Title

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Authors
Tang, Wei
Mokhtarian, Patricia
Handy, Susan

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by

Wei Tang
Transportation Technology and Policy Program
and Institute of Transportation Studies
University of California, Davis
One Shields Avenue, Davis, CA, 95616, USA
wtang@ucdavis.edu
voice 1-530-752-4957

Patricia L. Mokhtarian
Department of Civil and Environmental Engineering
and Institute of Transportation Studies
University of California, Davis
One Shields Avenue, Davis, CA, 95616, USA
plmokhtarian@ucdavis.edu
voice 1-530-752-7062, fax 1-530-752-7872

Susan L. Handy
Department of Environmental Science
and Policy and Institute of Transportation Studies
University of California, Davis
One Shields Avenue, Davis, CA, 95616, USA
slhandy@ucdavis.edu
voice 1- 530-752-5878, fax 1- 530-752-3350

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ABSTRACT

Working at home is widely viewed as a useful travel-reduction strategy, and partly for that reason, considerable research related to telecommuting and home-based work has been conducted in the last two decades. The contribution of this study is to examine the effect of residential neighborhood built environment (BE) factors on working at home. Using data from a survey of eight neighborhoods in Northern California, we develop a multinomial logit (MNL) model of work-at-home (WAH) frequency. To compare different approaches, other model structures were explored and are discussed also. Potential explanatory variables include sociodemographic traits, neighborhood preferences and perceptions, objective neighborhood characteristics, and travel attitudes and behavior. The results clearly demonstrate the contribution of built environment variables to WAH choices, in addition to previously-identified influences such as sociodemographic predictors (income, education level, and work status) and commute time. In the final MNL model, one subjective BE measure (perceived regional accessibility) and two objective BE characteristics (numbers of institutional establishments and eating out places within 400 meters) are found to be significant, and significant commute time, pro-walking, pro-biking, and pro-transit variables all have an indirect relationship with the BE. The findings suggest that land use and transportation strategies that are desirable from some perspectives will tend to weaken the motivation to work at home, and conversely, some factors that seem to increase the motivation to work at home are widely viewed as less sustainable. Accordingly, this research points to the complexity of trying to find the right balance among demand management strategies that sometimes act in competition rather than in synergy.

Key words: work at home; telecommuting; teleworking; binary logit model; multinomial logit; residential location; built environment

1. INTRODUCTION

Despite increases in nonwork travel over the past few decades, the journey to work arguably remains the most important trip purpose in urban areas. In the United States, it constituted about 22% of passenger trips and 27% of passenger vehicle miles traveled in 2001 (Hu and Reuscher, 2004). Another estimated 27% of trips were chained to the commute (FHWA, 2005). Commute travel continues to contribute to the rising congestion in major metropolitan areas (TTI, 2005). Accordingly, finding ways to alter the temporal or spatial patterns of the work trip is still a high priority for transportation planners and policymakers.

Working at home (WAH) is widely viewed as one promising strategy for reducing peak-period commute travel. WAH, however, comprises at least three relatively distinct segments. There is no consensus on definitions, but in keeping with previous distinctions made by one of the authors (Mokhtarian, 1991; Mokhtarian, et al., 2005), in this paper we distinguish telecommuters, home-based business (HBB) workers, and those whose home work is primarily overflow from the regular workplace. “Telecommuters” refers to *salaried employees* working at home or at a location close to home instead of commuting to a conventional workplace at the usual time, communicating with the office by phone and computer. “Home-based business (HBB) workers” refers to *self-employed individuals* whose business is primarily operated or managed from home. “Overtime home-workers” (also referred to as “*supplementers*”, e.g. by Kraut, 1988; or “*work permeators*” by Salomon, 1990) are those who conduct work at home on evenings or weekends, after making a conventional commute during the workweek. Since they have little or no impact on transportation, the last group is not of further interest in this study, except to note that they are generally included in publicized estimates of the number of people who WAH, and thereby contribute to an exaggerated view of the potential for WAH to reduce commute travel. For example, among the 20.7 million people reported to “usually” (at least once a week) do “some work at home as part of their primary job” by the U.S. Bureau of Labor Statistics Work at Home 2004 study, about 10.2 million were described as “just taking work home from the job” (www.bls.gov/news.release/homey.toc.htm, accessed July 31, 2006).

To better understand the potential transportation impacts of WAH, it is necessary to understand the kinds of people most likely to adopt it, and how often they choose to work at home. A number of studies (reviewed in the next section) have analyzed characteristics of home workers, and the adoption and frequency of telecommuting in particular. For the most part, however, those WAH-related choices have been related to sociodemographic characteristics, and occasionally to telecommuting and travel-related attitudes and lifestyle orientations. We are not aware of any studies that have investigated the impact of the built environment (BE) (aside from commute characteristics for salaried employees) on WAH choices. Yet, it is plausible to expect the BE to matter. Characteristics of one’s surroundings heavily influence how easy it is to travel, both locally and regionally, and how appealing it is to be at a particular location such as one’s residential neighborhood. Thus, such characteristics could also influence one’s choice to travel or to stay at home more. Under the assumption that the BE *does* matter, policymakers are inclined to try to change travel behavior by using land use-related policy instruments such as neo-traditional developments and smart growth principles, as well as improvements to the transportation network.

The purpose of this paper, then, is to explore the influence of the BE on the decision to WAH, and on the frequency with which to do so. The remainder of this paper is organized as follows. The next section briefly reviews previous related research. The subsequent section describes the data available to the study, followed by a discussion of our specific hypotheses, the conceptual model structure, and various potentially appropriate estimation methodologies. We then present and interpret our preferred model, a multinomial logit model of WAH frequency, together with alternative models The last section summarizes the study and suggests future research directions.

2. LITERATURE REVIEW

A number of studies have analyzed the characteristics of home workers (Mokhtarian and Henderson, 1998; Kuenzi and Reschovsky, 2001; Safirova and Walls, 2004; Plaut, 2005), adoption of telecommuting (Bernardino et al., 1993; Mahmassani et al., 1993; Mokhtarian and Salomon, 1996b, 1997; Walls et al., 2007) and frequency of telecommuting (Sullivan et al., 1993;

Olszewski and Mokhtarian, 1994; Mannering and Mokhtarian, 1995; Varma et al., 1996; Walls et al., 2007) in the last two decades. We will review selected studies from each of these three areas in turn.

2.1 Characteristics of home workers

As mentioned in Section 1, WAH consists of at least three relatively disparate segments – HBB workers, telecommuters and overtime home-workers – and we will focus on the first two. Numerous studies have compared these two groups of workers to each other and/or to non-home-based (conventional) workers. However, since in this subsection we focus on descriptive statistics rather than modeling results, sample representativeness is a critical consideration. Thus, we here report results only from studies using large-sample (national, statewide, or regional), general-purpose surveys where an effort is made to achieve representativeness, and not those from smaller studies where the data are subject to sampling biases (only certain firms, or small geographic areas, are surveyed) as well as non-response biases (self-selection into or out of a study which is specifically focused on the WAH topic).

In brief:

- ♦ Compared to HBB workers, telecommuters tend to have higher personal and household incomes, although HBB workers in turn have higher incomes, on average, than non-home-based workers (Mokhtarian and Henderson, 1998; Kuenzi and Reschovsky, 2001; Yeraguntla and Bhat, 2005; Safirova and Walls, 2004).
- ♦ Compared to conventional workers, telecommuters are more likely to be males; well-educated; in the finance, insurance and real estate (FIRE) industry; older (Safirova and Walls, 2004) and work part-time (Yeraguntla and Bhat, 2005; Drucker and Khattak, 2000; Popuri and Bhat, 2003).
- ♦ Compared to conventional workers, people who WAH are more computer-proficient and use computers more heavily (Drucker and Khattak, 2000); more likely to be female and well-educated (Kuenzi and Reschovsky, 2001); less likely to be 25 or younger, and more likely to be 55 or older (Plaut, 2005).
- ♦ Compared to conventional workers, HBB workers are no more likely to have health limitations (Pratt, 1993).

In addition, one study (Mokhtarian and Henderson, 1998) analyzed the travel behavior of telecommuters, HBB workers, and conventional workers. They found that HBB workers had the highest overall trip rate (6.1 trips per day, versus 5.2 and 5.3 for telecommuters and conventional workers, respectively), but the lowest total travel time (1.43 hours, versus 1.50 and 1.77). The time-of-day distribution for both groups of home-based workers was flatter than the typical two-peak distribution for conventional workers, with many trips of the first two groups falling into the midday off-peak period.

2.2 Telecommuting adoption

Although descriptive studies comparing home workers to conventional commuters on a variable-by-variable basis are useful, such comparisons can be misleading. Differences that are significant when viewed in isolation may be confounded with other variables that are the true sources of the difference; when these third-party variables are controlled for, the initial differences are no longer significant. And conversely, differences that are not significant in isolation may become so when other factors are taken into account. Accordingly, it is important to develop models of adoption that include multiple explanatory variables simultaneously. Several such models have appeared in the literature (in some cases modeling a stated hypothetical choice; in others modeling revealed preference or actual choice); their empirical findings are summarized in Table 1. Not surprisingly, factors that increase the monetary cost of telecommuting decrease the propensity to prefer or choose it, as do variables indicating job unsuitability, manager unwillingness, and a preference for social interaction. Long or stressful commutes increase the utility of telecommuting, as do perceptions that telecommuting will offer flexibility and other personal benefits, children at home and the presence of support infrastructure (such as computers) at home.

