. Jenkins. 2003. Multivariate probit regression using simulated maximum likelihood. *The Stata Journal* 3(3): 278-294.

Chib, Siddhartha, and Edward Greenberg. 1998. Analysis of multivariate probit models. *Biometrika* 5: 347-361.

Choo, Sangho, and Patricia L. Mokhtarian. 2008. How do people respond to congestion mitigation policies? A multivariate probit model of the individual consideration of three travel-related strategy bundles. *Transportation* 35(2): 145-163.

Deng, Huijing. 2013. Factors Influencing Full-day, Part-day and Overtime Telecommuting: An Investigation of Northern California Workers. MS Thesis in Civil Engineering. University of California, Davis.

Haddad, Hebba, Glenn Lyons, and Kiron Chatterjee. 2009. An examination of determinants influencing the desire for and frequency of part-day and whole-day homeworking. *Journal of Transport Geography* 17: 124-133.

Khan, M., R. Paleti, C. Bhat and R. Pendyala. 2012. Joint household-level analysis of individuals' work arrangement choices. *Transportation Research Record* 2323: 56-66.

Kuenzi, J. and C. Reschovsky. 2001. Home-Based Workers in the United States: 1997. Technical Report P70-78, U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau. URL http://www.census.gov/prod/2002pubs/p70-78.pdf (last accessed on July 31, 2014).

Lyons, Glenn and Hebba Haddad. 2008. Commute replacement and commute displacement: the rise of part-day home working. *Transportation Research Record* 2082: 1-7.

Mahmassani, H., J. Yen, R. Herman, and M. Sullivan. 1993. Employee attitudes and stated preferences toward telecommuting: An exploratory analysis. *Transportation Research Record* 1413: 31–41.

Mokhtarian, P. and D. Henderson. 1998. Analyzing the travel behavior of home-based workers in the 1991 CALTRANS Statewide Travel Survey. *Journal of Transportation and Statistics* 1(3): 25–41.

Mokhtarian, Patricia and Ilan Salomon. 1996. Modeling the choice of telecommuting: 2. A case of the Preferred Impossible Alternative. *Environment and Planning A* 28: 1859–1876.

Mokhtarian, Patricia L., Ilan Salomon, and Sangho Choo. 2005. Measuring the measurable: Why can't we agree on the number of telecommuters in the U.S.? *Quality and Quantity* 39: 423-452.

Moos, M. and A. Skaburskis. 2008. The probability of single-family dwelling occupancy: Comparing home workers and commuters in Canadian cities. *Journal of Planning Education and Research* 27(3): 319–340.

Ory, David T. and Patricia L. Mokhtarian. 2006. Which came first, the telecommuting or the residential relocation? An empirical analysis of causality. *Urban Geography* **27(7)**: 590-609.

Popuri, Y. and C. Bhat. 2003. On modeling choice and frequency of home-based telecommuting. *Transportation Research Record* 1858: 55–60.

Singh, P., R. Paleti, S. Jenkins and C. R. Bhat. 2013. On modeling telecommuting behavior: option, choice, and frequency. *Transportation* **40(2)**: 373-396.

Song, Xin-Yuan, and Sik-Yum Lee. 2005. A multivariate probit latent variable model for analyzing dichotomous responses. *Statistics Sinica* 15: 645-664.

Sullivan, M. A., H. S. Mahmassani, and J.-R. Yen. 1993. Choice model of employee participation in telecommuting under a cost-neutral scenario. *Transportation Research Record* 1413: 42–48.

Summary of Travel Trends, 2009 National Household Travel Survey. U.S. Department of Transportation, Federal Highway Administration. Report No. FHWA-PL-11-022. http://nhts.ornl.gov/2009/pub/stt.pdf. Accessed March 6, 2013.

Tang, Wei (Laura), Patricia Mokhtarian, and Susan Handy. 2011. The impact of the residential built environment on work at home adoption frequency: An example from Northern California. *Journal of Transport and Land Use* 4(3): 3-22.

Thompson, B. 1993. Calculation of standardized, non-centered factor scores: An alternative to conventional factor scores. *Perceptual and Motor Skills* 77: 1128-1130.

Van Sell, Mary, and Sheila M. Jacobs. 1994. Telecommuting and quality of life: A review of the literature and a model for research. *Telematics and Informatics* 11(2): 81-95.

Vitterso, J., S. Akselsen, B. Evjemo, T. E. Julsrud, B. Yttri and S. Bergvik. 2003. Impacts of home-based telework on quality of life for employees and their partners. Quantitative and qualitative results from a European survey. *Journal of Happiness Studies* 4(2): 201-233.

Wilton, Robert D., Antonio Páez and Darren M. Scott. 2011. Why do you care what other people think? A qualitative investigation of social influence and telecommuting. *Transportation Research Part A: Policy and Practice* 45(4): 269-282.

Ye, Liang, Patricia L. Mokhtarian, Giovanni Circella. 2012. Commuter impacts and behavior changes during a temporary freeway closure: The 'Fix I-5' Project in Sacramento, California. *Transportation Planning and Technology* 35(3): 341–371.

Yun, Meiping, David van Herick, Patricia L. Mokhtarian. 2011. Nonwork travel behavior changes during temporary freeway closure: The Fix I-5 Project in Sacramento, California. *Transportation Research Record* 2231: 1-9.