Online supplement to

"On Accommodating Spatial Interactions in a Generalized Heterogeneous Data Model (GHDM) of Mixed Types of Dependent Variables"

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SECTION 1

1.1 Description of Matrix M used to Derive the Distribution of Vector yu

Create a matrix **M** of size $\left[Q(E+\tilde{G}) \times Q(E+\tilde{G})\right]$ whose elemens are all initialized to zero. Then, for every individual q, consider a matrix \mathbf{M}_q of size $\left[(E+\tilde{G}) \times (E+\tilde{G})\right]$ filled with zeros. Insert an identity matrix of size E into the first E rows and E columns of the matrix \mathbf{M}_q . Next, consider the rows from E+1 to $E+I_1-1$, and columns from E+1 to $E+I_1$. These rows and columns correspond to the first nominal variable. Insert an identity matrix of size (I_1-1) after supplementing with a column of '-1' values in the column corresponding to the chosen alternative. Next, consider the rows $E+I_1$ through $E+I_1+I_2-2$ and columns $E+I_1+1$ through $E+I_1+I_2$ correspond to the second nominal variable. Again position an identity matrix of size (I_2-1) after supplementing with a column of '-1' values in the column corresponding to the chosen alternative for the second nominal variable. Continue this procedure for all G nominal variables. Insert this matrix \mathbf{M}_q in the matrix \mathbf{M} occupying the rows $\left[(q-1)*(E+\tilde{G})+(E+\tilde{G})+1\right]$ to $\left[(q-1)*(E+\tilde{G})+(E+\tilde{G})\right]$ and columns $\left[(q-1)*(E+\tilde{G})+1\right]$ to $\left[(q-1)*(E+\tilde{G})+(E+\tilde{G})\right]$.

1.2 Rearrangement Matrices R_y and $R_{\tilde{u}}$ used to Partition \widetilde{B} and $\widetilde{\Omega}$

Consider a rearrangement matrix **R** of size $\left[Q(E+\widetilde{G}) \times Q(E+\widetilde{G})\right]$ filled with zeros. Then, for every individual q, consider a identity matrix \mathbf{R}_q of size $(E + \widetilde{G})$. Insert first H rows of matrix \mathbf{R}_q into matrix **R** occupying rows $[(q-1)^*H+1]$ to $[(q-1)^*H+H]$ and columns $[(q-1)^*(E+\widetilde{G})+1]$ to $[(q-1)^*(E+\widetilde{G})+(E+\widetilde{G})]$. Next insert the remaining $(E+\widetilde{G}-H)$ rows of matrix \mathbf{R}_q into matrix \mathbf{R} occupying rows $\left[QH + (q-1)^* (E + \widetilde{G} - H) + 1 \right]$ to $\left[QH + (q-1)^*(E+\widetilde{G}-H) + (E+\widetilde{G}-H)\right] \text{ and } \qquad \text{columns} \qquad \left[(q-1)^*(E+\widetilde{G}) + 1\right] \text{ to}$ $[(q-1)^*(E+\widetilde{G})+(E+\widetilde{G})]$. Divide the matrix R into submatrices two $\mathbf{R}_{\mathbf{x}}(\mathbf{R}[1:QH,1:Q(E+\widetilde{G})])$ and $\mathbf{R}_{\widetilde{u}}(\mathbf{R}[QH+1:Q(E+\widetilde{G}),1:Q(E+\widetilde{G})])$. For example: Consider the case with two individuals and one continous, two ordinal, one count and two nominal variables with three alternatives each. Then the matrix **R** may be written as:

	Γ1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0		
	$\left \begin{array}{c} - \\ 0 \end{array} \right $	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0		
	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0		
	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0		
-	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0		
	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	$\left[\begin{array}{c} \mathbf{R}_{\mathbf{v}} \end{array} \right]$	
K =	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	$= \frac{1}{\mathbf{R}_{\tilde{u}}}$	
	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0		
	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0		
	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0		
	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0		
	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0		
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0		
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1		(S.1)

Now, consider the following re-arranged vectors and matrices:

 $\widetilde{\mathbf{B}}_{\mathbf{y}} = \mathbf{R}_{\mathbf{y}} \widetilde{\mathbf{B}} \left[(QH \times 1) \text{ vector} \right], \ \widetilde{\mathbf{B}}_{\widetilde{\mathbf{u}}} = \mathbf{R}_{\widetilde{\mathbf{u}}} \widetilde{\mathbf{B}} \left[(Q\widetilde{E} \times 1) \text{ vector} \right], \ \widetilde{\mathbf{\Omega}}_{\mathbf{y}} = \mathbf{R}_{\mathbf{y}} \widetilde{\mathbf{\Omega}} \mathbf{R}_{\mathbf{y}}' \left[(QH \times QH) \text{ matrix} \right], \\ \widetilde{\mathbf{\Omega}}_{\widetilde{\mathbf{u}}} = \mathbf{R}_{\widetilde{\mathbf{u}}} \widetilde{\mathbf{\Omega}} \mathbf{R}_{\widetilde{\mathbf{u}}}' \left[(Q\widetilde{E} \times Q\widetilde{E}) \text{ matrix} \right], \text{ and } \ \widetilde{\mathbf{\Omega}}_{\mathbf{y}\widetilde{\mathbf{u}}} = \mathbf{R}_{\mathbf{y}} \widetilde{\mathbf{\Omega}} \mathbf{R}_{\mathbf{u}}' \left[(QH \times Q\widetilde{E}) \text{ matrix} \right].$