2.3 Telecommuting frequency

Arguably, the frequency with which an individual works at home is even more important than the adoption choice itself: from the standpoint of transportation, air quality, and other impacts, it matters a great deal whether the adopted choice to WAH occurs five days a week or less than once a month. Aside from some descriptive studies (including those cited in Section 3.2.1), we are not aware of any empirical analyses of the frequency of WAH for HBB workers (perhaps because commute reduction is a moot point for most self-employed individuals). However, several models of telecommuting frequency have been developed, as summarized in Table 2. Naturally, telecommuting cost still works as a constraint on frequency, as it does in the adoption context. The need for social interaction with co-workers, telecommuting experience (ironically) and taking transit to work all have negative effects on telecommuting frequency. On the other hand, age, the presence of children in the household, and intensity of computer usage tend to increase telecommuting frequency. Interestingly, even discounting the Olszewski and Mokhtarian (1994) study, which involved a small sample, mixed results are found for gender and commute length: they are not always significant, nor always have impacts in the same direction.

A few studies have simply examined patterns of telecommuting frequency over time, without modeling frequency as a function of explanatory variables. For example, Varma et al. (1996) examined the duration and frequency of individuals' telecommuting participation. They found that higher-frequency telecommuters were less likely to have quit during the study period (suggesting that a stronger motivation explained both the persistence of engagement and the higher frequency), but among those who did quit, higher frequencies were associated with shorter durations (suggesting a potential "burnout" effect). In addition to the finding by Bernardino et al. (1993) that prior experience with telecommuting decreased its preferred frequency, several other studies found that actual telecommuting frequency decreased over time (Mokhtarian and Meenakshisundaram, 2002; Mokhtarian et al., 2004; Wernick and Khattak, 2005). Despite that fact, and despite telecommuters having longer one-way commute distances than non-telecommuters, Mokhtarian et al. (2004) found that people (at least in their specific sample) telecommuted often enough to more than compensate for their longer commutes, so that the total commute distance traveled for telecommuters was (on average) equal to or less than that of non-telecommuters.

Table 1. Empirical results of previous telecommuting adoption models

Study	Dependent variable	Significant explanatory variables (impact on propensity to adopt)
Bernardino and Ben-Akiva (1996)	Actual choice of telecommuting	**Positive impact:** Desire to improve lifestyle quality (flexibility to adjust one's schedule to the work load and personal needs and to avoid commuting), higher salary to telecommuters **Negative impact:** Increase in work-related costs, lower salary to telecommuters
Mokhtarian and Salomon (1996b)	Actual choice of telecommuting	**Positive impact:** Overtime, commute stress (attitudinal factor) **Negative impact:** Misunderstanding, lack of manager support, job unsuitability, technology requirements and office discipline (attitudinal factor relating to the negative aspects of working away from the normal office)
Yen and Mahmassani (1997)	Stated preference for telecommuting	**Positive impact:** 5% salary increase, number of children in the household, number of personal computers at home, commute distance, job suitability, family orientation (attitudinal factor) **Negative impact:** 5% salary decrease, telecommuting cost, need for face-to-face communication with co-workers, importance of social interactions with co-workers
Mokhtarian and Salomon (1997)	Preference for telecommuting	**Positive impact:** Perception of telecommuting as important in situations of disability/ parental leave, stress, perception of telecommuting providing personal benefits, commute stress, commute time, job suitability **Negative impact:** Importance of workplace interaction, household distractions, perception of the commute as beneficial
Popuri and Bhat (2003)	Actual choice of telecommuting	**Positive impact:** Female with children, licensed driver, drive to work, work in a private company, length of service, HH income, fax availability **Negative impact:** Female, transit to work
Walls et al. (2007)	Actual choice of telecommuting	**Positive impact:** Older than 30, college degree, white, other adult in HH, job in architecture/engineering/"other professional", sales, or management **Negative impact:** Children ages 6-17, working in transportation, communications, retail trade industries, employer having 25-249 employees, job in health services

Table 2. Empirical results of previous telecommuting frequency studies

Study	Dependent variable*	Explanatory variables (impact on frequency)
Bernardino et al. (1993)	Stated telecommuting frequency preference	**Positive impact:** Income increase, number of children in the household, commuting time savings, not offered chance to telecommute **Negative impact:** Telecommuting cost, 10% income reduction, prior experience with telecommuting.
Sullivan et al. (1993)	Stated telecommuting frequency preference	**Positive impact:** Round-trip commute time, commute stops per week, average time using computer per day, being female with children, being female, being married **Negative impact:** Length of time with firm, need for face-to-face communication, work end time
Olszewski and Mokhtarian (1994)	Actual frequency of telecommuting	**Positive impact:** Work as information professional **Negative impact:** Profession in policy/engineering/financial field **No significant impact:** Age, gender, commute length, presence of children
Mannering and Mokhtarian (1995)	Actual frequency of telecommuting	**Positive impact:** The presence of small children in the household, household income per capita, work computer availability indicator, family orientation indicator **Negative impact:** Prefer to work with team rather than solo, adoption of flextime, need for face-to-face control over work **No significant impact:** Commute length, recent departure time change in response to congestion, managerial/professional occupation, amount of time spent on face to face contacts
Mokhtarian and Meenakshisundaram (2002)	Actual frequency of telecommuting	**Positive impact:** Age, commute length **Negative impact:** Being female **No significant impact:** Education, income
Popuri and Bhat (2003)	Actual frequency of telecommuting	**Positive impact:** Female with children, age, being married, no. of vehicles, work in a private company, HH income, fax availability, multiple phone lines at home **Negative impact:** Transit to work
Walls et al. (2007)	Actual frequency of telecommuting	**Positive impact:** College degree, company has formal telework program, commute time, days worked in survey week, holds two or more jobs **Negative impact:** Full-time employee **No significant impact:** White, children, gender, tenure, works overtime, years of telecommuting

* Frequency reflects how many days people choose to telecommute over a specific time period. Different studies use different definitions. Generally, it is an ordinal variable such as: “never”, “once per month”, “1 or 2 days a week” and “more than 2 days a week”; or “never”, “infrequently”, “frequently” and “full time”, etc.

3. DATA, HYPOTHESES, AND METHODOLOGY

As noted earlier, the general purpose of this study is to explore the effect of residential neighborhood built environment (BE) traits (including preferences, perceptions and objective characteristics), as well as attitudes toward transportation, on WAH adoption and frequency. In some previous studies, attitudinal factors were included in telecommuting adoption models, but they were extracted from surveys specifically designed to analyze telecommuting. For example, both Mokhtarian and Salomon (1997) and Yen and Mahmassani (1997) found that attitudes related to the personal benefits, family effects, and workplace interaction effects of telecommuting were important to the preference for that option. Since the present study is based on a survey not originally designed for this purpose, we lack a number of variables relevant to telecommuting, which is a limitation. Instead, however, we have a rich collection of attitudinal and objective measures of the built environment, as well as general transportation-related attitudes, which have not previously been studied in the context of telecommuting. In the remainder of this section, we first describe the available data, then present some specific hypotheses to be tested in the study, next discuss potential methodological approaches together with the one finally selected, and finally describe the model development process.

3.1 Data collection

The data used in this study came from a self-administered 12-page survey mailed in two rounds in late 2003 to households in eight neighborhoods in Northern California. The neighborhoods were selected to capture variation on three dimensions: neighborhood type (traditional vs. suburban), size of the metropolitan area (larger vs. smaller city), and region of the state (Bay Area vs. Central Valley). Using data from the US Census, we screened potential neighborhoods to ensure that average income and other characteristics were near the average for the region. Four neighborhoods in the San Francisco Bay Area―two in the Silicon Valley area and two in Santa Rosa―had been previously studied (Handy, 1992). In the Central Valley, two neighborhoods from Sacramento (larger metro area – the state capital) and two from Modesto (smaller area) were selected to contrast with Bay Area neighborhoods (Fig. 1).

For each neighborhood, two databases of residents were purchased from a commercial provider, New Neighbors Contact Service (www.nncs.com; this service maintains an overall database of names and addresses for residences throughout the US constructed from a variety of public records. The database is largely used for commercial advertisement mailings): a database of movers and a database of non-movers. The movers included all current residents of the neighborhood who had moved within the previous year. From this database, we drew a random sample of 500 residents for each neighborhood. The database of non-movers consisted of a random sample of 500 residents not included in the movers list for each neighborhood.

Note: Light-background labels denote suburban neighborhoods; dark-background labels denote urban ones.

Figure 1. Location of neighborhoods

The survey was administered using a mail-out, mail-back approach. The initial survey was mailed out at the end of September 2003. Two weeks later, a reminder postcard was mailed to the entire sample using first-class mail. At the beginning of November, a second copy of the survey with a revised cover letter was sent to a shorter list that excluded incorrect addresses and individuals who had already responded to the survey. Two weeks later, a second reminder postcard was mailed to this list of residents. As an incentive to complete the survey, respondents were told they would be entered into a drawing to receive one of five $100 cash prizes; the winners were selected in December.

The original database consisted of 8000 addresses but only 6746 addresses turned out to be valid. The number of responses totaled 1682, for a response rate of 24.5%. This is considered quite good for a survey of this length; typical response rates for a survey administered to the general population are 10-40% (Sommer and Sommer, 1997). A comparison of sample characteristics to population characteristics (based on the 2000 US Census) shows (Handy et al., 2005, Table 1) that survey respondents tend to be older on average than residents of their neighborhood as a whole, and that households with children are underrepresented for most neighborhoods. Median household income for survey respondents was higher than the census median for all but one neighborhood, a typical result for voluntary self-administered surveys. However, since the focus of our study is to model relationships among variables, and sociodemographic differences are explicitly taken into account, it is not necessary that our sample be strictly representative (Singleton and Straits, 1999).

For the purposes of the present study, we first screened out the 408 cases who were missing data on the WAH question (described in detail in Section 3.2.1). We also screened out 27 retired and unemployed respondents, and one whose work status could not be ascertained, to leave 1246 workers constituting our study sample. Some key sociodemographic characteristics for the study sample as a whole and for the WAH subset of the sample are shown in Table 3. The table shows that relatively more males adopt WAH than females, since they constitute a higher share of the WAH adopters sample than for the sample as a whole. WAH adopters are also slightly (though significantly) more likely to be part time employees, but have higher household income and education levels than non-adopters. The remaining characteristics—age, commute distance and commute time—are similar for both groups.

