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MODELING HOUSEHOLD DECISIONS USING LONGITUDINAL DATA FROM HOUSEHOLD PANEL SURVEYS, WITH APPLICATIONS TO RESIDENTIAL MOBILITY

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Abstract

Many events occurring to married or cohabiting individuals are the result of decisions made jointly by both partners. However, studies of life-course events usually take an individual or head-of-household perspective and so do not explicitly reflect the joint nature of these decisions. Household panel studies and population registers are a rich resource for the study of household events, but analyzing such data presents major analytical challenges. Models should ideally allow for the influence of both partners in a couple's decision making and be flexible enough to handle the facts that individuals can change their partners and have periods when they are not in coresidential unions. In this article, the authors propose two types of multilevel random-effects models to address some of these issues: a ''multiple-membership'' model in which the outcome depends on a weighted combination of the random effects for each decision maker and a random-coefficients model that allows different random effects for individuals when they are single and

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partnered. All methods are discussed in terms of a binary household outcome before describing more general discrete-choice models for nominal outcomes. The proposed methods are compared with previously used approaches in a simulation study and illustrated in analyses of residential mobility using data from the British Household Panel Survey.

Keywords

multilevel modeling, multiple-membership model, household panel data, household effects

1. INTRODUCTION

The fact that many outcomes measured on married or cohabiting individuals are the result of decisions made jointly by both partners is one that has received little attention in life-course research. Examples of outcomes that are likely to reflect couples' rather than independent individuals' preferences (or circumstances) are household expenditure decisions, the allocation of time to market and domestic work, and life-course events such as moving house, childbearing, and union dissolution. Theoretically, the distinction between choices made individually and collectively has been explored in a number of disciplines. In economics, models of intrahousehold bargaining explicitly recognize that household members can have conflicting preferences and that household decisions will generally depend on the relative power of each person to influence others (see Lundberg and Pollack 1996, for a review). Sociological research has focused on the context and process of marital joint decision making, identifying a number of factors that affect a spouse's power to influence outcomes such as relative control over material resources (Vogler and Pahl 1994), emotional interdependence, communication style and bargaining skill (Godwin and Scanzoni 1989), and ideological and cultural factors (Komter 1989).

Event history analyses of the life course generally ignore the influence of other household members on an individual's decisions. This individual focus is perhaps a consequence of the heavy reliance on data from birth cohort studies, which are important because of the in-depth information collected on individuals' childhoods and early adult circumstances. Nevertheless, a limitation of these studies is that very little information is collected on the cohort members' partners or on any other household members; typically, only the start and end dates of coresidential unions are available to the analyst. However, household panel studies such as the U.S. Panel Study of Income Dynamics (PSID) and the British Household Panel Survey (BHPS), and the population registers available in many northern European countries, are also suitable for life-course research. Although less informative about early-life outcomes than cohort studies, panel studies typically provide information on every adult household member (apart from that lost due to nonresponse) and so are particularly suited to studying processes involving choices made by couples rather than individuals. Furthermore, panel studies follow individuals as they move between households of different types and change partners, so that individual and couple effects can potentially be disentangled.

Despite being highly suited to studying the events that result from household decisions, the appropriate analysis of household panel and register data still presents major challenges because individuals can change partners and have periods when they are not in coresidential unions. Murphy (1996) considered a range of scenarios that can lead to changes in household composition and concluded that ''without some additional conditions it is impossible to use the household as the unit of analysis across time.'' In other words, the analyst must be clear what a household is and what constitutes a change of household. These issues are particularly important for maturing panel studies in the United Kingdom and other Western countries, such as the PSID and BHPS, in which high rates of cohabitation and union dissolution lead to frequent changes of household. Despite this background, previous research has not addressed these issues, and the focus continues to be on individuals even when household data are available.

In this article, we have several aims. First, we discuss the implications of choosing a particular unit of analysis when using longitudinal household data, which is an important issue that has not been discussed previously in the literature. A second aim is to develop a general statistical framework for the analysis of individual and couple decision making using household panel data, which can be implemented in existing software. Finally, we present example analyses of residential mobility and offer some practical guidance for applied researchers.

Our general framework for modeling the timing of individual and household events, in which the event of interest occurs to all decision makers in the household, is based on two flexible families of multilevel models. First, we propose nonhierarchical ''multiple-membership'' models in which the joint household outcome is modeled as a function of individual-level and household-level covariates and a weighted sum of the individual random effects associated with each household member. Second, we extend previous models for the head of the household to allow separate random effects for single-person and multiple-person households and autocorrelation between two households when an individual left one household to form another.

The remainder of the article is organized as follows. In section 2, we focus on household decisions relating to residential mobility and review the literature. Section 3 provides an overview of individual- and household-based approaches used in previous research on the timing of residential moves. In section 4, we show how these methods can be viewed as special cases of a general class of multilevel models and describe two extensions that fall within our framework. Section 5 discusses the implications of model choice on estimates of unobserved heterogeneity and of covariate effects (averaged across these unmeasured factors), and section 6 presents a small-scale simulation study. In section 7, we consider more general discrete-choice models for nominal outcomes, including multinomial logit (MNL) and conditional logit (CL) models. Methods for both binary and nominal outcomes are then applied in analyses of residential mobility using data from the BHPS (sections 8 and 9). Finally, in section 10, we make some concluding remarks.

2. RESIDENTIAL MOBILITY

To fix ideas, the models we present are described in the context of a concrete example, namely, a study of residential mobility. Residential mobility is a key focus of research among scholars in demography, geography, sociology, and economics. Mobility rates reflect the ease with which households are able to adapt their dwelling and spatial locations to changing circumstances, with crucial implications for demographic trends, economic productivity, and individual welfare. Low residential mobility is associated with fewer vacancies in the housing market and decreased access to appropriate dwellings for those wanting to move for family formation, work, and education reasons. Internal migration is a key mechanism for matching the skills of workers with those needed by firms and reducing regional imbalances.

The life-course perspective has provided a coherent framework for a diverse range of studies exploring the determinants and consequences of residential mobility (Clark and Dieleman 1996). This perspective holds that individuals have housing ‘‘careers’’ in which dwellings are continually adapted to meet the changing needs of the household. The housing career interacts with careers in other domains such as union formation and childbirth (Feijten and Mulder 2002; Kulu 2008; Kulu and Milewski 2007) and employment (Böheim and Taylor 2002; Clark and Davies Withers 1999). Specific types of moves have also been the focus of numerous studies, such as transitions into owner-occupation (Clark, Deurloo, and Dieleman 1997; Di Salvo and Ermisch 1997; Mulder and Wagner 1998); exit from and reentry to the parental home (Clark and Mulder 2000; Ermisch 1999); the long-distance migration of two-earner couples (Mok 2007; Rabe 2011); moves between urban, suburban, and rural areas (Kulu 2005; Lindgren 2003); and moves into and out of different dwelling types (Kulu and Vikat 2007).

The residential location choices of couples as an issue of potential conflict have received a good deal of attention from social psychologists and geographers. A common approach is to use experiments in which data are collected on family members’ preferences for hypothetical locations with different attributes, with ratings made both individually and jointly. Preference structures of individual family members are generally found to differ from group preference structures (Marcucci et al. 2011; Molin, Oppewal, and Timmermans 1999; Timmermans et al. 1992). Analysis of longitudinal data on actual moves has also shown that subsequent mobility is affected by the stated desires to move of both members of a couple (Coulter, van Ham, and Feijten 2011). Gender inequalities in the economic outcomes of husbands and wives following a move have generated interest in the concept of ‘‘tied movers,’’ whereby one partner (usually the woman) moves for the sake of the other’s career (Bielby and Bielby 1992; Mincer 1978). On the other hand, the phenomenon of ‘‘tied stayers,’’ whereby one partner is inhibited from making a beneficial move because of the labor market ties of the other, has been put forward as an explanation for the lower residential mobility of two-earner compared with single-earner couples (Lichter 1982; Smits, Mulder, and Hooimeijer 2003).

3. PREVIOUS APPROACHES TO THE ANALYSIS OF RESIDENTIAL MOBILITY USING HOUSEHOLD PANEL DATA

Many of the insights from the work on residential mobility have been, or could be, straightforwardly incorporated into the type of longitudinal mobility studies discussed below by including both partners' observed characteristics (employment variables, gender role attitudes, etc.) as covariates. The influence of unobservable individual traits on the joint location decision, however, is generally neglected, perhaps because little can be inferred in this domain from cross-sectional or birth cohort data. Studies using household panel data can potentially exploit a rich source of information in the repeat decisions of the same individuals made in different circumstances, but to date, the residual structures of the models used imply strong assumptions that are far from transparent.

In this section, we briefly review the approaches adopted in previous longitudinal research on residential mobility, before setting out the statistical models, and their implicit assumptions about marital decision making, more formally in the next section. Because of our focus on methods for the analysis of household panel data, we do not review methods applied to surveys of individuals rather than households, including samples of women or singletons, for which the lack of household data necessitates an individual-focused approach.

We illustrate the implications of each approach for data analysis by considering a hypothetical set of individuals whose residential histories are shown in Table 1. It can be seen from Table 1 that individuals A and B are partners at waves 1 to 3, move together once, and split up between waves 3 and 4; individual A then continues as a singleton for waves 4 to 7, moving once; B partners with C (who enters the sample at this point), and they move once.

3.1. *Household-based Approach*

As we discussed above, researchers using household data to study residential mobility are faced with a dilemma about whether to take the household or individual household member as the unit of analysis. Proponents of the household perspective argue that the decision to move is made by the household as a whole. The simplest household-based approach models mobility between waves t and $t+1$ as a series of cross-sectional outcomes, with no allowance for dependency between observations from the same household (e.g., Clark and Huang 2003). Although difficult decisions about the treatment of households that change composition are avoided, this comes at the expense of the analysis not being truly longitudinal.

Table 1. Housing History for Three Hypothetical Individuals

Individual ID (i)	Wave (t)	HH Head at t	HH Type at t	Move (t, $t+1$)	Partner ID (j)
A	1	1	Couple	0	B
A	2	1	Couple	1	B
A	3	1	Couple	1	B
A	4	1	Single	0	-
A	5	1	Single	0	-
A	6	1	Single	1	-
A	7	1	Single	0	-
B	1	0	Couple	0	A
B	2	0	Couple	1	A
B	3	0	Couple	1	A
B	4	0	Couple	0	C
B	5	0	Couple	0	C
B	6	0	Couple	1	C
B	7	0	Couple	0	C
C	4	1	Couple	0	B
C	5	1	Couple	0	B
C	6	1	Couple	1	B
C	7	1	Couple	0	B

Note: Household (HH) head is coded 1 if individual i is the head of the household at t and 0 otherwise; Move is coded 1 if individual i moves between waves t and $t+1$ and 0 otherwise.

