Latent variable models for multivariate dyadic data with zero inflation: Analysis of intergenerational exchanges of family support

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Abstract

Understanding the help and support that is exchanged between family members of different generations is of increasing importance, with research questions in sociology and social policy focusing on both predictors of the levels of help given and received, and on reciprocity between them. We propose general latent variable models for analysing such data, when helping tendencies in each direction are measured by multiple binary indicators of specific types of help. The model combines two continuous latent variables, which represent the helping tendencies, with two binary latent class variables which allow for high proportions of responses where no help of any kind is given or received. This defines a multivariate version of a zero inflation model. The main part of the models is estimated using MCMC methods, with a bespoke data augmentation algorithm. We apply the models to analyse exchanges of help between adult individuals and their non-coresident parents, using survey data from the UK Household Longitudinal Study.

Keywords: Item response theory models; Latent class analysis; Mixture models; Non-equivalence of measurement; Two-step estimation

1 Introduction

In this article we propose and apply latent variable models for the joint distribution of variables within a dyad of two interacting units. This is motivated by research questions in sociology and social policy about exchanges of help and support between adult individuals and their non-coresident parents. In all societies such intergenerational transfers have major implications for individual, family, and societal wellbeing (Mason and Lee, 2018). Transfers between adult children and their parents are an important element of intergenerational linkages and a means of providing support to those in need (Künemund et al., 2005), especially in a context of shrinking social services (Pickard, 2015). Increases in life expectancy imply an increase in the volume of help needed by older people with age-related functional limitations. At the same time, there
may be an increased need for assistance in younger age groups as a result of delayed transitions to adulthood, precarious employment, and increasingly diverse and complex family life courses (Lesthaeghe, 2014; Henretta et al., 2018). Analysis of the factors associated with exchanges of support between generations is important in order to anticipate which population sub-groups may be at risk from lack of support in the future, either because of an increased unmet need for help or a reduced capacity to provide help among potential donors.

We consider two broad research questions on such intergenerational support: what characteristics of individuals and their parents are associated with different levels of help given and received between them, and what is the extent and nature of reciprocity of exchanges (i.e. to what extent do children with a high tendency to provide help to parents also have a high or low tendency to receive help). Previous research suggests that reciprocity, either contemporaneous or over the life course, is an important motivating factor in intergenerational exchanges of support (e.g. Grundy 2005; Silverstein et al. 2002). For example, studies that have analysed contemporaneous reciprocity have found a positive association between the provision of support to parents and the receipt of support by their adult offspring in the U.S. (Cheng et al. 2015) and Britain (Grundy 2005; Steele and Grundy 2021), and studies that have examined reciprocity across the life course have found that a higher level of parental support during childhood is associated with an increased propensity to help parents in later life (e.g. Silverstein et al. 2002). Another reason for considering the extent to which child-parent exchanges are balanced is that being unable to reciprocate support may have negative consequences for the mental health and wellbeing of older people (e.g. Davey and Eggebeen 1998).

Research on intergenerational support is framed by theoretical perspectives from sociology, social psychology and economics (see e.g. the discussions in Silverstein et al. 2002, Grundy 2005 and Kalmijn 2014, and references therein). A prominent distinction is between explanations which focus on altruism and ones which focus on considerations of the costs and benefits of giving support, although these motivations do not need to be mutually exclusive. The theories in turn inform considerations of possible explanatory variables for levels of support. Many of these variables can be seen as instances of two broad kinds of factors: capacity (financial and time resources) of the provider of help, and the needs of the recipient (Fingerman et al., 2015). A wide range of such predictors have been examined for exchanges of support between generations in different contexts (see the studies cited in this section, and references therein).

Our goal is to improve the methodology of analysing such questions. We consider the case of Britain, using cross-sectional survey data from the Family Network module of the UK Household Longitudinal Study (UKHLS). These data are described in Section 2. They include sixteen questions (‘items’) about exchanges of help within the dyad defined by a survey respondent and their non-coresident parent or parents. Eight of the items indicate whether or not the respondent gives each of eight specific types of help to the parents (for example, helping them with housework), and eight indicate types of help that they may receive from the parents. These items are regarded as measures of two latent variables, which we interpret as the general tendencies to give and to receive help. We thus have ‘doubly multivariate’ data, with two sets of observed binary items measuring two latent variables. The substantive research questions correspond to questions about the joint distribution of the latent variables, on their means and on the association between them.

The analysis of this situation should be handled with an appropriate form of latent variable modelling. Further, the data have two peculiar features which should be allowed for. First,
they display a multivariate form of zero inflation, where the proportion of respondents who give a zero response to all eight items for a latent variable (i.e. no help of any kind given, or none received) is larger than can be accounted for by basic models. Second, the signal value of specific types of help may be different for different types of respondents, especially for men and women (because of gendered patterns of helping) or for people who live at longer or shorter distances from their parents (because of different practicalities of different kinds of help). This can be seen as an instance of non-equivalence of measurement in the items.

We propose a general latent variable modelling framework for the analysis of such doubly multivariate data on dyads. Its starting point is a conventional model for two continuous latent variables given covariates, measured by binary items. Non-equivalence of measurement is represented by letting the measurement component of the model depend on some covariates. Zero inflation is allowed for by supplementing the bivariate continuous latent variable with a bivariate latent class variable which accounts for the excess of all-zero responses in one or both of the sets of items. This specification combines and extends several modelling elements, and draws on the corresponding literatures (we discuss this further in Section 3.2, after the models have been defined in Section 3.1). Beyond the analysis of exchanges of help within families, the models could also be applied to comparable dyadic data elsewhere, such as in applications in family psychology and organisational behaviour, when variables of interest for the dyads are latent variables measured with multiple indicators.

We contribute to the literature on intergenerational exchanges of support by addressing two major methodological limitations of previous research: the measurement of support given or received, and estimation of reciprocity of exchanges. Most previous studies using data similar to those collected in UKHLS have reduced the multivariate data on different types of exchange in a given direction to a single binary variable indicating whether any support was given or received. Another approach has been to analyse the sum score of the items using linear regression (e.g. Cheng et al. (2015)), which implicitly assigns equal weight to each item and ignores zero inflation. It is common to focus on one direction of exchange only, for example just support given to elderly parents (e.g. Silverstein et al. (2002)), or to analyse the receipt and provision of support separately. The disadvantage of both approaches is that they preclude investigation of reciprocity of exchanges, the importance of which has been widely acknowledged. Among the few studies that have investigated reciprocity, one approach has been to treat helping tendencies as categorical, by using first latent class analysis to identify a typology of exchanges and then modelling class membership using multinomial regression (Hogan et al. (1993); Chan (2008)), and another has been to treat them asymmetrically, by including the receipt of support as a predictor of provision of support, and vice versa (Grundy (2005); Cheng et al. (2015)). A recent study by Steele and Grundy (2021) models bidirectional exchanges between adult children and their parents jointly, interpreting the residual correlation as a measure of reciprocity, but it treats support given and received as univariate binary responses.

We estimate the models using a two-step approach where the parameters of the measurement model for the items given the latent variables are estimated first, and their values are then held fixed in the second step where the structural model for the latent variables is estimated. The second step is carried out using Markov Chain Monte Carlo (MCMC) methods. Because doing this with general MCMC packages was very slow (mainly because of the combination of continuous and categorical latent variables in the models), the estimation was implemented using a tailored algorithm written for these models. It has a convenient data augmentation structure which alternates between sampling the latent variables given the model parameters.
and the observed data, and sampling the parameters given the observed and latent data. These
methods of estimation are described in Section 4 with details of the MCMC algorithm given
in Appendix A.

Our analysis of intergenerational exchanges of help is then described in Section 5. The results
show a number of clear regularities in how the levels of help are associated with different aspects
of the individuals’ and their parents’ need for help and capacity to give help. Helping tenden-
cies in the two directions are positively correlated, conditional on the explanatory variables,
suggesting a substantial amount of reciprocity in helpfulness between the generations.