Table 3. Sample sociodemographic characteristics

	Pooled data	**WAH adopters only**
Number of cases	1246	302
Percent of females	51.1	47.8
Average age (years)	43.2	43.7
Median HH total annual income	75,000	90,000
Average work status (1=full-time; 0=part time)	0.89	0.85
Average education level [a]	3.2	3.6
Mean commute distance (miles) [b]	12.3	12.5
Mean commute time (minutes) [b]	20.0	19.7

[a] 1= High school diploma or less; 2=College or technical school; 3=Four-year college degree or technical school degree/certificate; 4=Graduate school; 5=Completed graduate degree(s).
[b] For those respondents who initially supplied commute information (see discussion in Section 3.2.2).

3.2 Variables

3.2.1 Dependent variables

The purpose of this study is to model the choice to WAH or not (adoption), and if so, how often to do so (frequency). The assortment of dependent variables we investigated were all created from the survey question asking, "How often do you work at home *instead* of making the trip to work? ___ days per month". Although we deliberately focused on home work as a substitute for commuting, it is likely that many respondents who work exclusively at home and would not otherwise have a conventional commute would answer this question as well (because if one does WAH at all, it could be unsatisfying to answer "0" to this question). Thus, in the remainder of the discussion, we assume that the 302 non-zero responses to this question ("WAH adopters") constitute a mixture of telecommuters and HBB workers. The remaining 944 cases, who work at home zero days per month, are classified as "non-adopters" for our binary adoption model, and in the "not at all" category for our final frequency model (see Section 3.4).

Figure 2 shows that for the 302 WAH adopters, if WAH frequency were grouped into categories, the distribution is somewhat bi-modal, with peaks at both low and high levels of frequency, and very few (only 16) cases working at home between 9 and 18 days per month. Note that this frequency distribution, if expressed on a days-per-week basis, would resemble the one obtained from the U.S. Census Bureau Survey of Income and Program Participation (SIPP, Kuenzi and Reschovsky, 2001), shown in Figure 3. From the figure it can be seen that in the SIPP data, the higher-frequency group is dominated by those who work exclusively at home, whereas the lower-frequency group is dominated by "mixed" workers who work elsewhere as well as at home. Although the SIPP study did not formally classify home workers as telecommuters or home-based business workers according to our definitions, it seems plausible to infer that the high-frequency WAH cases tend to be self-employed HBB workers, while the low-frequency ones are more likely to be salaried telecommuters.

Similarly, the 2004 Work at Home survey of the U.S. Bureau of Labor Statistics (http://www.bls.gov/news.release/homey.toc.htm, accessed on November 6, 2006) showed that among salaried employees, only about 14% worked at home for 35 hours or more per week, compared to almost 22% of self-employed workers. The average weekly time worked at home for salaried and self-employed workers in that study was 19 and 25 hours, respectively. These findings are also consistent with data from numerous small-sample studies of telecommuting specifically (Handy and Mokhtarian, 1995; Varma et al., 1998; Safirova and Walls, 2004; Mokhtarian et al., 2005), in which the average telecommuting frequency falls around 1.2 days a week (or 5 days a month). Unfortunately, our data do not permit us to make those classifications definitively, and using frequency alone is certainly not definitive (since some telecommuters WAH virtually full-time, and some self-employed workers only WAH a limited amount). However, based on the considerations above and on the commute data presented in the next section, in the discussions that follow we will treat the lower-frequency group (1 – 8 days/month) as being predominantly telecommuters, and the higher-frequency one (9 or more days/month) as being a mixture of telecommuters and HBB workers.

Given the differences between telecommuters and HBB workers that were discussed in Section 2, we experimented with excluding the higher-frequency group from the modeling exercise, and focusing only on telecommuters (see Section 4.4). However, by retaining both groups, we obtained satisfying results that made the most efficient use of the available information, while still providing insights into distinctions between the choices of each type of WAH. We also experimented with keeping the dependent variable as the ratio-scaled number of days per month, and with various combinations into ordinal categories. Ultimately, the best results were obtained by dividing the responses into five frequency categories: zero days, one day, 2-4 days, 5-8 days, and 9 or more days a month (respectively labeled Alternatives 0-4 in the discussion of results below).

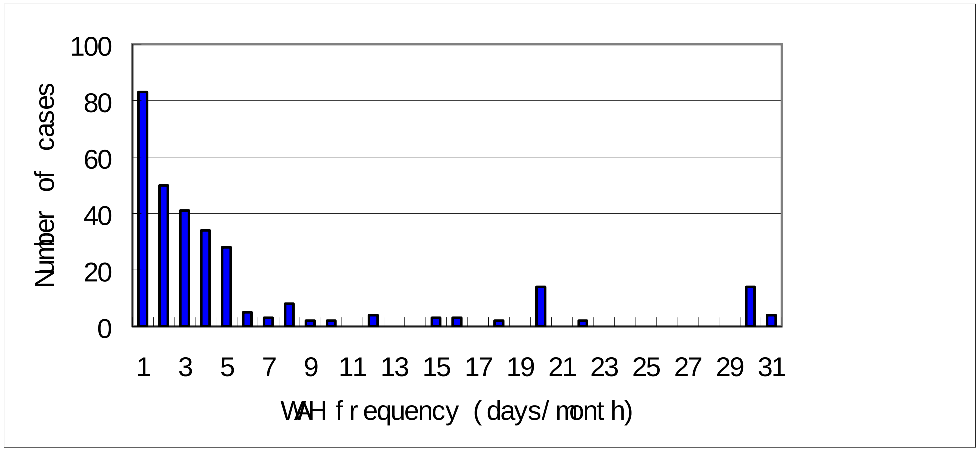
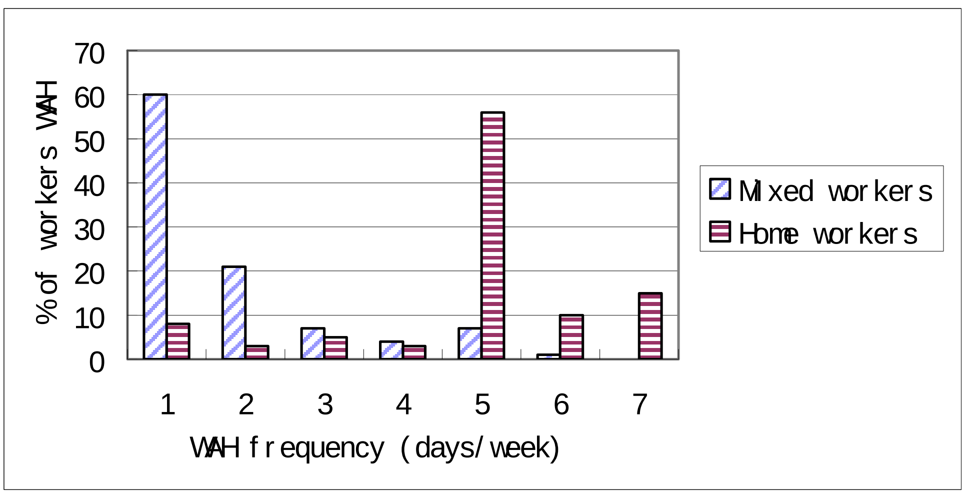


Figure 2. Distribution of work-at-home frequency in our sample (adopters only; N=302)



Source: Based on Kuenzi and Reschovsky (2001).

Figure 3. Distribution of work-at-home frequency in SIPP (1997)

3.2.2 Explanatory variables

The explanatory variables can be grouped into the following four categories:

Commute trip attributes: Both intuition and previous research (e.g. Nilles, 1988; Bernardino et al., 1993; Mahmassani et al., 1993; Sullivan et al., 1993; Mokhtarian and Salomon, 1997; Yen and Mahmassani, 1997) indicate that commute characteristics, particularly distance or time to work, influence the choice to work at home, at least for telecommuters. For example, Nilles

(1988) found that “[t]he propensity to telecommute is proportional to commute distance/time… the most highly motivated telecommuters tend to be those who live farthest from the office”. Similarly, Mokhtarian and Salomon (1997) found that longer commute times increased the propensity to prefer telecommuting. Thus, we consider the distance (miles) to the primary work place, travel time (minutes) needed to get to there, and travel speed to potentially affect the choice to WAH. However, this variable is somewhat troublesome, since individuals who are self-employed and WAH do not have a commute. Indeed, among the 50 highest-frequency home workers in the sample (those working at home 9 or more days a month), 26 had either responded “0” to the commute miles and minutes questions (16 cases), or left them blank (10 cases). For the latter 10 cases, we filled in zeroes on the assumption that they were self-employed and worked at home. This means, however, that we can expect a different role of commute length for telecommuters than for HBB workers: for the former group, the *longer* the commute, the more likely they are to WAH, and the more frequently they may be inclined to do so, whereas for the latter group, a *short* (in fact, zero) commute is associated with WAH, and doing so very frequently. Thus, commute variables in the models should be interpreted as interaction variables (the commute variable multiplied by a dummy variable that equals 1 for salaried employees who commute, and 0 for HBB workers), and their coefficients interpreted as representing the impact of commute characteristics *for those who have a commute*.