Pickles and Davies (1985) emphasized the importance of the longitudinal approach for analyzing housing careers and used it to analyze residential mobility and changes in housing tenure in the PSID. They took the household as the unit of analysis and included a household-specific random effect in their model to allow for correlation between multiple housing spells from the same household due to unmeasured time-invariant influences. As usual for random-effects models, a household identifier is required to link observations contributed by the same household at different times, and so it is necessary to define the changes in household composition that constitute a change in household (and household identifier). Pickles and Davies did not discuss this issue but instead considered the mobility of *intact* households, that is, households with the same household head throughout the observation period. So for the example histories in Table 1, the data set would consist of seven records: Observations for individuals A and B for waves 1 to 3 would be reduced to three couple-year records for (A,B), and A's person-year records for waves 4 to 7 as a singleton would be retained because A continues as the head of his household. Individual B's second union with C would either be excluded or treated as a new couple, with no connection allowed between couples (A,B) and (B,C) despite having B in common. Covariates are typically defined for the household as a whole (e.g., income) or for the head of household only, and therefore, the influence of partner characteristics is ignored.

3.2. *Individual-based Approach*

The main problem with household-based approaches is the difficulty in allowing for changes in household composition over time. Restricting the analysis sample to households that remain intact could lead to selection bias, especially for long observation periods, while defining a new household with every household change fails to recognize the dependency between households that share individuals. An alternative strategy is to study the housing careers of individuals rather than households, with changes in the composition of an individual's household captured by time-varying covariates (Davies Withers 1997). A similar approach was followed by Böheim and Taylor (2002) but with individual random effects included to allow for individuals who contributed multiple housing spells. Although both of these analyses used household panel data (the PSID and BHPS, respectively), neither explicitly allowed for any dependence between the decision making of individuals in the same household; individuals were treated as independent observations, which effectively led to ''double counting'' of couple households because partners who moved together had the same joint outcome. For the individuals in Table 1, the analysis file would contain records for both A and B for waves 1 to 3 and both B and C for waves 4 to 7 (as well as A for waves 4 to 7 as a singleton).

A potential advantage of the individual-based model is that it is straightforward to include both individual and household characteristics as covariates. However, previous applications consider very limited information about an individual's partner.

3.3. *Head-of-household-based Approach*

The third group of approaches can be viewed as a hybrid of the household- and individual-based approaches described above. The household is taken as the unit of analysis, but the household random effect is defined by the individual identifier of the head of household (Ioannides and Kan 1996; Rabe and Taylor 2010). In addition, Ioannides and Kan (1996) included covariates that related either to the household head or the household as a whole, thus ignoring the influence of the measured and unmeasured characteristics of the partner (usually the woman). In the example histories in Table 1, their approach leads to the exclusion of all records for individual B. Although Rabe and Taylor (2010) considered characteristics of both partners as covariates for couple mobility, the inclusion of a random effect on the basis of the identifier for A implies that, conditional on covariates, there is no distinction between periods with the same partner and periods with different partners.

3.4. *Distinguishing Couples and Singletons*

Although most previous studies have allowed the overall probability of a move to differ for singletons and couples, few have allowed the effects of covariates to depend on household type. However, there are strong arguments for treating the mobility of singletons and couples as different processes. For example, some covariates, such as partner characteristics, are relevant only for couples, and singletons can be treated as lone decision makers. A straightforward way to allow for household-type-specific covariate effects is to fit separate models for the mobility of singles and couples (Rabe and Taylor 2010), but there are two potential disadvantages to this approach: First, splitting the sample by partnership status precludes testing the equality of the effects of covariates that influence the mobility of both couples and singles, because such tests are only possible using a joint model of couple and single mobility, and second, separate analysis of singles and couples does not allow for individuals who move between the single and partnered states over the observation period (e.g., individual A appears in both single and couple samples in Table 1). Because Rabe and Taylor's analysis was restricted to eight waves of the BHPS, there was in fact little overlap between the single and couple samples, with only 5 percent of individuals appearing in both. However, we would expect a higher rate of movement between these samples in any panel study as it matures, especially among more recent birth cohorts, in which higher rates of union dissolution and repartnering lead to multiple transitions between the single and couple states. In our application, for example, using 17 waves of the BHPS, 20 percent are observed as both singletons and couples.

4. MULTILEVEL MODELS FOR COUPLE AND INDIVIDUAL DECISIONS

The aim of the previous section was to give a broad overview of the approaches used in earlier studies of residential mobility. We now consider in greater detail the statistical models used in these studies and their underlying assumptions, focusing on the random-effects models used for the head-of-household- and individual-based approaches (household-based approaches are excluded from further discussion because of the difficulty in defining a household random effect longitudinally). We present these models within a general multilevel modeling framework to highlight the differences and similarities between them and bring out potentially useful extensions. This leads us to propose two new models: an extension to the head-of-household model of Rabe and Taylor (2010) and a multiple-membership model (Goldstein et al. 2000) that allows explicitly for the influence of unmeasured characteristics of both partners.

Before proceeding with a description of the general statistical model, it is important to give precise definitions of both a household and a residential move. In the BHPS, a household is defined as a person living alone or a group of people who share either living accommodation or one meal a day. We adapt this definition for our application so that a ‘‘household’’ refers to coresident adults who can reasonably be assumed to make the decision to move house together. Following this definition, a (married or cohabiting) couple is a household, and a singleton is any adult not in a coresidential union. For example, a couple living with a single person is treated as two decision-making units or ‘‘households’’: a couple and a singleton. It is straightforward to generalize this definition to allow households comprising members other than partners who influence decisions, for instance, a household involving a parent and an adult child. In common with most previous research, we define residential mobility to exclude moves due to partnership formation or breakdown, leading to an outcome that applies to both partners in a couple household. (Further justification of this definition is given in section 8.1.)

4.1. *General Multilevel Model for Couple and Singleton Mobility*

The following general framework comprises two components, one for mobility of couples and the other for mobility of singletons, which allows for individuals who move between the two partnership states over the observation period.

Suppose that we begin at wave 1 with a sample of n individuals. To distinguish those in couples from singletons, denote by c_{it} an indicator of whether individual i is in a couple (marriage or cohabitation) at wave t, where

$$c_{it} = \begin{cases} 1 & \text{if individual } i \text{ is in a couple at } t, \\ 0 & \text{if individual } i \text{ is single at } t. \end{cases}$$

Let y_{it} be a binary response coded 1 if individual i moves (possibly with partner j) between waves t and $t+1$ and 0 otherwise. As noted above, we exclude moves due to union dissolution or formation; thus, $y_{it}=0$ if individual i moved in with a new partner, or separated from j, between waves; and if individual i is in a couple, $y_{it}=1$ always denotes a joint move. We model p_{it}, the probability that individual i moves between waves t and $t+1$, as a logistic function that varies according to whether individual i is in a couple (with partner j) or single at wave t:

$$\log\left(\frac{p_{it}}{1-p_{it}}\right) = c_{it}\left\{\mathbf{x}_{(ij)t}\boldsymbol{\alpha}^{C} + u^{C}_{(ij)}\right\} + (1-c_{it})\left\{\mathbf{x}_{it}\boldsymbol{\alpha}^{S} + u^{S}_{i}\right\}. \qquad (1)$$

The couple component of equation 1 includes a row vector of (possibly time-varying) covariates relating to the couple and their household, $\mathbf{x}_{(ij)t}$, and a couple-specific random effect $u^{C}_{(ij)}$. Couple covariates will typically include individual characteristics of each partner (e.g., level of education) and joint characteristics of the couple and their household (e.g., tenure and marital status). The component for singletons includes a row vector of covariates for individual i, $\mathbf{x}_{it}$, and an individual-specific random effect u^{S}_{i}. The regression coefficients for $\mathbf{x}_{(ij)t}$ and $\mathbf{x}_{it}$ are represented by the column vectors $\boldsymbol{\alpha}^{C}$ and $\boldsymbol{\alpha}^{S}$, respectively, and the couple and single subequations of equation 1 are linked by having individuals who are observed both in a couple and as a single person over time (e.g., individual A in Table 1).

Equation 1 allows the mobility propensity of person i to depend on whether he or she is single or in a couple as follows: a different underlying base propensity (the intercept), differential effects of the individual's own characteristics $\mathbf{x}_{it}$, inclusion of the partner's observed characteristics for couples, and a different random effect. All of these differences may capture aspects of the bargaining process by which individual preferences are reconciled into a group decision. The first three mechanisms are part of the model's ''fixed part'' and are common to all the approaches discussed below. As it stands, equation 1 makes no assumption about the relationship between individual tastes when single, u_i^S, and the joint tastes of the couple, $u_{(ij)}^C$. However, as we show below, approaches differ in the structure imposed on the random effects.

4.2. *Head-of-household Models*

Suppose that individual i is the head of household (HoH) in couple ij. The most commonly used of these approaches is to select records corresponding only to the head of household (e.g., Ioannides and Kan 1996), which is equivalent to setting $u_{(ij)}^C = u_i^S = u_i$ in equation 1, where $u_i \sim N(0, \sigma^2)$. Thus, partner j contributes to the outcome only through $\mathbf{x}_{(ij)t}$, and singletons and couples are assumed to come from the same population. We refer to this model as the *HoH-common model*, because the random effect is interpreted as being for the head of household, and a common random-effect distribution is assumed for couples and singletons. The implication of this is that the head's unobserved mobility propensity remains unchanged after union formation.

The approach of Rabe and Taylor (2010) is an extension of the HoH-common model that allows the unobserved heterogeneity to depend on household type. In other words, this model can also be viewed as a special case of equation 1 with $u_{(ij)}^C = u_i^C \sim N(0, \sigma_C^2)$ and $u_i^S \sim N(0, \sigma_S^2)$ as independent random effects. We refer to it as the *HoH-separate model*.

Although the HoH-separate model allows for differential heterogeneity for singletons and couples, the independence of the singleton and couple random effects does not allow for any association between outcomes of singles and couples involving the same head of household in different periods. In effect, this model relaxes the requirement that the head's random effect is unaffected by the presence of a partner after union formation but does assume that the individual's tastes when single are uncorrelated with the tastes of the couple.

Hence, a further generalization of the head-of-household approach, which has not been used previously, is to allow different residual variances for couples and singles within the joint modeling framework by fitting random coefficients u_i^C and u_i^S to the couple and single indicators c_{it} and $1 - c_{it}$ in equation 1. We then assume that u_i^C and u_i^S follow a bivariate normal distribution with covariance matrix

$$\Omega = \begin{pmatrix} \sigma_C^2 & \\ \sigma_{CS} & \sigma_S^2 \end{pmatrix}, \tag{2}$$

where σ_C^2 is the between-couple variance (based on household heads), σ_S^2 is the between-individual variance (for singles), and σ_{CS} is the couple-single covariance. The random-effect covariance σ_{CS} measures the extent to which a head of household's latent propensity to move when single is reflected in the joint preferences of the couple, and we would expect it to be positive. The strength of the correlation can be interpreted as capturing the degree to which the head's preferences dominate in the final decision. We refer to this random coefficients model as the *HoH-joint model*, and note that the HoH-separate model is a special case with $\sigma_{CS} = 0$.

4.3. *Multiple-membership Models: Allowing for Dynamic Household Structures*

The head-of-household approaches described above allow for the possibility that an individual can move between the single and couple states over time, but they assume that the effect of the head of household's partner is fully captured by the covariates $\mathbf{x}_{(ij)t}$ in equation 1. If all individuals remained with the same partner throughout the observation period, then the dependence between partners could be captured by couple-level random or fixed effects. In reality, however, households are dynamic constructs whereby individuals can leave households to form new ones, which leads to difficult decisions for the analyst about how to define a household longitudinally.

