A Joint Household Level Analysis of Work Arrangement Choices of Individuals

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ABSTRACT
This paper presents a comprehensive multi-dimensional multivariate binary probit model system capable of simultaneously representing multiple aspects of individual work arrangement decisions, while also accounting for interactions among household members in individual employment related choices. The model system is estimated on a survey sample drawn from the San Francisco Bay Area where a rich set of accessibility measures is available to account for built environment influences on work related decisions. Model results show that a host of demographic, socio-economic, built environment, and attitudinal variables influence individual choices regarding work arrangements; more importantly, the model shows that there is considerable interaction among household members in matters related to employment. The model system can be used to predict employment choices of individuals within larger microsimulation model systems of activity-travel demand.

1. INTRODUCTION

Work schedules and activities play a major role in the design of activity- or tour-based microsimulation model systems that are increasingly being deployed in practice. Activity-based microsimulation models of travel demand recognize that travel is derived from the need or desire to pursue activities that are distributed in time and space. As work schedules and work related travel place time-space constraints on individuals, the degrees of freedom that individuals enjoy in the context of pursuing maintenance and discretionary activities and travel are limited (*1*). Tour-based microsimulation models involve the generation of work tours and intermediate stops on work tours, and the scheduling of non-work tours and activities is dependent on the time-space constraints imposed by work tours (*2*,*3*). Within the more continuous time activity-based travel models (*4-8*), work activities and commute-related travel are scheduled first, and non-work related activities and travel get scheduled around the work activities. Workers often make non-work related stops on the way to or from work. Destinations that may be chosen for non-work activities are often constrained by the action space defined by home and work anchors.

The above discussion points to the important role that labor force participation and work schedules play in the modeling of activity-travel demand. Despite this importance, there is a lack of models that capture the multi-dimensional facets of work arrangement choices that can help inform travel forecasts. There is considerable literature, both within and outside the transportation domain, devoted to the understanding and modeling of personal employment decisions (for example, see (*9*), (*10*)). However, there are two fundamental issues with the way work decisions have been addressed by the literature. First, the literature has largely treated different work arrangement decisions in isolation of one another, ignoring the interaction among individual work-related choices. For example, an individual may choose to work full time or part time, be self-employed or not, telecommute or work from a traditional office location, hold a single job or multiple jobs, or choose not to be employed at all. Much of the literature has treated each of these choice dimensions separately without explicit recognition of the inter-dependencies across these facets of work arrangements. Second, the literature has generally considered labor force participation and work arrangement decisions as individual choices without due recognition of household-level interactions and negotiations that inevitably influence such decisions. Many work-related choices are influenced by household level variables such as lifecycle stage, number and age of children, market wage earning potential of individual members, and household monetary expenditures.

This paper attempts to fill this critical gap in the literature by formulating and presenting a simultaneous model of work arrangements decisions. The model system is a multivariate binary probit system capable of simultaneously modeling five binary choice decisions related to work. The five dimensions are: employed or not, work full-time or part-time, be self-employed or not, hold more than one job or not, and work at home or not. The model formulation accounts for household-level unobserved heterogeneity, individual-level unobserved heterogeneity, and unobserved error covariance across five work-related decisions at the individual level. The formulation treats a household as one cluster in making work related decisions for each individual (16 years or over), thus leading to a system that jointly models $5 \times N$ decisions, where N is the number of individuals 16 years or over in the household. The model includes a self-selection component because, for each individual in the household, four of the binary choices are observed only if there is a positive outcome on the labor force participation choice (employed or not). Overall, the model is capable of reflecting the joint nature of work related decisions, while accounting for common observed and unobserved factors affecting work decisions, both within-and between individuals in a household. The model system is estimated on a subsample of the 2009 US National Household Travel Survey drawn from the San Francisco Bay Area for which a rich set of accessibility and built environment variables are available.

The remainder of this paper is organized as follows. The next section presents a brief review of the literature on the topic of this paper. The third section presents the modeling methodology, while the fourth section presents a description of the data set used. The fifth section presents model estimation results and the sixth section offers concluding thoughts.

2. MODELS OF WORK ARRANGEMENT CHOICES

There is a vast body of literature dedicated to the modeling of employment choices of individuals. Within the scope of this paper, it would be impossible to provide a comprehensive literature review. This section is intended to offer a few highlights of past work that helped guide the model formulation and specification in this study. To begin with, labor force participation (to be employed or not) is defined by the US Bureau of Labor Statistics as an individual (16 years or over) being involved in any work for pay or profit, or involved in at least 15 hours per week of unpaid work in a family-operated enterprise. An individual who is not employed may be either unemployed or not in the labor force. The former category refers to unemployed individuals available to work, while the latter category refers to those who are not available to work (*e.g.*, retired persons, students, those not seeking work, disabled individuals). In general, it has been found that educational attainment, marital status, gender, age, spousal income, household lifecycle stage, and number and age(s) of children in the household are key factors influencing labor force participation, particularly for women (*11*). Considerations of race have also been examined in the context of labor force participation and unemployment rates with a view to determine whether racial discrimination is a factor in personal employment (*12*).

A person is considered self-employed (as opposed to a wage or salary worker) if the individual has control over time and how work is performed, is in direct contact with clients, and is responsible for all work equipment, training, and benefits (*e.g.*, retirement, insurance). In general, it has been found that gender, lifecycle stage, housing equity, personal wealth, spousal income, and educational attainment are key factors affecting decisions related to self-employment (*13*, *14*).

Another choice dimension of interest is whether an individual is employed full-time or part-time. An individual who works 35 hours or more per week is considered a full-time worker in the United States according to the Bureau of Labor Statistics. An individual may work part-time either voluntarily (by choice) or involuntarily (due to employer constraints). Yeraguntla and Bhat (*10*) identify three categories of part-time employees, including regular part-time employees, employees who share a full-time job with each worker being part-time, and moonlighters who hold multiple jobs, at least one or more of which is a part-time arrangement. In general, it has been found that part-time workers tend to be younger adults, older workers, women with household responsibilities, individuals with lower levels of education, and minorities (*15*).

The holding of multiple jobs may also be voluntary or involuntary. An individual may participate in an additional job out of some intrinsic interest in the activity (voluntary) or may hold an additional job due to sheer financial necessity (involuntary). In general, it is found that low wages or low earnings on the main job leads to moonlighting, with individuals holding multiple jobs to boost their income (*16*). However, Hipple (*16*) also find that individuals with higher levels of education are likely to hold multiple jobs, although their choice to do so may be more voluntary than others who hold a second job for increasing earnings. Individuals with flexible work schedules are more likely to hold multiple jobs; no significant gender differences were found in multiple job participation (*16*).