2 Data on exchanges of help between generations

We use data from the UK Household Longitudinal Study (UKHLS), also known as ‘Under-
standing Society’ [University of Essex et al. 2018; see Knees 2018 for more information on the
study). This is a longitudinal survey of the members of approximately 40,000 households (at
Wave 1 of UKHLS) drawn from the residential population living in private households in the
United Kingdom. UKHLS started in 2009, but it also subsumes the smaller British Household
Panel Survey (BHPS) which began in 1991.

Information on exchanges of help with parents living outside a respondent’s household was
collected in the Family Network module which was administered in 2001, 06, 11/12, 13/14, and
15/16 (BHSP Waves 11 and 16 and UKHLS Waves 3, 5, and 7). We carry out cross-sectional
analysis which uses only the last of these, Wave 7 (with the exception that the development
and estimation of the measurement models was done using pooled data across all five waves;
this is explained separately in Section 5.1). In this module, respondents with at least one
non-coresident parent were asked whether they ‘nowadays’ gave ‘regularly or frequently’ the
following eight types of help to their parent(s), each with a yes–no response: ‘giving them
lifts in your car (if you have one)’ [referred to as lifts below], ‘shopping for them’ (shopping),
‘providing or cooking meals’ (meals), ‘helping with basic personal needs like dressing, eating
or bathing’ (personal care), ‘washing, ironing or cleaning’ (housework), ‘dealing with personal
affairs e.g. paying bills, writing letters’ (personal affairs), ‘decorating, gardening or house
repairs’ (diy), and ‘financial help’ (financial). The same questions were asked about receipt
of support from the parents, but with the personal care item replaced by ‘looking after your
children’ (childcare).

Although respondents were asked to report on giving parents a lift in their car if they had
one, the recorded variable had only ‘yes’ or ‘no’ responses. We therefore used other survey
information to set this item to missing for respondents who did not have access to a car.
Similarly, the childcare item was coded as missing for respondents who did not have dependent
children aged 16 or under. For the item on receiving lifts from parents, we do not have
information on whether the parents have access to a car, so responses of ‘no’ to this item will
include also cases where they do not.

These family network data have several limitations, which are shared by other large-scale
studies of intergenerational exchanges. First, for practical reasons, data on exchanges with
non-coresident relatives were collected only from the perspective of the survey respondent, in
our case the child. As noted by Chan and Ermisch (2015), studies with matched pair data which
are collected from both non-coresident parents and children in the same family are rare and tend to be for small selective samples. For UKHLS this means that we have rich data on children, but much less information on their parents. Child responses may also suffer from reporting bias, for example over-reporting of help given and under-reporting of help received. Second, respondents were asked to report on exchanges with both parents collectively, even when both are surviving and non-coresident with the respondent, so it is not possible to distinguish between exchanges with the mother and with the father, even when they are living apart. Where a respondent had both biological and step/adoptive parents alive, the recorded responses refer to the ones that the respondent had most contact with.

A set of covariates was considered to capture factors that may be associated with help given or received between individuals and their parents. They are gender, age, partnership status and employment status of the respondent, the presence and age of children in their family, age of the oldest non-coresident parent, whether any parent lived alone, and the travel time between the respondent and the parent living closest.

The sample was first restricted to the 19,052 respondents in UKHLS Wave 7 who were aged 16 or over and who had at least one non-coresident parent but no coresident parent. Respondents living with a parent were mainly younger respondents who had not left the parental home; they were excluded because their exchanges with their non-coresident parent are likely to differ from those of respondents who do not live with either parent. Also excluded were respondents whose closest parent lived or worked abroad (n=2590) and those with missing data on any covariate or on all of the help items (n=1589). This gives our main analysis sample of 14,873 respondents. Most of the omissions from missing data (1226 cases) were due to the indicator of whether either parent lived alone, while nonresponse on the other covariates and the help items was much rarer.

The percentages of respondents in the analysis sample who reported giving and receiving each type of help are shown in Table 1 and descriptive statistics and coding for the covariates in Table 2. We note that less than half of the respondents report giving (43.3%) or receiving (40.0%) even one of these kinds of help. This large proportion of all-No responses is a feature that we will want allow for in modelling these data. The specification and estimation of the models is described in Sections 3 and 4. We will then return to the analysis of the data in Section 5.
Table 1: Percentage of respondents giving help to their non-coresident parents and receiving help from the parents, by item.

| Item                                      | Help given to parents | Help received from parents |
|-------------------------------------------|-----------------------|---------------------------|
| Lifts in car (lifts)                      | 29.2                  | 11.2                      |
| Shopping (shopping)                       | 20.7                  | 8.0                       |
| Providing or cooking meals (meals)        | 12.3                  | 13.9                      |
| Basic personal needs (personal care)      | 3.6                   | –                         |
| Looking after children (childcare)        | –                     | 40.3                      |
| Washing, ironing or clearing (housework)  | 7.7                   | 5.6                       |
| Personal affairs (personal affairs)       | 16.9                  | 2.3                       |
| Decorating, gardening or house repairs (diy) | 17.9               | 8.3                       |
| Financial help (financial)                | 6.3                   | 13.0                      |
| At least one of the eight kinds of help:  | 43.3                  | 40.0                      |

Data from UKHLS, Wave 7. Valid percentages, excluding cases with missing data. The sample sizes are $n = 14,866$ for items on help to parents, and $n = 14,867$ for help from parents. Of these, the lifts item is missing for the 19.0% of respondents who have no access to a car, and childcare is missing for the 52.3% who have no coresident dependent children.
Table 2: Descriptive statistics for the covariates used in the analysis (n=14,873).

| Variable                              | n   | Percent |
|---------------------------------------|-----|---------|
| **Respondent (child) characteristics**|     |         |
| Age (years)                           |     |         |
| Mean=42.7 SD=11.4                     |     |         |
| Gender                                |     |         |
| Female                                | 8570| 57.6    |
| Male                                  | 6303| 42.4    |
| Partnership status                    |     |         |
| Partnered                             | 11,354| 76.3   |
| Single                                | 3519 | 23.7    |
| Employment status                     |     |         |
| Employed                              | 11,527| 77.5   |
| Unemployed                            | 590 | 4.0     |
| Economically inactive                 | 2756| 18.5    |
| Age of youngest child                 |     |         |
| No children                           | 6022| 40.5    |
| 0 – 1 years                           | 1273| 8.6     |
| 2 – 4 years                           | 1696| 11.4    |
| 5 – 10 years                          | 2306| 15.5    |
| 11 – 16 years                         | 1724| 11.6    |
| > 16 years                            | 1852| 12.5    |
| **Parent characteristics**            |     |         |
| Age of oldest parent (years)          | Mean=71.1 SD=11.3 |
| At least one parent lives alone       |     |         |
| Yes                                   | 5626| 37.8    |
| No                                    | 9247| 62.2    |
| **Child-parent characteristics**      |     |         |
| Travel time to nearest parent         |     |         |
| 1 hour or less                        | 10,771| 72.4   |
| More than 1 hour                      | 4102 | 27.6    |
3 Latent variable models for dyadic data

Here we define, in Section 3.1, the latent variable models that we propose for analysing dyadic data like those introduced in Section 2. In Section 3.2 we discuss how different elements of this specification draw on previous literature. For ease of exposition the dyads and variables are mostly introduced with reference to their meaning in the application to intergenerational help, but we note that the models are also applicable to any data with a similar structure.

3.1 Model specification

Consider data on variables \((X_i, Y_{Gi}, Y_{Ri})\) for a sample of \(n\) dyads \(i = 1, \ldots, n\), where \(X_i\) is a \(q \times 1\) vector of covariates and \(Y_{Gi} = (Y_{G1i}, \ldots, Y_{Gpi})'\) and \(Y_{Ri} = (Y_{R1i}, \ldots, Y_{Rpri})'\) are two vectors of binary indicator variables (items). In our application, a dyad is composed of an individual (survey respondent) and their non-coresident parents, and the items are the questions on the \(p_G = p_R = 8\) specific types of help the respondent gives to the parents \((Y_{Gi})\) or receives from the parents \((Y_{Ri})\). Each item is coded 1 if that kind of help is given or received, and 0 if it is not. We treat \(Y_{Gi}\) as multiple indicators of a latent variable \(\eta_{Gi}\) which describes an individual’s tendency to give help to their parents, and \(Y_{Ri}\) as indicators of another latent variable \(\eta_{Ri}\) which describes the parents’ tendency to give help to the individual. We take \(\eta_{Gi}\) and \(\eta_{Ri}\) to be continuous variables. The goal is to estimate their joint distribution and how it depends on the covariates.