One approach that allows for changing household membership is a multilevel ''multiple-membership'' model in which an individual can be a member of more than one household over time. In its original form, an individual outcome can be influenced by a weighted sum of the random effects from every household he or she has been in, in which the weights are proportional to the time spent in each one (Goldstein et al. 2000). Such a model is theoretically appealing in applications in which the outcome of interest may reasonably be expected to depend on unmeasured attributes of previous coresidents (e.g., Chandola et al. 2005), but it is not suitable for analysis of household decisions involving current coresidents. (For further discussion and applications of multilevel multiple-membership models, see Browne, Goldstein, and Rasbash 2001; Goldstein 2010; Leckie 2009.)

4.3.1. *Multilevel Multiple-membership Model for Residential Mobility.* We propose a variant of the multiple-membership model in which the occurrence of household events between waves t and $t+1$ depends on characteristics (both observed and unobserved) of individual household members at wave t. By taking this approach, we avoid the need to link households longitudinally and the associated arbitrary decisions about the types of household change that lead to new households. Observations from the same individual are linked over time, as in standard models for panel data, but unlike in standard models, observations from coresidents at wave t are linked too.

In the proposed multiple-membership model, the couple random effect is decomposed as

$$u^{C}_{(ij)} = w_i u_i + w_j u_j, \tag{4}$$

where $u_i \sim N(0, \sigma^2)$ is an individual-specific random effect with weight w_i. The weights cannot be estimated in this framework but must be chosen by the analyst so that $w_i + w_j = 1$ (Browne et al. 2001). As such, it is important to assess the sensitivity of parameter estimates to different choices for the weights. Previous work provides conflicting evidence on whether, and which, partner might be given a stronger weight. Research on ''tied movers'' and the importance of traditional gender roles in marital decision making might suggest the male partner's random effect be weighted more heavily. However, there is evidence from diverse sources that, when it comes to residential mobility, the ultimate decision more closely accords with wives' rather than husbands' preferences (Coulter et al. 2011; Marcucci et al. 2011). Without prior information on which partner's preferences carry the most weight in the decision to move, a natural starting assumption might be that each member contributes equally so that $w_i = w_j = 0.5$. In our empirical application, below, we show how a comparison of results from different models can provide insights into the validity of this ''equality of influence'' assumption.

Turning to the single ($c_{it} = 0$) component of equation 1, we assume that $u^{S}_{i} = u_i$ and do not define different random effects for couples or singletons. Rather, we assume that each individual carries unmeasured attributes, represented by u_i, regardless of whether i is single or in a coresidential union. For example, the random-effect contribution to the mobility of individual A in Table 1 is $0.5(u_A + u_B)$ during his union with B and simply u_A while he is single. In this respect, the multiple-membership model is similar to the simplest head-of-household model described above (HoH-common).

The separation of the couple effect into contributions from each partner provides a way of tracking individuals as they form and dissolve unions over time. Thus, the multiple-membership residual structure allows for autocorrelations between the contributions from individuals at different waves, whether they are singletons or in cohabiting partnerships. The advantage of this approach over those used previously is that a new random effect does not have to be defined for a new couple when an individual changes partner, which would ignore that the two couples have an individual in common. For example, individual B has two partners, A and C, at different times, but the general model (equation 1) with multiple-membership structure (equation 4) for couples assumes that the random-effect contribution for B's mobility is $0.5(u_A + u_B)$ for $t \leq 3$ and $0.5(u_B + u_C)$ for $t > 3$ (assuming equal weight for each partner in both unions), which explicitly recognizes that B is common to both unions.

An assumption that must hold for the multiple-membership residual structure implied by equation 4 to be correct is that the unobserved mobility preferences of partners i and j, represented by random effects u_i and u_j, combine additively to affect their probability of moving. Thus couple ij, composed of a person with a strong preference toward moving ($u_i \gg 0$) and a person with a strong preference to remain in the same house ($u_j \ll 0$), will tend to have the average mobility probability for couples characterized by $\mathbf{x}_{(ij)t}$. Couples composed of an individual with a strong preference (in either direction) and an individual with a near average preference to move will also tend toward the average. Additivity of the random effects is commensurate with the idea that partners with opposing views will negotiate to reach a consensus and has received much support in the literature. For example, Corfman and Lehmann (1987) conceptualized the outcome of a group decision as ''a weighted function of the group members' individual preferences,'' an idea echoed in the collective household model from economics, in which the household utility function is defined by weighting the utility functions of the individual household members with a ''sharing'' parameter (Chiappori 1992). In general, the combined mobility of unequally matched partners will be quite different from the mobility of each acting alone.

A final observation about the multiple-membership structure (equation 4) is that it implies that the between-couple variance is

$$var\left(w_i u_i + w_j u_j\right) = \left(w_i^2 + w_j^2\right)\sigma^2, \tag{5}$$

which will be strictly less than the between-individual variance when $w_i + w_j = 1$ (and neither weight is zero). The minimum between-couple variance is $0.5\sigma^2$ and is obtained when equal weight is given to each partner. As a consequence of the restriction that the weights sum to 1, couples are less heterogeneous than individuals (with respect to unobserved factors determining mobility). It should be noted that equation 5 is based on the assumption that the random effects for all individuals, including partners, are mutually independent. The independence assumption implies that, conditional on covariates $\mathbf{x}_{(ij)t}$, partners are not matched on their latent mobility preferences. This assumption will be unrealistic if there is nonrandom sorting of individuals into couples such that individuals partner on the basis of unmeasured individual characteristics that are strongly associated with mobility preferences. The between-couple variance will be underestimated if the ignored correlation is positive and overestimated if it is negative, but the couple variance can never exceed the individual variance.

4.3.2. *Identification and Estimation.* The partitioning of the couple random effect into contributions from each partner in equation 4 is possible only if at least some individuals are observed as singletons and others change partners over the study period. In a sample with no union formation or dissolution, or in a survey design in which individuals are not followed after changes in the composition of their households, estimation of the single and couple equations in equation 1 would be based on entirely different samples of individuals, and the couple equation could be simplified to include a couple-level random effect. It follows that for two individuals who partner before wave 1 and remain together throughout the study period, we can identify only the weighted sum of their random effects rather than the contribution of each partner. However, this does not present an identification problem if we are interested in estimating only the variance of the random effect distribution rather than the individuals' random effects; the random-effect variance is identified by the normality assumption and the choice of weights w_i. Furthermore, in a long panel such as the BHPS or the PSID, there will usually be a substantial proportion of individuals who move between the single and couple states or who repartner after union dissolution.

The couple component of equation 1 is a model for the mobility of individual i, but symmetry means that $p_{jt} = p_{it}$ if i and j are partners. In other words, for couples, p_{it} is a model for the joint decision of partners i and j to move or not. When setting up the model, we do not therefore need to model both p_{it} and p_{jt} and so must ''switch off'' one partner's contribution to the likelihood. There are several ways to do this and avoid double counting. One approach is to weight the likelihood so that one partner is given a weight of 1 and the other excluded from the likelihood using a weight of 0. Equivalently, we can create a working data set from which we delete the records for one partner.

The head-of-household models described in section 4.2 are all hierarchical random-effects models and so can be fitted in a variety of software packages using maximum likelihood; for example, numerical quadrature (e.g., xtmelogit in Stata, PROC NLMIXED in SAS) and Markov-chain Monte Carlo (MCMC) methods (e.g., MLwiN or WinBUGS). The multiple-membership multilevel model is a type of nonhierarchical model in which the random effects for individual i and partner j are non-nested. MCMC methods provide greater flexibility for estimating such models (Browne et al. 2001) and are implemented in MLwiN and WinBUGS.

4.3.3. *Double Counting Partners.* In the section on individual-based approaches, we discussed how modeling both partners rather than the head of the household leads to ''double counting'' because both partners share the same outcome. In fact, it can be shown that this approach approximates a special case of the multiple-membership model provided that the probability of moving is small. More specifically, the random-effect contribution to the log odds that couple ij moves is approximately $u_i + u_j$ (see the Appendix for details). Thus, the individual-based model can be viewed as a multiple-membership model with weights $w_i = w_j = 1$, which from equation 5 implies a between-couple variance of $2\sigma^2$ (under the independence assumption). This choice of weights is consistent with a ''reinforcement'' effect whereby, for example, two individuals with strong preferences toward moving ($u_i \gg 0, u_j \gg 0$) will be more likely to move as a couple than as two singletons, in contrast to the ''consensus'' effect implied by a random-effect contribution of $0.5(u_i + u_j)$. Even if this were a reasonable representation of the interaction between partners' preferences, the standard errors must be adjusted to avoid double-counting bias (although this is not usually done in practice). The idea of a reinforcement effect, however, is one that seems at odds with the theories of joint decision making discussed above, which focus on bargaining to reach a compromise. The double-counting model implies, for example, that an individual with strong positive tastes for mobility coupled with someone with weak positive tastes is more likely to move when partnered than when single. We refer to this model as the *multiple-membership-double model*, or *MM-double model*, and the model with weights of 0.5 as the *MM-consensus model* (though we note that any multiple-membership model with nonzero weights that sum to 1 also implies a degree of compromise between partners). In the application, we compare the two multiple-membership models with other approaches to assess empirical support for reinforcement and consensus effects within couples.

5. SOME IMPLICATIONS OF MODEL SPECIFICATION

In this section, we consider in further detail the implications of model choice on estimates of the unobserved heterogeneity between individuals and between couples and on estimates of covariate effects that are averaged across individuals and couples with different (time-invariant) unmeasured characteristics. The residual structures of the head-of-household and multiple-membership random-effects models described above differ in the way that autocorrelations are allowed for and, in particular, the relationship between the individual and couple residual variances. In turn, differences in the assumed residual covariance structure affect the population-averaged covariate effects derived from a random-effects model.

5.1. *Comparison of Covariance Structures for Alternative Models*

Table 2 shows, for each of the head-of-household and multiple-membership models, the implied residual variances and covariance for a head-of-household observed at two waves t and t', according to union status at each wave. As noted previously, the HoH-common model forces the between-single and between-couple residual variances to be equal, which is relaxed in the HoH-separate and HoH-joint models through the

Table 2. Residual Variances for Head of Household i Observed at Waves t and t' and Covariance across Waves, by Partnership Status

	Variance at t (and t' if Different)	Covariance between t and t'
Single at t and t'		
HoH-common	σ^2	σ^2
HoH-separate	σ_S^2	σ_S^2
HoH-joint	σ_S^2	σ_S^2
MM-consensus	σ^2	σ^2
MM-double (reinforce)	σ^2	σ^2
Single at t, couple at t'		
HoH-common	σ^2	σ^2
HoH-separate	σ_S^2 (σ_C^2)	0
HoH-joint	σ_S^2 (σ_C^2)	σ_{CS}
MM-consensus	σ^2 ($0.5\sigma^2$)	$0.5\sigma^2$
MM-double (reinforce)	σ^2 ($2\sigma^2$)	σ^2
Couple at t, t' (same partner)		
HoH-common	σ^2	σ^2
HoH-separate	σ_C^2	σ_C^2
HoH-joint	σ_C^2	σ_C^2
MM-consensus	$0.5\sigma^2$	$0.5\sigma^2$
MM-double (reinforce)	$2\sigma^2$	$2\sigma^2$
Couple at t, t' (different partner)		
HoH-common	σ^2	σ^2
HoH-separate	σ_C^2	σ_C^2
HoH-joint	σ_C^2	σ_C^2
MM-consensus	$0.5\sigma^2$	$0.25\sigma^2$
MM-double (reinforce)	$2\sigma^2$	σ^2

Note: HoH = head-of-household; MM = multiple-membership.

inclusion of union-status-specific random effects. In contrast, the residual component of a multiple-membership model is composed entirely of individual-specific random effects: An individual is assumed to carry a set of unmeasured attributes, fixed over time, which are combined with those of their partner's when in a union. The multiple-membership model does not therefore have a separate parameter for the between-couple variance, and the ratio of the between-couple and between-individual variances is determined entirely by the choice of weights.

