Don't Work, Work at Home, or Commute? Discrete Choice Models of the Decision for San Francisco Bay Area Residents

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Executive Summary

Using socio-demographic, personality, and attitudinal data from 1,680 residents of the San Francisco Bay Area, we develop and estimate binary, multinomial, and nested logit models of the choice to work or not, whether or not to work at home, and whether to commute all of the time or some of the time (either by only working part time, or by working a compressed work week, or by telecommuting some of the time). To our knowledge, these are the first models of all these choices simultaneously. This work is relevant both to travel demand modeling, which usually bases trip or activity generation models on a given set of employment status inputs, and to labor force engagement modeling, which typically ignores the impact of travel-related variables. The model results indicate that the typical predictors of labor force engagement (gender, household income, and education) play an important role here, with family variables having an especially complex effect. Other interesting findings are that tele-commuters tend to be adventure-seekers and home-based workers tend to be workaholics; those who like travel tend to commute five or more times per week; and mobility constraints are significant in the decisions to work part-time and to commute full-time.

1. Introduction

One of the most fundamental decisions a household member can make is whether or not to work. Assuming one chooses to work, depending on household and personal needs, one may decide to work part-time or full-time, and may subsequently or simultaneously decide to commute five times per week, telecommute some days, work at home full-time or work a compressed schedule. These decisions may be made by the household member or, in some circumstances, the employer and repeated any number of times as the needs of the household evolve.

Such employment status/type decisions are vitally important to travel behavior and forecasting. Predicting travel patterns is greatly aided by first predicting employment type – the travel patterns of a fully commuting full-time worker are obviously different than those of a non-worker or telecommuter. As activity-based modeling has evolved in the past years the need for appropriate employment status models has been enhanced. Almost every existing activity-generation scheme starts with an assumed knowledge of employment status (see, e.g. Goulias, 2002); older, trip-based generation models typically require the same assumptions.

The purpose of this report is to develop a model of the sequential or simultaneous decisions to work or not work; to work full-time or part-time; and to commute each day, telecommute some days, work a compressed schedule, or work exclusively from home. Such a model will both enhance travel behavior modeling and provide insight into the behavior and characteristics driving these work and commute choices.

There is an extensive literature on the labor force engagement decision: to work or not. Much of this literature involves the decision of women to join the workforce. Heckman (1974) estimated a tobit model that simultaneously captured a woman's decision to work (versus not work), the number of hours spent working, her asking wage, and her offered wage. Cogan (1981) used the premise that working has a cost associated with being away from the family; he then used this idea to model the decision of married women to enter the workforce, and their number of hours worked, using a maximum likelihood estimator. Mallela and Wilcox-Göx (2003) build upon the Bureau of Labor Statistics' model of work life by adding past work experience as a predictor of current employment; both logit and probit models are estimated. Barkume and Horvath (1995) use gross flows statistics to examine the movements from being unemployed, employed, and not in the labor force. Key findings from this body of work are (not surprisingly) that gender, household assets, and the presence of small children influence the decision to work.

There is also a healthy body of literature on the decision to work part-time versus full-time. Williams (1995) used regression modeling and gross flows analysis to model the shifts from unemployment, full-time employment, part-time employment, and not being in the labor force; the end goal of his work was to measure gender differences in these behaviors. To assess gender discrimination in France, Moulin (2003) estimated probit models of the decision to work full-time (as opposed to part-time) separately for men and women, at two points in time (ten years apart). Lane (2004) compared the attitudes and performance of full-time and part-time nurses in the United Kingdom. Findings germane to the work at hand include the importance of education and gender in the decision to work full-time.

The impact of working a compressed schedule (e.g. working 80 hours over 9 days instead of 10) on transportation has been studied by Hung (1996), who found that such a practice can substantially reduce commuting. A much larger body of research involves the study of working flextime (usually defined as the ability to change the start and end time of the work day). Beers (2000) finds that, in 1997, nearly one-fourth of all full-time workers in the United States could vary their work day start and end times (one would expect a much smaller share working a compressed schedule). Golden (2001) finds that those working flexible schedules are often spending more time at work or switch to part-time status; he estimates a probit model of the likelihood of working flextime.

In this study, we use “telecommuting” to refer to a salaried employee working at home in lieu of commuting to the conventional work location some or all of the time. We distinguish telecommuters from self-employed home-based business workers. In comparison to other dimensions of the employment type choice, the literature on the decision to telecommute is perhaps somewhat more sparse. However, there are behavioral models of preference for home-based telecommuting (Bernardino and Ben-Akiva, 1996) and between home- and center-based telecommuting (Bagley and Mokhtarian, 1997), choice of home-based telecommuting (Mokhtarian and Salomon, 1996), and frequency of home-based (Yen and Mahmassani, 1997) and center-based (Ho, 1997) telecommuting. Findings relevant to the work here include the importance of commute distance in the telecommute decision.

Yeraguntla and Bhat (2005) separately model a handful of these decisions: to work part-time or full-time using a binary logit model; telework decision and frequency using an ordered-response model; and ease of working a flexible schedule, again using ordered response. Their findings fall in line with the work of others.

A primary aim of the present report is to bring the labor force engagement and travel behavior fields of inquiry together by estimating a single model that jointly predicts each of the discussed choices. When considering the various plausible nesting alternatives for these decisions that are presented later in the report, it is important to remember that they need not imply a temporally sequential structure to the decisions – they may simply represent possible correlation patterns among the alternatives in question. Either way, however, to our knowledge, this is the first empirical estimation of these choices jointly. It is also innovative in the use of subjective variables, such as attitudes and personality, to help explain those choices. One limitation of the study is that the labor-commute engagement decisions are modeled at the individual, rather than household, level. Though variables do capture the presence of other income and persons in the household, an ideal model would jointly predict this decision for each member of a household – but the data used here do not support such an estimation.

This report is organized as follows. The next section will introduce the data used in the modeling. Subsequent sections will discuss how the dependent variable was extracted from the data, the structures considered in the modeling, and the estimation results. A summary section concludes the report.

2. Empirical Setting and Available Data

The data analyzed in this study are collected from a 14-page self-administered survey of approximately 2,000 individuals in the San Francisco Bay Area. A total of 8,000 surveys were mailed (leading to a response rate of about 25%) to randomly-selected households in three neighborhoods, namely North San Francisco (half of the surveys), Concord (one-quarter) and Pleasant Hill (one-quarter). North San Francisco is an urban neighborhood, located close to the regional central business district (CBD) and well-served by transit. Concord and Pleasant Hill, in contrast, are suburban cities located across the San Francisco Bay from the regional CBD – reasonably well-served by BART (the regional rapid rail transit system), but with low levels of bus service. Although they are contiguous, they differ in that Pleasant Hill has higher densities and a more fragmented street pattern. Thus, together they represent some diversity in types of suburban development.

A summary of key demographic variables is included in Table 1 (note: of the 1,904 total respondents with relatively complete data, only 1,676 are included in the modeling, as discussed later). The table segments the data by the six choice categories used in the modeling, namely: non-worker, home-based worker, part-time worker, telecommuter, fully commuting worker, and compressed-schedule worker. Table 1 indicates that our sample is relatively balanced in terms of gender and neighborhood location. Higher incomes are over-represented compared to the Census (see Curry, 2000 for further discussion). However, as the focus of the work is to model the impact of income and other variables on the employment decision, rather than purely to ascertain the population distribution of such measures, it is more important simply to have a reasonable spread of incomes than that they be exactly representative (Babbie, 1998). The same is true of the dependent variable of interest.

The potential explanatory variables used in the models can be placed into seven general categories, namely: Commute Characteristics, Travel Liking, Attitudes, Personality, Lifestyle, Mobility Constraints, and Socio-demographics. Each category is described very generally in this section.

Commute Characteristics: Measures of one-way commute time and distance are used to possibly explain the decision to telecommute.

Travel Liking: Participants rated their liking for travel (segmented by purpose and mode, separately for short-distance and long-distance trips, where long-distance is defined as more than 100 miles one way, for consistency with the American Travel Survey of long-distance travel in use at the time of data collection) on a five-point scale ranging from “strongly dislike” to “strongly like”. The purposes considered here are overall, commuting to work or school, and for work/school-related activities. The modes considered are personal vehicle, bus, and train/light rail.

Attitudes: Attitudes towards travel, land use, and the environment were captured using responses on a five-point Likert-type scale, to 32 statements. Through factor analysis (see Redmond, 2000 or Mokhtarian, *et al.*, 2001 for details of the factor analyses on these as well as the Personality and Lifestyle variables), the statements were distilled into six basic dimensions, namely: travel dislike, pro-environmental solutions, commute benefit, travel freedom, travel stress, and pro-high density. Selected variables loading heavily on the Attitude, Personality, and Lifestyle factors are summarized in Table 2.