SECTION 2

The CML Estimation Approach

To develop the CML function corresponding to Equation (B.2) in Appendix B of the main paper, first we extract from the mean vector \tilde{B} and covariance matrix $\tilde{\Omega}$, relevant components $\tilde{B}_{qq'}$ and $\tilde{\Omega}_{qq'}$ (as well as $\tilde{\psi}_{qq',low}$ from $\tilde{\psi}_{low}$ and $\tilde{\psi}_{qq',up}$ from $\tilde{\psi}_{up}$) for each (and every) pair of individuals q and q'. To do so, define a selection matrix $\mathbf{D}_{qq'}$ of size $[2(E + \tilde{G}) \times Q(E + \tilde{G})]$ and $\mathbf{V}_{qq'}$ of size $(2\tilde{E} \times Q\tilde{E})$ (see Section A.1 Step-1 and Step-2 of Supplement Appendix A for construction details). Then the vectors $\tilde{B}_{qq'}$, $\tilde{\psi}_{qq',low}$, $\tilde{\psi}_{qq',up}$ and matrix $\tilde{\Omega}_{qq'}$ can be extracted from \tilde{B} , $\tilde{\psi}_{low}$, $\tilde{\psi}_{up}$ and $\tilde{\Omega}$ as follows: $\tilde{B}_{qq'} = \mathbf{D}_{qq'}\tilde{B}[2(E + \tilde{G}) \times 1)$ vector], $\tilde{\psi}_{qq',low} = \mathbf{V}_{qq'}\tilde{\psi}_{low} (2\tilde{E} \times 1 \text{ vector})$, and $\tilde{\Omega}_{qq'} = \mathbf{D}_{qq'}\tilde{\Omega}\mathbf{D}'_{qq'} [(2(E + \tilde{G}) \times 2(E + \tilde{G}))\text{matrix}]$. Next, for each pair of individuals, we partition vector $\tilde{B}_{qq'}$ and matrix $\tilde{\Omega}_{qq'}$ into components relevant to continuous variable components $(\mathbf{y}_{qq'})$ and ordinal, count and nominal variable components $(\tilde{u}_{qq'})$. To do so, define a selection matrix $\mathbf{R}_{qq'}$ of size $[2(E + \tilde{G}) \times Q(E + \tilde{G})]$ (see Supplement

Appendix A.1 Step-3 for construction details). Then vector $\widetilde{B}_{qq'}$ and matrix $\widetilde{\Omega}_{qq'}$ can be partitioned into the components corresponding to continuous and non-continuous variable components as follows: $\widetilde{B}_{qq',y} = \mathbf{R}_{qq',y} \widetilde{B}_{qq'} [(2H \times 1) \text{ vector}], \widetilde{B}_{qq',\tilde{u}} = \mathbf{R}_{qq',\tilde{u}} \widetilde{B}_{qq'} [(2\widetilde{E} \times 1) \text{ vector}],$ $\widetilde{\Omega}_{qq',y} = \mathbf{R}_{qq',y} \widetilde{\Omega}_{qq'} \mathbf{R}'_{qq',y} [(2H \times 2H) \text{ matrix}],$ $\widetilde{\Omega}_{qq',y} = \mathbf{R}_{qq',y} \widetilde{\Omega}_{qq'} \mathbf{R}'_{qq',\tilde{u}} [(2H \times 2H) \text{ matrix}],$ $\widetilde{\Omega}_{qq',y\tilde{u}} = \mathbf{R}_{qq',y} \widetilde{\Omega}_{qq'} \mathbf{R}'_{qq',\tilde{u}} [(2H \times 2\widetilde{E}) \text{ matrix}].$ That is, $\widetilde{B}_{qq'} = \begin{bmatrix} \widetilde{B}_{qq',y} \\ \widetilde{B}_{qq',\tilde{u}} \end{bmatrix}$ and $\widetilde{\Omega}_{qq'} = \begin{bmatrix} \widetilde{\Omega}_{qq',y} & \widetilde{\Omega}_{qq',y\tilde{u}} \\ \widetilde{\Omega}'_{aq',y\tilde{u}} & \widetilde{\Omega}_{qq',y\tilde{u}} \end{bmatrix}.$ (S.2)