Our data contain a substantial number of respondents for whom all of the items in \(Y_{Gi}\) or \(Y_{Ri}\) are 0 (see Table 1). The frequencies of such all-zero response patterns are higher than what would be expected under standard models with continuous latent variables. To allow for this, we introduce for each of the two sets of items a second, binary latent variable. It defines two latent classes, denoted by 0 and 1, where class 0 accounts for the excess zeros. For help to parents, this latent class variable is denoted \(\xi_{Gi}\). The measurement model for how \(Y_{Gi}\) measures the latent variables is then specified by

\[
\begin{align*}
p(Y_{Gi} = 0 | \xi_{Gi} = 0, X_i) &= 1 \quad \text{and} \quad (1) \\
p(Y_{Gi} | \xi_{Gi} = 1, \eta_{Gi}, X_i; \phi_G) &= p_1(Y_{Gi} | \eta_{Gi}, X_i; \phi_G) = \prod_{j} p_1(Y_{Gji} | \eta_{Gi}, Z_i; \phi_G) \quad (2)
\end{align*}
\]

where \(p(\cdot | \cdot)\) denotes a conditional distribution, \(p_1(\cdot | \cdot)\) indicates that a distribution is also conditional on \(\xi_{Gi} = 1\), \(Z_i\) are a subset of \(X_i\), and \(\phi_G\) are parameters. In other words, when \(\xi_{Gi} = 0\), a respondent is certain to answer ‘No’ to all the items in \(Y_{Gi}\). When \(\xi_{Gi} = 1\), the probabilities of the responses depend on the latent helping tendency \(\eta_{Gi}\) and covariates \(Z_i\), and the different items \(Y_{Gji}\) are taken to be conditionally independent of each other; this is a conventional latent variable model for the binary items, with the extension that the measurement may be non-equivalent with respect to some covariates \(Z_i\). Together, (1) and (2) define a zero-inflation model where the class \(\xi_{Gi} = 0\) allows for that part of the probabilities of \(Y_{Gi} = 0\) which are not accounted for by the distribution of \(\eta_{Gi}\) and the measurement model given \(\eta_{Gi}\).

The measurement model for \(Y_{Ri}\) given \((\xi_{Ri}, \eta_{Ri}, Z_i)\) is defined similarly, with parameters \(\phi_R\). We assume that \(Y_{Gi}\) do not depend on \((\xi_{Ri}, \eta_{Ri})\), \(Y_{Ri}\) do not depend on \((\xi_{Gi}, \eta_{Gi})\), and \(Y_{Gi}\) and \(Y_{Ri}\) are conditionally independent of each other, and define \(\phi = (\phi_G, \phi_R)\). Some of the
items in $Y_{Gi}$ and/or $Y_{Ri}$ may be missing, in which case the products over $j$ in (2) and the corresponding model for $Y_{Ri}$ are over only those items which are observed for that respondent. This implies that these missing data are assumed to be missing at random. We assume here that there are no missing data in the covariates $X_i$.

The model for the latent variables given the explanatory variables is specified by the distributions $p(\xi_{Gi} = j, \xi_{Ri} = k | X_i; \psi_\xi) \equiv \pi_{jk}(X_i; \psi_\xi)$ and $p(\eta_{Gi}, \eta_{Ri} | X_i; \psi_\eta)$, where $\psi = (\psi_\xi, \psi_\eta)$ are parameters, and $(\eta_{Gi}, \eta_{Ri})$ and $(\xi_{Gi}, \xi_{Ri})$ are taken to be independent of each other given $X_i$. We refer to this as the \textit{structural model} for the latent variables. It will be the focus of interest for substantive research questions about help between individuals and their parents.

Let $Y = (Y_G, Y_R)$ denote all of the observed data on $Y_i = (Y_{Gi}, Y_{Ri})$, and $X$ all the $X_i$. Define $G_i = 1$ if $Y_{Gi} \neq 0$ and $G_i = 0$ if $Y_{Gi} = 0$, and define $R_i$ similarly for $Y_{Ri}$. If we take the observations $i$ to be independent, the log-likelihood for the model is

$$
\log p(Y | X; \phi, \psi) = \sum_{i=1}^{n} \log \left[ \pi_{11}(X_i; \psi_\xi) \int \int p_1(Y_{Gi} | \eta_{Gi}, Z_i; \phi_G) p_1(Y_{Ri} | \eta_{Ri}, Z_i; \phi_R) p(\eta_{Gi}, \eta_{Ri} | X_i; \psi_\eta) \ d\eta_{Gi} d\eta_{Ri} 
\right.
\left. + (1 - R_i) \pi_{10}(X_i; \psi_\xi) \int p_1(Y_{Gi} | \eta_{Gi}, Z_i; \phi_G) p(\eta_{Gi} | X_i; \psi_\eta) \ d\eta_{Gi} 
\right.
\left. + (1 - G_i) \pi_{01}(X_i; \psi_\xi) \int p_1(Y_{Ri} | \eta_{Ri}, Z_i; \phi_R) p(\eta_{Ri} | X_i; \psi_\eta) \ d\eta_{Ri} 
\right.
\left. + (1 - G_i)(1 - R_i) \pi_{00}(X_i; \psi_\xi) \right].
$$

(3)

We further specify the structural model for each $i = 1, \ldots, n$ as

$$
p(\eta_{Gi}, \eta_{Ri} | X_i; \psi_\eta) \sim N \left( \begin{bmatrix} \beta_G' X_i \\ \beta_R' X_i \end{bmatrix}, \begin{bmatrix} \sigma_G^2 & \sigma_{GR} \\ \sigma_{GR} & \sigma_R^2 \end{bmatrix} \right)
$$

and

$$
\log \left[ \frac{\pi_{jk}(X_i; \psi_\xi)}{\pi_{00}(X_i; \psi_\xi)} \right] = \gamma_{jk}' X_i
$$

(4)

(5)

for $j, k = 0, 1$ with $\gamma_{00} = 0$, i.e. as a bivariate normal linear model for $(\eta_{Gi}, \eta_{Ri})$ and a multinomial logistic model for $(\xi_{Gi}, \xi_{Ri})$. Thus here $\psi_\eta$ includes $(\beta_G, \beta_R, \sigma_G^2, \sigma_R^2, \rho_{GR})$ in (4), and $\psi_\xi$ includes $(\gamma_{01}, \gamma_{10}, \gamma_{11})$ in (5). Finally, the measurement models given the continuous latent variables are specified as

$$
\logit[p_1(Y_{Gji} = 1 | \eta_{Gi}, Z_i; \phi_G)] = \tau_{Gj} + \delta'_{Gj} Z_i + (\lambda_{Gj} + \zeta_{Gj}' Z_i) \eta_{Gi}
$$

(6)

for $j = 1, \ldots, p_G$, so that $\phi_G$ consists of all the $\tau$, $\delta$, $\lambda$ and $\zeta$ parameters for $Y_{Gi}$, and the models for the items in $Y_{Ri}$ are specified similarly, with parameters $\phi_R$. The baseline parameters of these models are the intercepts (the $\tau$s) and the loadings of the latent $\eta$ variables (the $\lambda$s). These are then further modified by the covariates if any of the $\delta$ or $\zeta$ parameters are non-zero, in which case the measurement model for that item is non-equivalent with respect to the corresponding variables in $Z_i$. For simplicity, we consider only models where any non-equivalence in an item affects both the intercept and the loading, so that for that item the elements of $\delta$ and $\zeta$ corresponding to the same variable in $Z_i$ are either both zero or both non-zero. The motivation and choice of $Z_i$ in our application are discussed in Section 5.1.
3.2 Previous literature on the elements of the models

The model specified in Section 3.1 combines several existing modelling elements, and draws on the corresponding literatures. The starting point is the conventional general framework for latent variable modelling with covariates (see e.g. Skrandal and Rabe-Hesketh [2004] and Bartholomew et al. [2011]). If \((\eta_R, \eta_R)\) were the only latent variables, this would be a standard model for the joint distribution of two continuous latent variables given covariates \(X\). When, as here, all the measures \(Y\) of the latent variables are binary and the measurement models for them are logistic models, this is a common instance of what is known, especially in psychometrics and educational testing, as Item Response Theory (IRT) modelling (see e.g. de Ayala [2009] and van der Linden [2016]).