BE characteristics and neighborhood preferences: Thirty-four neighborhood characteristics were presented to respondents, and they were asked to rate each of them on a four-point scale from “not at all true” (1) to “entirely true” (4) (perceptions of their current residential neighborhood), as well as on a four-point scale from “not at all important” (1) to “extremely important” (4) (preferences for residential neighborhood characteristics). A previous factor analysis of these characteristics (Handy et al., 2005) had produced six factors. One of those factors was accessibility, which combined aspects of both local (“shopping areas within walking distance”) and regional (“easy access to the freeway”) accessibility. For the present study, however, that factor proved unsatisfactory. We hypothesized that an individual who is regionally-oriented might not choose to WAH at all, or, if choosing it, might WAH at a lower frequency, whereas a neighborhood-oriented (i.e. local-oriented) person might have a higher propensity to WAH or to WAH more frequently. Thus, we separated the statements related to regional accessibility and local accessibility, and then conducted separate factor analyses for each group of statements, in order to obtain a clearer picture of the effect of BE factors. From the regional-oriented statements (shown in Table 4), one factor was extracted; from the local-oriented statements, three factors were extracted as shown in the table. Thus, in total, four factors were generated: regional accessibility, safety and quietness, diversity, and outdoor appeal.

In addition, objective measures of accessibility were estimated for each respondent, based on distance along the street network from home to a variety of destinations classified as institutional (bank, church, library, and post office), maintenance (grocery store and pharmacy), eating-out (bakery, pizza, ice cream, and take-out), and leisure (health club, bookstore, bar, theater, and video rental). Accessibility measures included the number of different types of businesses within specified distances, the distance to the nearest establishment of each type, and the number of

Table 4. Factors for neighborhood characteristics

Factor [a]	Statement	Loading [b]
Regional accessibility	Easy access to the downtown	.677
	Easy access to a regional shopping mall	.659
	Easy access to freeway	.626
	Good public transit service (bus or rail)	.507
	Good bicycle routes beyond the neighborhood	.448
Safety and quietness	Quiet neighborhood	.736
	Low level of car traffic on neighborhood streets	.673
	Safe neighborhood for walking	.575
	Good street lighting	.554
	Attractive appearance of neighborhood	.434
	High level of upkeep in neighborhood	.397
	High quality living unit	.395
	Safe neighborhood for kids to play outdoors	.380
Diversity	Diverse neighbors in terms of ethnicity, race, and age	.530
	Other amenities such as a pool or a community center available nearby	.521
	High quality K-12 schools	.496
	Lots of people out and about within the neighborhood	.486
	Shopping areas within walking distance	.485
	Parks and open spaces nearby	.475
	Sidewalks throughout the neighborhood	.471
	Economic level of neighbors similar to my level	.459
	Safe neighborhood for kids to play outdoors	.396
	Lots of interaction among neighbors	.385
Outdoor appeal	Large front yards	.689
	Big street trees	.543
	Large back yards	.510
	Variety in housing style	.490
	Attractive appearance of neighborhood	.414
	Lots of off-street parking (garages or driveways)	.356

[a] To ensure the separation of factors, statements relating to regional accessibility were analyzed separately from the others. Principal axis factoring with varimax rotation was employed in both cases.
[b] Represents the correlation between the statement and the factor.

establishments of each business type within specified distances. Commercial establishments were identified using on-line yellow pages, and ArcGIS was used to calculate network distances between addresses for survey respondents and commercial establishments.

Travel attitudes: The survey asked respondents whether they agreed or disagreed with a series of 32 travel-related statements on a 5-point scale from "strongly disagree" (1) to "strongly agree" (5). Again, a previous factor analysis had been conducted, in which six underlying dimensions were identified: pro-bike/walk, pro-travel, travel minimizing, pro-transit/walking, safety of car, and car dependent (Handy et al., 2005). Using this factor analysis, however, we found it difficult to explain the effect of pro-transit/walking on WAH adoption and frequency: a pro-transit attitude is more related to regional accessibility and may decrease the propensity to WAH, as Popuri and Bhat (2003) found for actual transit usage (Table 1) (because seeing or using transit as an option may make the commute less stressful); whereas pro-walking is potentially more related to local BE characteristics (pro-walkers may be more inclined to WAH so that saved commute time can be spent on walking, perhaps in their pleasant local neighborhood). Because this factor was based on a series of statements comparing either walking or transit to driving, it was relatively easy to split it into two variables. We separated the survey statements related to comparing walking versus driving and taking transit versus driving, then simply mathematically averaged the responses in each category to generate two new variables: pro-walking and pro-transit. We performed a similar split for the original pro-bike/walk factor, separating out the biking-versus-driving items to create a "pure" pro-biking factor (the walking-versus-driving items were the same as those associated with the old pro-transit/walking factor, and thus were already separated into a pure pro-walking factor). Table 5 shows the items associated with each of the three new factors. Scores on the remaining four factors from the original analysis were retained as they were, but since none of those factors were significant in the final models of this study, we refer the reader elsewhere (e.g., Handy et al., 2005) for their detailed descriptions.

Table 5. Creation of new mode-preference factors

New factor (comparison)	Related statements
Pro-walking (walking versus driving)	Walking can sometimes be easier for me than driving Traveling by car is safer overall than walking[a] I prefer to walk rather than drive whenever possible I like walking
Pro-transit (transit versus driving)	Public transit can sometimes be easier for me than driving Traveling by car is safer overall than taking transit[a] I prefer to take transit rather than drive whenever possible I like taking transit
Pro-biking (biking versus driving)	Biking can sometimes be easier for me than driving Traveling by car is safer overall than riding a bicycle[a] I prefer to bike rather than drive whenever possible I like riding a bike

[a] Reversed by taking 6 minus the original response, so that a lower value is more favorable to driving for all statements.

Sociodemographics: The survey also captured variables such as gender, age, employment status (part time or full time), educational background, household income, household size, the number of children in the household, mobility constraints, residential tenure, and so on.

3.3 Hypotheses for the effects of explanatory variables on WAH adoption

The postulated effects of explanatory variables on WAH adoption are listed in Table 6. In some cases the expected direction of impact is reasonably clear; in other cases, either there is no strong hypothesis (but the relationship is of interest to explore) or hypotheses in both directions are plausible. For the most part, we have similar hypotheses with respect to frequency – i.e. the same variables expected to increase the propensity to adopt at all could be expected to increase the frequency of WAH. One exception, based on the literature, is for income. On average, home workers tend to have higher incomes than regular commuters, but HBB workers have lower incomes than "mixed workers" (Kuenzi and Reschovsky, 2001). So we expect income to have a positive sign for the WAH adoption model but a negative sign for the frequency model.

3.4 Methodological approaches

There are several reasonable approaches for modeling the decisions of WAH adoption and frequency. Some studies (e.g. Mokhtarian and Salomon, 1996b, 1997) have modeled adoption alone, as a binary preference or choice. With respect to modeling *both* adoption and frequency, however, there are three different approaches: as a single equation (which in turn has three different options), as two equations estimated jointly, and as two equations estimated separately. We discuss each of these approaches in turn.

The simplest method for addressing both adoption and frequency together is to model the two decisions with a single frequency variable that takes on values of "not at all" together with non-zero frequency levels (e.g. Sullivan, et al., 1993). With our frequency variable comprising count data rather than just ordinal categories as is often the case, we actually had at least three modeling approaches open to us under this method: the ordinal response (probit or logit) model such as that used by Bernardino et al. (1993), the multinomial logit model (MNL, potentially with nested logit variations) such as that used by Mannering and Mokhtarian (1995), and the negative binomial regression model (having Poisson regression as a special case), which to our knowledge has only been applied in this context by Ho (1997), but is a well-known method for dealing with count data (Cameron and Trivedi, 1998). Among these three, the first and third make explicit use of the respectively ordinal and interval (actually ratio) nature of the data, whereas the MNL approach treats each frequency category as nominal and makes no ordinal assumptions. Although that may seem to be a less desirable approach, it is actually a more flexible one in some ways (since it allows the influence of a given explanatory variable to differ by category), and has been found, in at least one auto ownership study comparing MNL to ordered logit on four independent data sets, to offer superior results (Bhat and Pulugurta, 1998).

Table 6. Hypothesized relationships between explanatory variables and WAH adoption

Variable Category	Variable	Hypothesis	Expected Sign
Commute trip attributes	**Miles to work**	For telecommuters, the longer the commute, the more likely WAH will be chosen.	+
	Minutes to work		
	Average speed of commute trip	Higher commute speeds imply less congestion and hence less motivation to WAH.	–
Neighbor-hood charac-teristics	**Neighborhood type**	**1. Suburban:** a) Those who work locally will be less inclined to WAH, since they have shorter commutes and probably experience less congestion; b) Those who work outside the neighborhood will be more inclined to WAH, since they have longer commutes and experience more congestion. **2. Urban:** a) More convenient public transportation and shorter distances mitigate the propensity to choose WAH; b) Heavy traffic and advanced telecommunication facilities make WAH more attractive.	–/+; –/+
	Preferences and perceptions of BE	**1. Accessibility:** a) The better the regional accessibility, the easier the commute trip is likely to be (and hence the less likely to WAH); b) The better the local accessibility, the more pleasurable WAH becomes. **2. The other three BE factors:** for the most part, higher values reflect a more appealing residential neighborhood, which will make WAH more attractive.	–/+; +
	Objective BE characteristics	1. More convenient and diversified activity opportunities make the neighborhood more appealing, which will make WAH more attractive; 2. Too much local activity might be considered a distraction if WAH.	+/–
Travel attitudes	**Attitudinal factors**	**1. Pro-walking, pro-biking, & travel minimizing:** More likely to choose WAH, to reduce travel (esp. auto travel), and/or to maximize the opportunities to walk/bike. **2. Pro-travel & pro-transit:** Less likely to choose WAH. **3. Safety of car & car dependent:** Affinity to car may mean less likely to choose WAH; desire to reduce overreliance on car may mean more likely to choose WAH.	+; –; –/+
Sociodemo-graphics	**Income**	The higher the income and education level, the more likely to choose WAH because those individuals normally have greater computer proficiency, higher-ranking jobs, and greater autonomy in their work.	+
	Education level		
	Mobility constraints	The stronger a mobility constraint, the more likely to choose WAH because it can help avoid commute inconvenience and stress. Salomon (1986) and Mahmassani et al. (1993) both mentioned related aspects of this variable.	+
	Gender	To the extent they still disproportionately bear child care and domestic maintenance responsibilities, women may be more likely to choose WAH to increase temporal and spatial flexibility. On the other hand, some studies (e.g. Safirova and Walls, 2004) have found telecommuters more likely to be male, perhaps because they are more likely to be in jobs offering autonomy and greater bargaining power.	+/-

	Work status	1. Some part-time jobs are intrinsically more flexible than some full time jobs, so part-time workers may be better able to WAH. 2. Since part-time work is already somewhat flexible, part-timers may have less need or inclination to WAH; since they often don't work every day, their supervisors may not want them to "miss" any more days at the regular workplace by WAH.	+/-
	Presence of children in the household	1. To better balance work and family responsibilities, WAH becomes more likely to be chosen. 2. To avoid distractions from the children and to maintain the efficiency of work, WAH is less likely to be chosen.	+/-

Note: A total of 42 variables are referenced by the above table. For "presence of children in the household", we created two binary variables, for children < 5 years old and < 18 years old, respectively; for "mobility constraints", we created two binary variables as well, for the presence of driving and non-driving mobility constraints, respectively.