Thus the conditional distribution of $\tilde{\boldsymbol{u}}_{qq'}$ given $\boldsymbol{y}_{qq'}$, may be written as: mean $\tilde{\boldsymbol{B}}_{qq',\tilde{\boldsymbol{u}}} = \tilde{\boldsymbol{B}}_{qq',\tilde{\boldsymbol{u}}} + \tilde{\boldsymbol{\Omega}}'_{qq',y\tilde{\boldsymbol{u}}} \tilde{\boldsymbol{\Omega}}_{qq',y}^{-1} (\boldsymbol{y}_{qq'} - \tilde{\boldsymbol{B}}_{qq',y})$ and variance $\tilde{\boldsymbol{\Omega}}_{qq',\tilde{\boldsymbol{u}}} = \tilde{\boldsymbol{\Omega}}_{qq',\tilde{\boldsymbol{u}}} - \tilde{\boldsymbol{\Omega}}'_{qq',y\tilde{\boldsymbol{u}}} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}}^{-1} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}}^{-1} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}}^{-1} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}}^{-1} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}}^{-1} \tilde{\boldsymbol{\Omega}}_{qq',y\tilde{\boldsymbol{u}}}$. In the last step, we arrange the elements inside the vector $\tilde{\boldsymbol{B}}_{qq',\tilde{\boldsymbol{u}}}, \tilde{\boldsymbol{\psi}}_{qq',low}, \tilde{\boldsymbol{\psi}}_{qq',up}$ and matrix $\tilde{\boldsymbol{\Omega}}_{qq',\tilde{\boldsymbol{u}}}$ so that the elements corresponding to all ordinal variables of both individuals q and q' (i.e., 2N ordinal variables) are stacked together, followed by elements corresponding to all count variables (i.e., 2C count variables) and in the end the elements corresponding to all nominal variables (i.e., 2G nominal variables). This arrangement makes it easy to enumerate pairs of observed outcomes for forming the CML function. To achieve such ordering, define a matrix $\mathbf{F}_{qq'}$ of size $(2\tilde{E} \times 2\tilde{E})$ (see Supplement Appendix A.1 Step-4 for construction details). Then the elements can be rearranged as follows: $\tilde{\boldsymbol{B}}_{qq',\tilde{u}} = \mathbf{F}_{qq'}\tilde{\boldsymbol{B}}_{qq',\tilde{u}}, \quad \tilde{\boldsymbol{\psi}}_{qq',low} = \mathbf{F}_{qq'}\tilde{\boldsymbol{\psi}}_{qq',up} = \mathbf{F}_{qq'}\tilde{\boldsymbol{\psi}}_{qq',up}$, and $\tilde{\boldsymbol{\Omega}}_{qq',\tilde{u}} = \mathbf{F}_{qq'}\tilde{\boldsymbol{\Omega}}_{qq',\tilde{u}} \mathbf{F}_{qq'}^{-1}$. Finally, replace the last $2\tilde{G}$ elements of the lower threshold vector $\tilde{\boldsymbol{\psi}}_{qq',low}$ from $-\infty$ to zero. That is, $\tilde{\boldsymbol{\psi}}_{qq',low}[2(N+C)+1:2\tilde{E}] = \mathbf{0}_{2\tilde{G}}$.

Now, to explicitly write the CML function in terms of standard (multivariate) normal density and cumulative distribution functions, define $\boldsymbol{\omega}_{\Delta}$ as the diagonal matrix of standard deviations of the matrix Δ , using $\phi_R(.;\Delta^*)$ for the multivariate standard normal density function of dimension R and correlation matrix Δ^* ($\Delta^* = \boldsymbol{\omega}_{\Delta}^{-1} \Delta \boldsymbol{\omega}_{\Delta}^{-1}$), and $\Phi_E(.;\Delta^*)$ for the multivariate standard normal density function of dimension R and correlation matrix Δ^* ($\Delta^* = \boldsymbol{\omega}_{\Delta}^{-1} \Delta \boldsymbol{\omega}_{\Delta}^{-1}$), and $\Phi_E(.;\Delta^*)$ for the multivariate standard normal cumulative distribution function of dimension E and correlation matrix Δ^* . Also, define a set of two selection matrices: \mathbf{H}_{vg} of size $[I_g \times (2\tilde{E})]$ and $\mathbf{Y}_{gg'}$ of size $[(I_g + I_{g'} - 2) \times (2\tilde{E})]$, constructed as described in Supplement Appendix A.2. Using these selection matrices, let $\hat{\Omega}_{qq',vg} = \mathbf{H}_{vg} \hat{\Omega}_{qq',\tilde{u}} \mathbf{H}'_{vg}$, $\hat{\Omega}_{qq',gg'} = \mathbf{Y}_{gg'} \hat{\Omega}_{qq',\tilde{u}} \mathbf{Y}'_{gg'}$, $\mu_{v,up} = \frac{[\vec{\psi}_{qq',up}]_v - [\vec{B}_{qq',\tilde{u}}]_v}{\sqrt{[\vec{\Omega}_{qq',\tilde{u}}]_{vy}}}$