Table 1: Key Socio-demographic Characteristics of Sample (N=1,676)

Characteristic		**Non-worker**	**Home-based**	**Part-time**	**Telecommuter**	**Fully-commuting**	**Compressed**	***All* (N)**
		Number (percent)						
Concord		62 (37.8)	26 (16.5)	50 (23.0)	10 (19.6)	245 (24.5)	13 (14.8)	406 (24.2)
Pleasant Hill		51 (31.1)	35 (22.2)	65 (30.0)	15 (29.4)	260 (26.1)	28 (31.8)	453 (27.0)
North San Francisco		51 (31.1)	97 (61.4)	102 (47.0)	26 (51.0)	493 (49.4)	47 (53.4)	817 (48.7)
Female[a]		100 (61.0)	83 (52.9)	158 (72.8)	25 (49.0)	459 (46.3)	48 (54.5)	873 (52.1)
Have a driver's license[b]		158 (96.3)	152 (96.8)	211 (97.2)	51 (100.0)	984 (98.8)	88 (100.0)	1,644 (98.1)
Personal income[c]	< $15,000	56 (37.3)	17 (11.6)	65 (30.7)	3 (5.9)	23 (2.4)	5 (6.0)	169 (10.1)
	$15,000 – 34,999	38 (25.3)	37 (25.2)	76 (35.8)	2 (3.9)	190 (19.5)	13 (15.5)	356 (21.2)
	$35,000 – 54,999	24 (16.0)	32 (21.8)	45 (21.2)	10 (19.6)	325 (33.3)	25 (29.8)	462 (27.6)
	$55,000 – 74,999	15 (10.0)	24 (16.3)	12 (5.7)	14 (27.5)	193 (19.8)	21 (25.0)	279 (16.6)
	$75,000 – 94,999	6 (4.0)	13 (8.8)	8 (3.8)	10 (19.6)	107 (11.0)	6 (7.1)	149 (8.9)
	> $95,000	11 (7.3)	24 (16.3)	6 (12.8)	12 (23.5)	138 (14.1)	14 (16.7)	205 (12.2)
Age[b]	18 – 23	6 (3.7)	1 (0.6)	18 (8.3)	2 (3.9)	23 (2.3)	1 (1.1)	51 (3.0)
	24 – 40	38 (23.2)	60 (38.5)	73 (33.6)	24 (47.1)	451 (45.2)	35 (39.8)	682 (40.7)
	41 – 64	120 (73.2)	82 (52.6)	101 (46.5)	25 (49.0)	506 (50.8)	51 (58.0)	885 (52.8)
	> 65	0 (0.0)	13 (7.3)	25 (11.5)	0 (0.0)	17 (1.7)	1 (1.1)	55 (3.3)
Characteristic		Mean (standard deviation)						
Total people in household (HH)		2.46 (1.30)	2.37 (1.14)	2.61 (1.29)	2.39 (1.02)	2.34 (1.22)	2.40 (1.10)	2.40 (1.22)
Total children under 18 in HH[a]		0.573 (1.03)	0.417 (0.857)	0.588 (0.956)	0.353 (0.688)	0.432 (0.827)	0.455 (0.801)	0.463 (0.865)
Total workers in HH (full/part-time)[d]		0.911 (0.847)	1.75 (0.754)	1.91 (0.826)	1.82 (0.623)	1.75 (0.812)	1.70 (0.714)	1.69 (0.842)
Number of personal vehicles in HH[e]		1.82 (1.21)	1.85 (0.999)	1.89 (1.21)	2.16 (1.30)	1.85 (1.04)	1.94 (0.975)	1.87 (1.08)
Total short distance travel (miles/week)[f]		134.0 (119.4)	156.9 (162.5)	156.7 (128.8)	305.0 (229.7)	231.5 (196.8)	188.8 (150.8)	205.2 (183.2)

[a] N=1,667; [b] N=1,673; [c] N=1,620; [d] N=1,666; [e] N=1,670; [f] N=1,675

Table 2: Factor Loadings for Selected Attitude, Personality, and Lifestyle Variables

Variable category	Factor name	Survey variable	Factor loading
Attitudes	Travel dislike	Traveling is boring.	0.621
		I like exploring new places.	-0.537
		The only good thing about traveling is arriving at your destination.	0.525
	Pro-environmental solutions	To improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicle.	0.641
		We should raise the price of gasoline to reduce congestion and air pollution.	0.617
		We need more public transportation, even if taxes have to pay for a lot of the costs.	0.612
	Commute benefit	My commute is a real hassle.	-0.695
		My commute trip is a useful transition between home and work.	0.583
		The traveling that I need to do interferes with doing other things I like.	-0.530
		I use my commute time productively.	0.467
	Travel freedom	In terms of local travel, I have the freedom to go anywhere I want to.	0.511
		In terms of long-distance travel, I have the freedom to go anywhere I want to.	0.422
	Pro-high density	Living in a multiple family unit wouldn't give me enough privacy.	-0.617
		I like living in a neighborhood where there is a lot going on.	0.486
	Travel stress	I worry about my safety when I travel.	0.544
		Traveling makes me nervous.	0.537
		Traveling is generally tiring for me.	0.410
		I tend to get sick when traveling.	0.318
		I am uncomfortable being around people I don't know when I travel.	0.297
Personality	Adventure seeking	Adventurous	0.776
		Variety seeking	0.695
		Spontaneous	0.574
		Risk taking	0.557
	Organizer	Efficient	0.624
		On time	0.371
	Loner	Like being alone	0.935
		Like being independent	0.314
	Calm	Aggressive	-0.599
		Patient	0.532
Lifestyle	Frustrated	I often feel like I don't have much control over my life.	0.720
		I am generally satisfied with my life.	-0.618
	Family/community oriented	I'd like to spend more time with my family and friends.	0.585
		My family and friends are more important to me than my work.	0.472
	Status seeking	To me, the car is a status symbol.	0.698
		A lot of the fun of having something nice is showing it off.	0.518
	Workaholic	I'm pretty much a workaholic.	0.652
		I'd like to spend more time on work.	0.373

Source: Redmond (2000).

Personality: Respondents rated 17 attributes expected to relate to their travel attitudes and/or behavior on a five-point scale (anchored by "hardly at all" to "almost completely"), in terms of how well the attributes described them. Here, the factor analysis revealed four personality types: adventure-seeker, organizer, calm, and loner.

Lifestyle: The survey contained 18 statements related to work, family, money, status, and the value of time. Respondents agreed or disagreed with the statements using a five-point Likert-type scale. Four lifestyle factors emerged: status seeker, workaholic, family/community related, and a frustrated factor.

Mobility Constraints: Constraints on one's ability to travel are also expected to affect one's decision to work and commute. Here, participants selected, on a three-point scale ("No limitation", "Limits how often or how long", "Absolutely prevents"), the degree to which physical conditions or anxieties prevented them from engaging in a variety of travel forms, including: "walking", "taking public transportation", and "driving on the freeway". The percentage of time an automobile is available to the participant is also considered to be a Mobility Constraint (oriented in the reverse direction).

Socio-demographics: The survey captured an extensive amount of typical socio-demographic data to allow for comparison of our sample with more general populations. The data included measures of age, income, household size, employment type, number of household workers, education level, gender, and make/model of the vehicle driven most often by the respondent.

3. Dependent Variable: Labor-Commute Engagement Decision

Ultimately, each individual in the sample will be placed into one of six categories: non-worker, home-based worker, part-time worker, telecommuter, fully-commuting worker, or compressed-schedule worker. Of course, further variations on these dimensions are certainly possible, such as someone telecommuting but only working part-time, but either the data available do not permit us to make those distinctions (as partially described in this section), or the numbers of cases in those categories are too small to be statistically robust.

Unfortunately, the survey instrument used to gather the data did not expressly capture all of these choices. As a result, certain assumptions had to be made to segment the sample. In this section, the decision trees for full-time, part-time, and non-working individuals are discussed separately. In the decision trees that follow, variables taken from the survey are used to segment the data. Table 3 provides the actual survey question and possible responses for each of the segmentation variables.

Table 3: Segmentation Variables and Corresponding Survey Questions

Segmentation Variable	Survey Question	Response Options
Employment status	What is your current employment status?	Full-time
		Part-time
		Homemaker
		Non-employed student
		Unemployed
		Retired
Commute to work or school frequency	Counting only **short-distance** trips (100 miles or less *one way*), please estimate about *how often* you typically make each of the following types of trips, by any means of travel: commuting to work or school	Never
		Less than once a **MONTH**
		1-3 times a **MONTH**
		1-2 times a **WEEK**
		3-4 times a **WEEK**
		5 or more times a **WEEK**
Applicability of home-to-work commute time and distance	How long does it usually take you to get to work (one way)?	Write in (mins.), or "Not applicable" check box
	How far do you live from work?	Write in (mi.), or "Not applicable" check box
History of telecommuting	We are interested in knowing which of the following you have already done **and why**… Telecommute (part- or full-time)	"Not done or not applicable" check box, and "Done: How long ago?" write in (yrs.)
History of working a compressed schedule	We are interested in knowing which of the following you have already done **and why**… Adopt a compressed work week (such as a "9/80" schedule)	"Not done or not applicable" check box, and "Done: How long ago?" write in (yrs.)
Age category	What is your age?	23 or younger
		24-40
		41-64
		65-74
		75 or older

Turning first to those who identified themselves to be working full-time on the survey instrument, the goal is to further segment these full-time workers into home-based workers, fully-commuting workers, compressed-schedule workers, and telecommuters. Figure 1 illustrates this process (note: the number of observations is denoted in parentheses in each box in the figure). The first variable used to divide the data is commute frequency. Those who commute less than once per month are placed in the home-based worker category. Conversely, those who commute five or more times per week, and provided one-way commute time and distance information, are considered fully-commuting workers. Those who, instead of providing one-way commute time and distance information, marked these boxes to be “not applicable”, are considered to be home-based workers. This assumption was made because the commute frequency variable actually captured trips to work *or* school, whereas the one-way commute distance and time variables referred only to work. As such, those who “commute to work or school” five plus times per week and work full-time, but state that a one-way home-to-work time is “not applicable”, are presumed to be traveling to school and working at home (note: there are only seven such individuals in this category).