To our knowledge, only Popuri and Bhat (2003) have modeled the two decisions as separate but joint choices, while others have modeled them either together in one equation or in one or two separate single equations. Yet joint models of adoption and frequency seem to constitute the most appropriate approach, for several reasons: (1) Conceptually, the two decisions *are* distinguishable, and although they are likely to have some explanatory variables in common, prior research as well as preliminary analyses of our data suggest that some influences will differ between the two. In addition to the income example discussed above (expected to have a positive influence on WAH adoption but a negative influence on frequency), gender might also work differently for the two decisions. In our data males are more likely to choose WAH (Safirova and Walls, 2004, also found telecommuters more likely to be male), but females who WAH are inclined to do so more frequently than males (consistent with the finding of Safirova and Walls that females are more likely to be home-based workers). (2) On the other hand, in most cases, it seems likely that the decisions to WAH and approximately how frequently to do so are made simultaneously rather than sequentially (as mentioned in Section 2.2), suggesting the need for a simultaneous rather than separate model structure. (3) It is likely that many of the unobserved characteristics relevant to each choice will also be common to both, in which case it is statistically more efficient to estimate both models together and allow their error terms to be correlated. And (4) a two-equation system falls naturally into the selection-model family of methods (e.g. Heckman, 1990), in which the binary adoption model represents the classic "participation" equation and the frequency model represents the "outcome" equation.

Thus, our original intention was to model adoption and frequency (conditioned on adoption) as a simultaneous two-equation system. We naturally initially explored separate models for each decision, and in the case of frequency explored all three single-equation approaches described above. The results for the ordinal response and negative binomial regression models[1] were decidedly unsatisfactory, with few significant variables and low goodness of fit (GOF). In contrast, the MNL approach provided meaningful results and a GOF within the typical range for

[1] We estimated these models on WAH adopters: given the disproportionate number of zero-frequency cases in the sample, i.e. non-adopters, it did not seem prudent to combine them with the positive-frequency cases. We also tried the zero-inflated Poisson model but it, too, gave unsatisfactory results.

disaggregate travel behavior models, and accordingly, we chose to retain this approach. However, in contrast to the cases for ordinal response (Greene, 2002) and negative binomial regression models (Hilbe, 2007; Greene, 1994), the theory pairing an *MNL* outcome model with a binary selection model has only recently been developed (personal communication with Chandra Bhat, July 27, 2006). Accordingly, in adopting the MNL approach to frequency estimation, we were necessarily left with the first and third options for modeling frequency and adoption: either with a single equation on the full sample, having "0" as the lowest frequency category, or with two separate equations – a binary adoption model on the full sample and an MNL frequency model for adopters. We developed satisfying models for both options, and present both in Section 4.

4. RESULTS

Using t- and chi-squared tests, most of the potential explanatory variables of Table 6 were initially tested for association with the dependent variables of WAH adoption and frequency, although, since such individual tests are not a conclusive indication of association (insignificant pairwise associations could become significant when other variables are controlled for, as well as the converse), they were considered advisory only. A correlation matrix for key explanatory variables was also computed, so that likely sources of collinearity could be identified. Then the potential explanatory variables were tested together in an initial model, insignificant variables (or those with counterintuitive signs) were screened out in successive stages, and variables screened out at earlier stages were selectively tested for inclusion at later stages. Thus, through a combination of systematic pruning and *ad hoc* trial-and-error, based on conceptual as well as statistical considerations, the final models were obtained. We first report and discuss our preferred model: the combined adoption/frequency MNL model on the full dataset. We then present the best separate models of adoption and frequency. Finally, to try to decrease the heterogeneity of the WAH included in the sample, we present adoption and frequency models on the subsample excluding the highest frequency category.

4.1 Combined adoption/frequency MNL model (preferred)

4.1.1 MNL model interpretation

Table 7 summarizes the estimation results of the combined adoption/frequency MNL model, taking "0 days/month" WAH as the lowest frequency category. The ρ^2 GOF measure (Ben-Akiva and Lerman, 1985) is 0.499 (based on the equally-likely model), which is considered very good in the context of disaggregate discrete travel behavior models. Since the choice shares are unbalanced (76.6%, 6.7%, 10.1%, 3.4% and 3.2% for the five categories respectively), the market share model has a ρ^2 of 0.474. However, re-estimation of the model without constant terms yields a ρ^2 of 0.425, indicating that most of the explanatory power of the model lies in the "true" variables (i.e. they are helping to explain *why* the shares are unbalanced), not just the constant terms.

Table 7. Combined adoption/frequency MNL model estimation results
(base alternative: 1 day/month, or very low)

Variables	Coefficient (p-value)			
	0 day/mo. (not WAH)	**2-4 days/mo. (low)**	**5-8 days/mo. (medium)**	**≥9 days/mo. (high)**
Constant				
ASC	3.836 (.000)	-1.197.(.007)	.534 (.154)	.423 (.254)
Subjective BE factors				
Perceived regional accessibility		-.298 (.044)	-.410 (.073)	
Objective BE characteristics				
Number of institutional establishments within 400m	.106 (.040)			
Number of eating out places within 400m		.179 (.033)		
Travel attitudes				
Pro-biking attitude		.334 (.010)		
Pro-transit attitude		.254 (.049)		
Commute trip attributes				
Square of commute time (mins.)	-.0000575 (.065)			
Sociodemographics				
Current annual household income[a]	-.00000985 (.000)			
Education level[b]	-.191 (.003)			
Full-time worker			-1.244 (.002)	-1.356 (.001)
Number of observations (820, 72, 109, 37, and 35, respectively, in the five frequency categories)				1073
Final log-likelihood, $L(\beta)$				-865.591
Log-likelihood for market share model, L (MS)				-908.676
Log–likelihood for equally-likely (EL) model, $L(0)$				-1726.927
Number of explanatory variables (including constants)				15
$\rho^2_{ELbase} = 1 - L(\beta) / L(0)$				0.499
Adjusted $\rho^2_{ELbase} = 1 - [L(\beta) - 15] / L(0)$				0.490
χ^2 (between the final model and the EL model)				1722.672
χ^2 (between the final model and the MS model)				86.170

[a] Income is a continuous number representing the current total annual combined income of all the working adults in the household (the number falls in the range from 0 to $120,000 or more). [b]As defined in Table 3.

Turning to the coefficients, in this model, all of them show the expected signs, and they are all significant at the 0.05 level or better, except for the ones on perceived regional accessibility (for the medium-frequency alternative) and commute time (having p-values around 0.07). However, a chi-squared test found that constraining these two coefficients to zero together significantly degraded the model (p-value = 0.037). Given that, and in view of their direct or indirect relationships with the built environment and their conceptual contributions to the model, we consider them useful variables and retain them in our final model.

In keeping with the apparently distinctive nature of each alternative, we discuss the variables associated with each frequency category in turn. Choice of the lowest frequency category (0 days/month) is based on one objective BE variable, commute time, household income and education level. As expected, commute trip attributes and sociodemographic characteristics help to explain WAH choices. Specifically, squared commute time has a negative impact on the propensity to not choose WAH at all – i.e. compared with the base alternative (1 day/month WAH), the longer the commute time, the less likely for people to choose a regular commute, which is consistent with the popular image of WAH as a trip reduction strategy. The fact that the best functional form is the square of commute time says that the longer the commute, the disportionately greater the impact on propensity to work at home, which is reasonable. With respect to income, although at least one stated preference model of the adoption of telecommuting (Bernardino et al., 1993) found no distinction in salary and benefits between commuters and telecommuters, other studies (Mokhtarian and Henderson, 1998; Kuenzi and Reschovsky, 2001; Yeraguntla and Bhat, 2005; Safirova and Walls, 2004) have found that telecommuters tend to have higher incomes than HBB workers, who in turn tend to have higher incomes than conventional (i.e. non-home-based) workers. Income is likely serving as a proxy for the skill-level of the job, with jobs requiring higher skills potentially being more information-oriented and hence more telecommutable; it probably also reflects a value-of-time effect, in which those making higher incomes are more motivated to save commuting time. Education probably also serves as a proxy for skill-level, with the significance in our model consistent with Mahmassani et al. (1993) and Walls et al. (2007), who found that individuals with higher education are more inclined than others to work independently and to prefer WAH.