$$, \ \mu_{v,low} = \frac{\left[\vec{\psi}_{qq',low}\right]_{v} - \left[\vec{B}_{qq',\tilde{u}}\right]_{v}}{\sqrt{\left[\vec{\Omega}_{qq',\tilde{u}}\right]_{vv}}}, \ \text{and} \ \rho_{vv'} = \frac{\left[\vec{\Omega}_{qq',\tilde{u}}\right]_{vv'}}{\sqrt{\left[\vec{\Omega}_{qq',\tilde{u}}\right]_{vv}\left[\vec{\Omega}_{qq',\tilde{u}}\right]_{vv'}}}, \ \text{where} \ \left[\vec{\psi}_{qq',up}\right]_{v} \ \text{represents the } v^{\text{th}}$$

element of $\tilde{\psi}_{qq',up}$ (and similarly for other vectors), and $[\tilde{\Omega}_{qq',\tilde{u}}]_{vv'}$ represents the vv'^{th} element of the matrix $\tilde{\Omega}_{qq',\tilde{u}}$. Then, one may write the CML function as follows:

$$L_{CML}(\boldsymbol{\lambda}) = \prod_{q=1}^{Q-1} \prod_{q'=q+1}^{Q} L_{CML,qq'}(\boldsymbol{\lambda}),$$
where $L_{CML,qq'}(\boldsymbol{\lambda}) = \left(\prod_{h=1}^{2H} \boldsymbol{\omega}_{\widetilde{\boldsymbol{\Omega}}_{qq',y}}\right)^{-1} \boldsymbol{\varphi}_{2H} \left(\left[\boldsymbol{\omega}_{\widetilde{\boldsymbol{\Omega}}_{qq',y}}\right]^{-1} \left[\boldsymbol{y}_{qq'} - \widetilde{\boldsymbol{B}}_{qq',y}\right] \widetilde{\boldsymbol{\Omega}}_{qq',y}^{*}\right] \boldsymbol{\lambda}$

$$\left(\prod_{v=1}^{2N+2C-1} \sum_{v'=v+1}^{2N+2C} \left[\Phi_{2}(\boldsymbol{\mu}_{v,up}, \boldsymbol{\mu}_{v',up}, \boldsymbol{\rho}_{vv'}) - \Phi_{2}(\boldsymbol{\mu}_{v,up}, \boldsymbol{\mu}_{v',low}, \boldsymbol{\rho}_{vv'}) \right] \right) \boldsymbol{\lambda}$$

$$\left(\prod_{v=1}^{2N+2C} \prod_{v'=v+1}^{2G} \left[\Phi_{1_{g}}(\boldsymbol{\omega}_{\boldsymbol{\Omega}_{qq',yg}}^{-1} + \mathbf{H}_{vg}(\boldsymbol{\psi}_{qq',up}, - \boldsymbol{B}_{qq',\tilde{u}}); \widehat{\boldsymbol{\Omega}}_{qq',vg}^{*} \right] - \Phi_{1_{g}} \left[\boldsymbol{\omega}_{\boldsymbol{\Omega}_{qq',yg}}^{-1} + \mathbf{H}_{qq',vg}(\boldsymbol{\psi}_{qq',low}, - \boldsymbol{B}_{qq',\tilde{u}}); \widehat{\boldsymbol{\Omega}}_{qq',vg}^{*} \right] \right) \boldsymbol{\lambda}$$

$$\left(\prod_{q=1}^{2G-1} \prod_{g'=g+1}^{2G} \Phi_{1_{g}+I_{g'}-2} \left[\boldsymbol{\omega}_{\boldsymbol{\Omega}_{qq',yg}}^{-1} + \mathbf{H}_{qq',\tilde{u}}; \widehat{\boldsymbol{\Omega}}_{qq',yg}^{*} \right] \right) \boldsymbol{\lambda}$$

$$\left(\prod_{q=1}^{2G-1} \prod_{g'=g+1}^{2G} \Phi_{1_{g}+I_{g'}-2} \left[\boldsymbol{\omega}_{\boldsymbol{\Omega}_{qq',yg}}^{-1} + \mathbf{H}_{qq',\tilde{u}}; \widehat{\boldsymbol{\Omega}}_{qq',yg}^{*} \right] \right) \boldsymbol{\lambda}$$

$$\left(\prod_{q=1}^{2G-1} \prod_{g'=g+1}^{2G} \Phi_{1_{g}+I_{g'}-2} \left[\boldsymbol{\omega}_{\boldsymbol{\Omega}_{qq',yg}}^{-1} + \mathbf{H}_{qq',\tilde{u}}; \widehat{\boldsymbol{\Omega}}_{qq',gg'}^{*} \right] \right) \boldsymbol{\lambda}$$

$$\left(\prod_{q=1}^{2G-1} \prod_{g'=g+1}^{2G} \Phi_{1_{g}+I_{g'}-2} \left[\boldsymbol{\omega}_{\boldsymbol{\Omega}_{qq',gg'}}^{-1} + \mathbf{H}_{qq',\tilde{u}}; \widehat{\boldsymbol{\Omega}}_{qq',gg'}^{*} \right] \right) \boldsymbol{\lambda}$$