Full-time workers who commute less than five times per week but more than once per month follow the branch of “some commute” in Figure 1; it is assumed that these individuals are home-based business workers, telecommuters, or working a compressed schedule. Thus, the first segmentation variable for this sub-group is the applicability of the home-to-work time and distance questions: those who state that these values are “not applicable” to them are again considered to be home-based workers. Those who did give commute time and distance responses are then divided into the telecommuter and compressed-schedule categories. The survey did not inquire about the current engagement of the respondents in telecommuting or working a compressed schedule. However, the survey did inquire about past adoption of these activities (without ascertaining whether a past adoption is still ongoing). Respondents who adopted telecommuting in the past but did not report adopting a compressed work schedule are considered to be telecommuters (and similarly for compressed work schedules); those who have adopted both are labeled based on which behavior they adopted more recently.

Partial commuters who have not engaged in telecommuting in the past are considered to be compressed-schedule workers. It should be noted that many (72) of these respondents did not report past adoption of a compressed work schedule, but were labeled as compressed schedule workers nonetheless. This decision was made under the assumption that full-time workers commuting less than five times a week but more than once a month, and not telecommuting, are likely to be working in some type of flexible work arrangement, which is more like a compressed-schedule than any of the other categories used in the modeling. Such a description even holds for service workers, such as plumbers, construction workers or taxi drivers, who may travel to a central business location several times a week, but otherwise travel directly to their customers’ locations. These workers may have the flexibility to schedule appointments during less congested hours, much like those working flexible arrangements in offices.

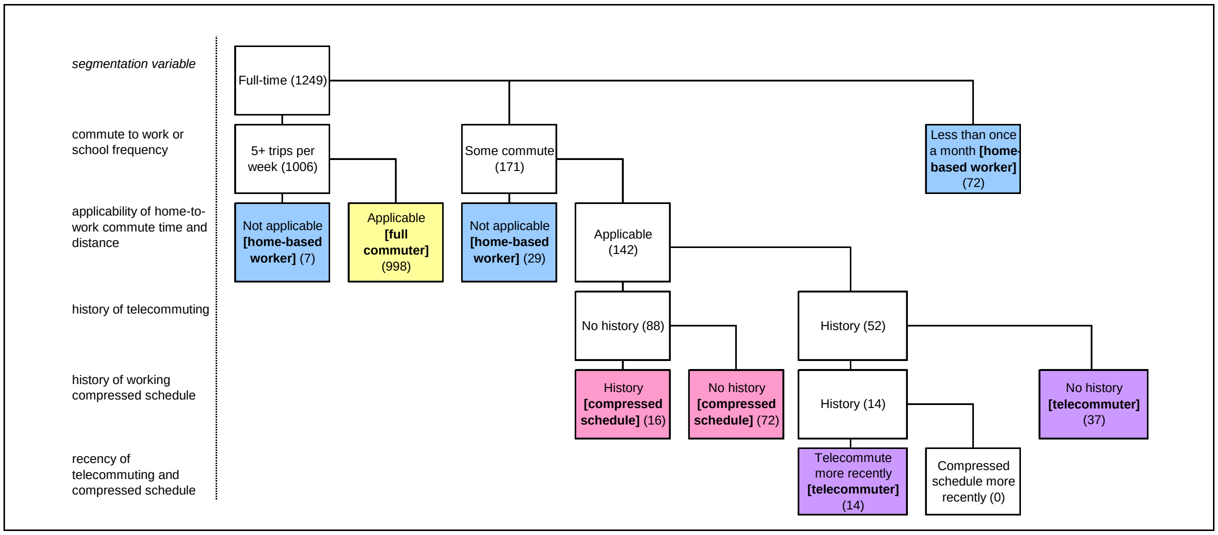

Figure 1: Segmentation of Full-time Workers

The segmentation of part-time workers is shown in Figure 2 (please note that the term "part-time worker" is being used as an initial segmentation variable as well as a label for an employment type category, i.e. as shown in the flow chart, not all part-time workers are ultimately placed in the part-time worker category). Here, only two variables are used to apportion the sample: work/school commute frequency and the applicability of the home-to-work time and distance questions. Our initial approach was to label part-time workers who either make less than one commute trip per month or who make more "commute" trips (which could be to school) but describe their one-way commute time and distance as "not applicable" as home-based workers; part-time workers not following these rules are labeled part-time workers. Such an approach assumes that the decision to work from home is more important to our modeling than the decision to work part-time; a logical premise due to the focus of our research on traveling. However, as we developed the models this assumption was re-examined. In certain instances, models were re-estimated after placing those who work part-time (whether in-home or out-of-home) in the part-time worker category (note: the 50 respondents labeled as home-based workers in this segment are referred to as "part-time home-based workers" in subsequent discussions).

Efficient model estimation ideally entails parsimonious but homogeneous choice categories. As we did not want to maintain a seventh choice category having only 50 cases, we had to determine to which of the remaining six choices these part-time home-based workers were most similar (although the telecommuting category had a similar number of cases, it was considered essential to keep it separate, which made it even less desirable to have another similarly small group). The two clear options are full-time home-based business workers or commuting part-time workers. As discussed in more detail in the subsequent sections regarding model estimation, we experimented with both approaches. For the remainder of this section, we will continue the description of the data with the segmentation presented in Figure 2.

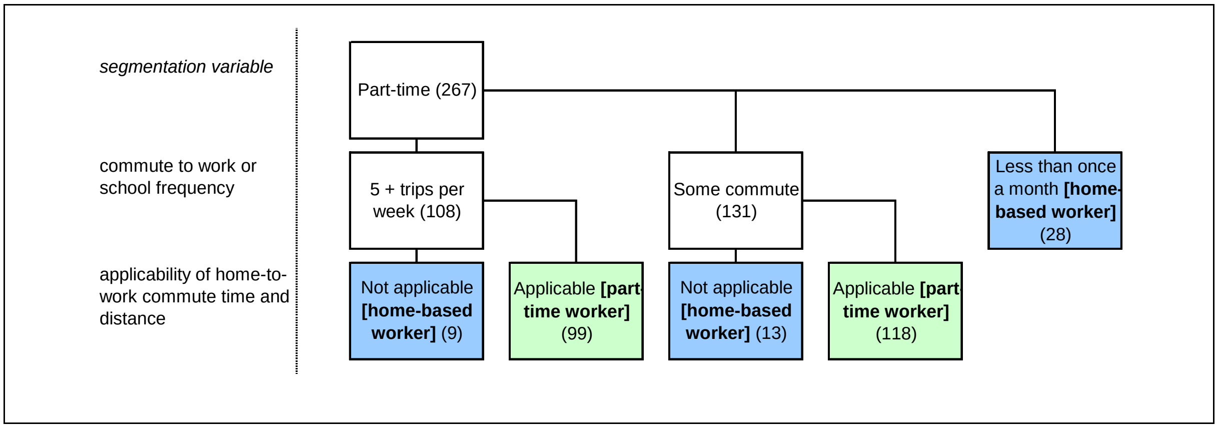

Figure 2: Segmentation of Part-time Workers

The final segmentation is made on those whose response to the survey employment status question was homemaker, non-employed student, retired, or unemployed. As shown in Figure 3, those in the homemaker, retired, and unemployed groups who are younger than 65 are categorized as non-workers, and those over 65 are excluded from the analysis; all non-employed students are excluded from the analysis as well.

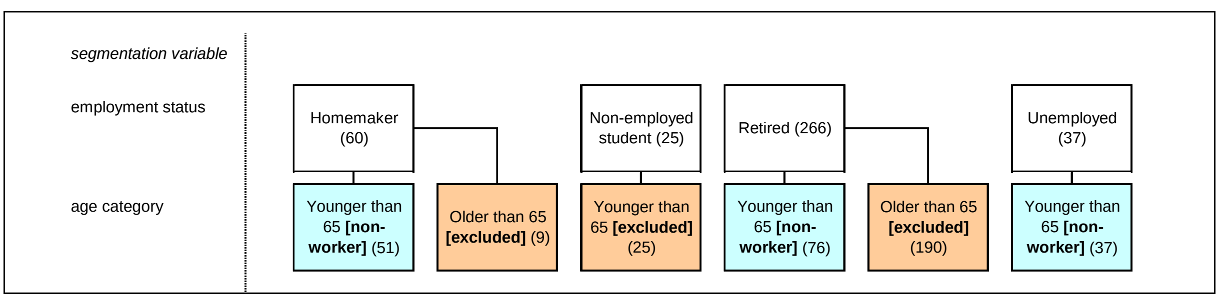

Figure 3: Segmentation of Homemakers, Non-employed Students, Retired Persons, and Unemployed Persons

In sum, 224 respondents are excluded; the six groups of interest have sample sizes as follows: 164 (9.8%) non-workers, 158 (9.4%) home-based workers, 217 (13.0%) part-time workers, 51 (3.0%) telecommuters, 998 (59.6%) fully-commuting workers, and 88 (5.3%) compressed-schedule workers.

4. Potential Model Structures

As discussed above, the goal in the modeling is to predict each individual's decision to not work, work entirely at home, work part-time, work full-time and telecommute, work full-time and commute five times per week, or work a compressed schedule full-time. In this section, we propose binary, multinomial, and nested structures to model this decision.