Although perceived BE characteristics were not significant in this frequency category, one objective BE characteristic—the number of institutional establishments within 400 meters—is included in our final model. The positive impact of the number of institutional establishments (church, library, post office, and bank) on the choice to commute is unexpected, but this variable may be a marker for the unpleasant side of a higher-density residential neighborhood: noise, traffic, crowdedness and potentially other disadvantages.

The choice of 2-4 days/month is based on one BE perception variable, an objective BE variable, and two travel attitudes (pro-transit and pro-biking). Those perceiving their neighborhood to have greater regional accessibility are less likely to WAH at that frequency (and similarly for the 5-8 days/mo., medium frequency category), compared to the low and high frequency levels. It is reasonable that if perceived regional accessibility is high, there is less incentive to reduce commuting for the salaried employee (pointing to very low or zero WAH frequencies), and greater access to the market supporting the operation of a home-based business (pointing to very high frequencies).

The objective BE variable—the number of eating out places within 400 meters—has the expected positive sign, suggesting a neighborhood with appealing coffee break and lunch options. Thus, the availability of nearby dining alternatives is an incentive to WAH at this frequency level, though other considerations are apparently more important for other frequency categories.

Two attitudes toward transportation are also significant to this WAH frequency category. The pro-biking attitude has a positive influence on the choice of this category. High scores on this measure tend to reflect a preference for biking over driving (see Table 5). Thus, this variable captures a desire to reduce auto travel by biking, and to some extent a desire to bike for its own sake. Such a person may be more inclined to WAH as yet another way to reduce auto travel and potentially to provide more time for recreational biking. Further, this variable has a rather high and statistically significant positive correlation (0.63) with the "travel minimizing" factor (which is derived from statements such as "I often use the telephone or the Internet to avoid having to travel somewhere" and "I prefer to organize my errands so that I make as few trips as possible"), suggesting that its presence in the model may also be tapping a desire to reduce traveling altogether.

Finally, the more positive one's views about transit, the more likely the individual is to WAH at this frequency level. The result for transit is somewhat counter to our expectations: we hypothesized that a positive perception of transit would reduce the motivation to WAH. However, since this factor represents a contrast between transit and driving, a high score means a more negative view of driving, and hence a greater motivation to WAH – at least at this low frequency – is plausible under those circumstances.

The choice to WAH at medium frequencies (5-8 days/month) is based on the same perceived regional accessibility factor discussed for the previous category, and work status. Full-time workers are less likely to WAH with medium (or high) frequency. This is consistent with Yeraguntla and Bhat (2005), who also found that part-time employees tend to telework more frequently, relative to full-time employees, as well as (with respect to adoption) Drucker and Khattak (2000) and Popuri and Bhat (2003). This may be because the same considerations motivating individuals to work part time (such as familial and other responsibilities) may also influence them to pursue jobs that provide other flexible work opportunities such as working at home.

Finally, WAH at the highest frequency only depends on full-time work status, and the explanation is the same as that discussed for the medium frequency category. The fact that only one variable is significant to high-frequency WAH is probably due to the heterogeneity of this category, as discussed in Section 3.2. Among the 36 cases in this category retained for the model (the remainder being excluded due to missing data on one or more of the significant variables), 22 report commute information while 14 appear to be "pure" HBB workers with no commutes at all. Given the differences between these two forms of WAH, it is not surprising that we have difficulty in predicting a choice in which they are (necessarily) lumped together.

4.1.2 Nested logit (NL) test for IIA violations

Since the dependent variable consists of five ordinal alternatives, it is reasonable to expect unobserved variables to be correlated across alternatives (especially, e.g., for adjacent alternatives), and thus for the Independence of Irrelevant Alternatives (IIA) assumption of the MNL model to be violated (Ben-Akiva and Lerman, 1985). We tested for IIA violations with the more general nested logit (NL) model formulation, having the MNL model as a special case.

The nested logit (NL) model is a generalization of MNL in which alternatives that are suspected of sharing unobserved characteristics are grouped together into nests, separate from other alternatives. IIA is assumed to hold for alternatives within a nest, but is not required to hold between alternatives in different nests. The MNL model is the special case of NL that results when the "inclusive value (IV) parameter" of each nest is equal to one. Thus, the IIA test is as follows:

Null hypothesis H_o: IV parameter $\theta = 1$.

Alternative hypothesis H_a: IV parameter $\theta \neq 1$.

Test-statistic: $\frac{\hat{\theta}-1}{s.e.(\hat{\theta})}$, where $\hat{\theta}$ is the estimated IV parameter and $s.e.(\hat{\theta})$ is the (estimated) standard error of the IV estimate. This statistic asymptotically follows the t-distribution with degrees of freedom equal to the number of observations minus the number of estimated parameters in the model.

We constructed a number of nested logit models, using the MNL specification of Section 4.1.1 as the base, and differing in how the alternatives were grouped into nests. The nested logit model structure having "0" and "positive" frequencies in the upper level, and all four frequency categories at the same level in the lower branch (see Figure 4), yielded a borderline test statistic on the IV parameter (-1.955, compared to a lower-bound critical value of -1.96; Table 8). In view of the test suggesting a conceptually more satisfying model (i.e. one that separates the zero choice from the non-zero ones), we tentatively concluded that the indicated NL model structure was superior to the MNL model. However, the NL model using the same variables as shown in the MNL model did not give us a satisfying result: among the 11 non-ASC explanatory variables, eight of them had p-values between 0.05 and 0.1. Then we started over, considering all potential explanatory variables, to find the "best" model specification for that NL structure. Unfortunately, for the best model we could find, five of the ten non-ASC explanatory variables had p-values between 0.05 and 0.1. In addition, its NL test failed to reject the null hypothesis that the IV coefficient equaled one (the test statistic was -1.454, compared to a critical value of -1.96) – thereby sending us back to the original MNL model. Additional NL tests for correlated error terms among the four non-zero frequency categories (discussed in Section 4.3.2.2 below), as well as Hausman-McFadden tests on the same four categories (discussed in Section 4.3.2.1), also failed to reject the simpler MNL structure. Accordingly, we retain the MNL structure of Table 7 as our final single equation adoption/frequency model.

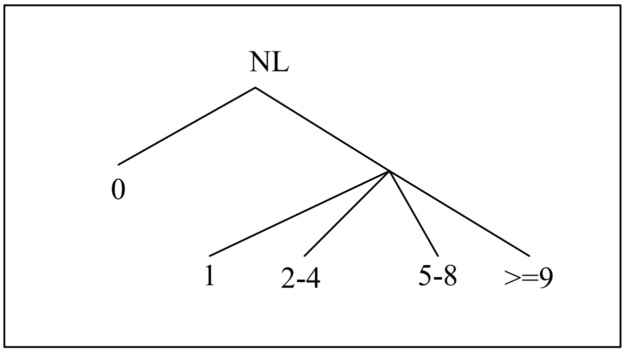


Figure 4. Nested logit model structure tested (WAH days/month) for the single equation model

Table 8. Nested logit (NL) test for IIA violations for the single equation MNL model

IV parameter ($\hat{\theta}$)	Standard error of $\hat{\theta}$	Test statistic ($\frac{\hat{\theta}-1}{s.e.(\hat{\theta})}$)
0.464	0.274	-1.955
Number of observations		1073
Estimated parameters		16
Degrees of freedom		1073-16=1057
95% critical value for t-distribution (two-tailed)		1.96
Conclusion		reject H_o

Although there was a conceptual basis for believing that these alternatives might have correlated error terms, the literature (McFadden, et al., 1977) reminds us that IIA holding or not is a property of the model specification (i.e. which variables are observed versus unobserved), not of the intrinsic qualities of the alternatives themselves. Changing variables from generic to alternative-specific is one potential remedy for a violation of IIA (Ben-Akiva and Lerman, 1985; McFadden, et al., 1977), and it has been our experience elsewhere (Mokhtarian and Bagley, 2000; Choo and Mokhtarian, 2004) that MNL models in which all or many variables are alternative-specific to start with often meet the IIA assumption. It has also been pointed out (Horowitz, 1991) that the omitted variables that are correlated across alternatives are often attitudes; hence a model (such as ours) in which attitudes are observed tends to reduce the correlations among the unobserved influences on choice.

4.2 WAH adoption

Table 9 summarizes the binary logit model of WAH adoption. The ρ^2 value is 0.256, which is considered quite acceptable in this context. The 0.256 value is based on the equally-likely model, and since the market shares are rather unbalanced (76.4% not choosing and 23.6% choosing WAH), the market-share model alone (the model containing just the constant term) has a ρ^2 of 0.212. Re-estimating the final model without a constant term, however, yields a ρ^2 of 0.222, which indicates (as in the previous section) that most of the explanatory power of the model lies in the "true" variables. All coefficient estimates are significant at the 0.04 level or better except for the one on preference for regional accessibility (with a p-value of 0.08). In view of its conceptual contribution to the model and its borderline significance, we consider it worth retaining. Most coefficients have the expected signs (in comparing to the model in Table 7, note that signs will be reversed because the base alternatives are different: 1day/month in Table 7 and 0 days/month here).

Seven of the nine explanatory variables in this model are identical to those in the combined adoption/frequency model of Table 7, with consistent signs and similar explanations (in point of fact, the separate adoption and frequency models of this section and the next one were developed prior to the single model of the previous section, which used the two separate models as a starting point for its own specification). One of the remaining two is preference for regional accessibility, replacing its perceived counterpart in the previous model. The other variable is a second subjective BE factor, preference for outdoor appeal.

The preference for regional accessibility has an expected negative sign: as discussed in Section 3.2, those who desire regional accessibility may be more inclined to commute and less inclined to WAH. The preference for outdoor appeal has a positive sign. This factor has some characteristics commonly associated with suburban neighborhoods (large yards, off-street parking) and some typical of more mature traditional neighborhoods (variety in housing styles, big street trees). In this sample, the means of both preference for and perception of outdoor appeal are somewhat higher for the traditional residents than for the suburban residents, and the two measures are moderately strongly correlated at 0.35. Since traditional residents are also significantly more likely to WAH (26%) than those living in suburban neighborhoods (22%), the positive coefficient is logical. In general, regardless of whether one's neighborhood is considered traditional, suburban, or something in between, it stands to reason that those who place a greater than average value on appealing residential surroundings would be more inclined to WAH so as to enjoy them more intensively.