Including covariates \(Z\) in a measurement model, as we do in (1), allows the measurement of a latent variable to be non-equivalent with respect to these covariates. This is also a standard approach in applications where such non-equivalence may be of concern, such as cross-national survey research and other ‘multigroup’ situations, as well as many applications of IRT, where non-equivalence of measurement is commonly known as differential item functioning (DIF). For overviews of these ideas and methods, see Kankaraš et al. [2011] and Millsap (2011).

The least familiar element of the model is the way we allow for the large number of all-zero responses by adding the latent class variables \((\xi_R, \xi_R)\). To motivate this, consider first models for a single non-negative variable \(Y\) with excess zeros, meaning that the observed probability \(P(Y = 0)\) is greater than can be expected under an assumed distribution \(p(Y)\) for \(Y\). There are, broadly, three ways of representing this situation, depending on how many of the zero values are taken to be accounted for by \(p(Y)\): (1) all of them—censoring models where it is assumed that \(Y\) could actually be negative but that all such values are recorded as 0, so that \(P(Y = 0) = p(Y \leq 0)\); (2) none of them—hurdle models where we model separately \(P(Y = 0)\) and \(p(Y|Y > 0)\); or (3) some of them—zero-inflated models where \(P(Y = 0) = \pi + (1 - \pi)p(Y = 0)\) with an additional probability parameter \(\pi\) for the proportion of zeros which is not accounted for by \(p(Y)\) (see e.g. Tobin [1958], Cragg [1971], Mullahy [1986], Lambert [1992], and Min and Agresti [2005] for introductions and comparisons of these possibilities).

We are interested in latent-variable models for multivariate items. Denote for the moment a generic continuous latent variable by \(\eta\), and its indicators by \(Y\), omitting covariates, so that the model is specified by \(p(Y|\eta)p(\eta)\), and suppose that the observed proportion of \(Y = 0\) is so high that we want to allow for it specially. Here the basic model is in effect already a censoring model, in that estimates of its parameters will be determined so that they accommodate these zeros. This, however, can distort the parameters in a way which leaves the model as a whole badly specified to account for the non-zero patterns of responses (see Wall et al. [2015] for a discussion of the biases which can arise when a latent-variable model is poorly specified in this way). A hurdle model is also unappealing here, because it would involve conditioning on the observed items \(Y\). This leads us to consider zero-inflated models, extended to multivariate \(Y\).

These models can be seen as an instance of finite mixture models. The general form of them is here \(\sum_g p_g(Y|\eta)p_g(\eta)\pi_g\), where \(\pi_g = P(\xi = g)\) are probabilities of a latent-class variable \(\xi\). One type of such models is obtained when \(p_g(Y|\eta) = p(Y|\eta)\), i.e. when the measurement model is the same in every class \(g\). Then the model becomes \(p(Y|\eta)p^*(\eta)\) where \(p^*(\eta) = \sum_g p_g(\eta)\pi_g\) is a finite mixture distribution. This provides a way of specifying the basic latent variable
model with a more flexible distribution for $\eta$ than is possible with a single parametric (for example normal) distribution. Mixture modelling with this purpose is discussed by Wall et al. (2012) and Wall et al. (2015). Here, in contrast, we particularly need models where the measurement models do depend on the class. This represents a situation where the latent classes correspond to individuals with different response styles, i.e. different relationships between the latent variable $\eta$ and its measures $\mathbf{Y}$. This idea has been used in various contexts of measurement, especially in applications of psychological and educational testing; see Wall et al. (2015), Huang (2016), and references therein.

A zero-inflation model for multivariate $\mathbf{Y}$ involves two response styles: one where $\mathbf{Y} = \mathbf{0}$ always, and one where $\mathbf{Y}$ follows an IRT model given $\eta$. This has been proposed for models where the items are binary (Muthen and Asparouhov 2006; Finkelman et al. 2011; Wall et al. 2015), ordinal (Magnus and Liu 2017) or count variables (Magnus and Thissen 2017), sometimes with extensions such as separate classes for all-0 and all-1 response patterns or more than one class for general response patterns. Our model is similar to the previous ones for binary items (although different versions use ostensibly different but equivalent specifications for $\eta$ in the all-zero class for $\xi$). To accommodate the dyadic data, however, we have extended them to include two latent variables ($\eta_G$ and $\eta_R$), with separate zero-inflation classes for each of them.

4 Estimation of the models

4.1 Two-step estimation

We employ a two-step approach to estimate these models. What this means is that the measurement model is first selected and estimated separately, and its parameters $\mathbf{\phi}$ are then fixed at their estimated values for all subsequent exploration and estimation of the structural model. These two steps for our models are described separately in Sections 4.2 and 4.3 below.

This idea of two-step estimation of latent variable models goes back to Burt (1976, 1973), and the theory and application of it have been developed more recently by Xue and Bandeen-Roche (2002) and Bakk and Kuha (2018). Our motivation for using it here is twofold. First, it substantially reduces the computational demands compared to the ‘one-step’ method of estimating all parts of the models together. This is beneficial here, where the estimation of even the structural model on its own is demanding. Second, and as importantly, the two-step approach means that the measurement models — and thus the exact definition of the latent variables — remain fixed in subsequent analyses, and do not change when the specification of the structural model is changed, for example when covariates are added or removed. In our work, this extends also to other analyses of intergenerational exchanges of family support outside this paper, where we also want to keep the definitions of the latent variables fixed in this sense.
4.2 Estimation of the measurement models

In the first step of the estimation, the measurement models for $Y_G$ and $Y_R$ are estimated separately and conditional on $Z$ alone. This means that for $Y_G$ we consider the log likelihood

$$
\log p(Y_G|Z; \phi_G, \psi_G^*) = \sum_{i=1}^{n} \log \left[ \pi_G(Z_i; \psi_{G\xi}^*) \int p_1(Y_{Gi}|\eta_{Gi}, Z_i; \phi_G) p(\eta_{Gi}|Z_i; \psi_{G\eta}^*) d\eta_{Gi} \right] + (1 - G_i) \left( 1 - \pi_G(Z_i; \psi_{G\xi}^*) \right)
$$

where $p_1(Y_{Gi}|\eta_{Gi}, Z_i; \phi_G)$ is as before. The structural model here consists of $\pi_G(Z_i; \psi_{G\xi}^*) = P(\xi_i = 1|Z_i; \psi_{G\xi}^*)$ and $p(\eta_{Gi}|Z_i; \psi_{G\eta}^*)$, specified as a binary logistic and a normal linear model, and $\psi_G^* = (\psi_{G\xi}^*, \psi_{G\eta}^*)$ are the parameters of these models. Here (7) is obtained by integrating (3) over $p(Y_R, X_*|Z)$, where $X_*$ denotes the variables in $X$ but not in $Z$. This is actually only approximately true, because if (4)–(5) holds given $X$, then the structural models given $Z$ only are generally not exactly of binary logistic and normal linear form. We ignore this small approximation and maximize (7) to estimate $\phi_G$. The parameters $\phi_R$ are estimated similarly from a model like (7) for $Y_R$. Denote these estimates by $\hat{\phi} = (\hat{\phi}_G, \hat{\phi}_R)$. The estimates of $\psi_G^*$ and $\psi_R^*$ from this step are discarded.

