

Alma Mater Studiorum Università di Bologna
Archivio istituzionale della ricerca

Multivariate cluster-weighted models based on seemingly unrelated linear regression

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

Published Version:

Cecilia Diani, Giuliano Galimberti, Gabriele Soffritti (2022). Multivariate cluster-weighted models based on seemingly unrelated linear regression. COMPUTATIONAL STATISTICS & DATA ANALYSIS, 171(July), 1-24 [10.1016/j.csda.2022.107451].

Availability:

This version is available at: <https://hdl.handle.net/11585/897816> since: 2022-10-27

Published:

DOI: <http://doi.org/10.1016/j.csda.2022.107451>

Terms of use:

Some rights reserved. The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

This item was downloaded from IRIS Università di Bologna (<https://cris.unibo.it/>).
When citing, please refer to the published version.

(Article begins on next page)

Multivariate cluster-weighted models based on seemingly unrelated linear regression

Cecilia Diani, Giuliano Galimberti, Gabriele Soffritti*

Abstract

A class of cluster-weighted models for a vector of continuous random variables is proposed. This class provides an extension to cluster-weighted modelling of multivariate and correlated responses that let the researcher free to use a different vector of covariates for each response. The class also includes parsimonious models obtained by imposing suitable constraints on the component-covariance matrices of either the responses or the covariates. Conditions for model identifiability are illustrated and discussed. Maximum likelihood estimation is carried out by means of an expectation-conditional maximisation algorithm. The effectiveness and usefulness of the proposed models are shown through the analysis of simulated and real datasets.

Keywords: cluster analysis, ECM algorithm, Gaussian mixture model, multivariate linear regression, parsimonious model

2010 MSC: 62J05, 62H12, 62F12

1. Introduction

Cluster-weighted modelling is a flexible framework for data analysis introduced by Gershensfeld (1997) in which the joint distribution of a given random vector is modelled by assuming that this vector is composed of an outcome \mathbf{Y}

*Corresponding author
Department of Statistical Sciences, University of Bologna
via delle Belle Arti 41, 40126 Bologna, Italy
Tel.: +39 051 2098192
Fax: +39 051 2086242
Email address: gabriele.soffritti@unibo.it
ORCID: <https://orcid.org/0000-0002-7575-892X>

This is the accepted version of an article published by Elsevier:

<https://doi.org/10.1016/j.csda.2022.107451>

(response, dependent variable) and its explanatory variables \mathbf{X} (covariates, predictors); in order to account for the possible presence of unknown clusters of observations, a finite mixture is embedded into the model. Thus, cluster-weighted models are useful to perform multivariate regression analysis with random covariates in the presence of unobserved heterogeneity. Such models play a prominent role when the sample observations come from several sub-populations, the distribution of the outcome as well as the effect of the covariates on the response change with the sub-populations and the covariates are not under the control of the researcher.

An intense research into cluster-weighted models has been carried out over the last decade. Ingrassia et al. (2012) and Ingrassia et al. (2014) have developed models for continuous variables under both Gaussian and Student t mixture distributions. Solutions suitable for dealing with various types of responses are detailed in Punzo and Ingrassia (2013), Punzo and Ingrassia (2015), Ingrassia et al. (2015) and Di Mari et al. (2020). Models with non-linear relationships or many covariates have been proposed by Punzo (2014) and Subedi et al. (2013), respectively. Robustified solutions have been developed by Subedi et al. (2015) and Punzo and McNicholas (2017). As far as vectors of continuous random variables with a multivariate response are concerned, Dang et al. (2017) have developed a family of parsimonious Gaussian cluster-weighted models, where suitable constraints are imposed on the eigen-decomposition of the component-covariance matrices so as to mitigate the problem of a large number of model parameters when dealing with several variables. An underlying assumption in the family of parsimonious Gaussian cluster-weighted models introduced by Dang et al. (2017) is that all the covariates in the model affect each examined response. However, in some situations there may be prior information concerning the absence of certain covariates from the linear term employed in the prediction of a certain response, and different covariates may be expected to be relevant in the prediction of different responses, as in the seemingly unrelated regression context (Srivastava and Giles, 1987). This approach to multivariate regression has been extensively employed in the modelling of multivariate economic