We now turn to the residual covariances implied by each model. These parameters index the residual covariance between y_{it} and $y_{it'}$ for $t \neq t'$. The second panel of Table 2 shows $\text{cov}(u_i^C, u_i^S)$, the residual covariance for a head of household who is coupled at one wave and single at the other. The HoH-common model assumes $u_i^C = u_i^S$, which implies that the residual covariance is equal to the residual variance (regardless of union status at each wave) and so always positive. The HoH-separate model assumes that the couple-single covariance is zero, while the HoH-joint model includes a separate covariance parameter, σ_{CS}. The multiple-membership residual structure implies that $\text{cov}(u_i^C, u_i^S) = \text{cov}\left(w_i u_i + w_j u_j, u_i\right) = w_i \sigma^2$ (assuming independence of random effects for partners).

For head-of-household models, the residual covariance for an individual coupled at both waves is equal to the between-couple variance, regardless of whether this individual changed partner (panels 3 and 4 of Table 2). Only the multiple-membership models allow the covariance to change with partner; in both models, the covariance for an individual who changes partner is half the covariance for an individual who remains with the same partner.

5.2. *Population-averaged Effects*

Coefficients of the general model (equation 1), and the special cases we consider in this article, have the same subject-specific (or conditional) interpretation as any model with individual-specific random effects (e.g., Neuhaus, Kalbfleisch, and Hauck 1991). For example, the coefficient α of a couple covariate $x_{(ij)t}$ is the effect of a one-unit change in x on the log-odds that couple *ij* moves, conditional on other covariates and on the unmeasured time-invariant characteristics of each partner represented by random effects u_i and u_j. Often, however, the objective is to make inferences about average differences in an outcome between groups, for example between married and cohabiting couples, rather than the effect of a change in marital status on a couple's outcome. For this reason, it is common to present population-averaged (or marginal) effects in analyses of clustered binary data, which can be viewed as the average of subject-specific effects across individuals with different unobserved characteristics. Population-averaged effects can be estimated directly using a generalized estimating equations approach (Liang and Zeger 1986), or they can be derived from subject-specific effects.

Zeger, Liang, and Albert (1988) proposed an approximation for obtaining a population-averaged coefficient α^{PA} from a subject-specific coefficient α^{SS}, namely,

$$\alpha^{PA} \approx \frac{\alpha^{SS}}{\sqrt{1+k^2\sigma_C^2}}, \tag{6}$$

where $k = 16\sqrt{3}/15\pi$, and σ_C^2 is the between-couple variance implied by the model. In the case of the MM-consensus model, for example, $\sigma_C^2 = 0.5\sigma^2$. The same approximation can be used to derive population-averaged effects for single mobility, but with σ_C^2 replaced by the between-individual variance (σ^2 for the multiple-membership model).

Because population-averaged parameters depend on the amount of unobserved heterogeneity in the population, σ^2, it is of particular importance to specify the residual part of the model correctly if marginal effects are the target of inference.

6. SIMULATION STUDY

Before applying the head-of-household and multiple-membership models described in section 4 in an analysis of residential mobility, we use a simulation study to demonstrate the potential impact of failing to allow correctly for the unmeasured preferences of both partners when modeling couple-level outcomes. In this study, we assume that the mechanism through which mobility decisions for couples are determined follows the MM-consensus model. Data are then generated under this model, and the estimates obtained from fitting the five models presented in Table 2 to these data are compared.

To ensure that these simulation results are relevant to the observable features of our application, we simulate patterns of singletons and couples, and of union formation and dissolution, to be comparable with those found in the BHPS. A household panel structure was simulated for 5,000 individuals over 15 waves. Each individual was assigned to one of three broad categories of union history in proportions that mirror the BHPS sample used in the application: (1) single throughout (20 percent), (2) partnered throughout (60 percent), and (3) both single and in a couple (20 percent). For the last two conditions, individuals could have one (80 percent), two (15 percent), or three (5 percent) partners over the observation period, with partners selected at random from within this subset of the population. Individuals' union histories were fixed across replications of the simulation study.

After simulation of union histories, it remains to simulate the mobility among the individuals and couples in these groups. Two time-varying covariates and an individual-specific random effect were generated independently: $x_{1it} \sim N(0, 1)$, $x_{2it} \sim \text{Bernoulli}(0.5)$, and $u_i \sim N(0, 1)$. In waves in which individual i was in a union with individual j, couple versions of the covariates were computed as $x_{1(ij)t} = 0.5(x_{1it} + x_{1jt})$ and $x_{2(ij)t} = \max(x_{2it}, x_{2jt})$. Denoting by p_{it} and $p_{(ij)t}$ the probabilities that individual i and couple ij move between waves t and $t + 1$, binary indicators of a move for singles and couples were then generated from the following equations of a multiple-membership model, according to the union status of individual i at wave t:

$$\text{logit}(p_{it}) = -2 + 0.5x_{1it} - 0.7x_{2it} + u_i \text{ for singles,}$$

$$\text{logit}(p_{(ij)t}) = -2 + 1.2x_{1(ij)t} - 1x_{2(ij)t} + 0.5u_i + 0.5u_j \text{ for couples.}$$

A total of 50 data sets were generated from the above multiple-membership model, and the five models were fitted to each. Table 3 shows the mean of the parameter estimates and estimated standard errors across the 50 replications, together with those of the between-individual and between-couple variances. In both multiple-membership models and the HoH-common model, the between-individual variance σ^2 is freely estimated, and the between-couple variance is implied by the model. Under the true model in this study, we know that the between-individual variance is $\sigma^2 = 1$, which implies a between-couple variance of $0.5\sigma^2 = 0.5$ because each partner contributes equally to the decision to move, and the weights must sum to 1. As expected, these estimates are recovered when the MM-consensus model is fitted to data generated under this model. More interestingly, however, there are substantial differences between estimates of the individual and couple residual variances for the other, incorrectly specified, models, even though each model is correctly specified for singles: It is misspecification of the couple component of the MM-double and HoH-common models that leads to biased estimates of the between-couple and between-individual variances.

Double counting of partners (MM-double) leads to understatement of between-individual heterogeneity if the MM-consensus model is true because partners have identical outcomes. Furthermore, incorrectly

Table 3. Results from Fitting Alternative Random-effects Models to 50 Simulated Data Sets Generated from a Multiple-membership Model

		HoH-common		HoH-separate		HoH-joint		MM-consensus		MM-double	
Variable	True	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Couple equation											
Constant	–2	–2.0512	0.0448	–1.9943	0.0443	–1.9879	0.0442	–2.0007	0.0427	–2.0334	0.0314
x_1	1.2	1.2142	0.0356	1.1917	0.0353	1.1885	0.0353	1.1939	0.0350	1.2096	0.0251
x_2	–1	–1.0099	0.0482	–0.9914	0.0476	–1.0110	0.0475	–0.9919	0.0473	–1.0013	0.0339
Single equation											
Constant	–2	–1.9417	0.0362	–2.0022	0.0404	–2.0025	0.0407	–2.0155	0.0395	–1.9126	0.0343
x_1	0.5	0.4844	0.0222	0.4949	0.0227	0.5022	0.0226	0.4971	0.0227	0.4790	0.0220
x_2	–0.7	–0.6728	0.0440	–0.6875	0.0448	–0.7060	0.0448	–0.6902	0.0447	–0.6656	0.0437
Residual variance											
Between-individual	1	0.7323	0.0433	0.9800	0.0724	1.0046	0.0731	1.0402	0.0617	0.6223	0.0320
Between-couple	0.5	0.7323	0.0433	0.5107	0.0539	0.5289	0.0539	0.5206	0.0308	1.2446	0.0640
Single-couple covariance	0.5	0.7323	0.0433	0	–	0.4810	0.0820	0.5206	0.0308	0.6223	0.0320
Number of variance parameters		1		2		3		1		1	

Note: HoH = head-of-household; MM = multiple-membership. Estimates are the mean effects and standard errors across replications. Coefficients are subject-specific effects.

treating partner observations for the same wave as independent implies that the random-effect contribution for couple *ij* is approximately $u_i + u_j$, which leads to a between-couple variance of $2\sigma^2$. Joint estimation of the couple and single equations and forcing the between-couple and between-individual variances to be equal (HoH-common) leads to an underestimate of σ^2 approximately equal to the mean of the true couple and individual variances. Fitting two separate models for single and couple mobility (HoH-separate) leads to unbiased estimates of both the between-couple and between-individual variances.

The random-coefficient model (HoH-joint) combines the best features of the other head-of-household models: Single and couple equations are estimated jointly with separate between-individual and between-couple variances. The HoH-joint model additionally allows for a nonzero correlation between the couple and single random effects. The data-generating multiple-membership model (MM-consensus) implies that the residual covariance between single and couple mobility is $0.5\sigma^2$ (see Table 2), and we find that the mean estimate of the random-effect covariance σ_{CS} for HoH-joint is close to the expected value of 0.5. Thus, fitting a random coefficients model with bivariate-normal single and couple random effects successfully recaptures the residual structure of the MM-consensus model. However, the HoH-separate model without the additional covariance parameter yields near-unbiased estimates of the residual variances and has almost identical standard errors, so there is no gain in terms of bias or efficiency from fitting the HoH-joint model. Nevertheless, the standard errors for the residual variance estimates are larger for the HoH-separate and HoH-joint models than for the true MM-consensus model, especially for the between-couple variance: Unlike the other models, the multiple-membership model pools information from both partners.

Estimates of covariate effects on couple mobility are approximately unbiased for all models, but there is a suggestion of a slight downward bias in the coefficients for single mobility in the HoH-common and MM-double model, especially in the intercept for MM-double. Although these models are correctly specified for singles, joint estimation with an incorrectly specified couple equation affects estimates of the single equation coefficients.