4.3 Estimation of the structural models

In the second step of estimation, the structural models are then estimated, treating the estimated measurement parameters $\hat{\phi}$ from the first step as known numbers. In other words, the log-likelihood for the second step is (3) but in the form $\log p(Y|X; \hat{\phi}, \psi)$ where only $\psi$ are unknown parameters. We omit below the fixed $\hat{\phi}$ from the notation for simplicity. We further write $\zeta = (\xi, \eta)$, where $\xi$ denotes all the values of the latent $(\xi_{Gi}, \xi_{Ri})$ for the dyads $i$ in the sample, and $\eta$ all the values of $(\eta_{Gi}, \eta_{Ri})$.

In our analyses, this step was carried out in the Bayesian framework and using MCMC methods of estimation. The estimation algorithm has a data augmentation structure, which alternates between sampling the latent variables and sampling the model parameters:

- **Imputation step**: Given the observed data $(Y, X)$ and the most recently sampled value of the parameters $\psi$, sample a value for the latent variables $\zeta$ from the conditional distribution

  $$
  p(\zeta|Y, X, \psi) \propto p(Y|\zeta, X) p(\zeta|X; \psi).
  $$

  This is further split into sampling $\xi$ from $p(\xi|\eta, Y, X, \psi)$, using $\eta$ from the previous iteration, and then $\eta$ from $p(\eta|\xi, Y, X, \psi)$.

- **Posterior step**: Given the observed data $(Y, X)$ and the most recently sampled value of the latent variables $\zeta$, sample a value for the parameters $\psi$ from the conditional distribution

  $$
  p(\psi|Y, X, \zeta) = p(\psi|X, \zeta) \propto p(\zeta|X; \psi) p(\psi)
  $$

  where $p(\psi) = p(\psi_\xi)p(\psi_\eta)$ is the prior distribution of the parameters, taking $\psi_\xi$ and $\psi_\eta$ to be independent a priori. The conditional distribution then further splits into

  $$
  p(\psi|X, \zeta) = p(\psi_\xi|X, \xi) p(\psi_\eta|X, \eta) \propto [p(\xi|X, \psi_\xi) p(\psi_\xi)] [p(\eta|X, \psi_\eta) p(\psi_\eta)].
  $$
which can be sampled separately and in parallel for $\psi_\xi$ and $\psi_\eta$. This does not depend on the measurement items $\mathbf{Y}$, because they are not in the ‘Markov blanket’ of $\psi$ (in the directed acyclic graph for the model, $\mathbf{Y}$ are not parents, children or co-parents of children of $\psi$). The posterior step thus involves sampling the parameters of two regression models given $\mathbf{X}$, a multinomial logistic model for $\xi$ and a bivariate linear model for $\eta$, exactly as if from their posterior distributions if the most recently imputed values of $\xi$ and $\eta$ were real observed data.

We note that since the measurement models are fixed, the structural model is straightforwardly identified here. In particular, ‘label switching’, where the numbering of the latent classes changes between MCMC iterations, cannot occur.

The details of these steps are described in Appendix A. We wrote bespoke code to implement them, because the implementation using general MCMC packages was slow; this was mainly due to the sampling of the categorical latent variables $\xi$.

5 Analysis of intergenerational exchanges of help

5.1 Measurement models

We use measurement models which are non-equivalent with respect to two covariates $\mathbf{Z}$: the gender of the respondent, and the distance between where the respondent and their parents live. It is substantively to be expected, and empirically confirmed in these data, that the patterns of what kinds of help a person gives and receives may vary by these covariates. Some types of help are strongly gendered among the generations considered here, with men and women expressing their helpfulness in different ways and receiving different kinds of help from their parents. Similarly, for obvious practical reasons a longer distance between the parties may affect some types of help more than others. This being the case, the expected levels and patterns of different kinds of help may be different between men and women and between respondents at different distances from their parents, even for individuals who actually have a similar latent tendency to give or receive help. The non-equivalent measurement models allow for this possibility. We thus define $\mathbf{Z}_i = (Z_{gi}, Z_{di})$, where $Z_{gi}$ is an indicator variable for a female respondent and $Z_{di}$ an indicator for a respondent who lives at a distance of an hour or more’s travel time from their parents.

The measurement models were estimated using more of the UKHLS data than are used for the second step of estimation discussed in Section 5.2 below. This was because these models were intended for use in multiple analyses of the data from the Family Networks module, and were developed prior to the analysis described here. The models were first explored for data from the 2001 Wave 11 of BHPS, to identify items for which non-equivalence with respect to gender and/or distance was substantial enough that it should be allowed for. This selection was done using a combination of likelihood ratio tests and the AIC and BIC statistics. The selected models were then re-estimated using pooled data from all the five available waves of UKHLS/BHPS, to maximize the amount of data which contributed to these estimates (longitudinal observations for a respondent in these pooled data are not independent; ignoring this, however, affects only the standard errors of the parameter estimates, which are not needed
Figure 1: Item response curves for the item \textit{diy} (decorating, gardening or house repairs) for help that respondents give to their parents, for probability of giving help conditional on the latent variable $\eta_G$ (tendency to give help), separately for the combinations of gender of the respondent and distance between respondent and their parents. The dotted vertical line is approximate mean of $\eta_G$.

The selected measurement models include some non-equivalence in most items, especially with respect to distance. Of the items on help to parents ($Y_G$), \textit{financial}, \textit{lifts} and \textit{diy} are non-equivalent with respect to gender, and all but \textit{personal affairs}, \textit{personal care} and \textit{financial help} with respect to distance. Of the items on help from parents ($Y_R$), \textit{financial} and \textit{meals} are non-equivalent with respect to gender, and all but \textit{personal affairs} and \textit{financial} with respect to distance. The intercept and loading parameters of \textit{personal care}, which was fully equivalent for both $\eta_G$ and $\eta_R$, were fixed at 0 and 1 respectively in both measurement models, to fix the measurement scales of the two latent variables. For each of $\eta_G$ and $\eta_R$ at least two items which measure them are equivalent with respect to gender, and at least two with respect to distance. This means that the structural models for ($\eta_G, \eta_R$) given gender and distance are also identified, separately from the measurement models. However, information that is available for estimating these associations is clearly reduced, especially for distance, when the non-equivalent measurement models account for much of the observed association between distance and the items $Y_G$ and $Y_R$. The associations between other variables in $X$ and ($\eta_G, \eta_R$) in the structural model are then conditional on gender and distance in this sense, i.e. they refer to the latent variables as they are defined by these measurement models with this adjustment for non-equivalence.
An illustrative example of the estimated measurement model is shown in Figure 1, for the DIY item (decorating, gardening or house repairs) on help given to the parents. The model for this item is non-equivalent with respect to both covariates. The plot shows the estimated probabilities of giving such help as a function of the latent tendency of helpfulness \( \eta \), separately for each combination of gender and distance. Considering the genders, it can be seen that, at the same level of this tendency, men are more likely to give this kind of help. The non-equivalence with respect to distance shows most clearly in the loading (or ‘discrimination’) parameters. These are larger — and the probability curves thus steeper — when a respondent lives further away from their parents, so that giving such help is a more discriminating signal of helpfulness for such respondents than for those who live near their parents.

5.2 Models for help between respondents and their parents

Fixing the parameters of the measurement models at their estimated values from Section 5.1, we then estimated the structural models which are our focus of interest. The MCMC algorithm described in Section 4.3 and the Appendix was run for two MCMC chains of 110,000 iterations each, from different starting values. Discarding the first 10,000 iterations of each, conventional convergence diagnostics indicated that the chains had converged. The two chains were then combined, so the estimates below are based on 200,000 draws from the posterior distributions of the parameters.