2.1 Binary model structures

To begin the modeling effort, four simple binary logit models are estimated. Here, we are examining the factors that influence what we see as fundamental decisions: to work or not to work; to work part-time or full-time; to fully commute or partially (or not) commute; and, to work some or completely at home or completely out-of-home. Table 4 describes how each of the six primary choices is combined to form each of the binary choices.

As discussed in the previous section, individuals working part-time and not commuting were initially placed in the home-based worker category. While this assumption is reasonable when considering all of the categories individually, it does not hold when modeling the decision to work full-time or part-time, as is done here in the second model. As such, we place the 50 part-time home-based workers in the part-time category for the second binary model shown in Table 4. For the fourth model (work some at home or not), part-time workers are excluded.

Table 4: Composition of Binary Model Categories

Model	Choice 1	Groups combined in Choice 1	Choice 2	Groups combined in Choice 2
1	Work	home-based, part-time, telecommute, full commute, compressed schedule (N=1,512)	Don't Work	non-worker (N=164)
2	Full-time	full-time home-based, telecommute, full commute, compressed schedule (N=1,245)	Part-time	part-time, part-time home-based (N=267)
3	Full commute	full commute (N=998)	Partial/non-commute	home-based, telecommute, compressed schedule (N=297)
4	Work some at home	full-time home-based, telecommute (N=209)	Work away from home	full commute, compressed schedule (N=1,086)

2.2 Multinomial logit model structure

The multinomial model, illustrated in Figure 4, considers each of the six primary choices individually. Here, we make the potentially restrictive assumption that the random components of utilities for each of the six choices are independent from one another. Two separate multinomial models are considered: the first places the part-time home-based workers in the home-based worker category, and the second places these individuals in the part-time worker category.

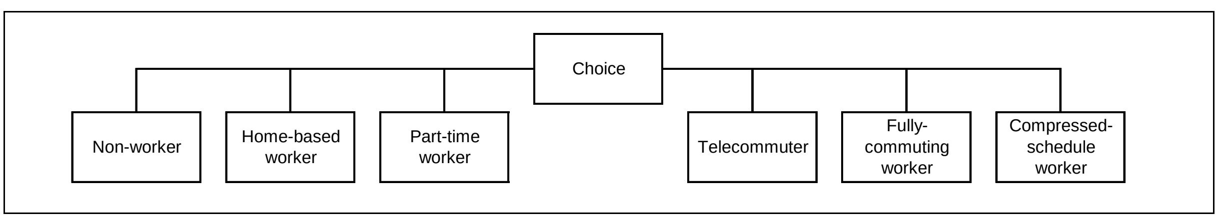

Figure 4: Multinomial Model Structure

2.3 Proposed nested logit model structures

As indicated, the assumption of independence across the six alternatives is a strong one. Conceptually, one may expect the unobserved influences on certain choices, such as working a compressed schedule and telecommuting, to be correlated. To account for this correlation, three nesting structures are proposed and estimated. Each of the nesting structures is described below, named after the category comprising the alternatives in the lowest-level nest. In each case, all of the work choices are nested separately from the non-work choice.

Nesting structure A: Full-time workers

The first nesting structure assumes the decisions to work full-time are related, regardless of commute frequency. In this structure, shown in Figure 5, fully-commuting workers, home-based workers, telecommuters, and compressed-schedule workers are placed under a common “full-time” nest, which itself is in a “work” nest along with part-time workers. The upper two models constitute two of the four binary models described in the first part of this section, while in lieu of the other binary models, we here distinguish the three partly/non-commuting alternatives. As in the full-time/part-time binary model, part-time home-based workers are placed in the part-time worker group since, given the branching structure in this model, that is the only group to which they belong (they are not full-time workers).

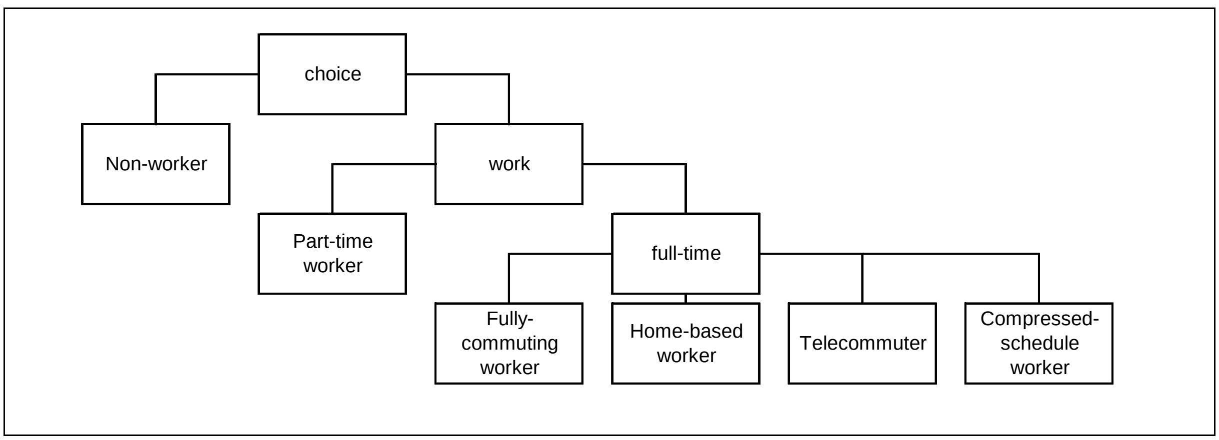

Figure 5: Nesting Structure for Model A

Nesting structure B: Partial commuters

In the second nesting structure, presented in Figure 6, partial commuters are nested separately from those working from home and those commuting full-time, and all of these groups are separated from non-workers. This nesting structure assumes that unobserved influences on the utility for working part-time are correlated with those for telecommuting and compressed work schedules. For example, the utility of all three alternatives may be related to a preference for avoiding congestion, or to a desire for flexibility to support family needs. Here, part-time home-based workers are placed in the home-based worker category, again because in view of the branching structure of this model, that is the only category to which they belong.

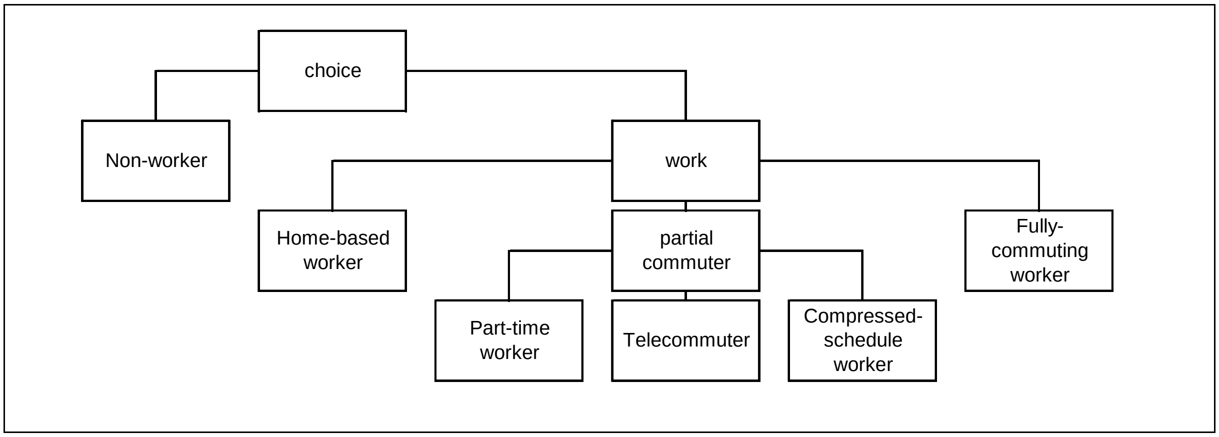

Figure 6: Nesting Structure for Model B

Nesting structure C: Partial/non-commuter

The final nesting structure is similar to the partial commuter nesting structure presented in Figure 6, only it includes home-based workers in the partial nest, which becomes a "partial\non-commuting" nest, as shown in Figure 7. Here, the utilities for each way of avoiding the commute trip are assumed to have correlated error terms. Because the part-time and home-based choices are at the same nesting level, this model was estimated in two separate ways: first with the part-time home-based workers labeled as home-based workers, and next with these individuals labeled as part-time workers.

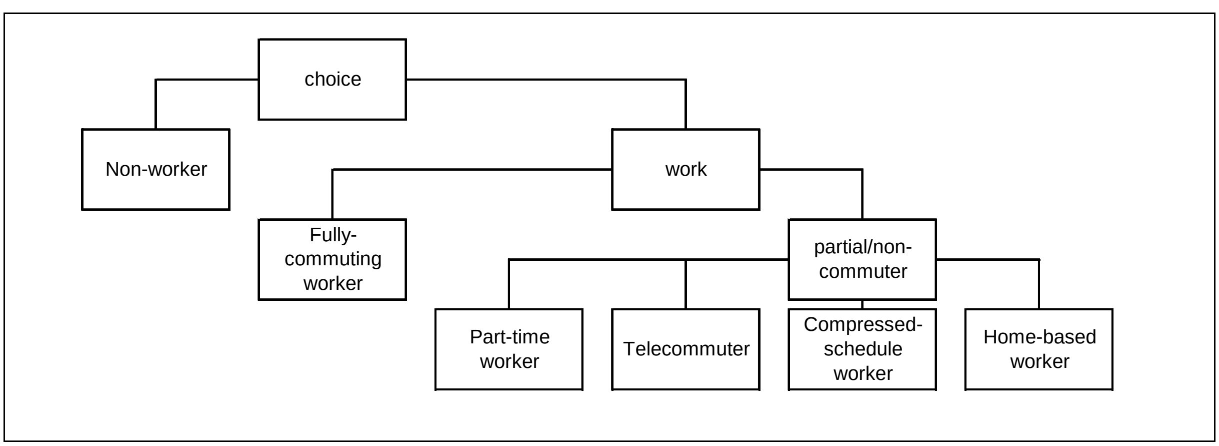

Figure 7: Nesting structure for Model C

5. Model Estimation Results

The estimation results for the models introduced in the previous section are presented and discussed here.