$$\left(\prod_{q=1}^{2G-1} \prod_{g'=g+1}^{2G} \Phi_{1_{g}+I_{g'}-2} \left[\boldsymbol{\omega}_{\boldsymbol{\Omega}_{qq',gg'}}^{-1} + \mathbf{H}_{qq',\tilde{u}}; \widehat{\boldsymbol{\Omega}}_{qq',gg'}^{*} \right] \right) \boldsymbol{\lambda}$$

$$\left(\prod_{q=1}^{2G-1} \prod_{g'=g+1}^{2G} \Phi_{1_{g}+I_{g'}-2} \left[\boldsymbol{\omega}_{\boldsymbol{\Omega}_{qq',gg'}}^{-1} + \mathbf{H}_{qq',gg'}; \widehat{\boldsymbol{\Omega}}_{qq',gg'}^{*} \right] \right) \boldsymbol{\lambda}$$

In Equation (S.3), for each pair of individuals q and q', the first component corresponds to the marginal likelihood of the continuous outcomes for the two individuals, the second component corresponds to the likelihood of pairs of outcomes across all ordinal and count outcomes, the third component corresponds to the pairwise likelihood of ordinal/count outcomes and nominal outcomes, and the last component corresponds to the pairwise likelihood for the nominal outcomes.

Among all the multivariate normal cumulative distribution (MVNCD) integrals in Equation (S.3), the maximum dimension of integration is the sum of alternatives of nominal variables with the two highest numbers of alternatives minus 2. To solve such MVNCD integrals within the CML estimation routine, Bhat (2011) proposed the use of an analytic approximation method. This approach, labelled the MACML approach, as demonstrated by Bhat and Sidharthan (2011), is at least as accurate as simulation based approaches in retrieving model parameters, albeit computationally much faster and robust in that the approximate CML surface is smoother and easier to maximize than the traditional simulation-based likelihood surfaces.

We write the resulting equivalent of Equation (S.3) computed using the analytic approximation for MVNCD as $L_{MACML}(\lambda) = \prod_{q=1}^{Q-1} \prod_{q'=q+1}^{Q} L_{MACML,qq'}(\lambda)$. The MACML estimator is then

obtained by maximizing the logarithm of $L_{MACML}(\lambda)$, which involves computation of pairwise loglikelihoods (i.e., $\log L_{MACML,qq'}(\lambda)$) for Q(Q-1)/2 pairs. The asymptotic covariance matrix of the parameters $V_{MACML}(\lambda)$ may be estimated by the inverse of Godambe's (1960) sandwich information matrix.

$$\mathbf{V}_{MACML}(\boldsymbol{\lambda}) = \frac{\left[\hat{\boldsymbol{G}}(\boldsymbol{\lambda})\right]^{-1}}{Q} = \frac{\left[\hat{\boldsymbol{H}}^{-1}\right]\left[\hat{\boldsymbol{J}}\right]\left[\hat{\boldsymbol{H}}^{-1}\right]}{Q}$$
(S.4)

The reader is referred to Zhao and Joe (2005), Bhat (2014), and Sidharthan and Bhat (2012) for more details on the calculations of the Hessian matrix (\hat{H}) and the Jacobian matrix (\hat{J}) in the above expression (Sidharthan and Bhat, 2012 provide these details for spatial models).

As spatial dependency decreases with an increase in the distance between any two individuals, one can reduce the number of pairings (between individual observations) in the MACML function by neglecting all the pairings beyond a certain threshold distance. To determine this threshold distance, analyst can estimate the model with different threshold distances and choose the one that minimizes the total variance across all parameters as given by the trace of the asymptotic covariance matrix $V_{MACML}(\lambda)$.

One final consideration relevant to model estimation is that the matrix $\tilde{\Sigma}$ for each observation has to be positive definite. The simplest way to guarantee this is to ensure that the $(L \times L)$ correlation matrix Γ is positive definite, and each matrix $\check{\Lambda}_g$ (g=1,2,...,G) is also positive definite. To do so, we parameterize the CML function in terms of the Cholesky parameters for these matrices. Further, because the matrix Γ is a correlation matrix, we write each diagonal element (say the *aa*th element) of the lower triangular Cholesky matrix of Γ as $\sqrt{1-\sum_{i=1}^{a-1} p_{ai}^2}$, where

the P_{aj} elements are the Cholesky factors to be estimated. In addition, note that the top diagonal element of each $\breve{\Lambda}_{g}$ matrix has to be normalized to one (as discussed in Appendix A of the main paper), which implies that the first element of the Cholesky matrix of each $\breve{\Lambda}_{g}$ is fixed to the value of one. Also, the spatial autoregressive parameter δ_{l} (l = 1, 2, ..., L) should be constrained between 0 and 1 ($-1 < \delta_{l} < 1 \forall l$), for which we parameterize the spatial autoregressive parameter as $\delta_{l} = \pm (1/[1 + \exp(\tilde{\delta}_{l})]) \forall l$. However, in our case, we expect the parameter to be positive, because the spatial dependence is being introduced in the latent pschological constructs, and this impose the '+' sign.