Table 9. WAH adoption model estimation results

Variable	Coefficient	P-value
Constant	-2.973	.0000
Subjective BE factors		
Preference for regional accessibility	-.198	.0797
Preference for outdoor appeal	.223	.0384
Objective BE characteristics		
Number of institutional establishments within 400m	-.158	.0092
Number of eating out places within 400m	.152	.0367
Travel attitudes		
Pro-walking	.283	.0029
Commute trip attributes		
Square of commute time (minutes)	.0000808	.0089
Sociodemographics		
Current annual household income [a]	.00000923	.0006
Education level [b]	.177	.0089
Full time worker	-.701	.0038
Number of observations (778 non-adopters; 240 adopters)		1018 [c]
Final log-likelihood, $L(\beta)$		-524.79
Log-likelihood for market share model, L (MS)		-555.97
Log–likelihood for equally-likely (EL) model, $L(0)$		-705.62
Number of explanatory variables (including constant)		10
$\rho^2_{ELbase} = 1 - L(\beta) / L(0)$		.256
Adjusted $\rho^2_{ELbase} = 1 - [L(\beta) - 10] / L(0)$		.242
χ^2 (between final model and the EL model)		361.67
χ^2 (between the final model and the MS model)		62.36

[a] Income is a continuous number representing the current total annual combined income of all the working adults in the household (the number falls in the range from 0 to $120,000 or more). [b]As defined in Table 3. [c]The difference in sample size from that of Table 7 is due to missing data on the "preference for outdoor appeal" variable.

4.3 WAH frequency modeling (adopters only)

4.3.1 MNL model interpretation

To model WAH frequency (for WAH adopters only), we retained the same four positive frequency categories as before (WAH days/month): 1 (very low), 2-4 (low), 5-8 (medium) and 9 or more (high). In the initial model-building stages, we allowed Limdep to automatically expand the explanatory variables to a full set of alternative-specific variables (ASVs), with 1 day/month as the base alternative. To preserve degrees of freedom and reduce the cognitive clutter in the model, however, we then manually created ASVs and pruned out insignificant ones on an alternative-by-alternative basis. As a post-hoc justification of this approach, it can be seen that in the resulting best model of Table 10, only three variables (perceived regional accessibility, commute distance and work status) are significant to more than one frequency category. This not only confirms the need for manual fine-tuning, it also illuminates why the ordinal response and negative binomial regression approaches to modeling frequency were not successful: it appears that, in effect, each frequency category represents a distinct segment, motivated by substantially different considerations.

Table 10. WAH monthly frequency model estimation results
(base alternative: 1 day/month, or very low)

Variables	**Coefficient (p-value)**		
	2-4 days/mo. (low)	**5-8 days/mo. (medium)**	**≥ 9 days/mo. (high)**
Constants			
Alternative-specific constant	-1.575 (.004)	.434 (.345)	.989 (.127)
Subjective BE factors			
Perceived regional accessibility	-.834 (.000)	-.977 (.002)	
Objective BE characteristics			
Number of eating out places within 400m	.238 (.045)		
Travel attitudes			
Pro-biking	.659 (.000)		
Commute trip attributes			
Commute distance (miles)	.0302 (.009)		.0285 (.034)
Commute time squared (mins.)		.000110 (.049)	
Sociodemographics			
Current annual household income[a]			-.0000124 (.038)
Full-time worker		-.960 (.048)	-1.201 (.011)
Number of observations (73, 110, 36, and 35, respectively, in the four frequency categories)			254
Final log-likelihood, $L(\beta)$			-294.66
Log-likelihood for market share model, L (MS)			-322.78
Log–likelihood for equally-likely (EL) model, $L(0)$			-352.12
Number of explanatory variables (including constants)			13
$\rho^2_{ELbase} = 1 - L(\beta) / L(0)$			0.163
Adjusted $\rho^2_{ELbase} = 1 - [L(\beta) - 13] / L(0)$			0.126
χ^2 (between the final model and the EL model)			114.93
χ^2 (between the final model and the MS model)			56.26

[a] Income is a continuous number representing the current total annual combined income of all the working adults in the household (the number falls in the range from 0 to $120,000 or more).

The ρ^2 goodness of fit measure for this model (0.163) is lower than for the adoption model, but that is to be expected for a four-alternative choice, and it is still within the typical range. Compared with a ρ^2 of 0.083 for the MS model, our final model does significantly better, and given that the ρ^2 for the same final model except without the constant terms is 0.145, it is again apparent that the true explanatory variables are carrying most of the explanatory power of the model.

It is interesting, and on first thought unexpected, however, to note that the ρ^2 for the *five*-alternative adoption/frequency model of Section 4.1 (even after adjusting for the differing number of parameters estimated) is substantially higher than those for both the binary adoption model of the previous section and the *four*-alternative frequency model presented here. Ordinarily, the higher the number of alternatives, the more difficult it is to predict their choice, and the lower the resulting model GOF. Compared to the binary model, however, a logical explanation lies in the heterogeneity of the "adopted" alternative: since the various frequency categories are shown in both Table 7 and Table 10 to have quite different utility specifications, in retrospect it is not surprising that forcing those disparate segments to share a common utility function, as in the binary adoption model, would substantially degrade the model GOF.

But then why is the adjusted ρ^2 for the five-alternative model of Table 7 so much higher (0.490) than that of the four-alternative model of Table 10 (0.126)? Because adding the 820 non-adopters in the former case provides a great deal of supplemental information to the model, compared to that afforded by the 250+ adopters alone: each non-zero frequency alternative suddenly has a lot more information about the kinds of people who *don't* choose that alternative, which can be used to improve the model's explanatory power.

Comparing this model with the model in Table 7, most of the variables for these three categories (low, medium, high) are the same, with each frequency level here capturing one or two explanatory variables that were associated with the zero alternative in Table 7, in addition to all the variables associated with the corresponding non-zero alternative there. In particular, either commute distance or time is significant to each frequency category here, indicating that the longer the commute, the more likely the individual is to WAH at that (higher) frequency (compared to the base category of very low frequency).

At the highest frequency level, this relationship (as indicated in Section 3.2.2.) should be interpreted as the effect of commute distance on those (the 22 out of 36 cases in this category for this model) who have commutes. For those 22 cases, the average commute length is about 22.9 miles, compared with 10.8 for those in the very low frequency (base) category, 14.6 (low-frequency category), and 8.8 (medium-frequency category). It is interesting that the relationship of commute length to WAH frequency is not monotonic, which is further confirmation of the need to use the MNL approach rather than one of the other two approaches to modeling frequency. In any case, however, it is natural that the group whose commutes are considerably longer than average would tend to WAH the most frequently.

With respect to the household income variable significant to the highest frequency category, the negative sign is consistent with other studies (Mokhtarian and Henderson, 1998; Kuenzi and Reschovsky, 2001) finding that small business owners tend to have lower incomes than telecommuters. It also suggests that in some cases an explicit tradeoff between income and flexibility is made, with an individual accepting a lower income in exchange for maximum flexibility.

4.3.2 Testing for IIA compliance

As discussed in Section 4.1.2, it is reasonable to expect unobserved variables to be correlated across these ordinally-related alternatives, and thus for the IIA assumption of the MNL model to be violated. Here we tested for IIA violations in two ways: with the Hausman-McFadden test (Hausman and McFadden, 1984), comparing the coefficients of the model estimated on the full choice set with those of a model estimated on a subset of alternatives, and with the more general nested logit (NL) model formulation having the MNL model as a special case.

4.3.2.1 Hausman-McFadden test

The idea behind this test is that if the IIA property holds, the parameters of a model involving the full choice set should be the same as those involving only a subset of the full choice set. The test can be expressed as follows:

Null hypothesis H_o: $\beta^R = \beta^U$, where β^R is the vector of (true) parameters for the model involving the restricted choice set, and β^U is the vector of (true) parameters for the model involving the unrestricted or full choice set.

Alternative hypothesis H_a: $\beta^R \neq \beta^U$.

Test-statistic: $[\hat{\beta}^R - \hat{\beta}^U]'[V^R - V^U]^{-1}[\hat{\beta}^R - \hat{\beta}^U]$, where $\hat{\beta}^U$ and V^U are, respectively, the vector of coefficient estimates and the estimated variance-covariance matrix of $\hat{\beta}$ for the unrestricted model; and $\hat{\beta}^R$ and V^R are the vector of estimated coefficients and variance-covariance matrix of $\hat{\beta}$ for the restricted model. This statistic is asymptotically chi-squared distributed with the degrees of freedom equal to the number of identifiable parameters in $\hat{\beta}^R$.

We conducted the Hausman-McFadden test on six reduced choice sets, namely dropping alternatives 2, 3, 4, 2 & 3, 3 & 4 and 2 & 4, respectively. In every case, the test statistic could not be computed. However, this is quite common since this test "requires inversion of the difference between two closely related matrices, which may be non-positive-definite or nearly singular and thus cause computational and inference problems" (Small and Hsaio, p. 619). In other words, if IIA holds, by definition $\beta^R = \beta^U$, and therefore the variance-covariance matrices of the two vectors of parameter estimators, V^R and V^U, are likely to be nearly equal as well. If that is true, then their difference will be a matrix of relatively small numbers, and inverting such a matrix to compute the test statistic will be analogous to division by zero. Thus, the computational failures are suggestive that IIA holds, but cannot be considered conclusive of that.