5.1 Work versus Don't work binary logit model

The results of the work versus don't work binary model are presented in Table 5, with variables specific to the work choice separated from variables specific to the non-work choice (this assignment is arbitrary – since a given variable could just as easily have been associated with the other alternative, having the opposite sign – but is chosen for ease of interpretation and comparison with the later, more complex, models). The overall goodness-of-fit, as measured by the adjusted likelihood ratio index $\mathbf{D}^2$, is 0.145, which is in the range of the values of 0.13 to 0.40 found in the literature presented in the Introduction. It is expected that our model will have a lower goodness of fit than models based on more specific populations, such as Heckman's (1974) work with married Caucasian women ages 30 to 44.

The models include variables in a variety of categories including Socio-demographics, Travel Liking, and Mobility Constraints. Those with higher education levels are more likely to work – an expected result. The other two variables specific to work fall into the Travel Liking category, and counteract each other to a large degree. Those who enjoy commuting more than overall short-distance travel are more likely to work, whereas those who enjoy overall travel more than commuting are more likely not to work. Previous analysis of these data found similar trade-offs: the overall enjoyment of short-distance travel is both hindered by having to work (leaving less time for such travel) and reduced by having less enjoyable experiences while traveling to work (i.e. negative feelings may be transferred to non-work travel) (see Ory and Mokhtarian, 2005, for more discussion of this issue). Figure 8 presents a histogram of these two variables' combined contribution to the overall observed utility of the work choice; it shows that for most of the sample (male and female alike), the net effect of these two variables on utility is positive, i.e. that affective beliefs about travel are more often a positive than a negative influence on the decision to work. The inclusion of the Travel Liking variables does raise the issue of endogeneity: does a fondness for travel influence the decision to work? Or do those who work grow to enjoy the benefits of travel? Certainly both directions are possible (Ory and Mokhtarian, 2005), and we believe the modeled direction to be eminently plausible.

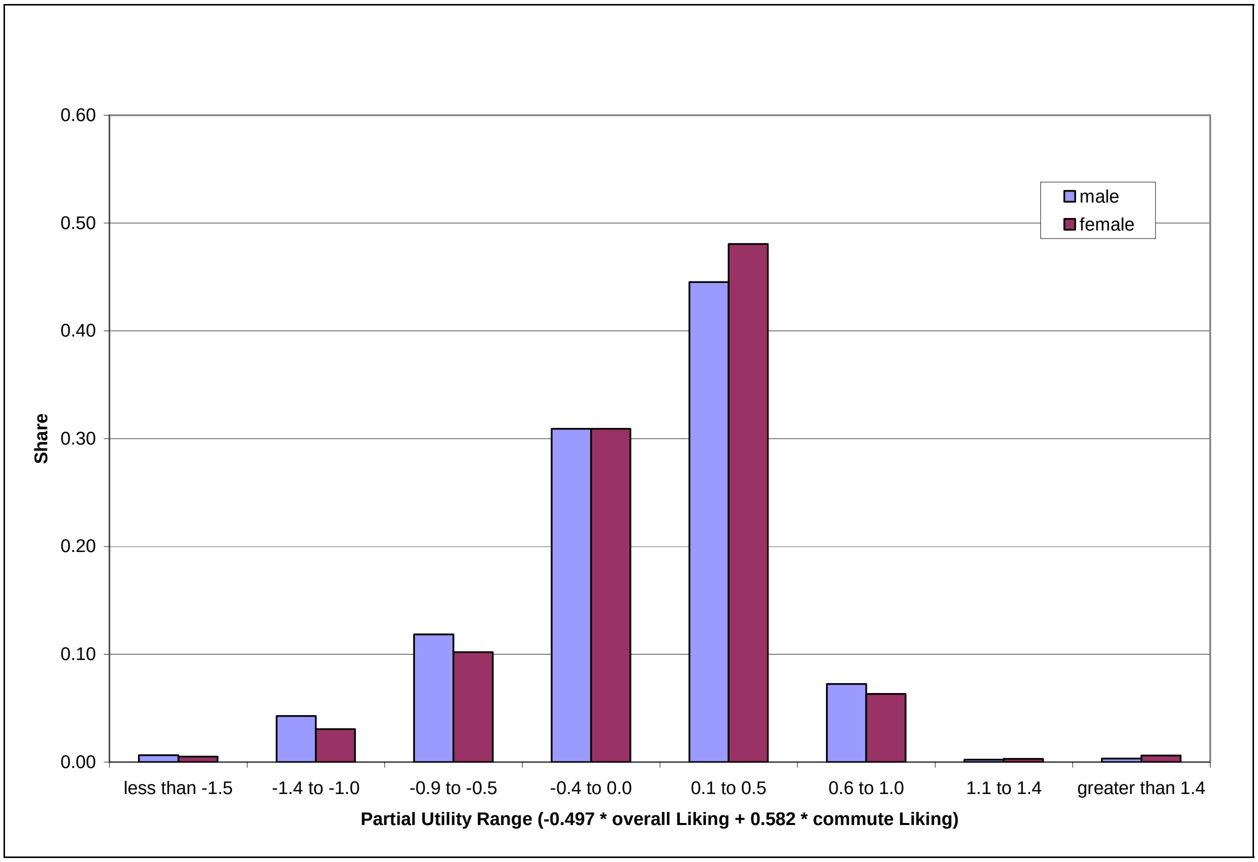

Figure 8: Partial Utility Contributions of Travel Liking Variables

Variables specific to the non-work choice follow expectation. Female respondents with children under the age of 15 are less likely to work; this effect is stronger when the children are under the age of 6 and when multiple children are present in the household. These results are consistent with the traditional role of women as caretakers. The positive coefficient on the dummy variable specific to the 41 to 64 age category indicates that, compared to those ages 18 to 41, persons in this age group are less likely to work and may be opting for an early retirement. Last, individuals who are unable or are limited in their ability to walk are, unsurprisingly, more likely to be non-workers.

Table 5: Work versus Don't Work Binary Model Results (N=1,657)

Dependent Variable : Work or Don't Work

Explanatory Variables	**Coefficient**	**t-statistic**
Constant (specific to Work)	3.58	5.85
Variables specific to Work choice		
Education level [1,…,6]	0.284	3.82
Liking for all short-distance travel [1,…,5]	-0.497	-3.86
Liking for commuting to work or school [1,…,5]	0.582	5.97
Variables specific to Non-work choice		
Ages 41 to 64 [0,1]	1.19	5.70
Number of persons in household under age 6 (specific to females) [0,1,…]	1.03	6.00
Number of persons in household age 6 to 15 (specific to females) [0,1,…]	0.424	2.96
Physical or psychological limitation on walking [1,2,3]	1.25	5.76

[ ] = range of possible responses

Log-likelihood at convergence = -451.37

Log-likelihood with constant only = -530.49

Adjusted rho-squared = 0.145; rho-squared = 0.149

5.2 Full-time versus Part-time binary logit model

The second binary model compares the decision to work full-time versus part-time. Here, those in the non-worker category are excluded from consideration. The results of the binary logit model are presented in Table 6, which again arbitrarily segments the variables by alternative. The adjusted $\mathbf{D}^2$ value is 0.179, similar to the values of 0.174 to 0.251 found in the part-time/full-time probit models of Moulin (2003).

Variables specific to the full-time choice include age 24 to 40 and 41 to 64 dummies, both with positive coefficients; a logical result in that those less than 24 or older than 65 seem more likely to work part-time. A Mobility Constraint variable, percentage of time a vehicle is available, enters specific to the full-time choice with a positive coefficient – confirming the well-known result that having a car to use makes working full-time easier (see, e.g., Wachs and Taylor, 1998). The final variable specific to the full-time choice is the workaholic lifestyle factor score, which enters with a positive coefficient. Statements such as, "I'd like to spend more time on work” and “I’m pretty much a workaholic” load positively on this factor. Thus, those who tend to agree with these statements also tend to work full-time – not an unexpected result.

Variables specific to the part-time choice are largely gender-specific. As expected, females caring for young children are more likely to work part-time as are females in households with other income earners. Also, females who find travel stressful are more likely to work part-time; this factor represents such statements as “traveling makes me nervous” and “I often worry about my safety when I travel”. This result highlights the travel-related aspects of the labor-force engagement decision.

An interesting result is the opposing signs of the coefficients on the gender-specific two-plus adults with no children household status variables. Men in such households are more likely to work part-time, whereas women are more likely to work full-time. This finding is consistent with the stereotype of married women supporting their husbands while the husbands return to college in an effort to advance their careers. It probably also represents the stereotypes of women as domestic care-givers and men as financial providers: women are more likely to work full-time when there are no children to physically care for, whereas men are more likely to work full-time when there are children needing financial support.