However, there is a larger impact of model misspecification on population-averaged effects due to the similarity of the subject-specific coefficients combined with the large differences in between-individual and between-couple variances across models. Table 4 shows the mean

Table 4. Mean Population-averaged (PA) Effects Derived from Alternative Random-effects Subject-specific (SS) Models: Results from 50 Simulated Data Sets Generated from a Multiple-membership Model

	True		Mean PA Estimate				
Variable	SS	PA	HoH-common	HoH-separate	HoH-joint	MM-consensus	MM-double
Couple equation							
Constant	–2	–1.847	–1.832	–1.839	–1.828	–1.842	–1.700
x_1	1.2	1.108	1.085	1.099	1.093	1.099	1.011
x_2	–1	–0.923	–0.902	–0.914	–0.930	–0.913	–0.837
Single equation							
Constant	–2	–1.724	–1.734	–1.730	–1.725	–1.729	–1.735
x_1	0.5	0.431	0.433	0.428	0.433	0.426	0.435
x_2	–0.7	–0.603	–0.601	–0.594	–0.608	–0.592	–0.604

Note: HoH = head-of-household; MM = multiple-membership.

marginal effects obtained by applying equation 6 to each of the subject-specific estimates obtained from fitting the five random-effects models of Table 3 to the 50 simulated data sets. Methods that underestimate the amount of residual variation between individuals (HoH-common and MM-double) are expected to produce overestimates of the population-averaged effects for singles, because the adjustment in the denominator of equation 6 is too small. However, in this case, the overestimation in the population-averaged effects for these models is small because it is countered by an underestimation of subject-specific effects for singles (Table 3). Similarly, overestimation of a residual variance will lead to downward bias in the population-averaged effect when the subject-specific effect is unbiased (as in the couple equations for the HoH-common and MM-double models). In contrast, the population-averaged effects for HoH-separate and HoH-joint are close to the true values because estimates of the corresponding residual variances between couples and between individuals are unbiased. As noted earlier, the size of the bias is related to that of the estimates for the between-individual and between-couple variances.

In summary, these simulations have shown that misspecifying the residual structure can lead to biased estimates of the random-effect variances and population-averaged covariate effects but that the impact on the subject-specific covariate estimates is less pronounced. The HH-common and MM-double models, both of which are widely used in the literature, do not account correctly for the autocorrelation structure and so are most affected here; in the latter case, the substantive impact of any bias will be exacerbated unless the standard errors are corrected for underestimation due to double-counting. Both the HH-joint and the HH-separate models perform equally well here: Allowing distinct variances for couples' and individuals' random effects captures the multiple-membership structure; the main advantage of the HH-joint over the HH-separate is that coefficients in the single and couple models can be formally compared. Finally, the MM-consensus model is shown to yield smaller estimated standard errors for the random-part parameters because the assumptions that couples mix independently and that decisions follow a consensus model are true. It should be noted that the scenarios described here are fairly benign, and we would expect the differences between the models to be more pronounced when applied to real data. We discuss differences between the various approaches in our applications in sections 8 and 9.

7. GENERALIZATIONS TO INCLUDE INFORMATION ON DESTINATIONS

The models discussed in previous sections are for a binary indicator of any change in residence between two waves. More generally, we can use information on the destination of the move, either to distinguish between different types of move (e.g., based on distance between origin and destination) or to study how choice of residence is influenced by attributes of competing destinations (e.g., area characteristics). Bruch and Mare (2012) provided a comprehensive review of the use of discrete-choice models in the analysis of individual residential mobility that incorporate data on destinations. In this section, we consider multilevel generalizations of two discrete-choice models for household panel data: the multinomial logit (MNL) model for a nominal mobility response indicating destination type and the conditional logit (CL) model that includes characteristics of potential destinations as covariates.

7.1. *MNL Model Distinguishing Types of Move*

Previous research on residential mobility has distinguished between different types of moves in a number of ways, for example short and long distance (Belot and Ermisch 2009), within or between regions or housing markets (Böheim and Taylor 2002; Sandefur and Scott 1981), urban or rural (Kulu 2005), housing type (Kulu and Vikat 2007), and housing tenure (Ermisch and Di Salvo 1996; Ioannides and Kan 1996; Pickles and Davies 1985). Such questions can be investigated using an MNL model for a categorical response y_{it}, where $y_{it}=r$ if a move of type r occurs ($r=1, \ldots, R$) and $y_{it}=0$ if there is no move between t and $t+1$, and $p_{it}^{(r)} = \Pr(y_{it}=r)$. An MNL extension of the general multilevel model for couple and singleton mobility in equation 1 contrasts the log odds of a move of type r versus no move:

$$\log\left(\frac{p_{it}^{(r)}}{p_{it}^{(0)}}\right) = c_{it}\left\{\mathbf{x}_{(ij)t}\boldsymbol{\alpha}^{\mathrm{C}(r)} + u_{(ij)}^{\mathrm{C}(r)}\right\} + (1-c_{it})\left\{\mathbf{x}_{it}\boldsymbol{\alpha}^{\mathrm{S}(r)} + u_{i}^{\mathrm{S}(r)}\right\}, \ r=1, \ldots, R, \tag{7}$$

where r superscripts on the regression coefficients ($\boldsymbol{\alpha}^{\mathrm{C}(r)}$ and $\boldsymbol{\alpha}^{\mathrm{S}(r)}$) and the couple and individual random effects ($u_{(ij)}^{\mathrm{C}(r)}$ and $u_i^{\mathrm{S}(r)}$) allow covariate effects and unobserved heterogeneity to vary across types of move. As in the binary case, models may differ according to the specification of the random effects. For example, in the multinomial generalization of the HoH-common model of section 4.2, $u_{(ij)}^{C(r)} = u_i^{S(r)} = u_i^{(r)} \sim N(0, \Omega)$ where Ω is an $R \times R$ covariance matrix, and the most general random-coefficient model (HoH-joint) has separate random effects for couples and singletons for each destination type r, leading to $2R$ random effects with a $2R \times 2R$ covariance matrix. A common feature of all models is that nonzero correlation is permitted between random effects for different types of move, which allows for unmeasured time-invariant characteristics that influence the probability of any move. Including random-effect correlations may provide some protection against departures from the ''independence of irrelevant alternatives'' assumption (Ben-Akiva and Lerman 1985), as similarity between response alternatives will be reflected in higher residual correlations. These correlations can be identified only using longitudinal data in which some individuals are observed to make both types of move.

All multilevel binary logit models described in section 4 can be extended to the MNL case, and we illustrate their application to intra- and interregional mobility in section 9.

7.2. *CL Model for Destination Choice*

The MNL model is appropriate when there is a small set of destination types that is fixed across individuals, and interest centers on the effects of individual and household characteristics on the probability of making a particular type of move. The CL model is a variant of the MNL model for situations in which the set of alternatives may be large and may vary across individuals, and the research focus is the effects of destination characteristics on an individual's choice of destination.

To demonstrate the close correspondence between the MNL and CL models, we present each model in terms of the response probabilities. The general form of a discrete-choice model is

$$p_{it}^{(r)} = \frac{\exp\left(\eta_{it}^{(r)}\right)}{\sum_{k=0}^{R} \exp\left(\eta_{it}^{(k)}\right)}, \quad r = 0, \ \ldots, \ R, \tag{8}$$

where $\eta_{it}^{(r)}$ is the linear predictor. For the MNL model of equation 7,

$$\eta_{it}^{(r)} = c_{it}\left\{\mathbf{x}_{(ij)t}\boldsymbol{\alpha}^{C(r)} + u_{(ij)}^{C(r)}\right\} + (1 - c_{it})\left\{\mathbf{x}_{it}\boldsymbol{\alpha}^{S(r)} + u_i^{S(r)}\right\},$$

and we impose the identification constraint that the coefficients and random-effect parameters associated with the reference category $r = 0$ are equal to zero, which implies that $\eta_{it}^{(0)} = 0$.

Now suppose that an individual or couple chooses between $R + 1$ destination areas, including the current area, when considering a move between waves t and $t + 1$. In a CL model, the probability of choosing destination r ($r = 0, 1, \ldots, R$) depends on area characteristics $\mathbf{z}_{(ij)t}^{(r)}$, with values that may vary across time and between individuals or couples (e.g., a measure of the difference in the quality of schools or house prices between the current area and area r at wave t). The linear predictor is thus

$$\eta_{it}^{(r)} = c_{it}\left\{\mathbf{z}_{(ij)t}^{(r)}\boldsymbol{\beta}^{\mathrm{C}} + \mathbf{x}_{(ij)t}\mathbf{z}_{(ij)t}^{(r)}\boldsymbol{\gamma}^{\mathrm{C}} + u_{(ij)}^{\mathrm{C}(r)}\right\} + (1 - c_{it})\left\{\mathbf{z}_{it}^{(r)}\beta^{\mathrm{S}} + \mathbf{x}_{it}\mathbf{z}_{it}^{(r)}\boldsymbol{\gamma}^{\mathrm{S}} + u_{i}^{\mathrm{S}(r)}\right\}, \tag{9}$$

where $\boldsymbol{\beta}^{\mathrm{C}}$ and $\boldsymbol{\beta}^{\mathrm{S}}$ are the coefficients of the destination-specific attributes for couples and singletons, which may interact with couple or individual characteristics $\mathbf{x}$ with coefficients $\boldsymbol{\gamma}^{\mathrm{C}}$ and $\boldsymbol{\gamma}^{\mathrm{S}}$. Bruch and Mare (2012) applied a special case of equation 9 in an analysis of individual mobility among 65 census tracts in Los Angeles County over a two-year period, where area choice depended on its racial composition ($z^{(r)}$) and the interaction between area-level race and a person's own race ($x_i z^{(r)}$). To allow for the fact that many individuals will prefer to remain in their current area of residence rather than move, Bruch and Mare suggested including an indicator variable $D_{it}^{(r)}$, coded 1 if individual i is resident in area r at wave t and 0 otherwise, which may be interacted with destination characteristics to allow for differential judgments when making comparisons with the current area. Alternatively, $\mathbf{z}_{it}^{(r)}$ could be defined as the difference between the characteristics of area r and the current area (where $\mathbf{z}_{it}^{(r)} = 0$ for residents of r at t).

Although there is a close similarity between the CL and MNL models, the inclusion of destination characteristics in the CL model requires the analysis file to be in ''long'' form with $R + 1$ records for each person-wave, one for each potential destination. This can lead to a prohibitively large data file when the choice set is large, especially in a large-scale long-running panel study such as the BHPS. The solution recommended by Bruch and Mare (2012) is to retain the record corresponding to the alternative actually chosen, sample from the records for the other (unselected) alternatives with probability $q^{(r)} \ll 1$, and include $-\log(q^{(r)})$ as an offset term in equation 9. A further consideration in the multilevel CL model is that it will not usually be feasible to estimate between-individual random-effect variances for every area (and covariances between areas), and therefore some restriction on the random effects will be necessary. A possible approach is to fix $u_i^{(r)} = \mu^{(r)} u_i$ where $\mu^{(r)}$ are random-effect loadings, although further simplification may be necessary when R is large (e.g., constraining loadings to be equal for areas in the same region or of similar types).

It is straightforward to combine the MNL and CL models in a hybrid model that includes characteristics of both individuals or couples and destinations in the linear predictor $\eta_{it}^{(r)}$ (Hoffman and Duncan 1988).