The estimated parameters of the bivariate linear model for the continuous latent variables \((\eta_G, \eta_R)\) are shown in Table 3. The coefficients of the multinomial logistic model for the categorical latent variables \((\xi_G, \xi_R)\) are less convenient for interpretation, because they express comparisons of the probabilities in the joint distribution of the variables, relative to the case \((\xi_G, \xi_R) = (0,0)\). Instead, in Table 4 we summarise this model with a focus on the marginal distributions of \(\xi_G\) and \(\xi_R\), using comparisons of fitted probabilities. We first calculated the probabilities \(p(\xi_G = j, \xi_R = k | X_i; \psi_\xi)\) for \(j, k = 0,1\) given selected covariate values \(X_i\) for each of the \(n = 14,873\) respondents \(i\) and for each of the 200,000 MCMC draws of the parameters \(\psi_\xi\). Table 4 shows these fitted probabilities, averaged over both respondents and parameter draws. It also shows the odd ratios between \(\xi_G\) and \(\xi_R\) calculated from these averages, as well as the average marginal probabilities \(p(\xi_G = 1)\) and \(p(\xi_R = 1)\) that a respondent belongs to the class 1 where they may give and receive help respectively. Different choices are considered for the \(n\) values of \(X_i\). In the first row of the table, these are the actual values for the respondents in the observed sample. On the other rows, one covariate in turn is fixed at a single value for every respondent, while the other covariates are left at their sample values. For example, the second row of the table shows the results for a hypothetical sample where every respondent is aged 35. For cases with different fixed values of the same covariate, the table also shows the differences of the marginal probabilities between them, and posterior standard deviations of these differences over the parameter draws.

As discussed in Section 3, we interpret \((\eta_G, \eta_R)\) as continuous latent tendencies to give and to receive help. Although \(\xi_G\) and of \(\xi_R\) were introduced primarily to account for zero inflation, on the face of it they can also be interpreted in terms of binary helping tendencies, with class 0 of each being the class of firm ‘non-givers’ or ‘non-receivers’ of help. In this sense we can interpret both higher conditional means of \(\eta_G\) and \(\eta_R\), and higher conditional probabilities of class 1 of \(\xi_G\) and of \(\xi_R\), as indications of higher levels of helpfulness of the respondent to the parents.
or vice versa; here we refer to both of these as ‘positive associations’ between a covariate and helpfulness. We note first that the average marginal probability of class 0 is here 0.27 for $\xi_G$ and 0.32 for $\xi_R$. Each of these accounts for about half of the proportions of all-zero responses to the corresponding items (which were 0.57 and 0.60 respectively, as shown in Table [1]).

Considering first the models for help given by respondents to the parents, covariates which are strongly and positively associated with it in the linear model for $\eta_G$ are higher age of the oldest parent, at least one parent living alone, and the respondent being single or not employed. Respondents who have no young children at home (i.e. have no children, or only older children) also tend to help more, although this association is less clear. In the model for $\xi_G$, significant positive associations are also found for age of oldest parent and a parent living alone, and additionally for younger age of the respondent. Considering then help received from parents, characteristics which are positively associated with it in the model for $\eta_R$ are the parents not living alone and the respondent being younger, single, not employed or having no children at home. Similar associations are seen in the model for $\xi_R$ for younger and single respondents, and, in addition, there is a negative association between help from parents and the respondent having only older children at home.

For help received from parents, associations with $\eta_R$ and $\xi_R$ are in different directions for employment status and for having no children at home. Respondents who are unemployed or economically inactive, rather than employed, are more likely to be in the no-help-received class $\xi_R = 0$ but, if they are not in this class, the level of help they do receive ($\eta_R$) tends to be higher. Similarly, respondents with no children at home have higher probability of $\xi_R = 0$, but otherwise tend to receive more help. These diverging findings for the categorical and continuous parts of the model are intriguing, but we hesitate to offer firm substantive interpretations for them.

In the discussion above, we omitted comments about associations involving gender of the respondent and the distance between them and the nearest parent. As discussed in Section [4.2], the interpretation for these covariates is somewhat different because they are also included in the measurement models for the non-equivalent items in $Y_G$ and $Y_R$. This means, in effect, that the estimated associations for gender and distance in Tables [3] and [4] are informed only by those items which are equivalent with respect to them. Even so, these associations are strong for $\eta_G$ and $\eta_R$, with women tending to both give and to receive more help than men, and the level of help in both directions being lower when children and parents live far apart.

How, then, should we summarise these results? One way to do so is to think of the covariates as different instances of two broad categories of characteristics: an actor’s (the child’s or the parents’) capacity to give help, and the other actor’s need to receive help. Considering the models for help to parents in this light, there is a clear positive association between the parents’ need and help given: older parents and ones who live alone tend to receive more help from their children. In terms of the children’s capacity to help, the respondent characteristics which are positively associated with helping (being single and not having young children at home) can perhaps be interpreted in these terms, if we take ‘capacity’ to mean ‘opportunity’ in the sense of having fewer other commitments. Conversely, in the models for help received by the respondents, the negative association of helpfulness with the parent(s) living alone perhaps reflects their reduced capacity to help, while the positive associations with the child being younger, single or not employed may be interpreted as instances of higher need by the child. We also observe a reduction of helping behaviour for respondents who live with a partner
and/or have young children at home. Other things being equal, such respondents are less likely both to give help to their non-coresident parents and to receive help from them. We might perhaps think of this situation as one of a self-contained family unit whose support activities may be more likely to be directed within the family rather than outside of it.

The models also give estimates of the associations between the levels of help in the two directions, allowing us to examine reciprocity of support between children and their parents. Here these estimated associations are strong. For the categorical part of the model, the odds ratios between $\xi_G$ and $\xi_R$ (which depend on the covariates) are typically between 5 and 10. For the continuous part, the conditional correlation between $\eta_G$ and $\eta_R$ is 0.50. This is in fact substantially higher than their marginal correlation, estimated from a model without covariates (not shown here), which is 0.23. This difference is mainly due to the age variables. The ages of the respondent and their oldest parent are strongly associated, with a sample correlation of 0.87. If we include either one of them alone in the models, the conditional correlation between $\eta_G$ and $\eta_R$ is already about 0.50, and the age variable has a strong positive association with help given and a negative one with help received (the models where both are included, as in Tables 3 and 4 further indicate, more specifically, that older respondents tend to receive less help, and older parents tend to receive more help). The two age effects thus naturally pull in different directions, so that the marginal correlation of help given and received is somewhat suppressed. If, however, we condition on the ages, i.e. account for the different levels of help we would expect on average from children and parents of given ages, the correlation between them is substantially higher. In this sense, the results suggest a high level of reciprocity in helpfulness between the generations.

6 Conclusions

In this paper we have developed methods for analysing intergenerational help and support that is exchanged between individuals and their non-coresident parents. This involved specifying latent variable models for data where the help given and received are measured by multiple items for different types of help. The models include a multivariate zero inflation component to allow for the fact that a large proportion of people in our data gave or received no help of any kind. Estimation of the models was done in a two-step fashion, where the measurement model for the help items given latent helping tendencies was estimated and fixed first, before the structural model for the joint distribution of these latent variables given explanatory variables was then estimated. The estimation of the structural model was carried out using an MCMC algorithm implemented specifically for these models.

We analysed data from the UK Household Longitudinal Study, where the respondents (the children in the parent-child dyads) are aged around 40 on average, and their parents around 70. The results of the analysis indicated some strong predictors of helping, which may be interpreted in terms of the capacities and needs of the two parties. The levels of help given by the parents and by the children were positively correlated, suggesting substantial cross-sectional reciprocity of help between the generations. The survey data that we have used is extensive and rich in many respects, but it also has some limitations. In particular, because only one member of the dyad — here the children — were interviewed, the data on their parents is limited. It
would be preferable to survey both parties directly, but this data collection design is difficult to implement on a large scale.

The model proposed here is immediately applicable also to other applications with the same structure, that is ‘doubly multivariate’ data with two sets of observed binary items measuring two latent variables. For example, it could be used to analyse attitudes among couples, when the interest was also on the concordance between the partners. Further, the model could be extended in different ways, both for this and for other applications. This would involve, in essence, combining the kinds of structural models that would be used in each situation if the variables of interest were directly observed with the kinds of measurement models considered here when they are latent rather than observed. For example, data where the dyads are grouped in natural clusters could be accommodated in this way by including random effects (higher-order latent variables) to allow for within-cluster associations. An important instance of this is longitudinal data on dyads, which will be needed for questions about levels and reciprocity of intergenerational help over time. Models for longitudinal data can also be specified in other ways; for example, Steele and Grundy (2021) consider a dynamic (autoregressive) panel model that allows for unequal spacing between the measurements, but simplifying the analysis in another way by reducing giving and receiving help each to a binary variable.