Variables entering the models with no segmentation by gender include the Mobility Limitation on walking and Travel Liking for overall short-distance travel (both with positive coefficients specific to part-time work). The re-appearance of the Travel Liking measure gives further credence to the hypothesized relationship presented in the previous model description.

Table 6: Full-time versus Part-time Employment Binary Model Results (N=1,442)

Dependent Variable : Full-time or Part-time Employment

Explanatory Variables	Coefficient	t-statistic
Constant (specific to Part-time)	-1.06	-1.73
Variables specific to Full-time choice		
Age 24 to 40 [0,1]	2.35	8.59
Age 41 to 64 [0,1]	1.87	7.37
Percent of time a vehicle is available [0, 20, …, 100]	0.0139	5.38
Workaholic lifestyle [-2.1, 2.3]	0.335	3.15
Variables specific to Part-time choice		
Female gender [0,1]	0.997	3.55
Number of persons in household under age 6 (specific to females) [0, 1, …]	0.576	2.91
Two-plus adults with no children HH status (specific to females) [0,1]	-0.616	-2.87
Two-plus adults with no children HH status (specific to males) [0,1]	0.660	2.34
Household income less personal income (specific to females) [0, …, 5]	0.513	6.52
Physical or psychological limitation on walking [1,2,3]	0.648	2.37
Travel stress attitude [-1.9,2.9]	0.311	2.71
Liking for all short-distance travel [1,…,5]	0.255	2.33

[ ] = range of possible responses

Log-likelihood at convergence = -543.45

Log-likelihood with constant only = -668.15

Adjusted rho-squared = 0.179; rho-squared = 0.187

5.3 Full versus Partial commute binary logit model

The third binary model aims to predict the choice of full-time workers to commute fully, or partially or not at all. The results for the estimation are summarized in Table 7. The adjusted D^2 value is only 0.041 for this model, indicating the difficulty in predicting such a choice, either in general, or specific to the variables found in our data. The eight variables in the model, however, are logical and informative.

Variables specific to the fully commuting choice include the number of children age 6 to 15 in the household and the family/community lifestyle factor score, which is based on such statements as “my family and friends are more important to me than my work” and “I’d like to spend more time on social, environmental, or religious ‘causes’”. Both of these variables enter the model with positive coefficients, which, in combination with the number of persons under age 6 variable in the partial/no commute choice, illustrate trade-offs many families have to make. Although individuals with children may view themselves as being primarily family-centric, the ability to support that family may be enhanced by commuting to work each day. Further, traveling to work may provide welcome solitary time away from the obligations of family, and the commute and time at an out-of-home work location may provide a valued change of roles from the domestic one (for a more detailed discussion on the benefits of commuting specifically, see Ory, *et al.*, 2004). The final variable specific to the fully commuting choice is the travel freedom attitude factor score, which is based on variables such as “I have the freedom to go anywhere I want to”. The positive coefficient of this variable suggests that such an attitude may be more relevant to the choice to commute fully than objective measures such as percentage of time a vehicle is available; it may be capturing the reliability of automobile or transit travel. Alternatively (or in addition), it may be reflecting an affect for the independence offered by the ability to travel freely, an affect manifested by the choice to commute daily rather than less often or not at all.

Women are more likely to commute less than full time, as represented by the partial/no commute choice, as are individuals with household members age 41 to 64. It may be that women enjoy or need the flexibility, which helps them fill their traditional role as primary caretakers, and those in the older age category have the ability to work differing schedules due to their experience and abilities. A pro-environmental attitude (“to improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicle”) increases the probability of commuting only partially or not at all. This is a natural finding in that those holding these beliefs may see travel as doing harm to the environment and, as such, try to avoid it (although a number of studies such as Tanner (1999) have shown that one’s behavior with respect to auto use is not always consistent with one’s environmental attitudes). Finally, those with adventure-seeking personalities (“risk-taking”, “adventurous”) are more likely to commute partially – they may see the non-conventional work arrangement as an adventure of sorts, or use the freedom it offers to engage in other adventures.

Table 7: Full versus Partial/No Commute Binary Model Results (N=1,280)

Dependent Variable : Full or Partial/No Commute

Explanatory Variables	**Coefficient**	**t-statistic**
Constant (specific to Partial/No)	-0.747	-3.19
Variables specific to Full Commute Choice		
Age 24 to 40 [0,1]	0.355	2.24
Liking for commuting to work or school [1,…,5]	0.280	3.82
Family/community lifestyle (specific to females) [-3.9,2.1]	0.461	3.49
Variables specific to Partial/No Commute Choice		
Number of persons in household under age 6 (specific to females) [0,1,…]	1.10	5.13
Other persons age 41 to 64 in household [0,1,…]	0.344	2.34
San Francisco neighborhood [0,1]	0.376	2.54
Pro-environmental solutions attitude (specific to females) [-2.3,2.4]	0.352	2.64
Adventure-seeker personality [-2.6,2.7]	0.171	2.18

[ ] = range of possible responses

Log-likelihood at convergence = -656.57

Log-likelihood with constant only = -689.79

Adjusted rho-squared = 0.0414; rho-squared = 0.0482

5.4 Work some at home versus Work out-of-home binary logit model

The final binary model describes the choice to work some or completely at home (telecommuters and home-based workers, respectively) or exclusively out-of-home (fully commuters and compressed schedule workers). Part-time workers (regardless of other characteristics) are excluded from this analysis.

The model results are shown in Table 8; the adjusted $\mathbf{D}^2$ measure is 0.094. The variables are again segmented by the two choices.

Logically enough, those living farther from work are also more likely to telecommute or work exclusively from home. Consistent with stereotype, females are more likely to work some at home, with the effect more pronounced for women with children under the age of 6. However, the effect of children is partly counteracted by the household status variable. Two-plus adults couples without children are more likely than their single or child-bearing counterparts to work some at home. Although counter to the stereotype that home-based work is attractive as a strategy for balancing family and work obligations, this result is consistent with anecdotal accounts of telecommuters and non-telecommuters, that the home environment is more conducive to working when children are absent. Taken together, these demographic variables point to a multi-faceted role of gender and family in the decision of *where* to work, with competing influences often involved even within a single household.

Variables entering the model associated with the other alternative include liking for short-distance travel overall. The reappearance of this variable is interesting and begins to solidify the importance of travel-related attitudes in these decisions. Males with calm personalities and individuals of either gender who find life frustrating are also more likely to work exclusively out of home. Those with a calm nature may be more capable of dealing with the stress of a daily commute and those who feel frustrated may not see in-home options as possible or realistic.

Table 8: Work Some at Home versus All Out-of-Home Binary Model Results (N=1,280)

Dependent Variable : Work some at home or all out-of-home

Explanatory Variables	**Coefficient**	**t-statistic**
Constant (specific to All out-of-home)	2.80	4.24
Variables specific to Work some at home choice		
One-way commute distance [>=0]	0.0224	3.35
Female gender [0,1]	1.40	3.29
Number of persons in household under age 6 (specific to females) [0, 1, …]	0.722	2389
Two-plus adults with no children HH status [0,1]	1.41	3.17
Variables specific to Work all out-of-home choice		
Liking for all short-distance travel [1,…,5]	0.563	3.17
Calm personality (specific to males) [-2.9,2.4]	0.595	2.51
Frustrated personality [-2.0,2.7]	0.348	2.09

[ ] = range of possible responses

Log-likelihood at convergence = -234.49

Log-likelihood with constant only = -260.58

Adjusted rho-squared = 0.0938; rho-squared = 0.100

5.5 Multinomial logit model

The results of the multinomial logit estimation are shown in Table 9. The adjusted $\mathbf{D}^2$ value for the model is 0.110, which is on the low end of the range for the models discussed in the Introduction, but more noteworthy for having been achieved with a six-alternative choice set rather than the binary one treated in most models. First looking at the variables specific to the ***non-work choice***, Table 9 shows expected results, with education decreasing the likelihood of not working, and being female with children (ages 6 to 15) or with other household income increasing the likelihood.

Turning to the ***home-based worker choice***, those in production/construction/crafts occupations are more likely to work at home, as are those living in San Francisco (relative to the East Bay suburbs). These results fit the stereotype of small contractors working out of their homes, or of artists and craftspeople working from home (or in studio living/working space), especially near the city center.

Three personality and lifestyle factor score variables enter the model specific to home-based workers: calm, frustrated, and workaholic. The coefficients of these variables indicate that home-based workers are likely *not* to be calm, or frustrated, but do tend to be workaholics. It is certainly possible that those working at home may be less frustrated because they are not commuting, or because they have more work autonomy and/or more time with family – i.e. that frustration level is an effect rather than a cause of one's work status. However (based on the variables loading heavily on the factor, such as those shown in Table 2), we are assuming here that the frustrated factor score represents a general approach towards life, and that those who do not have a difficulty with these frustrations are more likely to tackle the often difficult task of working entirely at home. Of course, the other two variables indicate they aggressively (i.e. not calmly) pursue working at home, which fits their workaholic nature.

Variables specific to the ***part-time*** choice include the number of children ages 6 to 15 and other household income, both specific to females; the coefficients estimated for these variables carry the same sign (and, thus, the same interpretation) as those specific to the non-work choice. A Mobility Constraint variable, percentage of time a vehicle is available, enters with a negative coefficient – as in the binary model. Last, persons older than 65 are more likely to work part-time than their younger counterparts – a logical result.