7.3. *Further Extensions and Software*

Another natural extension to the multilevel framework is to allow for unmeasured destination characteristics by including destination-specific random effects that are fixed across individuals but possibly time-varying and different for couples and singles. An important issue when considering models for destination choice is that neighboring areas may share unobserved characteristics that affect their attractiveness as places to live. Bhat and Guo (2004) proposed a spatially correlated logit model for residential choice at a cross-section that includes a parameter representing the dissimilarity between adjacent spatial units. An alternative approach is to extend the multilevel model to include destination-specific random effects (as described above) and to allow the probability of moving to destination r to depend not only on the random effect for area r but on a weighted sum of the random effects of areas adjacent to r. Such a model is another form of multiple-membership model in which the weights might be proportional to the distance between area centroids (see Browne et al. 2001 for further discussion of the use of multiple-membership models in spatial analysis).

The binary logit models described in section 4 can be generalized to MNL and CL models, although their multilevel versions are available in a more limited range of software packages. MNL and CL head-of-household models, with hierarchical random effects, can be fitted using SAS PROC NLMIXED (maximum likelihood via numerical quadrature) and MLwiN (MCMC). Multiple-membership MNL and CL models cannot be fitted using maximum likelihood methods and, to the best of our knowledge, can be fitted only using MCMC methods in WinBUGS.

8. APPLICATION 1: ANALYSIS OF ALL RESIDENTIAL MOVES

8.1. *Data and Definitions*

We now apply the modeling approaches considered in the simulation study in an analysis of residential mobility. The data come from the BHPS, which began in 1991 with 10,300 adult (aged 16 years and older) residents in 5,500 households (Institute for Social and Economic Research 2009). These original sample members (OSMs) are followed as they move house and interviewed annually. A person who forms a household with an OSM after 1991 is referred to as a temporary sample member, but these people become permanent sample members only if they have children with OSMs. Like OSMs, permanent sample members are then followed as they move house (with or without their OSMs). Tracking of individuals as they change address and experience changes in household composition means that sample members may be observed as singletons and with multiple partners, which allows us to disentangle individual and couple effects.

Our response variable is an indicator of whether an individual (or couple) moves house between waves t and $t+1$. Moves that coincide with union formation or dissolution are treated as right censored for two reasons. First, we wish to disentangle the processes of union formation and dissolution from the process of residential mobility so that the individual random effects in our statistical model represent, as far as possible, underlying individual mobility preferences. Second, it is unclear in such cases who should contribute to the moving decision and when they should start or cease to influence each other. The timing of union formation is likely to depend on the future partner of the sample member, but the point at which this future partner influences the probability of a move due to formation is unknown. Similarly, although we may assume that a move made together by a couple is the result of a joint decision, we might expect that an individual's decision to move is no longer influenced by the partner's mobility preference once it has been decided to separate. In treating these moves as censored, we are implicitly assuming that, conditional on covariates, formation and dissolution propensities are uncorrelated with mobility preferences; this may be unreasonable if, for example, people with a preference toward stability are less likely to end a union and less likely to move. One way of allowing for such residual correlation would be to model union transitions jointly with mobility. Boyle et al. (2008) adopted this approach in a study of moving and union dissolution among Austrian couples and found that there was no significant residual correlation between mobility and union dissolution.

We use data from waves 2 to 17, which correspond to the period from 1992 to 2008 (wave 1 is omitted because movement is defined only from wave 2 onward). The analysis is further restricted to adults aged 18 to 60 years who are not in full-time education. Contributions from individuals with missing data are included where they were present at two consecutive waves t and $t+1$, because all covariates refer to an individual's status at the start of wave t, and mobility is determined only at the start of wave $t+1$. The final analysis sample contains a total of 11,464 individuals, of whom 20.4 percent were single throughout the observation period, 58.8 percent were always partnered, and 20.8 percent were observed both single and with a partner. In total, there are 20,820 person-year observations for singletons and 31,562 couple-year observations for couples. The proportions who move between consecutive waves t and $t+1$ (excluding moves due to union formation and dissolution) are 0.12 for singles and 0.08 for couples.

A range of individual and couple characteristics were considered as covariates. The following time-varying covariates were included in models of mobility for both singletons and couples: housing tenure, area (London vs. other), the number of rooms per person, age (of the head of the household for couples), postschool education (of both partners for couples), employment status (of both partners for couples), the presence of children, and the age of the youngest child. All time-varying covariates were measured at wave t (i.e., prior to any move before $t+1$). The models additionally included gender for singletons and union type (married or cohabiting) for couples. The predictors also include the duration of residence in the current home at wave t, so the models can be viewed as random-effects discrete-time event history models (e.g., Steele, Goldstein, and Browne 2004).

The analysis was carried out using MLwiN (Rasbash et al. 2009) via Stata's runmlwin command (Leckie and Charlton 2013). Reparameterization methods (orthogonal parameterization and parameter expansion) were used to improve MCMC efficiency (Browne et al. 2009). The runmlwin syntax for fitting the HoH-joint and MM-consensus models can be found in the online Appendix.

8.2. *Comparison of Estimates of Residual Variance and Duration Dependency across Models*

Estimates of the between-individual and between-couple residual variances (implied by the random-effect variance σ^2) are shown in the bottom panel of Table 5. The estimates for the HoH-separate model are very similar to those from the more general HoH-joint model and so are suppressed. With a few exceptions, the pattern of estimates is similar to those obtained in the simulation study (Table 3). Of particular note is the similarity of both the between-individual and between-couple variance estimates for the MM-consensus and HoH-joint models. The true model is unknown here, but the HoH-joint model is the most flexible model, if not the most efficient, because it has additional parameters for the between-couple variance and couple-single covariance. Therefore, the closeness of the two sets of residual variance estimates suggests that the true decision-making model for couples is closer to consensus than it is to reinforcement (as in MM-double), which manifests itself in greater heterogeneity between individuals than couples. Further evidence that unobserved couple mobility preferences are not systematically aligned with the preferences of the head is provided by the relatively low estimate of the single-couple covariance in the HoH-joint model (recall that this covariance captures the association of the head's random effect when single and the couple random effect).

Table 5 also shows estimates of the effect of the duration of residence in the current house at wave t on the log odds of moving between t and $t+1$. As is usual in a discrete-time event history model, some function of duration of residence at t is included as a set of time-varying explanatory variables. In this case, a piecewise-constant baseline hazard is specified by treating duration as a categorical variable with the first year as the reference category, dummies for each of the next 10 annual intervals, and a single dummy for durations exceeding 11 years. Alternative, more parsimonious, specifications of the duration dependency include polynomial or spline functions. For all models, and for both singles and couples, we find that the mobility rate is highest in the first year and then remains fairly constant for subsequent years before dropping sharply after a person or couple has stayed in the same house for 11 years or more (consistent with an ''inertia effect''; McGinnis 1968). However, there are some differences in the strength of the duration effect across models.

Table 5. Estimates of Duration Effects and Residual Variances from Alternative Models of Residential Mobility, British Household Panel Study

Variable	HoH-common		HoH-joint		MM-consensus		MM-double	
	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Couple mobility								
Constant	–1.079	0.132	–1.049	0.130	–1.073	0.130	–1.079	0.095
Years since last move (reference $\leq$ 1)								
(1,2]	–0.560	0.074	–0.560	0.074	–0.561	0.075	–0.592	0.055
(2,3]	–0.629	0.084	–0.639	0.083	–0.633	0.083	–0.643	0.061
(3,4]	–0.570	0.092	–0.589	0.091	–0.577	0.091	–0.587	0.066
(4,5]	–0.508	0.100	–0.534	0.100	–0.515	0.098	–0.473	0.071
(5,6]	–0.537	0.109	–0.566	0.108	–0.547	0.108	–0.502	0.077
(6,7]	–0.434	0.116	–0.469	0.115	–0.445	0.114	–0.445	0.083
(7,8]	–0.456	0.124	–0.500	0.124	–0.469	0.122	–0.504	0.091
(8,9]	–0.688	0.147	–0.731	0.146	–0.703	0.146	–0.606	0.101
(9,10]	–0.691	0.158	–0.737	0.157	–0.708	0.157	–0.738	0.115
(10,11]	–0.516	0.159	–0.568	0.158	–0.536	0.157	–0.538	0.114
$>$11	–1.027	0.104	–1.080	0.105	–1.046	0.100	–1.046	0.076
Single mobility								
Constant	–1.700	0.129	–1.759	0.136	–1.768	0.132	–1.685	0.128
Years since last move (reference $\leq$ 1)								
(1,2]	–0.689	0.068	–0.691	0.068	–0.692	0.069	–0.689	0.067
(2,3]	–0.941	0.085	–0.930	0.085	–0.929	0.085	–0.944	0.085
(3,4]	–0.979	0.099	–0.959	0.101	–0.957	0.100	–0.983	0.099
(4,5]	–1.022	0.115	–0.997	0.118	–0.993	0.116	–1.031	0.114

(continued)

Table 5. (continued)

	HoH-common		HoH-joint		MM-consensus		MM-double	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
(5,6]	–1.173	0.139	–1.141	0.142	–1.136	0.140	–1.181	0.138
(6,7]	–1.262	0.155	–1.233	0.159	–1.223	0.157	–1.272	0.155
(7,8]	–1.034	0.153	–0.999	0.156	–0.991	0.158	–1.044	0.154
(8,9]	–1.249	0.184	–1.212	0.188	–1.204	0.186	–1.260	0.182
(9,10]	–1.127	0.185	–1.087	0.185	–1.082	0.186	–1.137	0.182
(10,11]	–1.403	0.222	–1.366	0.223	–1.354	0.225	–1.409	0.222
>11	–1.429	0.090	–1.390	0.094	–1.383	0.093	–1.438	0.089
Residual variance								
Between-individual	0.143	0.036	0.218	0.059	0.234	0.046	0.119	0.028
Between-couple	0.143[a]	0.036[a]	0.085	0.043	0.117[a]	0.023[a]	0.238[a]	0.056[a]
Single-couple covariance	—	—	0.027	0.053	0.117[a]	0.023[a]	—	—

Note: HoH = head-of-household; MM = multiple-membership. The estimated coefficients and their standard errors are the means and standard deviations of parameter values across 50,000 Markov-chain Monte Carlo samples, after a burn-in of 5,000.

[a]Parameter estimate (standard error) that is implied by the between-individual variance (standard error).

For couples, the magnitude of the estimated coefficient for a given duration is generally largest for the HoH-joint model (especially at longer durations) and smallest for HoH-common, with the estimate for MM-consensus lying in between. Thus, the negative duration effect is strongest for HoH-joint and weakest for HoH-common. This pattern is in line with the estimates of the between-couple variance for these two models (smallest for HoH-joint and largest for HoH-common). It is well known that failure to account for unobserved heterogeneity in duration models leads to overstatement of a negative duration dependency (e.g. Vaupel, Manton, and Stallard 1979). By analogy, it follows that biased estimates of the unobserved heterogeneity will also lead to biased duration effects; in particular, overstatement of unobserved heterogeneity (as seems likely in HoH-common) will lead to an understatement of a negative duration dependency.

Turning to singles, the HoH-joint and MM-consensus models produce similar estimates of the duration dependency (as expected because of the closeness of their between-individual variance estimates). A stronger duration effect is suggested by MM-double, which has a between-individual variance that is almost half that estimated by the HoH-joint and MM-consensus models. The $w_i = w_j = 1$ weighting of partners in the couple component of MM-double therefore leads to an overstatement of the negative duration dependency among singles.