Another straightforward extension of the model is obtained by allowing multiple latent variables for each member of the dyad, each measured by their own multiple indicators. This would be needed, for example, if we wanted to consider forms of financial and practical help separately from each other. It is also possible for the same individuals to appear in multiple dyads. For some such cases the structural model would be an obvious extension of the models considered in this paper, for example if we analysed data where survey respondents were asked about help that they exchanged with their children as well as with their parents. In more complex situations, such as for ‘round-robin’ data where each individual is paired with more than one other individual, the models should include further role-specific latent variables for ‘actors’ and ‘partners’ (or ‘givers’ and ‘receivers’), as well as group (e.g. family) effects. This would define multivariate extensions of different versions of the Social Relations Model (Kenny and LaVoi, 1984; Snijders and Kenny, 1999). Gin et al. (2020) have recently proposed latent-variable formulations for such situations, and our measurement models would add to them the element of zero inflation. These combinations remain to be explored in future research.

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Table 3: Estimated parameters of the linear models for the tendency to give help to \((\eta_G)\) and to receive help from \((\eta_R)\) individuals’ non-co-resident parents, from the estimated model for data from Wave 7 of the UK Household Longitudinal Study described in Section 5.2. The estimates are posterior means from MCMC samples (with posterior standard deviations in parentheses).

|                                      | Help to parents | Help from parents |
|--------------------------------------|-----------------|-------------------|
| **Coefficients of explanatory variables (\(\hat{\beta}_G\) and \(\hat{\beta}_R\)):** |                 |                   |
| Intercept                            | −2.31*** (0.08) | −4.14*** (0.09)   |
| **Respondent (child) characteristics** |                 |                   |
| Age \((\times 10 \text{ years})\)     | 0.04 (0.04)     | −0.55*** (0.06)   |
| Gender                               |                 |                   |
| Female \(\text{ (vs. Male)}\)        | 0.88*** (0.05)  | 0.72*** (0.06)    |
| Partnership status                   |                 |                   |
| Partnered \(\text{ (vs. Single)}\)   | −0.25*** (0.06) | −0.68*** (0.07)   |
| Employment status \(\text{ (vs. Employed)}\) |       |                   |
| Unemployed                           | 0.33*** (0.13)  | 0.47*** (0.14)    |
| Economically inactive                 | 0.42*** (0.06)  | 0.25*** (0.08)    |
| Age of youngest child in the respondent’s own household \(\text{ (vs. 0–1 years)}\): |       |                   |
| No children                          | 0.20* (0.10)    | 0.21** (0.10)     |
| 0–1 years                            | 0               | 0                 |
| 2–4 years                            | −0.01 (0.12)    | −0.00 (0.10)      |
| 5–10 years                           | 0.21* (0.11)    | 0.04 (0.10)       |
| 11–16 years                          | 0.16 (0.12)     | 0.12 (0.13)       |
| > 16 years                           | 0.21* (0.12)    | −0.12 (0.15)      |
| **Parent characteristics**           |                 |                   |
| Age of oldest parent \(\times 10 \text{ years}\) | 0.32*** (0.04) | 0.04 (0.05)       |
| At least one parent lives alone \(\text{ (vs. No)}\) | 0.56*** (0.05) | −0.32*** (0.06)  |
| **Child-parent characteristics**     |                 |                   |
| Travel time to nearest parent        |                 |                   |
| More than 1 hour \(\text{ (vs. 1 hour or less)}\) | −1.05*** (0.08) | −0.46*** (0.09) |
| **Residual variances \(\hat{\sigma}^2_G\) and \(\hat{\sigma}^2_R\):** | 2.13*** (0.09)  | 2.43*** (0.11)    |
| **Residual correlation \(\hat{\rho}_{GR}\):** | 0.50*** (0.02)  |                   |

The posterior credible interval excludes zero at level 90% (*), 95% (**) or 99% (**).
Table 4: Fitted probabilities of the zero-inflation latent classes ($\xi_G, \xi_R$), from the estimated model described in Section 5.2, averaged over parameter values in MCMC samples and over covariate values $X_i$ in the sample of dyads $i$ of a respondent and their parent(s), and odds ratios (OR) calculated from these averages. On the first row the values of $X_i$ are all as in the observed data, while on the other rows one covariate is set to the same value for every dyad as indicated, while the rest keep their sample values. The last six columns show the average marginal probabilities of classes $\xi_G = 1$ and $\xi_R = 1$ (those who may give or receive help), their differences between different covariate settings, and standard deviations of these differences across the MCMC samples.

| Covariate setting | $p(\xi_G = j, \xi_R = k)$ | OR | Marginal probabilities with difference (and its SD) |
|-------------------|---------------------------|----|-----------------------------------------------|
| Sample            | .17 .10 .15 .59 .71 .73 | .68 |
| **Respondent (child) characteristics** |
| **Age**           |                           |    |                                               |
| 35 years          | .13 .11 .10 .66 .80 .76   | .77 |
| 45 years          | .22 .09 .13 .56 10.4 .69 -0.08*** (.01) .65 -0.12*** (.02) |
| **Gender**        |                           |    |                                               |
| Male              | .19 .06 .14 .61 14.6 .75   | .67 |
| Female            | .16 .12 .15 .55 4.7 .72 -0.03* (.02) .69 +0.02 (.02) |
| **Partnership status** |
| Single            | .15 .11 .09 .65 9.3 .74   | .76 |
| Partnered         | .18 .09 .16 .57 6.7 .73 -0.01 (.02) .66 -0.10*** (.02) |
| **Employment status** |
| Employed          | .16 .10 .14 .60 6.7 .73   | .70 |
| Unemployed        | .20 .06 .20 .54 8.6 .74 +0.00 (.04) .61 -0.09*** (.04) |
| Inactive          | .22 .07 .17 .54 9.7 .71 -0.03 (.02) .61 -0.09*** (.02) |
| **Age of youngest child in the respondent’s own household** |
| No children       | .20 .07 .14 .58 11.9 .73 -0.02 (.03) .65 -0.12*** (.04) |
| 0–1 years         | .12 .13 .11 .64 5.1 .75   | .77 |
| 2–4 years         | .11 .13 .10 .66 5.3 .76 +0.01 (.04) .79 +0.02 (.04) |
| 5–10 years        | .14 .14 .12 .59 4.7 .72 -0.04 (.03) .74 -0.04 (.04) |
| 11–16 years       | .22 .08 .20 .50 7.4 .70 -0.05 (.04) .58 -0.20*** (.04) |
| > 16 years        | .19 .07 .14 .60 11.1 .74 -0.01 (.04) .67 -0.10** (.05) |
| **Parent characteristics** |
| **Age of oldest parent** |
| 70 years          | .22 .10 .07 .61 20.0 .67 | .71 |
| 80 years          | .12 .11 .17 .60 4.0 .77 +0.10*** (.01) .70 -0.01 (.02) |
| **At least one parent lives alone** |
| No                | .20 .12 .12 .56 7.6 .68   | .68 |
| Yes               | .13 .05 .17 .64 9.6 .81 +0.13*** (.02) .69 +0.01 (.02) |
| **Child–parent characteristics** |
| **Travel time to nearest parent** |
| 1 hour or less    | .15 .12 .17 .57 4.3 .74   | .69 |
| > 1 hour          | .23 .04 .09 .63 37.9 .72 -0.02 (.04) .67 -0.01 (.03) |

The posterior credible interval excludes zero at level 90% (*), 95% (**) or 99% (***).
A Appendix: Details of the MCMC algorithm

Here we describe the details of the tailored MCMC sampling algorithm for the estimation of the structural model parameters $\psi$ which was outlined in Section 4.3. The algorithm has been packed into an R package [R Core Team 2020] which will be available open source on an author’s GitHub page. The main part of the algorithm was programmed in C++, where two techniques are used to speed up the sampling procedure. First, for sampling steps with non-standard distributions, adaptive rejection sampling (Gilks and Wild 1992) is used, exploiting log-concavity of the posterior density functions. This is used for two of the four main steps of the algorithm, for sampling $\phi$, and (some of) $\eta$, while the other two (sampling $\psi$ and $\xi$) can be done very efficiently from standard distributions. Second, parallel sampling techniques, spread out across multiple processors, are used within each MCMC iteration when there is no dependence between the quantities being sampled. This can be done when sampling the latent variables $\zeta$ for different units $i$, and also when sampling the two subsets of structural parameters $\phi$ and $\psi$, separately from each other. This parallelisation is implemented through OpenMP C++ API [Dagum and Menon 1998].