Home-based workers have been defined in various ways. Yeraguntla and Bhat (*10*) consider home-based workers as those who work completely from within their home. However, the US Bureau of Labor Statistics defines a home-based worker as an individual who performed any amount of his or her work at home as part of the primary job. Choo *et al.* (*17*) note that a home-based worker may either be a salaried employee of an organization or an individual running a home-based business. The differing definitions of home-based workers makes it difficult to track changing trends in home-based employment (*18*); however, the basic idea is that these workers undertake at least some work from home and often employ telecommunications in a significant way to carry out their duties. Thus, telecommuters fall within the class of home-based workers. Findings in the literature indicate that home-based workers are more likely to be male, married, homeowners, aged 35 or more, in a household with children, well-educated, comfortable working alone, adept at using technology, and family-oriented (*18*, *19*).

Overall, it can be seen that there are a host of socio-economic, demographic, built environment, and attitudinal variables that affect personal work arrangement choices. Much of the literature has treated each of the choice dimensions in isolation of one another, thus preventing the ability to model correlated choice processes in a joint framework. Moreover, despite the recognition that household level variables affect personal work choices, virtually none of the models jointly consider work arrangement decisions of multiple household members simultaneously. This paper presents a joint model system that is capable of modeling multiple dimensions that define work choices, while considering the unobserved and observed heterogeneity and interactions that are likely to characterize labor force participation.

3. MODELING METHODOLOGY

In this study, the work arrangement decisions of all individuals (16 years or over) in a household are jointly modeled to account for the correlated nature of these decisions. Such a modeling procedure recognizes that there may be common observed and unobserved factors affecting the different work arrangement decisions, both within- and between individuals in a household. Five dimensions that characterize work arrangement decisions of an individual are considered:

1) Employed or not
2) Self-employed or not
3) Employed part time or full time
4) Hold more than one job or not
5) Home-based work location or not

The latter four dimensions are conditional on a positive outcome in the first decision of whether to participate in the labor force or not. This leads to the presence of self-selection wherein several choice variables exist only for those who self-select themselves to be employed. For all other individuals, the latter four dimensions are irrelevant. The modeling methodology presented in this section may be viewed as a multivariate binary probit model system with self-selection. The remainder of this section presents the modeling methodology.

Let h ($h = 1, 2,\ldots, H$), j ($j = 1, 2,\ldots, J$), and q ($i = 1, 2,\ldots, Q_h$) be indices for households, decisions, and individuals in household h, respectively, where H is the total number of households in the sample, J is the total number of decisions for each individual, and Q_h is the number of individuals in household h . Note that, in the current empirical context $J = 5$. In the usual binary response notation, the latent propensity y^*_{hjq} associated with the decision j for an individual q in household h is written as a function of a $(K_j \times 1)$-vector of observed covariates $\mathbf{x}_{hjq}$ (including a constant) as:

$$\begin{aligned} y^*_{hjq} &= \boldsymbol{\beta}'_{hjq}\mathbf{x}_{hjq} + \eta_{hj} + \varepsilon_{hjq} \\ &= (\mathbf{b}_j + \tilde{\boldsymbol{\beta}}_{hj} + \tilde{\tilde{\boldsymbol{\beta}}}_{hjq})'\mathbf{x}_{hjq} + \eta_{hj} + \varepsilon_{hjq} \\ y_{hjq} &= 1 \quad if\ y^*_{hjq} > 0, \text{ else } \ 0 \end{aligned} \tag{1}$$

In the above specification of the $\boldsymbol{\beta}_{hjq}$ vector, $\mathbf{b}_j$ is a $(K_j \times 1)$-vector whose elements capture the mean effects of the corresponding elements of the $\mathbf{x}_{hjq}$ variable vector. The elements of the $\tilde{\boldsymbol{\beta}}_{hj}$ vector (also of dimension $(K_j \times 1)$) correspond to unobserved household factors specific to household h and decision j that are common to all individuals in the household, and that affect individual sensitivity to exogenous variables. For instance, individuals in a family that strongly believes in caring for children at home may have a greater propensity to be unemployed, self-employed, or part-time employed. On the other hand, individuals in a household that believes in having children interact with other children in an external setting may have a greater propensity to be employed (rather than stay at home as caregivers). These types of unobserved factors that influence how individuals in a household respond to specific exogenous variables (presence of young children, for example) get captured in the elements of $\tilde{\boldsymbol{\beta}}_{hj}$. The presence of the unobserved $\tilde{\boldsymbol{\beta}}_{hj}$ vector also generates covariance across individuals in the same household h for the j^{th} choice decision. Similarly, $\tilde{\tilde{\boldsymbol{\beta}}}_{hjq}$ corresponds to unobserved individual-specific factors that may increase or decrease the propensity of an individual q in household h in the context of the j^{th} decision. For instance, an individual q in household h may have a particularly strong desire to remain at home with a young child, even if other individuals in the household do not feel the same way. Then, compared to observationally equivalent peers, this q^{th} individual in the h^{th} household will have a lower propensity to work outside home if a young child is present.

In Equation (1), for ease of presentation, the elements of $\tilde{\boldsymbol{\beta}}_{hj}$ and $\tilde{\tilde{\boldsymbol{\beta}}}_{hjq}$ corresponding to the constant in the vector $\mathbf{x}_{hjq}$ are separated and written as η_{hj} and ε_{hjq}, respectively. Then, the elements of $\tilde{\boldsymbol{\beta}}_{hj}$ and $\tilde{\tilde{\boldsymbol{\beta}}}_{hjq}$ corresponding to the constant are set to zero. The motivation for introducing the η_{hj} term is as follows. Suppose the j^{th} decision under consideration is employment status. There may be unobserved factors such as "wanting to be in the market place" that increase the employment propensity of all individuals in the household. It is also possible that there are other unobserved factors such as income from non-market sources that may reduce the employment propensity of all individuals in a household. These household-specific factors get captured in η_{hj} for the j^{th} choice decision. Similarly, ε_{hjq} captures unobserved individual-specific factors that make an individual more or less predisposed to making a positive choice on the j^{th} decision.