The above differences between models are not sufficiently large to affect substantive conclusions. However, this is unsurprising because of the small amount of unobserved heterogeneity. In other applications with a larger amount of unexplained variation due to time-invariant characteristics, we would expect the differences to be larger.

8.3. *Estimated Covariate Effects*

Tables 6 and 7 show estimates of the (subject-specific) effects of covariates on the log odds of moving house for couples and singles, respectively. The most notable finding is the substantial underestimation of the standard errors for the couple effects (Table 6) using the MM-double model due to double counting partners. In line with the results of the simulation study, estimates of the covariate effects differ little across models for either couples or singles. The few differences that emerge are for couples: Although estimates for models HoH-joint and MM-consensus are almost identical for all covariates, there are some

Table 6. Estimates of Covariate Effects from Alternative Models of Residential Mobility of Couples, British Household Panel Study

	HoH-common		HoH-joint		MM-consensus		MM-double	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Tenure								
Owned-mortgage	0	—	0	—	0	—	0	—
Owned-outright	0.297	0.097	0.291	0.097	0.297	0.096	0.289	0.070
Private rented	1.517	0.067	1.490	0.066	1.506	0.064	1.496	0.048
Social rented	0.235	0.075	0.229	0.074	0.233	0.075	0.245	0.055
Living with parents	1.465	0.193	1.449	0.193	1.466	0.193	1.528	0.150
London residence	–0.017	0.088	–0.017	0.087	–0.015	0.088	–0.032	0.065
Rooms per person	–0.515	0.047	–0.505	0.047	–0.509	0.046	–0.507	0.034
Age, centered at 40 years	–0.028	0.003	–0.027	0.003	–0.028	0.003	–0.027	0.002
(Age, centered at 40 years)^2	–0.0005	0.0002	–0.0005	0.0002	–0.0005	0.0002	–0.0005	0.0002
Number of dependent children								
0	0	—	0	—	0	—	0	—
1	0.252	0.077	0.253	0.076	0.252	0.076	0.254	0.055
≥ 2	–0.284	0.082	–0.273	0.080	–0.280	0.081	–0.255	0.059
Age of youngest child								
Pregnant or <1 year	0	—	0	—	0	—	0	—
1–4 years	–0.439	0.072	–0.433	0.071	–0.433	0.072	–0.440	0.051
5–10 years	–0.629	0.087	–0.622	0.086	–0.622	0.086	–0.639	0.062
11–15 years	–0.750	0.110	–0.738	0.108	–0.741	0.109	–0.827	0.081
16–18 years	–0.892	0.158	–0.870	0.154	–0.875	0.156	–0.920	0.113
19–22 years	–0.811	0.138	–0.798	0.141	–0.800	0.141	–0.847	0.100

(continued)

Table 6. (continued)

Variable	HoH-common		HoH-joint		MM-consensus		MM-double	
	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Cohabiting (vs. married)	–0.041	0.058	–0.049	0.057	–0.042	0.058	–0.024	0.042
Postschool education								
Neither partner	0	—	0	—	0	—	0	—
Man only	0.259	0.072	0.256	0.071	0.256	0.071	0.261	0.052
Woman only	0.317	0.078	0.313	0.077	0.314	0.078	0.298	0.057
Both	0.367	0.071	0.356	0.070	0.360	0.071	0.379	0.051
Employment status								
Both employed	0	—	0	—	0	—	0	—
Only man employed	0.027	0.059	0.028	0.058	0.029	0.060	0.034	0.042
Only woman employed	0.017	0.115	0.015	0.114	0.018	0.113	–0.011	0.082
Neither employed	0.207	0.092	0.208	0.091	0.209	0.091	0.228	0.066

Note: HoH = head-of-household; MM = multiple-membership. The estimated coefficients and their standard errors are the means and standard deviations of parameter values across 50,000 Markov-chain Monte Carlo samples, after a burn-in of 5,000.

Table 7. Estimates of Covariate Effects from Alternative Models of Residential Mobility of Singles, British Household Panel Study

	HoH-common		HoH-joint		MM-consensus		MM-double	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Tenure								
Owned-mortgage	0	—	0	—	0	—	0	—
Owned-outright	–0.032	0.125	–0.033	0.128	–0.027	0.128	–0.034	0.124
Private rented	1.186	0.072	1.205	0.075	1.215	0.074	1.181	0.071
Social rented	0.044	0.089	0.042	0.091	0.050	0.092	0.048	0.089
Living with parents	–0.008	0.085	–0.008	0.089	–0.002	0.087	–0.007	0.085
London residence	0.044	0.077	0.042	0.079	0.043	0.079	0.041	0.075
Rooms per person	–0.020	0.024	–0.021	0.024	–0.021	0.024	–0.019	0.024
Age, centered at 40 years	–0.026	0.003	–0.026	0.003	–0.027	0.003	–0.026	0.003
(Age, centered at 40 years)^2	0.0006	0.0002	0.0006	0.0002	0.0006	0.0002	0.0006	0.0002
Number of dependent children								
0	0	—	0	—	0	—	0	—
1	0.058	0.147	0.064	0.149	0.068	0.148	0.062	0.144
≥ 2	0.091	0.147	0.093	0.149	0.090	0.149	0.090	0.144
Age of youngest child								
Pregnant or <1 year	0	—	0	—	0	—	0	—
1–4 years	–0.170	0.156	–0.169	0.157	–0.175	0.158	–0.170	0.154
5–10 years	–0.125	0.159	–0.125	0.161	–0.131	0.162	–0.129	0.158
11–15 years	–0.320	0.186	–0.325	0.187	–0.324	0.191	–0.318	0.182
16–18 years	–0.142	0.238	–0.149	0.238	–0.153	0.240	–0.144	0.235
19–22 years	–0.103	0.216	–0.117	0.221	–0.114	0.218	–0.111	0.214
Female	0.048	0.055	0.052	0.053	0.056	0.056	0.050	0.054
Postschool education	0.185	0.058	0.193	0.059	0.196	0.059	0.183	0.057
Employed	–0.132	0.063	–0.134	0.064	–0.138	0.064	–0.132	0.063

Note: HoH = head-of-household; MM = multiple-membership. The estimated coefficients and their standard errors are the means and standard deviations of parameter values across 50,000 Markov-chain Monte Carlo samples, after a burn-in of 5,000.

discrepancies between the estimates for MM-double and those for the other methods, for example, in the effects of tenure and the number of children and age of the youngest child. For covariates that are truly exogenous (as in the simulations), misspecification of the model residual structure will not have an impact on coefficient estimates, because the random effects and covariates are uncorrelated. In practice, however, some covariates may share unmeasured influences with mobility, so estimates of these effects may be affected by failure of the random-effects assumption.

Among couples, living in private rented accommodation or with parents is associated with a higher probability of moving (Table 6). The number of rooms per person and the age of the man are both negatively associated with mobility. (The age of the woman was also considered in preliminary analysis but was dropped because of its high correlation with the man's age.) The main effect of having one dependent child (0.253 in HH-joint) is the effect on the log odds of having one child under the age of one year (or in utero) versus no children. The difference between the coefficients for two or more and one child ($-0.273 - 0.253 = -0.526$) is the effect of having two or more versus one child (independent of the age of the youngest child). We find an increased chance of a move during pregnancy and shortly after birth but lower mobility among larger families and a decline in mobility with the age of the youngest child. To investigate whether a couple's decision to move house is more heavily influenced by the observed characteristics of one partner or whether those of both partners play a role, we considered the effects of the education and employment status of both the man and the woman. Although having postschool education is associated with a higher mobility rate, there is little evidence to suggest that one partner's education is more important than the other's. We also find that the employment status of both partners is important with increased mobility for couples with neither partner in employment but no main effects of male and female employment. In light of these findings for measured partner characteristics, we might also expect both partners' *unobserved* characteristics to influence housing decisions, as in the multiple-membership model.

For singles, we again find an increased mobility rate among private renters and individuals with postschool education (Table 7). Age and nonemployment are associated with a decreased chance of moving. The number of rooms per person, the presence and ages of children, and gender are all found to be unrelated to the decision to move.

Certain of our findings are common to virtually all studies of residential mobility. A strong decline in the moving propensity with age and a positive association with educational attainment have been found in studies of mobility in Britain, the United States, the Netherlands, and Austria, among others (Böheim and Taylor 2002; Ioannides and Kan 1996; Kulu 2008; Michielin and Mulder 2008). Clark, Deurloo, and Dieleman (1984) reported that housing size (square meters per person) was the most consistent single (negative) predictor of the propensity to move among households of all tenures in their Dutch study, and the importance of space has been confirmed by others (Böheim and Taylor 2002; Clark and Davies Withers 2007; Clark and Huang 2003). Another key regularity found in many studies is that homeowners are less mobile than renters because, it is often argued, they have greater locational capital and face higher costs of moving (Clark and Huang 2003). Negative duration effects were reported for singles by Belot and Ermisch (2009) and for all households by Böheim and Taylor (2002). Although less studied, our results on the interactions of spouses' employment status are consistent with those of Böheim and Taylor, who showed that the positive effect of male unemployment on household mobility is offset entirely if the spouse is employed. Studies have shown less consistency in the effects of presence and age of children on mobility rates, but those that included births as ''trigger'' events, as we do, have found a sharp increase in moving propensities for couples around the time of conceptions and immediately following birth (e.g., Clark and Davies Withers 2007; Kulu 2008).

9. APPLICATION 2: DISTINGUISHING LOCAL AND MIGRATORY MOVES

We extend the analysis of residual mobility in the BHPS to distinguish between local moves (which did not cross a regional boundary) and migratory moves (interregional moves). Our response variable is now coded 0 for no move between t and $t+1$, 1 for a local move, and 2 for a migratory move. Migratory moves account for 30 percent of all moves in our sample. A small number of individuals ($n = 29$) had to be dropped from the analysis because of missing information on location at either t or $t+1$, leading to an analysis sample of 20,756 person-years for singletons and 31,524 couple-years. Migratory moves were more common for singletons than for couples (33 percent vs. 25 percent of all moves).

Four variants of the general multilevel MNL model of equation 7 were fitted, which differed according to the specification of the random effects. The *HoH-common* model now has two correlated random effects, one for local and one for migratory moves, which allow the residual variance to differ for the two types of move. As in the binary logit version of section 4.2, however, the between-individual and between-couple variances are assumed equal for a given destination type. This restriction is relaxed in the *HoH-separate* model, which has separate destination-specific random effects for couples and singletons; this model allows the residual variance to differ according to both type of move and partnership status, but separate estimation of the single and couple equations means that random effects across partnership states are uncorrelated. In the most general *HoH-joint* model, the single and couple equations are estimated simultaneously, and covariances between every pair of four random effects are estimated. Finally, the *MM-consensus* model has random effects for local and migratory moves (as for the HoH-common model) but with random-effect contributions from both partners for couples. All models included the same set of predictors considered in the analyses of any move of section 8, and these were included in the contrasts for both local and migratory moves with no move.