4.3.2.2 NL test

The four nested logit (NL) model structures that we tested are shown in Figure 5; the test results are tabulated in Table 11.

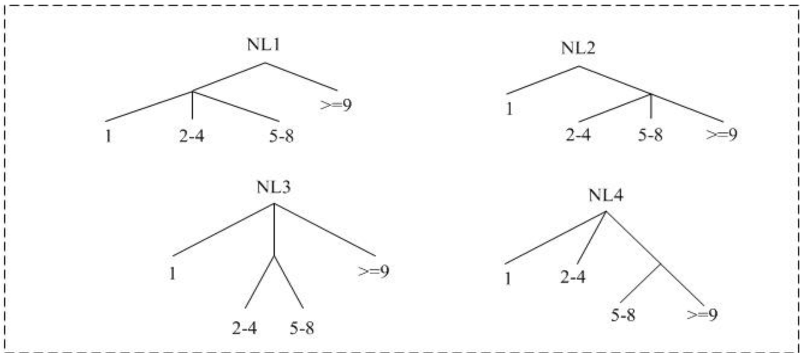


Figure 5. Nested logit model structures tested (WAH days/month)

Table 11. Nested logit (NL) test for IIA violations

	NL1	NL2	NL3	NL4
IV parameter ($\hat{\theta}$)	0.658	1.024	0.898	1.375
Standard error of $\hat{\theta}$	0.407	0.400	0.433	0.737
Test statistic ($\frac{\hat{\theta}-1}{s.e.(\hat{\theta})}$)	-0.840	0.060	-0.236	0.509
Number of observations			254	
Estimated parameters			14	
Degrees of freedom			254-14=240	
95% critical value for t-distribution (two-tailed)			1.97	
Conclusion	fail to reject H_o	fail to reject H_o	fail to reject H_o	fail to reject H_o

For the second and fourth structures, the estimates of the IV parameter were greater than one, which is theoretically impermissible. However, for all four structures we failed to reject the null hypothesis that the parameter was equal to one, indicating that they are equivalent to the MNL model. Hence, the evidence of both sets of tests for IIA supports the assumption, and thus we retain the MNL structure of Table 10 as the final model of frequency for WAH adopters.

4.4 Adoption and frequency models without the highest frequency category

Because the factors significant to working at home could be substantially different for telecommuters than for HBB workers, and because the highest-frequency category is expected to be an indistinguishable mixture of both kinds of WAH, we estimated a second set of models without the 50 cases in the highest-frequency category. The best resulting adoption and frequency models for those 1196 cases are shown in Tables 12 and 13, respectively.

Table 12. WAH adoption model estimation results (excluding the high frequency category, N=1196)

Variable	Coefficient	P-value
Constant	-3.353	.0000
Subjective BE factors		
Preference for regional accessibility	-.224	.0601
Preference for outdoor appeal	.230	.0435
Objective BE characteristics		
Number of institutional establishments within 400m	-.154	.0156
Number of eating out places within 400m	.176	.0192
Travel attitudes		
Pro-walking	.256	.0117
Commute trip attributes		
Square of commute time (minutes)	.0000722	.0283
Sociodemographics		
Current annual household income[a]	.0000103	.0003
Education level[b]	.189	.0085
Full time worker	-.515	.0597
Number of observations (778 non-adopters; 206 adopters)		984
Final log-likelihood, $L(\beta)$		-476.49
Log-likelihood for market share model, L (MS)		-504.88
Log–likelihood for equally-likely (EL) model, $L(0)$		-682.06
Number of explanatory variables (including constant)		10
$\rho^2_{ELbase} = 1 - L(\beta) / L(0)$		.301
Adjusted $\rho^2_{ELbase} = 1 - [L(\beta) - 10] / L(0)$		.287
χ^2 (between final model and the EL model)		411.14
χ^2 (between the final model and the MS model)		56.80

[a] Income is a continuous number representing the current total annual combined income of all the working adults in the household (the number falls in the range from 0 to $120,000 or more). [b]As defined in Table 3.

The WAH binary model in Table 12 has the same specification as the one using the whole dataset; it improved the ρ^2 somewhat to 0.301 (from 0.256) and the adjusted ρ^2 to 0.287 (from 0.242). The new frequency model (see Table 13) has a very similar specification to the corresponding alternatives of its full-sample counterpart, and also has a higher ρ^2 (0.191, compared to 0.163) and adjusted ρ^2 (0.150, compared to 0.126). In the latter case, however, the comparison to the GOF of the model on the full data set is confounded by the fact that there is one fewer alternative

Table 13. WAH monthly frequency model estimation results (excluding the high frequency category, N=1196)

(base alternative: 1 day/month, or very low)

Variables	**Coefficient (p-value)**	
	2-4 days/mo. (low)	**5-8 days/mo. (medium)**
Constant		
ASC	-1.607 (.006)	.851 (.100)
Subjective BE factors		
Perceived regional accessibility	-.801 (.004)	-1.000 (.005)
Objective BE characteristics		
Number of eating out places within 400m	.240 (.061)	
Travel attitudes		
Pro-biking	.696 (.000)	
Commute trip attributes		
Commute distance (miles)		-.0905 (.006)
Commute time squared (mins.)	.000440 (.070)	.000766 (.006)
Sociodemographics		
Current annual household income[a]		
Full-time worker		-.894 (.070)
Number of observations (74, 111, and 36, respectively, in the three frequency categories)		221
Final log-likelihood, $L(\beta)$		-196.44
Log-likelihood for market share model, L (MS)		-222.73
Log–likelihood for equally-likely (EL) model, $L(0)$		-242.79
Number of explanatory variables		10
$\rho^2_{ELbase} = 1 - L(\beta) / L(0)$		0.191
Adjusted $\rho^2_{ELbase} = 1 - [L(\beta) - 10] / L(0)$		0.150
χ^2 (between the final model and the EL model)		92.71
χ^2 (between the final model and the MS model)		52.58

[a] Income is a continuous number representing the current total annual combined income of all the working adults in the household (the number falls in the range from 0 to $120,000 or more).

in the new model (which, all else equal, would tend to elevate the ρ^2). All things considered, although these results are consistent with the expectation of a certain amount of heterogeneity within the highest frequency category, the reduced sample models do not substantively alter our findings for the remaining categories, and so because of the further insight provided for the highest-frequency WAH segment, we prefer the original set of models.

5. CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This study modeled the adoption and frequency of working at home on the part of more than 1000 residents of eight neighborhoods in northern California, with particular attention to the influence of the residential neighborhood built environment (BE). In addition to confirming the expected influence of commute length (measured in time or distance), work status (full- or part-time), household income and education level on both decisions, we found that several variables related to the BE played important and often complex roles in the models.

In the preferred single-equation MNL adoption/frequency model, several subjective and objective BE characteristics were significant for at least one frequency category each. Individuals who perceive high regional accessibility for their neighborhood tend to WAH either very little (perhaps because commuting is less burdensome) or a great deal (perhaps because they operate a HBB that is well-positioned with respect to its customer base). Two objective measures of density, the number of eating-out places and the number of institutional establishments within 400 meters of the residence, had opposite effects. The higher the density of eating-out places in the neighborhood, the greater the frequency of WAH 2-4 days a month (compared to lower and higher frequencies), whereas the higher the density of institutions (such as churches, libraries, post offices, and banks – likely a proxy for negative aspects such as heavy traffic, noise, and crowdedness), the lower the propensity to WAH at all. The counteracting effects of these two variables are each plausible, but point to the "mixed blessing" offered by higher density neighborhoods.

The pro-walking, pro-biking and pro-transit attitude variables significant in the preferred model are indirectly related to the built environment as well. One's liking/preference for walking or biking probably depends in part on how pleasant it is to do in one's neighborhood, and the positive influence of this attitude on the choice to WAH is consistent with that view as well as potentially also reflecting a general desire to reduce automobile use. On the other hand, those preferring transit over driving are more likely to WAH at low frequencies than at higher frequencies (perhaps because their predilection for transit reduces the stress of commuting) or not at all (reflecting a desire to avoid at least some commute travel, particularly if driving is involved).

In the separate binary logit model of WAH adoption, we found a preference for regional accessibility to be negatively related to WAH, while a preference for outdoor appeal was positively related; both results are reasonable. In the companion MNL frequency model for adopters only, an interesting non-monotonic effect of commute length (measured by time as well as distance) on WAH frequency emerged.

Overall, then, we found considerable nuance in the relationships of the BE to WAH, with correspondingly complex policy implications. Improving regional accessibility, for example, may support HBBs but reduce the motivation of salaried employees to telecommute, even though telecommuting would bring other public benefits as well. Increasing the commercial density near residential areas may increase the attractiveness of WAH for some, while diminishing it for others. "Outdoor appeal" is positively linked to WAH adoption – but increasing it could mean reducing density (increasing lot sizes) as much as increasing aesthetic appeal in other ways. Thus, land use and transportation strategies that are desirable from some perspectives will tend to weaken the motivation to work at home, and conversely, some factors that seem to increase the motivation to work at home are widely viewed as less sustainable. In an independent study that reinforces this point, Moos et al. (2006) found that teleworking tended to increase housing consumption (from investing in non-work-related amenities to increase the comfort of spending much more time at home, to furnishing the home office, to adding another room to the residence, to moving to a larger home). Accordingly, these results point to the complexity of trying to find the right balance among demand management strategies that sometimes act in competition rather than in synergy.

Several directions for future research are indicated. Using the same data set, one could explore refined model specifications, including the more theoretically elegant joint equation system. Perhaps more importantly, however, this study suggests that it would be valuable to further investigate the role of the BE in the choice to WAH, through a survey particularly designed from that standpoint. Such a survey would collect data on various aspects of the BE as well as on the individual's suitability and preferences for WAH specifically, and would facilitate a more thorough analysis of these intriguing relationships than was possible with the current data set.

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