Let $\mathbf{IDEN}_{\boldsymbol{E}}$ be the identity matrix of size E, $\mathbf{1}_E$ be a column vector of size E with all of its elements taking the value of one, and $\mathbf{1}_{EE}$ be a square matrix of size $E \times E$ with all unit elements. We next define a few additional vectors and matrices to help in the presentation of the methodological framework:

$$\mathbf{y}_{hj} = \left(y_{hj1}, y_{hj2}, \ldots\ldots y_{hjQ_h}\right)' - Q_h \times 1 \text{ vector}$$

$$\mathbf{y}^*_{hj} = \left(y^*_{hj1}, y^*_{hj2}, \ldots\ldots y^*_{hjQ_h}\right)' - Q_h \times 1 \text{ vector}$$

$$\mathbf{y}_h = \left(\mathbf{y}'_{h1}, \mathbf{y}'_{h2}, \ldots\ldots \mathbf{y}'_{hJ}\right)' - (Q_h * J) \times 1 \text{ vector}$$

$$\mathbf{y}^*_h = \left(\mathbf{y}^{*\prime}_{h1}, \mathbf{y}^{*\prime}_{h2}, \ldots\ldots \mathbf{y}^{*\prime}_{hJ}\right)' - (Q_h * J) \times 1 \text{ vector}$$

$$\mathbf{b} = \left(\mathbf{b}'_1, \mathbf{b}'_2, \ldots\ldots \mathbf{b}'_J\right)' - \sum_{j=1}^{J} K_j \times 1 \text{ vector}$$

$$\tilde{\boldsymbol{\beta}}_h = \left(\tilde{\boldsymbol{\beta}}'_{h1}, \tilde{\boldsymbol{\beta}}'_{h2}, \ldots\ldots \tilde{\boldsymbol{\beta}}'_{hJ}\right)' - \sum_{j=1}^{J} K_j \times 1 \text{ vector}$$

$$\boldsymbol{\gamma}_{hj} = \left(\tilde{\tilde{\boldsymbol{\beta}}}'_{hj1}, \tilde{\tilde{\boldsymbol{\beta}}}'_{hj2}, \ldots\ldots \tilde{\tilde{\boldsymbol{\beta}}}'_{hjQ_h}\right)' - \left(Q_h * K_j\right) \times 1 \text{ vector}$$

$$\boldsymbol{\gamma}_h = \left(\boldsymbol{\gamma}'_{h1}, \boldsymbol{\gamma}'_{h2}, \ldots\ldots \boldsymbol{\gamma}'_{hJ}\right)' - \left(\left(\sum_{j=1}^{J} K_j\right) * Q_h\right) \times 1 \text{ vector}$$

$$\tilde{\boldsymbol{\eta}}_h = \left(\eta_{h1}, \eta_{h2}, \ldots\ldots \eta_{hJ}\right)' - J \times 1 \text{ vector}$$

$$\boldsymbol{\eta}_h = \left(\tilde{\eta}_h \otimes \mathbf{1}_{Q_h}\right) - (Q_h * J) \times 1 \text{ vector}$$

$$\boldsymbol{\varepsilon}_{hj} = \left(\varepsilon_{hj1}, \varepsilon_{hj2}, \ldots\ldots \varepsilon_{hjQ_h}\right)' - Q_h \times 1 \text{ vector}$$

$$\boldsymbol{\varepsilon}_h = \left(\boldsymbol{\varepsilon}'_{h1}, \boldsymbol{\varepsilon}'_{h2}, \ldots\ldots \boldsymbol{\varepsilon}'_{hJ}\right) - (Q_h * J) \times 1 \text{ vector}$$

$$\mathbf{x}_{hj} = \left(\mathbf{x}_{hj1}, \mathbf{x}_{hj2}, \ldots\ldots \mathbf{x}_{hjQ_h}\right)' - Q_h \times K_j \text{ matrix}$$

$$\mathbf{x}_h = \begin{bmatrix} \mathbf{x}_{h1} & 0 & 0 & 0 & 0 \\ 0 & \mathbf{x}_{h2} & . & 0 & 0 \\ 0 & 0 & \mathbf{x}_{h3} & . & 0 \\ 0 & 0 & . & . & 0 \\ 0 & 0 & . & . & \mathbf{x}_{hJ} \end{bmatrix} - \left(Q_h * J\right) \times \left(\sum_{j=1}^{J} K_j\right) \text{ matrix}$$

$$\tilde{\mathbf{x}}_{hj} = \begin{bmatrix} \mathbf{x}'_{hj1} & 0 & 0 & 0 & 0 \\ 0 & \mathbf{x}'_{hj2} & . & 0 & 0 \\ 0 & 0 & \mathbf{x}'_{hj3} & . & 0 \\ 0 & 0 & . & . & 0 \\ 0 & 0 & . & . & \mathbf{x}'_{hjQ_h} \end{bmatrix} - \left(Q_h\right) \times \left(K_j * Q_h\right) \text{ matrix}$$

$$\tilde{\mathbf{x}}_h = \begin{bmatrix} \tilde{\mathbf{x}}_{h1} & 0 & 0 & 0 & 0 \\ 0 & \tilde{\mathbf{x}}_{h2} & . & 0 & 0 \\ 0 & 0 & \tilde{\mathbf{x}}_{h3} & . & 0 \\ 0 & 0 & . & . & 0 \\ 0 & 0 & . & . & \tilde{\mathbf{x}}_{hJ} \end{bmatrix} - (Q_h * J) \times \left(\left(\sum_{j=1}^{J} K_j \right) * Q_h \right) \text{ matrix}$$

Using the above notation, Equation (1) for all choice occasions j and all individuals q in household h can be written as:

$$y_h^* = \mathbf{x}_h \mathbf{b} + \mathbf{x}_h \tilde{\boldsymbol{\beta}}_h + \tilde{\mathbf{x}}_h \boldsymbol{\gamma}_h + \boldsymbol{\eta}_h + \boldsymbol{\varepsilon}_h \tag{2}$$