Let $\zeta = (\zeta^{(t)}, \eta^{(t)})$ and $\psi = (\psi^{(t)}, \psi^{(t)}_\eta)$ denote the values of the latent variables and the structural parameters sampled in iteration $t = 0, 1, 2, \ldots$, where 0 denotes the initial values. Given $\zeta^{(t-1)}$, $\psi^{(t-1)}$ and the observed data $(Y, X)$, the values for the next iteration $t$ are sampled as follows:

**Imputation step:** Generating values for the latent variables $\zeta$, given the observed data and current values of the parameters $\psi$:

1. Sampling $\xi^{(t)}$ from $p(\xi | \eta^{(t-1)}, Y, X, \psi^{(t-1)})$: Draw $\xi^{(t)}_i = (\xi^{(t)}_{Gi}, \xi^{(t)}_{Ri})$ independently for $i = 1, \ldots, n$, from multinomial distributions with probabilities

$$p(\xi_G = j, \xi_R = k | \eta^{(t-1)}_i, Y_i, X_i, \psi^{(t-1)})$$

$$\propto p(Y_{Gi} | \xi_G = j, \eta^{(t-1)}_Gi, X_i; \phi_G) p(Y_{Ri} | \xi_R = k, \eta^{(t-1)}_Ri, X_i; \phi_R) p(\xi_G = j, \xi_R = k | X_i; \psi^{(t-1)}_\xi)$$

for $j, k = 0, 1$, where the structural model for $\xi$ is specified by (5), the measurement model is specified as in (10–12) for $Y_{Gi}$ and similarly for $Y_{Ri}$, and the parameters of the measurement models are fixed at their estimated values $\hat{\phi}_G$ and $\hat{\phi}_R$ from the first step of the two-step estimation (as described in Section 4.2) throughout. Note that here the probabilities which involve $\xi_G = 0$ are zero when $Y_{Gi} \neq 0$, and the ones which involve $\xi_R = 0$ are zero when $Y_{Ri} \neq 0$. Conversely, when $Y_{Gi}$ and/or $Y_{Gi}$ is 0, the imputation assigns such a unit $i$ either to the corresponding zero-inflation class 0 or to class 1 for the duration of iteration $t$.

2. Sampling $\eta^{(t)}$ from $p(\eta | \xi^{(t)}, Y, X, \psi^{(t-1)})$: Draw $\eta_i^{(t)} = (\eta^{(t)}_{Gi}, \eta^{(t)}_{Ri})$ independently for $i = 1, \ldots, n$, as follows. First, draw $\eta_i^{(t)}_{Gi}$ from

$$p(\eta_G | \eta^{(t-1)}_{Ri}, \xi_i^{(t)}, Y, X, \psi^{(t-1)}) \propto p(Y_{Gi} | \xi^{(t)}_{Gi}, \eta_G, \phi_G) p(\eta_G | \eta^{(t-1)}_{Ri}, X_i; \psi^{(t-1)}_\eta)$$

and then $\eta_i^{(t)}_{Ri}$ from

$$p(\eta_R | \eta^{(t)}_{Gi}, \xi_i^{(t)}, Y, X, \psi^{(t-1)}) \propto p(Y_{Ri} | \xi^{(t)}_{Ri}, \eta_R, \phi_R) p(\eta_R | \eta^{(t)}_{Gi}, X_i; \psi^{(t-1)}_\eta)$$
where the conditional distributions for η_G and η_R on the right-hand sides are the univariate normal distributions implied by (4). When ζ_G(t) = 0, in which case always Y_Gi = 0, the probability for Y_Gi in (A2) is 1 by (4), and ζ_G(t) is generated directly from this normal distribution, whereas adaptive rejection sampling is used when ζ_G(t) = 1; the procedure for ζ_Ri(t) is analogous, depending on whether or not Y_Ri is 0.

**Posterior step:** Drawing values for the model parameters ψ from their distributions given the observed data and current imputed values of the latent variables ζ. These are standard posterior distributions of the parameters of regression models for ζ given X, the bivariate linear model (4) for η and the multinomial logistic model (5) for ζ. These do not depend on each other, so these sampling steps can be carried out in either order or in parallel.

(3) Sampling ψ from its posterior distribution p(ψ|X, η(t)) ∝ p(η(t)|X; ψ) p(ψ). These parameters are handled in two blocks, β = (β′_G, β′_R)′ = vec(B) where B = [β_G β_R], and (γ^2_G, γ^2_R, q_G R) which define the conditional covariance matrix in (4), which we denote Σ_η. Here we define the notation specifically as X = [X_1 ... X_n]′, η_G = (η_G1, ..., η_Gn), η_R = (η_R1, ..., η_Rn)′ and η = [η_G η_R]. The bivariate linear model (4) can then be written as vec(η) ∼ N(vec(XB), Σ_η ⊗ I_n), where I_n denotes the n × n identity matrix.

We specify the prior distribution as p(ψ) = p(β)p(Σ_η), where p(β) ∼ N(0, σ^2_β I_{2q}) with σ^2_β = 100, and p(Σ_η) ∼ W^{-1}(I_2, 2), an inverse Wishart prior for Σ_η. This is a ‘semi-conjugate’ prior for ψ_η, meaning that conditional on Σ_η, the posterior distribution of β is also multivariate normal, and conditional on β the posterior of Σ_η is inverse Wishart. Specifically, β(t) is then sampled from the distribution

\[
p(β; η(t), X, Σ_{η(t-1)}) ∼ N(μ_β(t), V_β(t))
\]  

(A4) where

\[
V_β(t) = \left( I_{2q}/σ^2_β + (Σ_{η(t-1)})^{-1} ⊗ (X′X) \right)^{-1}
\]  

(A5) and

\[
μ_β(t) = V_β(t) (Σ_{η(t-1)})^{-1} ⊗ X′ \text{vec}(η)
\]  

(A6) where ⊗ denotes the Kronecker product, and Σ_η(t) is sampled from

\[
p(Σ_η|β(t), X, η(t)) ∼ W^{-1}(I_2 + (η(t) - XB(t))′(η(t) - XB(t)), n + 2).
\]  

(A7)

(4) Sampling ψ_ξ = γ(t) = (γ_00, γ_{01}, γ_{10}, γ_{11})′, where γ_00 = 0, from the posterior distribution p(ψ_ξ|X, ξ(t)) ∝ p(ξ(t)|X; ψ_ξ)p(ψ_ξ). This is done using conditional Gibbs sampling, one parameter at a time. We specify the prior distribution as p(ψ_ξ) ∼ N(0, σ^2_ξ I_{3q}), with σ^2_ξ = 100. Letting γ_{jkr} denote the rth element of γ_{jkr}, we cycle over all r = 1, ..., q and over (j, k) = (0, 1), (1, 0), (1, 1) to draw γ_{jkr} from

\[
p(γ_{jkr}|γ_{jkr(t-1)}, X, ξ(t)) ∝ \prod_{i=1}^n \sum_{u,v=0,1} \frac{exp(γ_{uvr}^{(t-1)}X_i)}{exp(γ_{uvr}^{(t-1)}X_i)} p(γ_{jkr})
\]  

(A8) where γ_{uvr} are vectors where all the γ-parameters except for γ_{jkr} are fixed at their most recently sampled values (from iteration t − 1 or t), γ_{jkr(t-1)} denotes all of these fixed parameter
values, $\xi_{iw}^{(t)} = I(\xi_{Gi}^{(t)} = u, \xi_{Hi}^{(t)} = v)$, and $p(\gamma_{jkr})$ is the prior density of $\gamma_{jkr}$ implied by $p(\psi)$, in our case $p(\gamma_{jkr}) \sim N(0, 100)$. These $\gamma_{jkr}$ are generated using adaptive rejection sampling.

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