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Supplement Appendix A: Construction of Selection Matrices

A.1. To Extract Relevant Components from \tilde{B} and $\tilde{\Omega}$ for a pair of individuals q and q', and rearrange elements in the order of ordinal, count and nominal variables

To build the CML function, we use a set of selection matrices such that one can extract the relevant components from vectors \tilde{B} and matrix $\tilde{\Omega}$ for a pair of individuals q and q'. The selection matrices are described below:

Step-1: A matrix $\mathbf{D}_{qq'}$ of size $\left[2(E+\widetilde{G}) \times Q(E+\widetilde{G})\right]$ filled with zeros. Insert an identity matrix of size $(E+\widetilde{G})$ in first $(E+\widetilde{G})$ rows and columns $\left[(q-1)*(E+\widetilde{G})+1\right]$ to $\left[(q-1)*(E+\widetilde{G})+(E+\widetilde{G})\right]$. Next, insert another identity matrix of size $(E+\widetilde{G})$ in rows $(E+\widetilde{G}+1)$ to $\left[2(E+\widetilde{G})\right]$ and columns $\left[(q'-1)*(E+\widetilde{G})+1\right]$ to $\left[(q'-1)*(E+\widetilde{G})+(E+\widetilde{G})\right]$.

Step-2: A matrix $\mathbf{V}_{qq'}$ of size $(2\widetilde{E} \times Q\widetilde{E})$ filled with zeros. Insert an identity matrix of size (\widetilde{E}) in first (\widetilde{E}) rows and columns $[(q-1)^*(\widetilde{E})+1]$ to $[(q-1)^*(\widetilde{E})+\widetilde{E}]$. Next, insert another identity matrix of size (\widetilde{E}) in rows $(\widetilde{E}+1)$ to $(2\widetilde{E})$ and columns $[(q'-1)^*(\widetilde{E})+1]$ to $[(q'-1)^*(\widetilde{E})+\widetilde{E}]$.

Step-3: A matrix $\mathbf{R}_{qq'}$ of size $\left[2(E+\widetilde{G}) \times Q(E+\widetilde{G})\right]$ filled with zeros. Then, for individual q, consider an identity matrix \mathbf{R}_q of size $(E+\widetilde{G})$. Insert first H rows of the matrix \mathbf{R}_q into matrix $\mathbf{R}_{qq'}$ occupying first H rows and columns $\left[(q-1)^*(E+\widetilde{G})+1\right]$ to $\left[(q-1)^*(E+\widetilde{G})+(E+\widetilde{G})\right]$. Next insert the remaining $(E+\widetilde{G}-H)$ rows of matrix \mathbf{R}_q into matrix $\mathbf{R}_{qq'}$ occupying rows $\left[2H+1\right]$ to $\left[2H+(E+\widetilde{G}-H)\right]$ and columns $\left[(q-1)^*(E+\widetilde{G})+1\right]$ to $\left[(q-1)^*(E+\widetilde{G})+(E+\widetilde{G})\right]$. For individual q', Insert first H rows of matrix $\mathbf{R}_{q'}$ into matrix $\mathbf{R}_{qq'}$ occupying rows $\left[2H+1\right]$ to $\left[2H+(E+\widetilde{G}-H)\right]$ and columns $\left[(q'-1)^*(E+\widetilde{G})+1\right]$ to $\left[(q'-1)^*(E+\widetilde{G})+(E+\widetilde{G})\right]$. For individual q', Insert first H rows of matrix $\mathbf{R}_{q'}$ into matrix $\mathbf{R}_{qq'}$ occupying rows $\left[2H+1\right]$ to $\left[2H+2\widetilde{E}\right]$ and columns $\left[(q'-1)^*(E+\widetilde{G})+1\right]$ to $\left[(q'-1)^*(E+\widetilde{G})+(E+\widetilde{G})\right]$. Divide the matrix $\mathbf{R}_{qq'}$ into two submatrices $\mathbf{R}_{qq',y}(\mathbf{R}_{qq'}[1:2H,1:Q(E+\widetilde{G})])$ and $\mathbf{R}_{qq',\tilde{u}}(\mathbf{R}_{qq'}[2H+1:2(E+\widetilde{G}),1:Q(E+\widetilde{G})])$.

Step-4: Now, define a matrix $\mathbf{F}_{qq'}$ of size $(2\tilde{E} \times 2\tilde{E})$ filled with zeros. Next, perform the steps described below to arrange the elements inside the vector $\mathbf{B}_{qq',\tilde{u}}$ and matrix $\mathbf{\Omega}_{qq',\tilde{u}}$ in the order of ordinal, count and nominal variables.

Step-4.1 Insert an identity matrix of size N in first N rows and N columns. Insert another identity matrix of size N in rows (N+I) to (2N) and columns $(\tilde{E}+1)$ to $(\tilde{E}+N)$.