Lastly, certain distributional assumptions are made to complete the model specification. $\tilde{\boldsymbol{\beta}}_{hj} \sim N(0, \boldsymbol{\Omega})$; $\tilde{\tilde{\boldsymbol{\beta}}}_{hjq} \sim N(0, \tilde{\boldsymbol{\Omega}})$; and $\tilde{\boldsymbol{\eta}}_h \sim N(0, \boldsymbol{\Lambda})$ The error terms ε_{hjq} are assumed to be independent and identically distributed across all individuals and households. However, correlations across all decisions of individual q are allowed by specifying the error terms as realizations from a multivariate normal distribution with a mean vector of zeros and correlation matrix[1] given by:

$$\boldsymbol{\Sigma} = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & . & . & . & \rho_{1J} \\ \rho_{12} & 1 & \rho_{23} & . & . & . & . \\ \rho_{13} & \rho_{23} & . & & & & . \\ . & . & & . & & & . \\ . & . & & & . & & . \\ . & . & & & & 1 & . \\ \rho_{1J} & . & . & . & . & . & 1 \end{bmatrix}_{J*J} \tag{3}$$

One important aspect of the problem at hand is that there is a selection process at work, because all decisions j where $j \geq 2$ are conditional on a positive first decision ($y_{h1q} = 1$) for each individual. To account for this, and for ease of presentation, define the following vectors and matrices:

$$\mathbf{z}_{h1} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & . & 0 \\ 0 & . & -1 & 0 \\ 0 & 0 & . & -1 \end{bmatrix}_{Q_h \times Q_h} \quad \text{and } \mathbf{z}_{hj} = \begin{bmatrix} 1-2y_{hj1} & 0 & 0 & 0 \\ 0 & 1-2y_{hj2} & . & 0 \\ 0 & . & . & 0 \\ 0 & 0 & . & 1-2y_{hjQ_h} \end{bmatrix}_{Q_h \times Q_h} \quad (\forall\ j \neq 1)$$

$$\mathbf{z}_h = \begin{bmatrix} \mathbf{z}_{h1} & 0 & 0 & 0 \\ 0 & \mathbf{z}_{h2} & . & 0 \\ 0 & . & . & 0 \\ 0 & 0 & . & \mathbf{z}_{hJ} \end{bmatrix}_{(Q_h * J) \times (Q_h * J)}$$

Multiplying Equation (2) by z_h will give:

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[1]The scale of ε_{hjq} term must be normalized to 1 for identification.

$$\tilde{\mathbf{y}}_h^* = \mathbf{z}_h \mathbf{y}_h^* = \mathbf{z}_h \mathbf{x}_h \mathbf{b} + \mathbf{z}_h \left(\mathbf{x}_h \tilde{\boldsymbol{\beta}}_h + \tilde{\mathbf{x}}_h \boldsymbol{\gamma}_h + \boldsymbol{\eta}_h + \boldsymbol{\varepsilon}_h \right) \tag{4}$$

Then, the probability of observing the sequence of decisions $\mathbf{y}_h$ in household h is given by:

$$\Pr(\tilde{\mathbf{y}}_h^* < 0) = N\left(\mathbf{z}_h \mathbf{x}_h \mathbf{b};\ \boldsymbol{\Psi}_h\right) \tag{5}$$

where $N(.)$ is multivariate normal cumulative distribution (MVNCD) function and $\boldsymbol{\Psi}_h$ is the complete covariance matrix of all unobserved factors given by:

$$\begin{aligned} \boldsymbol{\Psi}_h &= \mathbf{z}_h [Cov(\mathbf{x}_h \tilde{\boldsymbol{\beta}}_h + \tilde{\mathbf{x}}_h \boldsymbol{\gamma}_h + \boldsymbol{\eta}_h + \boldsymbol{\varepsilon}_h)] \mathbf{z}'_h \\ &= \mathbf{z}_h [\mathbf{x}_h \boldsymbol{\Omega} \mathbf{x}'_h + \tilde{\mathbf{x}}_h \tilde{\boldsymbol{\Omega}} \tilde{\mathbf{x}}'_h + \Lambda \otimes \mathbf{1}_{Q_h, Q_h} + \boldsymbol{\Sigma} \otimes \mathbf{IDEN}_{Q_h})] \mathbf{z}'_h \end{aligned} \tag{6}$$

For households which have individuals with a negative outcome for the first choice decision (*i.e.*, if the household has unemployed individuals), the corresponding probability of the sequence of choices observed can be obtained by extracting only the corresponding rows and columns that are active from $\tilde{\mathbf{y}}_h^*$ and $\boldsymbol{\Psi}_h$.

It can be observed from Equation (5) above that the probability expression involves the evaluation of a multivariate integral of dimension up to $Q_h * J$, which is computationally very intensive. For this reason, Bhat's (*20*) maximum approximate composite marginal likelihood (MACML) approach is used, wherein the probability function in Equation (5) is evaluated using an analytic approximation.

4. DATA DESCRIPTION

The data set used in this study is derived from the 2009 National Household Travel Survey (NHTS) of the United States. The subsample chosen for analysis is that from the San Francisco Bay Area in California, encompassing nine different counties including Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma. This subsample has been chosen specifically because a rich set of built environment and network level of service variables are available for this region, and these measures can be appended to the travel survey records so that the effects of such variables on work arrangement choices can be adequately reflected in the model. Bhat and Guo (*21*) provide a comprehensive description of the built environment and accessibility measures developed for the region and how such secondary data may be appended to travel survey records. The accessibility measures take a Hansen type form in our analysis: $A_i = \left[\sum_{j=1}^{N} \left(\frac{Size\,Measure_j}{t_{ij}} \right) \right] \Big/ N$, where $Size\,Measure_j$ may denote any size measure of zone j such as retail employment, basic employment, and vacant land acreage, t_{ij} is the travel time from zone i to zone j by the auto mode, and N is the total number of TAZs. An elaborate geographic information system (GIS) based process was used to match traffic analysis zone (TAZ) level measures to household travel survey records where households were geocoded to census tracts. At the end of the comprehensive data preparation process, a sample of 6,844 individuals aged 16 years or over was obtained. Only individuals in this age group were considered as the focus of the paper is on employment related decisions.

Dependent variable indicators were constructed based on responses to survey questions. A person is considered employed if he or she worked for pay or profit in the week before the telephone interview. The survey included a specific question regarding self-employment status, thus allowing the construction of an indicator for this work arrangement decision. An employed person who worked at least 35 hours per week is defined as a full-time worker. Home-based workers are those who have a fixed workplace to perform their work, but do not require any travel to reach their workplace. Those who simply bring work home to catch up or finish up a task are not considered home-based workers. The survey also included a question asking whether individuals held multiple jobs. Responses to this question were used to construct a "multiple jobs or not" indicator.