Moving to the ***telecommuting*** alternative, individuals choosing this option are more likely to be adventure seekers and tend to live farther from work. The finding that those who live farther from work are more likely to engage in telecommuting agrees with the results of Mokhtarian, *et al*. (2004) and others. We speculate that adventure seekers would be disproportionately drawn to the still-novel, potentially career-risky option of telecommuting, as a way of achieving or manifesting greater work autonomy, and perhaps as a way to save time (by commuting less) that can be allocated to more adventurous pursuits instead (Cao and Mokhtarian, 2005; Clay and Mokhtarian, 2004).

The ***fully commuting*** choice holds the largest share of individuals in the sample and also has the largest number of variables entering into the model. Females with young children (less than six years old) are less likely to commute fully, but, interestingly, females with slightly older children (age 6 to 15) are more likely to fully commute. This variable enters the non-worker, part-time worker, and fully commuting worker utility functions with positive coefficients in each case, suggesting that if a woman with children in this age range does choose to work full time, she is likely to do so in a manner that allows for at least some separation from the children by commuting some or all of the time. Individuals ages 41 to 64 are less likely to commute fully, perhaps demonstrating the flexibility they've gained through years of working. On the other hand, however, men in households with other adult(s) and children are more likely to commute fully (reinforcing the workaholic variable mentioned below), perhaps in an effort to climb the career ladder to provide for their families, or as an escape from domestic distractions or stresses, or both. Also, individuals who are unable or are limited in their ability to walk are, unsurprisingly, less likely to commute fully.

A host of attitude, lifestyle, and personality variables also enter the fully commute utility specification. Not surprisingly, those who enjoy commute travel tend to do so, as do workaholics and those who feel they have freedom to travel when and where they want to. Another expected result is that those with stronger pro-environmental feelings are less likely to commute fully, as they may see doing so as needlessly harming the ecosystem. Interestingly, the family/community lifestyle variable enters with a positive coefficient, meaning that those who value family and friends are *more* likely to fully commute. This result suggests the paradox that a family-oriented person may feel that the best way to benefit the family is through the financial support that may be maximized by commuting fully.

An unexpected result is seen in the pro high-density factor attitude variable (specific to women) entering with a positive coefficient. One interpretation is that those who live in high density areas may not have the space to accommodate working from home, even some of the time. Another is that those individuals tend to have shorter commutes and hence less motivation to reduce them. A third interpretation is that this variable could be a marker for the young, upwardly-mobile professional who values the social and professional opportunities at the workplace, as well as the shopping, entertainment, and other synergistic activities available around a dense urban work location.

The ***compressed-schedule*** utility function contains three variables, each of which was described in the fully commuting discussion. One minor difference is the pro-environmental solutions attitude entering specific to males.

As mentioned previously, the multinomial logit model was estimated in two different ways. The first placed the part-time home-based workers into the home-based worker category, and the second (selected) placed these individuals into the part-time worker category. The goodness-of-fit measure for the first estimation was slightly lower than for the second (presented in Table 9), with an adjusted $\mathbf{D}^2$ value of 0.101. This result seems to indicate that part-time home-based workers are more similar to part-time workers than to full-time home-based workers, which is quite plausible. If working part-time is by choice, these workers may see employment as a secondary drive in their lives, behind going to school, enjoying retirement, or caring for young children. Such a population sits in stark contrast to full-time home-based workers who may be taking enormous risks to start and/or continue operating their own businesses from home.

Table 9: Multinomial Logit Model Results (N=1,580)

Dependent Variable : Non-worker, home-based worker, part-time worker, telecommuter, fully-commuting worker, or compressed-schedule worker

Explanatory Variables	Coefficient	t-statistic
Variables specific to Non-worker choice		
Education level [1, …, 6]	-0.277	-3.66
Number of persons ages 6 to 15 in household (specific to females) [0, 1,…]	1.15	3.21
Household income less personal income (specific to females) [0, 1, …, 5]	0.191	2.38
Variables specific to Home-based worker choice		
Constant	-1.93	-5.36
Production/construction employment type [0,1]	1.20	3.15
San Francisco neighborhood [0,1]	0.879	3.74
Calm personality [-2.9,2.4]	-0.470	-3.41
Workaholic lifestyle (specific to females) [-2.1,2.3]	0.752	3.48
Frustrated personality [-2.0,2.7]	-0.497	-3.28
Variables specific to Part-time worker choice		
Constant	0.282	0.739
Number of persons ages 6 to 15 in household (specific to females) [0,1,…]	1.19	3.41
Age 65 to 74 [0,1]	2.79	7.51
Age 75 or older [0,1]	3.01	5.33
Household income less personal income (specific to females) [0, 1, …, 5]	0.449	7.05
Percent of time a vehicle is available [0, 20, …, 100]	-0.0143	-5.81
Variables specific to Telecommuter choice		
Constant	-2.26	-6.28
One-way commute distance [>=0]	0.0184	2.78
Adventure-seeker personality [-2.6,2.7]	0.577	3.46
Variables specific to Fully commuting choice		
Constant	1.67	3.97
Number of persons under age 6 in the household (specific to females) [0,1,…]	-0.955	-.540
Number of persons ages 6 to 15 in household (specific to females) [0,1,…]	0.770	2.25
Age 41 to 64 [0,1]	-0.547	-4.54
Two-plus adults with children HH status (specific to males) [0,1]	0.821	3.42
Physical or psychological limitation on walking [1,2,3]	-0.818	-3.81
Liking for commuting to work or school [1,…,5]	0.194	3.27
Family/community lifestyle [-3.9,2.1]	0.273	3.39
Workaholic lifestyle [-2.1,2.3]	0.309	4.00
Travel freedom attitude [-3.0,2.3]	0.244	3.07
Pro-environmental solutions attitude [-2.3,2.4]	-0.316	-3.76
Pro high-density attitude (specific to females) [-2.5,2.3]	0.316	3.50
Variables specific to Compressed-schedule choice		
Constant	-1.62	-4.84
Two-plus adults with children HH status (specific to males) [0,1]	1.37	3.79
Pro-environmental solutions attitude (specific to males) [-2.3,2.4]	-0.598	-3.03
Pro high-density attitude (specific to females) [-2.5,2.3]	0.609	3.68

[ ] = range of possible responses

Log-likelihood at convergence = -1751.93

Log-likelihood with constant only = -1977.13

Adjusted rho-squared = 0.110; rho-squared = 0.114

5.6 Nested logit model

The final model results emerge from the three nesting structures described in Figures 5, 6, and 7. During the estimation process, nesting structures A (full-time workers) and C (partial\non-commuter) collapsed into a multinomial model (i.e. the nesting coefficients were not statistically different from 1.0). As the multinomial model presented in the previous sub-section is superior, in terms of goodness-of-fit, to the resulting collapsed models, the nested estimation results for models A and C are not presented here.

The nested model that holds a portion of its structure, interestingly, is structure B: partial commuters. During estimation, the upper level nest collapsed (due to its inclusive value coefficient not differing significantly from 1.0), leaving the model shown in Figure 9. It is interesting but logical that unobserved variables for the part-time work option are correlated with those for the partial commuting choices of telecommuting and compressed work schedules. These three groups are able to avoid commuting and perhaps add some flexibility to their lives by working in a slightly different way than the norm, while maintaining the relative security of being salaried employees (with fringe benefits). Home-based workers, by contrast, are probably most often self-employed, which is a very different way of gaining flexibility. Such workers may be more interested in having autonomy in their careers than in avoiding commute travel.

The final nesting coefficient is 0.643 and is significantly different from 1.0 at the 95% confidence level. This yields an estimated correlation of unobserved variables for alternatives in the nest of 0.587. The overall goodness of fit for this model is slightly lower than for the multinomial model, with an adjusted $\mathbf{D}^2$ of 0.089.

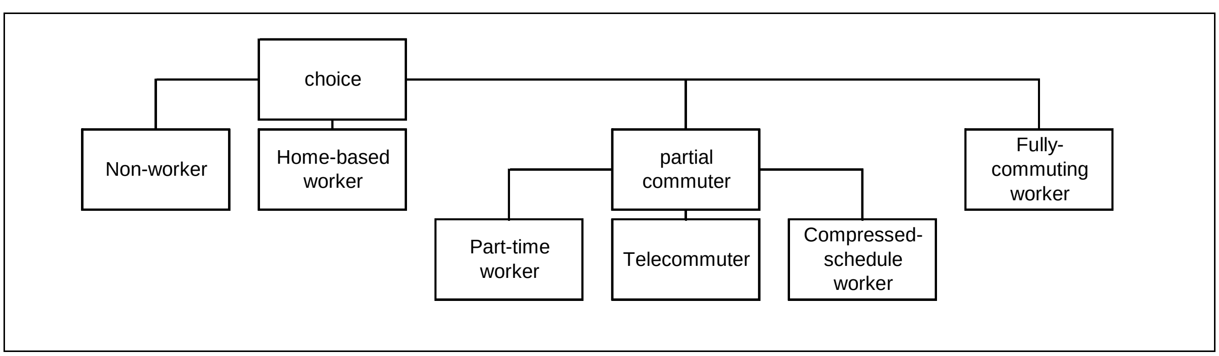

Figure 9: Collapsed Nesting Structure B

The results for the nested model are shown in Table 10. As many of the results have been discussed in the preceding sections, only two new results are highlighted here. For the non-worker and part-time worker alternatives, the two-plus adults with children household status variable specific to females enters with a positive coefficient, indicating the influence of traditional gender roles. In the fully commuting choice, the calm personality variable appears with a negative coefficient specific to females. This finding suggests that a somewhat more aggressive personality is found in women who undertake the historically male-dominated behavior of fully commuting. Note however that the same variable (gender-neutral) appears in the utility for home-based work, with a similar coefficient (as was seen in the multinomial logit model of Table 9). Thus, home-based work is also more appealing to those who are more aggressive, which is natural in view of the initiative required to succeed at a home-based business.