Step-4.2 Again, insert an identity matrix of size C in rows (2N+1) to (2N+C) and columns (N+1) to (N+C). Insert another identity matrix of size C in rows (2N+C+1) to (2N+2C) and columns $(\tilde{E}+N+1)$ to $(\tilde{E}+N+C)$.

Step-4.3 Finally, insert an identity matrix of size \tilde{G} in rows (2N + 2C + 1) to $(2N + 2C + \tilde{G})$ and columns (N + C + 1) to (\tilde{E}) . Insert another identity matrix of size \tilde{G} in rows $(2N + 2C + \tilde{G} + 1)$ to $(2\tilde{E})$ and columns $(\tilde{E} + N + C + 1)$ to $(2\tilde{E})$.

A.2. To write the CML function in terms of standard normal density and cumulative distribution functions

Define a set of two selection matrices as follows: (1) \mathbf{H}_{vg} is a $I_g \times (2\tilde{E})$ selection matrix with an entry of '1' in the first row and the v^{th} column and an identity matrix of size $I_g - 1$ occupying the last $I_g - 1$ rows and the $2N + 2C + \left[\sum_{j=1}^{g-1} (I_j - 1) + 1\right]^{th}$ through $2N + 2C + \left[\sum_{j=1}^{g} (I_j - 1)\right]^{th}$ columns (with the convention that $\sum_{j=1}^{0} (I_j - 1) = 0$), and entries of '0' everywhere else, (2) $\mathbf{Y}_{gg'}$ is a $(I_g + I_{g'} - 2) \times (2\tilde{E})$ selection matrix with an identity matrix of size $(I_g - 1)$ occupying the first $(I_g - 1)$ rows and the $2N + 2C + \left[\sum_{j=1}^{g-1} (I_j - 1) + 1\right]^{th}$ through $2N + 2C + \left[\sum_{j=1}^{g} (I_j - 1)\right]^{th}$ columns (with the convention that $\sum_{j=1}^{0} (I_j - 1) = 0$), and another identity matrix of size $(I_g - 1)$ occupying the first ($I_g - 1$) rows and the $2N + 2C + \left[\sum_{j=1}^{g-1} (I_j - 1) + 1\right]^{th}$ through $2N + 2C + \left[\sum_{j=1}^{g} (I_j - 1)\right]^{th}$ columns (with the convention that $\sum_{j=1}^{0} (I_j - 1) = 0$), and another identity matrix of size $(I_{g'} - 1)$ occupying the last ($I_{g'} - 1$) rows and the $2N + 2C + \left[\sum_{j=1}^{g'-1} (I_j - 1) + 1\right]^{th}$ through $2N + 2C + \left[\sum_{j=1}^{g'} (I_j - 1)\right]^{th}$ columns (with the convention that $\sum_{j=1}^{0} (I_j - 1) = 0$), and another identity matrix of size ($I_{g'} - 1$) occupying the last ($I_{g'} - 1$) rows and the $2N + 2C + \left[\sum_{j=1}^{g'-1} (I_j - 1) + 1\right]^{th}$ through $2N + 2C + \left[\sum_{j=1}^{g'} (I_j - 1)\right]^{th}$ columns (with the convention that $\sum_{j=1}^{0} (I_j - 1) = 0$), and another identity matrix of size ($I_{g'} - 1$) occupying the last ($I_{g'} - 1$) rows and the $2N + 2C + \left[\sum_{j=1}^{g'-1} (I_j - 1) + 1\right]^{th}$ through $2N + 2C + \left[\sum_{j=1}^{g'} (I_j - 1)\right]^{th}$ columns; all other elements of $\mathbf{Y}_{gg'}$ take a value of zero.

Variable	Categories	Percentage
	5-10 years old	47.37
Age of school going children	11-15 years old	40.83
	16-18 years old	11.80
	Boys	51.80
Gender of school going children	Girls	48.20
	Less than 25K	7.70
	25K – 49,999	16.18
Household monthly income	50K – 74,999	16.68
	75K – 99,999	16.77
	100K or more	42.67
	Caucasian	69.78
	African-American	7.39
Race	Asian	9.72
	Hispanic	12.07
	Others	1.04
	High school degree or less	25.45
Households with fraction of adults (25	Some college degree	25.73
or more) with	Bachelor's degree	27.69
	Graduate degree	21.13
	19-30 years	7.87
Households with fraction of adults in	31-45 years	51.70
age group	46-60 years	36.43
	61 or more	4.00
	0	5.21
Households with number of full-time	1	58.66
workers	2	33.36
	3 or more	2.77
Households with number of part time	0	67.93
workers	1	28.80
workers	2 or more	3.27
Households with number of workers	0	75.62
with the option to work from home	1	21.43
with the option to work from nome	2 or more	2.95
Households with number of workers	0	42.26
with flexible work time	1	44.52
	2 or more	13.22
Family type	Nuclear	93.41
	Single-parent	6.59
	Detached	81.75
Housing type	Duplex	6.54
	Apartment or townhouse	11.71
Tenure	Own	80.05
	Kent	19.95
	Less than $\frac{1}{4}$ mile	11.29
	Between $\frac{1}{4}$ to $\frac{1}{2}$ mile	10.37
Distance to school	Greater than $\frac{1}{2}$ mile and less than or equal	14.47
	Greater than 1 mile and loss than or asset	21.42
	to 2 miles	21.43
	More than 2 miles	42 44
1	more man 2 miles	+∠.++