After extensive cleaning and eliminating observations with missing data on dependent variables, the final sample for analysis included 5,364 individuals in 2,874 households. Of these, 2,929 (54.6 percent) are workers. Among the workers, 600 individuals (20.5 percent) are self-employed, 712 individuals (24.3 percent) worked part-time, 284 individuals (9.7 percent) hold multiple jobs, and 444 individuals (15.2 percent) are home-based workers. Table 1 presents descriptive statistics for the sample of 5,364 individuals. Nearly 80 percent of the sample is greater than 40 years of age, with an approximately equal split between those in the 41-60 year group and those aged over 60 years. There is a reasonably even split between males and females in the sample with 47 percent of respondents being male. More than 70 percent of all respondents are married and 20 percent are immigrants. At the household level, a vast majority of households have one or two adults; these two household groups account for 86 percent of the respondent sample. Over three-quarters of the households in which respondents reside have no children. A little more than one-third of the households have at least one senior adult aged 65 years or over. These two indicators (children and senior adult presence) are potentially important determinants of work arrangement decisions as these two demographic groups generally place greater levels of responsibility in care giving on the adults in the household. In terms of income, more than one-half of the sample reports household income greater than $75,000, suggesting that households are fairly affluent – although one should recognize that average income levels tend to be high in the San Francisco Bay Area. Indeed, the American Community Survey data of the US Census Bureau shows that the average household income for the San Francisco Bay Area is $76,476, which is about $25,000 higher than the national average.

As expected, there are key differences between the worker and non-worker samples. Table 1 offers descriptive statistics separately for these demographic groups (these are presented to obtain a general picture of the sample, and should not be considered as providing any substantial insights since the effects of one variable are presented without controlling for the effects of other variables). A far greater percentage of non-workers are in the highest age bracket of over 60 years, suggesting that many non-workers are of retirement age. A large percent of workers are in the younger age groups. A larger percent of non-workers are females; the trend is reversed for workers with a larger percent of workers being males. More than 75% of workers are married, relative to about 65% of non-workers. Also, immigrants are more likely to be in the pool of workers than non-workers. Non-workers tend to reside in smaller households and more than 85 percent of them reside in households with no children. Senior adults are more likely to be non-workers than workers. The percent of non-workers in the highest income category households is considerably smaller than for households in which workers reside. These major differences between worker and non-worker samples further underscore the need to accurately model labor force participation decisions and their implications for activity-travel behavior.

Several other potential explanatory variables of interest were also examined. In the context of education, individuals in the sample are well educate-quarter having graduate or professional Degree, another quarter having a Bachelor's degree, and another quarter having some college education or an Associate Degree. These percentages are generally in line with American Community Survey (ACS) statistics furnished by the US Census Bureau. Caucasian households are over-represented in the sample. About 77 percent of the respondent households are Caucasian, which is nearly 20 percent more than the corresponding number reported in the American Community Survey. Average household size is 2.6 persons per household and average vehicle ownership is 2.25 vehicles per household. Households located in an urban area dominated the sample with a little over 40 percent of the sample, followed by households located in suburban area at a little over 30 percent. The most populous county, Santa Clara County, is well-represented in the sample with nearly a quarter of households residing in that county. Overall, the data set is suitable for the type of analysis undertaken in this paper.

5. MODEL ESTIMATION RESULTS

This section presents a discussion of the model estimation results, which are presented in Table 2. The model system is a multivariate binary probit with sample selection that accounts for unobserved and observed heterogeneity due to household- and person-specific factors, while simultaneously reflecting jointness in decision processes through the estimation of error covariances. In general, the joint model system estimated here is statistically superior to an independent model system that considers each of the five binary choice decisions separately. The log-likelihood value of the joint model is –7008.1 while that of the independent model system is –7439.9. The likelihood ratio statistic value of 863 is greater than the critical χ^2 value at 12 degrees of freedom at any level of significance. Only results of the joint model system are presented in the paper for the sake of brevity. The remainder of this section considers each of the five work arrangement decisions in turn, followed by a final discussion on the relevance and significance of the error covariances.

5.1 Employment Decision

A host of socio-economic and demographic attributes affect the choice of whether to participate in the labor force or not. As expected, and in line with previous research that shows that women tend to take on a greater share of household and child care responsibilities (see (*15*)), women are less likely to work than their male counterparts and this effect is particularly pronounced if the women is married. Young adults between 16 and 25 years of age without a driver's license are also less likely to work, even when compared with older adults over 60 years of age. However, when such young individuals have a driver's license (see the interaction variable "16 to 25 years and having a driver's license" toward the end of the "Age" variables), they are slightly more likely to be employed than those in the "over 60 years" age group (the net effect on employment propensity becomes +0.261 (=1.119–0.858)). However, this positive effect is not statistically significant, implying that the employment propensity of a young adult with a driver's license is about the same as that of an individual over 60 years of age. Clearly, however, those who are between 26-60 years of age have the highest predisposition to be employed, indicating strong life-cycle associations with employment. Higher education levels (high school education or below is the base category) are associated with a greater propensity to participate in the labor force, ostensibly due to two forces at play. Those with a higher education level generally will have more employment opportunities, and these individuals are also likely to want to work to put their educational qualifications to use. Racial differences are found with Caucasians showing a higher propensity for employment than minorities. This may be a result of cultural differences, though it could also be a result of continued discrimination in the market place (see (*12*) for studies focusing on this sensitive subject). Although not statistically significant, immigrants (those not born in the United States) are less likely to be employed than US born counterparts. However, as the number of years that the immigrant lives in the United States increases, this difference in employment propensity decreases, possibly an indication of assimilation effects over time in society (the tipping point is about 20 years, after which an immigrant is more likely to work than a domestic-born American).

Among household attributes, the “presence of children <=15 years” and the “female with presence of children <=15 years” variables need to be interpreted together. The results indicate that, when a household has one or more children, men in the household are more likely to work (than men in households with no children) and women are less likely to work (compared to women in households with no children). This reinforces the stereotype of the man being the “breadwinner” and the woman being the “child-care provider” in the family (see (*22*), who indicates that such gender differences still seem quite entrenched in US society). Further, in combination with the female-related effects discussed earlier, the results clearly indicate that married women with children are the least likely to work relative to other women. Finally, individuals in households with senior adults are less likely to work, presumably due to care giving responsibilities.