Table 10: Nested Logit Model Results (N=1,580)

Dependent Variable : Non-worker (base), home-based worker, part-time worker, telecommuter, fully-commuting worker, or compressed-schedule worker

Explanatory Variables	Coefficient	t-statistic
Variables specific to Non-worker choice		
Education level [1, …, 6]	-0.464	-3.12
Two-plus adults with children HH status (specific to females) [0,1]	1.23	3.09
Variables specific to Home-based worker choice		
Constant	-2.36	-3.27
Production/construction employment [0,1]	1.72	2.77
San Francisco neighborhood	0.908	2.56
Travel freedom attitude [-3.0, 2.3]	-0.535	-2.34
Workaholic lifestyle (specific to females) [-2.1, 2.3]	0.670	2.20
Calm personality [-2.9, 2.4]	-0.600	-2.73
Variables specific to Part-time worker choice		
Constant	-0.184	-0.334
Female gender [0,1]	0.708	2.92
Age 65 to 74 [0,1]	2.55	4.30
Age 75 and older [0,1]	4.04	3.98
Two-plus adults with children HH status (specific to females) [0,1]	0.841	3.07
Household income less personal income [0, 1, …, 5]	0.271	3.25
Percent of time a vehicle is available [0, 20, …, 100]	-0.0195	-5.21
Variables specific to Telecommuter choice		
Constant	-2.74	-5.21
One-way commute distance [>=0]	0.0255	5.22
Adventure-seeker personality [-2.6,2.7]	0.529	3.17
Variables specific to Fully commuting choice		
Constant	2.77	3.04
Number of persons under age 6 in the household (specific to females) [0, 1,…]	-1.26	-3.16
Two-plus adults with children HH status (specific to males) [0,1]	1.14	2.91
Physical or psychological limitation on walking [1,2,3]	-1.41	-3.10
Liking for commuting to work or school [1, …, 5]	0.368	2.98
Liking for all short-distance travel [1, …, 5]	-0.293	-2.03
Family/community lifestyle [-3.9, 2.1]	0.458	3.14
Workaholic lifestyle [-2.1, 2.3]	0.441	2.91
Calm personality (specific to females) [-2.9, 2.4]	-0.544	-2.89
Variables specific to Compressed-schedule choice		
Constant	-1.96	-4.01
Two-plus adults with children HH status (specific to males) [0,1]	1.45	3.56
Pro high-density attitude (specific to females) [-2.5, 2.3]	0.665	3.03
Partial commuting nesting coefficient	0.643	2.77*

[ ] = range of possible responses; * - t-statistic tests significant difference from 1.00 rather than zero

Log-likelihood at convergence = -1820.27

Log-likelihood with constants only = -2005.323

Adjusted rho-squared = 0.0887; rho-squared = 0.0923

6. Summary and Discussion

This report presents binary, multinomial, and nested logit models of the decision to not work, work part-time, work full-time and commute fully, work full-time and telecommute, work full-time from home, and work full-time via a compressed schedule. Such an exploration is interesting and useful to both the field of travel demand modeling, which uses employment status as an input to models of activity and trip generation, and to labor force engagement modeling, which explores the driving factors behind these decisions.

Using data collected from 1,680 individuals residing in the San Francisco Bay Area, a number of discrete choice models were estimated, with the preferred multinomial logit model discussed in most detail. The binary logit models included the choices to work or not work, work full-time versus part-time, commute fully or partially/not at all, and, for full-time workers, to work completely out-of-home or partially/completely in-home. The multinomial model simultaneously evaluated the choice among all six options, and the nested models included a structure that nested the partial commute choices: part-time worker, telecommuter, and compressed-schedule worker.

In general, the model specifications fell in line with traditional models of labor force engagement: gender, education level, and the presence of young children played important roles. Travel variables also were significant in the models, especially variables describing Mobility Limitations, such as the absence of an available automobile and the inability, due to physiological or psychological reasons, to walk.

Part of what makes this work unique is the inclusion of Travel Liking, Attitude, Lifestyle and Personality variables; at least one of these measures proved significant in each of the models. Consistent throughout the estimation results was the role the Travel Liking measures played: those who enjoyed commuting tended to do so five or more times per week and those who enjoyed short-distance travel overall tended to commute less, suggesting these individuals value the ability to travel without the hindrance of frequent commuting or the negative psychological impact of traveling in congested traffic (which could lessen the enjoyment of other types of travel). The key Attitude variables were pro-environmental solutions, whose proponents typically chose to commute less frequently; pro-high density (female-specific), which was associated with commuting more often; and travel freedom, which was associated with full commuting. The key Lifestyle variable was the workaholic factor score, associated with both home-based and fully-commuting employment; the adventure-seeker Personality variable played a significant role in predicting the telecommuting choice.

One interesting finding was the complex and conflicting roles of family, work, and travel. In the multinomial logit model, the findings indicate that while women with very young children are less likely to commute full time, women with children ages 6 to 15 tend to prefer the non-worker, part-time worker, or fully commuting worker choices. One interpretation of this latter result is that women with school-aged children who choose to work, do so in a manner to allow for some separation between their children and themselves. In related findings, men in households with other adult(s) and children are more likely to commute fully, as are those who state that family and friends are a primary focus of their lives; in each case, one could speculate that commuting fully offers the best chance to climb the career ladder, which would allow for the individual to better provide for their families. These results are consistent with the findings of Ory, *et al.* (2004), and suggest a tension between the desire to be with family, the desire to provide for them, and perhaps the desire to escape from them (Hochschild, 1997).

Overall, though the estimated coefficients had reasonable and insightful interpretations, the goodness-of-fit measures were on the low end of results typically found in disaggregate models of labor force engagement. There could be several reasons for this: the absence of important exogenous variables, unclear endogenous variables, insufficient data, or a broad population. As most of the models in the literature (see, e.g. Heckman, 1974) use socio-demographic variables similar to ours (such as gender, net assets, and education level), without the additional variables we also have, the problem of missing exogenous variables seems comparatively minor, at worst, in this work. Unclear endogenous variables could definitely be problematic in that the survey did not directly inquire about current telecommuting or flexible scheduling, nor did it distinguish, in some instances, between being unemployed and not in the labor force (i.e. someone on permanent disability may have had difficulty finding a proper employment status option in the survey). Insufficient data could have also reduced the goodness-of-fit measures, as relatively small numbers of telecommuters and compressed-schedule workers (fewer than 100 in both cases) were observed in the sample. Finally, as mentioned previously, this work tackled the task of trying to predict a relatively complicated choice for all individuals age 18 to 64; such a broad population sits in stark contrast to the work of others (see, e.g. Heckman, 1974), who focused on much narrower populations (e.g., married Caucasian women ages 30 to 44).

It is interesting that the multinomial model fit the data better than any of the nesting structures. Although several groups of alternatives are conceptually correlated (as shown in the hypothesized structures of Figures 5, 6, and 7), a violation of the assumption of independent error terms is a function of the model specification, not of similarities among alternatives per se (McFadden, *et al*., 1977). Two remedies commonly-suggested for violation of this assumption are (1) to change variables from generic (having the same coefficient across all alternatives) to alternative-specific (allowing the coefficient to vary across alternatives), and (2) to improve the model specification by adding new variables (thereby moving more of the utility function from unobserved to observed and decreasing the correlations across alternatives of the remaining unobserved variables). In our case, remedy (1) is implemented automatically: since none of our variables differ across alternatives, they must necessarily have different coefficients for at least one alternative compared to the others, or they will not be able to influence the choice among alternatives. We believe remedy (2) is in place through the inclusion of our attitudinal and other non-demographic variables. We have seen these variables enter multiple alternatives, and thus when they are unobserved in other studies, they contribute to correlations of the error term across alternatives. The empirical superiority of the conceptually simpler multinomial logit model in our context supports the advice of Horowitz (1991), to improve the specification of the *observed* portion of utility as much as possible before developing ever more elaborate models of the unobserved error terms. In particular, this work demonstrates again the importance of "internal", subjective variables such as attitudes in determining behavior.

As this work represents one of the first efforts to model the joint labor-commute engagement decision, directions for future research are numerous. A first priority is to more accurately capture the dependent variable, both the chosen alternative as well as truly available but non-chosen alternatives (i.e. properly identifying each individual's choice set), both for the respondent and other members in the respondent's household (to facilitate modeling joint decisions among household members). Other viable and potentially interesting enhancements include: explicitly capturing the trade-offs in leisure time and income associated with changing job status; more detailed information about conditions at home (e.g. is the home large enough to hold an office?) and the workplace (e.g. is management receptive to the idea of flexible schedules?); and, capturing more detailed transportation supply variables (i.e. what modes are available for travel? Is walking possible?).

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