Table 1. Descriptive statistics of independent variables

SECTION 4

Table 2. Parameter estimates of exogenous variable effects on non-nominal variables

	Constants]	Thresholds	for ordinal							
			A little	bit of an	Somewhat of an		Very much an		Dispersion		Variance	
Dependent variables			issue & somewhat of an issue		issue & very much an issue		issue & a serious issue		parameter*			
	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
Household average commute	2 120	2 80									0.770	1.06
distance (miles)	2.428	5.80									0.770	4.00
Walk/bike issue:	0.072	1 67	0.410	10.22	0.770	12.01	1.025	1754				
violence/crime along the route	0.072	1.07	0.419	10.22	0.779	15.91	1.055	17.34				
Walk/bike issue: speed of	2 5 4 2	2 27	1 154	6 71	2 757	11 16	4 1 1 7	15.65				
traffic along the route	5.545	2.37	1.134	0.71	2.131	11.10	4.11/	15.05				
Walk/bike issue: amount of	2 667	2 5 2	1 2 5 2	10.22	2010	15 56	1 268	19.16				
traffic along the route	5.007	2.32	1.555	10.55	2.040	15.50	4.208	16.10				
Number of biking episodes in	2 255	2.01							0.062	86.62		
past week	-2.333	-5.01							0.002	80.05		
Number of walking episodes in												
past week												
Number of times public transit	0.424	2.65							0.008	86.00		
used in past week	0.424	2.05							0.098	80.00		
Vehicle ownership	1.384	4.79										
At least one working adult uses public transit/walk/bike as mode to work	-0.097	-2.31										

* The t-stat for dispersion parameter is calculated with respect to numerical value of 5 as oppose to zero. This is due to the fact that negative binomial count model collapses to Poisson count model for a dispersion parameter value of 5 or more.

Dependent variables	Number of children (18 years or less) in		Household income (base: 75K or more)							Number of full- time workers		Number of part- time workers	
Dependent variables	the household		Less than 25K		25K-49,999		50K-74,999						
	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	
Household average commute distance (miles)	0.052	1.73	-0.720	-6.37	-0.372	-4.96	-0.118	-2.66			-0.162	-3.38	
Walk/bike issue: violence/crime along the route													
Walk/bike issue: speed of traffic along the route													
Walk/bike issue: amount of traffic along the route													
Number of biking episodes in past week													
Number of walking episodes in past week													
Number of times public transit used in past week													
Vehicle ownership	0.017	2.27	-0.308	-1.91	-0.110	-2.18			0.229	2.63	0.234	4.78	
At least one working adult uses public transit/walk/bike as mode to work													

Table 2 (cont.) Parameter estimates of exogenous variable effects on non-nominal variables

	Number of	f workers		Housi (base: d	Tenure (base: owned)			
Dependent variables	with the o	m home	Dup	lex	Apartn Town	nent or house	Rented	
	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
Household average commute distance (miles)								
Walk/bike issue: violence/crime along the route								
Walk/bike issue: speed of traffic along the route								
Walk/bike issue: amount of traffic along the route								
Number of biking episodes in past week								
Number of walking episodes in past week								
Number of times public transit used in past week								
Vehicle ownership	-0.039	-3.08	-0.257	-2.42	-0.610	-5.65	-0.176	-2.34
At least one working adult uses public transit/walk/bike as mode to work								

Table 2 (Cont.) Parameter estimates of exogenous variable effects on non-nominal variables

	Residential location (base: less than 1000 housing units per sq mile)									
Variables	1000-	1999	2000-	3999	4000 or more					
	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat				
Constants	0.584	6.42	0.563	11.04	0.238	1.75				
Family type (base: nuclear family)										
Single-parent			0.018	1.44	0.018	1.44				
Household income (base: less than 100K)										
100K or more			-0.037	-2.47						
Housing type (base: detached)										
Duplex					0.099	6.60				
Apartment or Townhouse			0.072	2.44	0.302	4.65				
Number of workers with the option to work from home			-0.028	-2.15	-0.028	-2.15				

Table 3. Parameter estimates of exogenous variable effects on residential location choice

In addition to the above observed effects of exogenous variables, we estimated the following covariance matrix (t-statistics in parenthesis) between the differences of error terms with respect to the error term of the lowest density residential location alternative:

 $\begin{bmatrix} 1.00 \text{ (fixed)} \\ 0.97 (1.98) & 1.13 (2.61) \\ 0.59 (3.37) & 0.76 (2.74) & 0.59 (1.70) \end{bmatrix}$

Note that the terms in the parentheses represent the t-statistic values. Since this is a differenced errorcovariance matrix (Λ), a clear interpretation of the elements of this matrix is not straightforward.