5.2 Self-Employment Decision

Higher levels of self-employment may be observed among married individuals, those in the age range of 41-70 years (especially if male), highly educated individuals (bachelor’s degree or higher), and Caucasians. Those with higher education levels probably have the knowledge and skills required to be self-employed (start their own business, for example) and may also have a desire to “be their own boss” (*23*). Individuals in the manufacturing, construction, maintenance, or farming (MCMF) industry and in the sales/services profession are more likely to be self-employed than those in professional, managerial, or technical (PMT) occupations. This is to be expected, since those in the PMT occupations can sell their services in the market place, while those in the MCMF and in sales/services are more likely to be selling products in the market place and may see more benefits in being self-employed in the production of these products (see (*24*, *25*)). The results also indicate that men in sales/services are somewhat less likely to be self-employed than women in sales/services. Once again, as in the case of employment, immigrants are initially less likely to be self-employed, but the difference in self-employment between immigrants and US born individuals decreases as the number of years the immigrant lives in the US increases (see (*26*)). It is quite surprising that the tipping point is once again about 21-22 years, after which an immigrant tends to be more represented in the pool of self-employed individuals than a domestic-born.

An interesting finding is that household income negatively impacts the choice to be self-employed. It is possible that many of the self-employed individuals in this particular sample are self-employed out of necessity, in part due to the timing of the survey (the survey was conducted in 2008-2009 during a deep recession in the US economy). Individuals who are otherwise unemployed and do not have a steady job and income may have been compelled to self-employment due to circumstances (*27*).

Among built environment attributes, individuals in Marin, San Francisco, or Sonoma Counties have a higher propensity to be self-employed. Individuals in urban areas and those in neighborhoods with high shopping accessibility also appear more inclined to be self-employed.

On the other hand, and more intuitively, individuals in neighborhoods with high levels of access to employment opportunities have a low propensity to be self-employed. This last finding may, at least in part, be due to self-selection effects at play, with individuals seeking salaried work locating in residential neighborhoods with high levels of access to employment opportunities.

5.3 Part-Time or Full-Time Employment Decision

In this equation, the effects of the "married" dummy variable and the "married female" dummy variable need to be considered together. The indication is that married men, if employed, are more likely to be employed full-time than part-time, while married women, if employed, are more likely to be employed part-time than full-time. These effects appear to be "extension" effects of the employed versus unemployed effects of gender, and reinforce the "male-female" differences in household-level work-family choices. Individuals in the younger age bracket of less than or equal to 25 years have a higher propensity to be part-time workers, possibly because they have not been able to find full-time employment as yet or are also going to school. Consistent with expectations, those in the age group of 25-60 years are the most pre-disposed to be employed full-time, once again reinforcing the lifecycle demands on this age group that make them more likely to be employed in the first place. Similarly, it is only reasonable that those with high education (college degree or higher) should be inclined to work full-time, since the opportunity cost of foregoing hours of work in the market place is higher for such individuals than for those who only have a high school education. Employees in sales/services and in clerical/administrative support roles have a higher propensity to work part-time, perhaps because the market supply of such jobs loads more on the part-time spectrum than other kinds of jobs (*28*) and/or due to individuals in such jobs having a lower opportunity cost of reducing their hours in the market place. Other individual demographic effects include the higher propensity of individuals with medical conditions to work part-time and the lower propensity of immigrants to work part-time.

Finally, the effects of household demographics further reinforce the notion of women being the primary child care providers in the family (women with young children tend to work more on a part-time basis than women without young children). Also, individuals in households with senior adults are more likely to work part time, possibly because of care giving responsibilities at home. Also, it is possible that a household with senior adults is a retiree household with individuals cutting back on work, and just working part- time.

5.4 Decision to Work Multiple Jobs

The findings in this model are generally consistent with those reported earlier in the literature. Young adults less than or equal to 25 years of age have a higher propensity than other individuals to hold multiple jobs. These individuals are likely to be students or those with limited experience; as they may have fewer job opportunities in the market place, it is likely that they will work part time (as observed earlier) at multiple jobs. It is also interesting to note that those with high education tend to hold multiple jobs. Unlike the case of young adults, this tendency may be a reflection of the job opportunities such individuals have in the market place as well as the market wage-earning potential of these individuals by working multiple jobs. As expected, the decision to hold multiple jobs is dependent on household income. As household income increases, the likelihood of working multiple jobs decreases.

With respect to built environment attributes, the results show that individuals in rural households are more disposed to hold more than one job, while individuals in neighborhoods with high levels of access in terms of street block mileage, and zonal accessibility are less disposed to hold multiple jobs. These results are perhaps indicative of the wider array of desirable full-time employment opportunities to choose from in non-rural areas and in areas with good accessibility to jobs. In other words, access to jobs seems to be an important component of neighborhood vitality and economic well-being of households and individuals (*29*).

5.5 Decision to be a Home-Based Worker

Home-based workers tend to be older adults over 40 years of age than adults who are 26 to 40 years of age and younger adults who are 25 years of age or younger, suggesting the need to establish some job credentials first before home-based work becomes a viable option. This is reinforced by the finding that those with higher education levels (bachelor's degree or above) are more represented in the pool of home-based workers. Caucasians are more likely to be home-based workers than other groups. In terms of job types, individuals in the PMT and clerical/administrative support jobs are less likely to be home-based workers.

Among household attributes, individuals in households with young children (5 years of age or younger) have a higher predisposition to be home-based workers, yet another reflection of individuals attempting to maintain a work-family life balance when children are present.

In the context of built environment attributes, higher levels of access to recreational activity locations (as represented by "Accessibility to recreational opportunities" and "Density (per square mile) of natural recreational sites") are associated with a greater propensity to be a home-based worker. It is possible that individuals residing in such locations make a decision to work from home so that they can take advantage of recreational opportunities; conversely, those who work from home may purposefully choose to locate in neighborhoods with good accessibility to recreational activities so that they can avail of such opportunities. Further research is warranted to disentangle the nature of the relationship seen here.

5.6 Jointness of Decisions

The model estimation did not yield any statistically significant household level and individual level heterogeneity in the impact of different variables, *i.e.*, all of the elements in $\boldsymbol{\Omega}$ and $\tilde{\boldsymbol{\Omega}}$ (which are the covariance matrices of $\tilde{\boldsymbol{\beta}}_{hj}$ and $\tilde{\tilde{\boldsymbol{\beta}}}_{hjq}$ respectively), turned out to be zero. However, several elements in $\boldsymbol{\Lambda}$ and $\boldsymbol{\Sigma}$, which capture covariances of the $\boldsymbol{\eta}_h$ and $\boldsymbol{\varepsilon}_h$ terms, are statistically significant. Table 3 presents the results of these covariance matrices.