The models were fitted using MCMC methods, in MLwiN for the head-of-household models and in WinBUGS (Spiegelhalter, Thomas, and Best 2000) for the multiple-membership model. MLwiN is used when possible because it is more computationally efficient, but WinBUGS provides the greater flexibility needed for nonhierarchical multinomial models. The runmlwin and WinBUGS syntax for fitting the multilevel MNL forms of the HoH-joint and MM-consensus models can be found in the online Appendix.

Table 8 shows the parameter estimates and standard errors for the variance and covariance parameters for each of the four models. The most flexible models, HoH-separate and HoH-joint (with 6 and 10 parameters in the random part of the model, respectively), suggest that for local moves, the between-couple variance is about half the between-individual variance. These estimates are consistent with the ''consensus'' decision-making assumption of the multiple-membership model with equal weights, and therefore the residual variance estimates for local moves are similar across the three models. In contrast, the residual

Table 8. Estimates of Residual Variances and Covariances from Alternative Multilevel Multinomial Logit Models of Local and Migratory moves, British Household Panel Study

	HoH-common		HoH-separate		HoH-joint		MM-consensus	
	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Local								
Between-individual	0.020	0.012	0.094	0.057	0.079	0.041	0.091	0.044
Between-couple	0.020[a]	0.012[a]	0.042	0.017	0.031	0.012	0.045[a]	0.022[a]
Single-couple covariance	—	—	—	—	–0.000	0.013	—	—
Migratory								
Between-individual	1.026	0.117	1.052	0.192	1.100	0.166	1.455	0.160
Between-couple	1.026[a]	0.117[a]	1.020	0.163	1.065	0.156	0.727[a]	0.080[a]
Single-couple covariance	—	—	—	—	0.587	0.175	—	—
Local-migratory covariances								
Individual	0.007	0.046	0.059	0.087	0.051	0.065	0.079	0.069
Couple	0.007[a]	0.046[a]	0.034	0.056	0.028	0.045	0.039[a]	0.034[a]
Couple local–individual migratory	—	—	—	—	–0.014	0.053	—	—
Couple migratory–individual local	—	—	—	—	–0.012	0.083	—	—
Number of variance-covariance parameters estimated	3		6		10		3	

Note: HoH = head-of-household; MM = multiple-membership. The estimated coefficients and their standard errors are the means and standard deviations of parameter values across 50,000 Markov-chain Monte Carlo samples, after a burn-in of 5,000.

[a]Parameter estimate (standard error) that is implied by the between-individual variance (standard error).

variance estimate for the most restrictive HoH-common model is lower than for the other models.

Turning to the estimates for migratory moves, there are two main points to note. First, the unobserved heterogeneity is substantially higher than for local moves. Second, the between-individual variance is almost the same as the between-couple variance for both the HoH-separate and HoH-joint models, so the equality constraint in the simpler HoH-common model is reasonable. It is now the MM-consensus model that is out of line with the more flexible models, although the average residual variance estimate across individuals and couples is close to the estimates from the head-of-household models ($0.5[1.455 + 0.727] = 1.091$). These results suggest that the ''consensus'' assumption of equal weights is less appropriate for migratory moves. One possibility is that the smaller between-couple variance from the multiple-membership model indicates nonrandom sorting on unmeasured characteristics associated with the propensity to migrate. A tendency for individuals with similar preferences to partner would lead to a positive correlation between the random effects of partners, leading to underestimation of the between-couple variance in the multiple-membership model (see section 4.3.1). However, the strong (and significant) positive covariance between the head's migratory random effect when single and the combined couple effect from the HoH-joint model provides evidence that the heads' tastes dominate couples' outcomes. This is consistent with a gender perspective and a great deal of the ''tied mover'' literature on family migration that finds asymmetries in the role of husbands' and wives' characteristics (Bielby and Bielby 1992; Mok 2007; Smits et al. 2003). It is notable that the equivalent covariance is essentially zero for local mobility decisions, highlighting that the influence of the head of household in couple decision-making can vary over different issues. This is also consistent with the view taken in much of the mobility literature that decisions on local moves, which are primarily dwelling and family related, are made by a different process than more disruptive migratory moves involving changes in labor markets and social networks (Böheim and Taylor 2002; Helderman, Mulder, and van Ham 2004).

10. DISCUSSION

In this article, we consider the problem of analyzing the outcomes from a couple's decision-making process using individual data on each partner. We highlight that this problem has been little discussed in the literature, and we critique the limitations of how previous approaches handle individuals who change between singleton and couple status and change partners to form a new couple. A general framework is developed that allows comparison of the methods used in previous research with respect to implicit assumptions about how decisions are made within a household. Two new multilevel models are proposed to address the limitations of earlier work: the ''HoH-joint'' and ''MM-consensus'' models. The HoH-joint model specifies distinct but correlated random effects for singletons and couples, while the MM-consensus model is a multiple-membership model that treats a couple as a weighted combination of its individual partners. Both of these approaches allow singletons and couples to be modeled simultaneously, which allows differential covariate effects for singletons and couples to be tested. Moreover, both models allow for residual autocorrelation between couples and singletons involving the same individuals following partnership formation or dissolution. Models for both binary and nominal household decisions are considered.

The HoH-joint model is the most flexible of the approaches we consider because (for binary outcomes) it includes three random-effect parameters, which allow the between-individual and between-couple variances and the single-couple covariance to be freely estimated. The multiple-membership model is conceptually attractive because it treats households as collections of individuals and allows each individual to influence a household decision. Moreover, the MM-consensus model offers potential efficiency gains because it includes just one random effect parameter, and it is the only approach that tracks all individuals (not just household heads) as they move between partners, thereby allowing for correlation between the outcomes of couples who share a partner. However, this model relies on strong assumptions about the relative influence of each partner in reaching a decision, which is reflected in the choice of weights. The MM-consensus model also assumes independence of partners' mobility preferences (conditional on covariates). The simulation study demonstrated that different assumptions about the residual structure of models for household outcomes can lead to substantially different estimates of the between-individual and between-couple variances. We also show that although there was little difference in estimates of subject-specific covariate effects across models, incorrect specification of the residual structure has a greater impact on population-averaged effects derived from random-effects models. In particular, the widely used approach of pooling singletons and couples and constraining the between-individual and between-couple variances to be equal leads to overestimation of the between-couple variance, which leads to understated population-averaged covariate effects for couples. More substantial downward bias was found in population-averaged effects for the couple component of the MM-double model, which treats couples as two independent singletons rather than joint decision makers.

In our first application to residential mobility using a binary indicator of any move, the between-individual and between-couple variance estimates were markedly similar for the HoH-joint and MM-consensus models. Furthermore, the finding that the between-couple variance was approximately half the between-individual variance in the HoH-joint model lends support to the consensus model of decision making with partners, on average, contributing equally to the decision. There were larger differences in estimates of subject-specific covariate effects across models than observed in the simulation study, which might suggest differential effects of model misspecification such as correlation between covariates and the random effects. However, none of the differences were sufficiently large to affect the substantive conclusions. The most striking difference between methods was the underestimation of standard errors for the MM-double model due to fitting the couple model to a person-based rather than couple-based file. There was also little evidence, in this case, that the MM-consensus model was more efficient than the head-of-household models. This is likely to be due to the design of the BHPS: Although OSMs are followed as they change partners and partnership status, many of their partners are in the BHPS only while coresident with the OSMs, which limits the number of individuals who can be observed with more than one partner. Greater efficiency gains would be expected from the multiple-membership model when applied to population data in which more complete information is available on the residential histories of all individuals.

In our extended analysis of mobility that distinguished local and migratory moves, estimates of the residual variances for migratory moves differed between the MM-consensus model and the more flexible HoH-joint model. This suggests that the consensus assumption, with equal weights assigned to each partner's unmeasured mobility preferences, is too strong in the case of interregional moves. Another possible explanation for the divergence between models is that the multiple-membership assumption of independence between partner's random effects is unreasonable. As the validity of these assumptions will not be known a priori, we recommend the HoH-joint model because it is the least restrictive, and, in our simulation study, we see that it captures features of the residual structure if the correct model is MM-consensus. This is achieved through separate random-effect variance parameters for the single and couple populations and a covariance between the single and couple random effects. In theory, the advantage of the MM-consensus model is smaller standard errors through pooling information from individuals regardless of their union status. In practice, however, we did not find these gains to be great, in either our simulation or our empirical examples.

The types of model developed in this article can be applied to a very wide range of housing-related issues. However, they could also be used in the analysis of any decision that is made repeatedly by both singletons and couples throughout the life course. Purchasing decisions are particularly amenable to this type of analysis, such as the choice of savings and investment vehicles with differing degrees of riskiness, to give one example. Whatever approach is adopted, it is important to consider covariates that summarize characteristics of both partners in a couple. For example, in our applications, the education levels and employment of both partners were found to influence residential mobility. Household panel studies provide longitudinal data on both partners and additionally offer a way to extend our understanding of the process under study by incorporating individual unobserved time-invariant traits into the analysis. The residual structure of models of household choices has received little attention, but we find that it is potentially informative about aspects of the household decision-making process.

APPENDIX

For couple ij between waves t and $t+1$, suppose that we specify separate mixed logistic-normal models for y_{it} and y_{jt}. Write these models as

$$\log\left(\frac{p_{kt}}{1-p_{kt}}\right) = \mathbf{x}_{(ij)t}\boldsymbol{\alpha}^* + u_k,$$

for $k = i, j$, where u_i and u_j are independent $N(0, \sigma^2)$ random effects. If the moving probability is small, we can use the approximations

$$p_{kt} \approx \exp\left(\mathbf{x}_{(ij)t}\boldsymbol{\alpha}^* + u_k\right) \text{ and } 1 - p_{kt} \approx 1, \tag{A1}$$

which we take to hold for all waves and for all singletons or couples. On the basis of these models, the conditional likelihood contribution (given the marginal distribution of the random effects) for i and j at t is

$$\left(p_{it}p_{jt}\right)^{y_{(ij)t}}\left((1 - p_{it})(1 - p_{jt})\right)^{1-y_{(ij)t}}$$

because both individuals in the couple have a joint outcome such that $y_{it} = y_{jt} = y_{(ij)t}$.

Under equation A1, it follows that

$$p_{it}p_{jt} \approx \exp\left(\mathbf{x}_{(ij)t}\boldsymbol{\alpha}^C + u_i + u_j\right) = p_{(ij)t},$$

where $\boldsymbol{\alpha}^{\mathrm{C}} = 2\boldsymbol{\alpha}^*$ is an arbitrary reparameterization. Using equation A1 again, it also follows that

$$(1 - p_{it})\left(1 - p_{jt}\right) \approx 1 - p_{it}p_{jt} \approx 1 - \exp\left(\mathbf{x}_{(ij)t}\boldsymbol{\alpha}^C + u_i + u_j\right),$$

because $1 + p_{it}p_{jt} \approx 1 - p_{it}p_{jt}$. Thus, the likelihood contribution is approximately

$$p_{(ij)t}{}^{y_{(ij)t}}\left(1 - p_{(ij)t}\right)^{1-y_{(ij)t}},$$

which is that for a multiple-membership model with $w_{it} = w_{jt} = 1$.

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