The elements of the covariance matrix $\boldsymbol{\Lambda}$ (upper matrix in Table 3) indicate the presence of household level unobserved factors affecting the different dimensions of work arrangement decisions of each individual in the household. First, except for the decision to hold more than one job, all other work decisions of individuals are impacted by unobserved household factors, as can be observed from the significant variance terms along the diagonal of $\boldsymbol{\Lambda}$. Thus, for example, there are unobserved factors (such as non-work income or general perspectives about employment outside home) that decrease or increase the employment tendency of all individuals in a household. In addition, there are several statistically significant off-diagonal terms, indicating correlation effects across work decisions at the household level. For instance, consider a household that, as an entity, believes in having control over work arrangements and schedules. This lifestyle attitude will increase the propensity of all individuals in the household being self-employed and being a home-based worker, which is reflected in the positive covariance estimate between the self-employed and home-based worker dimensions in the upper matrix of Table 3. Other covariance elements may be similarly interpreted.

In the context of the person-level covariance matrix (the lower matrix in Table 3), all variances are set to unity for identification purposes. In terms of the non-diagonal elements, once again, there is very high covariance between unobserved factors affecting the decision to be self-employed and the decision to be a home-based worker. For example, an individual who likes to work alone and control his or her own time and schedule (likes to be his or her own boss) may be more amenable to being self-employed and/or working at home. However, such attitudinal variables are rarely included in model specifications, which would lead to the presence of correlated unobserved factors affecting these work dimensions. Significant error covariances are also found between self-employment and part or full time employment, and between self-employment and holding multiple jobs. The part time or full time dimension has correlated unobserved factors with two other dimensions, namely, the decision to hold more than one job and the decision to be a home-based worker. In general, estimation results confirm the presence of common unobserved factors that simultaneously impact multiple work related decisions, both within- and between individuals in a household.

6. CONCLUSIONS

In this paper, five specific work related decisions are examined. They are the decision to be employed or not, and if employed, to be self-employed or not, a home-based worker or not, a full-time or part-time worker, and a multiple-job worker or not. As these are all decisions related to work, it is possible that there are unobserved factors affecting these decisions that are correlated with one another. The presence of correlated unobserved factors affecting multiple work related decisions may occur both within- and between individuals. Previous research has treated the multiple work decisions independent of one another ignoring the within-person correlations that might exist. Also, previous research has treated the employment decisions of each household member independent of the decisions of other household members, thus ignoring the between-person interactions (and associated correlations) that may exist.

This paper overcomes these limitations by formulating and estimating a multivariate binary probit model system that accounts for unobserved heterogeneity due to household and individual factors, self-selection (to be employed), and correlated unobserved factors affecting work arrangement decisions both within- and between individuals in a household. The model system is estimated on a subsample of the 2009 National Household Travel Survey data drawn from the nine county San Francisco Bay Area. Model estimation results show that there are numerous demographic and socio-economic attributes at the household and person level that significantly impact work arrangement decisions. Moreover, several built environment attributes and accessibility variables also affected work related choices. More importantly, it was found that there are correlated unobserved factors simultaneously affecting multiple work related choices as evidenced by the significant error covariance terms both at the household and individual levels. However, within the empirical context considered in this paper, no significant unobserved heterogeneity was found to exist, both at the household and individual levels. Further research is warranted to determine whether this finding applies to other empirical contexts as well.

The work presented in this paper is relevant from several perspectives. First, the model system can be used in the context of activity-based microsimulation models of travel to simulate employment related choices of individuals (*30*). After synthesizing a population using a synthetic population generator, the model system of this paper can be used to simulate work arrangement decisions for each person aged 16 years or over while accounting for the jointness in decisions within- and between individuals in a household. Work schedules can be determined based on the choices simulated, thus providing a robust framework for modeling discretionary activity-travel engagement through the course of a day.

Second, the results of this paper shed light on the importance of built environment attributes and accessibility measures on employment related decisions. It appears that individuals with greater level of access to jobs and a wider array of job opportunities are likely to be able to work full time and not have to hold multiple jobs (working each one on a part-time basis). The model system can therefore be used to assess the potential impacts of different jobs access programs on work related choices and decisions, while accounting for the fact that such programs may simultaneously impact multiple dimensions through correlated unobserved factors. Policies can be formulated to encourage and promote entrepreneurship and start-up businesses, and specific programs can be targeted to the types of individuals who have a proclivity to choose these types of work arrangements. The model provides insights into the types of demographic groups towards whom such programs can be targeted.

Third, demographic shifts are constantly taking place over time and it is critically important to have a robust model system capable of predicting the impacts of such shifts. In the US, for example, the aging of the population is a phenomenon that is likely to have far reaching implications for the work force composition and arrangements of tomorrow. As the population ages, what types of work arrangements should be promoted or implemented to best accommodate the preferences and styles of an aging work force? Should telecommuting programs be enhanced, more part-time consulting opportunities be created, or home-based business assistance programs be implemented? What types of shifts in work choices is the nation going to experience as people age, technology becomes increasingly ubiquitous, and an increasing share of the population has a college education? To better understand and predict the work arrangements of the future in response to shifting demographics, models of the nature presented in this paper need to be deployed.

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LIST OF TABLES

TABLE 1 Sample Characteristics

Variable	Sample Share (Percent)		
	Workers (N=2929)	Non-Workers (N=2435)	Total (N=5364)
Individual Level			
Age (years)			
16 to 25	6.5	8.8	7.5
26 to 40	18.0	7.1	13.0
41 to 60	58.8	20.5	41.5
Greater than 60	16.7	63.6	38.0
Gender			
Female	48.2	58.8	53.0
Male	51.8	41.2	47.0
Marital Status			
Married	76.6	64.7	71.2
Immigration Status			
Immigrant	22.2	18.3	20.4
Household Level			
Number of Adults (Age ≥ 16 years)			
1	22.3	35.9	30.6
2	43.6	46.6	55.9
3	17.5	10.2	10.6
4 or more	16.6	7.2	2.9
Presence of Children			
No children	68.6	86.8	77.5
0 to 5 years	10.9	5.1	8.0
6 to 10 years	14.2	5.8	7.6
10 to 15 years	15.3	5.7	6.9
Presence of Senior Adults (Age ≥ 65 years)			
No Senior Adults	89.6	39.1	65.0
At least one senior adult	10.4	60.9	35.0
Household Income (US dollars)			
<30,000	8.7	27.1	17.7
30,000 to 75,000	23.6	37.5	30.4
>75,000	67.7	35.4	51.9

TABLE 2 Empirical Results for Joint Model (N= 5364 Individuals)

	Employed (versus not employed)		Self-employed (versus not)		Part time (versus Full time)		More than One Job (versus one job)		Home Based Worker (versus not)	
Explanatory Variables	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	-0.303	-3.087	-1.446	-2.228	-0.514	-3.708	0.583	0.937	-1.904	-11.782
Individual Demographics										
Female	-0.172	-2.723	-	-	-	-	-	-	-	-
Married	-	-	0.234	3.123	-0.475	-5.292	-	-	-	-
Married Female	-0.237	-3.507	-	-	0.844	10.191	-	-	-	-
Age:	-	-	-	-	-	-	-	-	-	-
16 to 25 years	-0.858	-4.289	-	-	0.768	4.953	0.260	2.097	-0.439	-2.546
26 to 40 years	0.758	7.919	-	-	-0.552	-4.289	-	-	-0.229	-2.102
41 to 60 years	0.804	10.897	-	-	-0.345	-3.398	-	-	-	-
41 to 70 years	-	-	0.295	3.757	-	-	-	-	-	-
16 to 25 years and having driver's license	1.119	5.555	-	-	-	-	-	-	-	-
Male *41 to 70 years	-	-			-	-	-	-	-	-
Education Level (high school or lower is base)										
Some college or Associate's degree	0.384	6.329	-	-	-0.225	-2.832	0.257	2.554	-	-
Bachelor's degree	0.469	7.518	0.513	6.959	-0.225	-2.832	0.257	2.554	0.408	4.628
Graduate or Professional Degree	0.590	8.852	0.513	6.959	-0.225	-2.832	0.257	2.554	0.408	4.628
Race (non-Caucasian is base)										
Caucasian	0.141	2.358	0.464	5.042	-	-	-	-	0.500	5.020
Job type:										
Professional, managerial, or technical (PMT)	-	-			-	-	-	-	-0.491	-6.041
Manufacturing, construction, maintenance, or farming (MCMF)	-	-	0.765	6.890	-	-	-	-		
Sales/Service	-	-	0.646	6.717	0.385	5.215	-	-		
Male * Sales/Service	-	-	-0.098	-0.902	-	-	-	-	-	-
Clerical / administrative support	-	-			0.217	2.450	-	-	-0.501	-3.584
Others:										
Have medical condition making it hard to travel	-	-			0.375	2.617	-	-	-	-
Immigrant	-0.099	-1.087	-0.265	-1.647	-0.471	-2.800	-	-	-	-
Duration of stay in US (in years)	0.005	1.575	0.012	2.652	0.010	1.944	-	-	-	-

TABLE 2 (continued) Empirical Results for Joint Model (N= 5364 Individuals)

Explanatory Variables	Employed (versus not employed)		Self-employed (versus not)		Part time (versus Full time)		More than One Job (versus one job)		Home Based Worker (versus not)	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Household Demographics										
Presence of young children (age ≤ 5 years)	-	-	-	-	-	-	-	-	0.183	1.581
Presence of children (age ≤ 15 years)	0.411	2.311	-	-	-	-	-	-	-	-
Female with young children (age ≤ 5 years)	-	-	-	-	0.332	2.582	-	-	-	-
Female with children (age ≤ 15 years)	-0.457	-2.527	-	-	-	-	-	-	-	-
Presence of senior adults (age ≥ 65 years)	-1.135	-14.189	-	-	0.750	5.939	-	-	-	-
Logarithmic of Household Income in $	-	-	-0.091	-1.578	-	-	-0.173	-3.120	-	-
Built Environment Characteristics										
County:	-	-	-	-	-	-	-	-	-	-
Marin, San Francisco, or Sonoma	-	-	0.285	3.224	-	-	-	-	-	-
Others:	-	-	-	-	-	-	-	-	-	-
Block level:										
Urban	-	-	0.087	1.016	-	-	-	-	-	-
Rural	-	-	-	-	-	-	0.425	3.298	-	-
Zonal level										
Accessibility Measures	-	-			-	-	-	-	-	-
Accessibility to shopping (retail employment) (/10)	-	-	0.214	1.555	-	-	-	-	-	-
Accessibility to employment (/100)	-	-	-0.781	-1.904	-	-	-	-	-	-
Accessibility to recreational opportunities	-	-	-	-	-	-	-	-	0.764	2.859
Density (per square mile) of natural recreation sites	-	-	-	-	-	-	-	-	0.069	1.368
Network Related Measures										
Length of street blocks in miles (A4-A7 roads) (/100)	-	-	-	-	-	-	-0.305	-2.300	-	-
Number of accessible zones:	-	-	-	-	-	-	-	-	-	-
by bike within 16 mile from the zone (/100)	-	-	-	-	-	-	-0.096	-2.124	-	-
Log Likelihood Value	-7008.119									

TABLE 3 Error Covariance Matrices of Joint Model

Employment Decision	Covariance Matrix Λ (at Household Level)				
	Employed (versus not employed)	Self-employed (versus not)	Part time (versus Full time)	More than One Job (versus one job)	Home Based Worker (versus not)
Employed (versus not employed)	0.1285 (2.69)				
Self-employed (versus not)	0.2457 (5.66)	0.3794 (3.50)			
Part time (versus Full time)	0	0	0.1243 (1.40)		
More than One Job (versus one job)	0	0	0	0	
Home Based Worker (versus not)	0.1513 (3.12)	0.2234 (2.58)	0	0	0.4052 (2.86)
Employment Decision	Covariance Matrix Σ (Individual Level)				
	Employed (versus not employed)	Self-employed (versus not)	Part time (versus Full time)	More than One Job (versus one job)	Home Based Worker (versus not)
Employed (versus not employed)	1				
Self-employed (versus not)	0	1			
Part time (versus Full time)	0	0.3620 (7.80)	1		
More than One Job (versus one job)	0	0.2719 (7.04)	0.1992 (4.29)	1	
Home Based Worker (versus not)	0	0.9084 (19.91)	0.4004 (8.42)	0	1