36 data, where some given aspects of economic behaviour are typically assumed to
 37 depend on different economic variables according to a certain general theory.
 38 Classical examples can be found in White and Hewings (1982) and Giles and
 39 Hampton (1984), where multivariate regression models with different vectors
 40 of covariates were specified and estimated based on employment equations and
 41 Cobb-Douglas production functions in different geographical locations, respec-
 42 tively. Other fields in which the same approach has been successfully employed
 43 are medicine, food quality, tourism economics, quality of life and health (see,
 44 e.g., Keshavarzi et al., 2012; Cadavez and Henningsen, 2012; Keshavarzi et al.,
 45 2013; Disegna and Osti, 2016; Heidari et al., 2017). Other regression models for
 46 multivariate responses based on finite mixture models have been introduced by
 47 Soffritti and Galimberti (2011); Dang and McNicholas (2015); Galimberti et al.
 48 (2016). The `flexmix` package (Grün and Leisch, 2008) in the `R` environment
 49 (`R` Core Team, 2020) provides a general framework for the specification and
 50 estimation of finite mixtures of regression models.

51 This paper introduces a class of multivariate seemingly unrelated Gaussian
 52 linear cluster-weighted models. Models from this class are able to capture both
 53 the linear dependencies among responses and the linear effects of the covariates
 54 on the responses from sample observations coming from heterogeneous popu-
 55 lations. Furthermore, with these models the researcher is enabled to specify
 56 a different vector of covariates for each response. The paper addresses the
 57 model identification and maximum likelihood (ML) estimation. This latter task
 58 is carried out by resorting to an expectation-conditional maximisation (ECM)
 59 algorithm. In order to keep the total number of parameters as low as possi-
 60 ble, parsimonious models are included into the novel class, where parsimony is
 61 attained by constraining the component-covariance matrices using a parameteri-
 62 sation for such matrices which is based on their spectral decomposition (see, e.g.,
 63 Celeux and Govaert, 1995). With this approach, fourteen different covariance
 64 structures are allowed for both the covariates and the responses. The useful-
 65 ness and the great flexibility of the resulting model class is shown through two
 66 studies, based on the analysis of real datasets, aiming at determining the effect

of prices and promotional activities on sales of canned tuna and at evaluating the link between tourism flows and attendance at museums and monuments. The effectiveness of an approach based on the proposed model class in terms of parameter recovery and classification recovery is demonstrated through Monte Carlo studies.

The paper is organised as follows. Section 2.1 defines the novel class of cluster-weighted models. Section 2.2 shows how the models belonging to this class relate to some existing models. Information on model identifiability is provided in Section 2.3. Details about the ML estimation are given in Section 2.4 and the Appendices. The initialisation and convergence of the ECM algorithm and the issue of model selection are treated in Sections 2.5 and 2.6. Parsimonious models are introduced in Section 2.7. Results of the analyses of simulated and real datasets are summarised in Sections 3 and 4, respectively. Section 5 provides some concluding remarks.

2. Multivariate seemingly unrelated linear cluster-weighted analysis

2.1. Multivariate seemingly unrelated linear cluster-weighted models

Following Dang et al. (2017), in a cluster-weighted model the random vectors \mathbf{X}_i and \mathbf{Y}_i containing the P covariates and the D responses for the i th observation, respectively, come from a population Ω which is assumed to be partitioned into K disjoint groups $\Omega_1, \dots, \Omega_K$. Thus, $\Omega = \Omega_1 \cup \dots \cup \Omega_K$; furthermore, $\Omega_k \cap \Omega_{k'} = \emptyset \ \forall k \neq k'$. In the models proposed here both \mathbf{X}_i and \mathbf{Y}_i are continuous random vectors, \mathbf{X}_i takes values in \mathbb{R}^P , \mathbf{Y}_i takes values in \mathbb{R}^D and the probability density function (p.d.f.) of $(\mathbf{X}_i, \mathbf{Y}_i)$ can be written as

$$f(\mathbf{x}_i, \mathbf{y}_i) = \sum_{k=1}^K \pi_k f(\mathbf{x}_i | \Omega_k) f(\mathbf{y}_i | \mathbf{x}_i, \Omega_k), \quad (1)$$

where $\pi_k = \mathbb{P}(\Omega_k)$ is the mixing weight and represents the prior probability of the k th group, $f(\mathbf{x}_i | \Omega_k)$ is the p.d.f. of \mathbf{X}_i given Ω_k and $f(\mathbf{y}_i | \mathbf{x}_i, \Omega_k)$ is the conditional p.d.f. of the response \mathbf{Y}_i given the value \mathbf{x}_i of the covariates \mathbf{X}_i and the group Ω_k . As far as the mixing weights are concerned, they are supposed to

95 be positive ($\pi_k > 0 \forall k$); in addition, they have to sum to 1 ($\sum_{k=1}^K \pi_k = 1$). Here
 96 $\mathbf{X}_i|\Omega_k$ is assumed to follow a P -variate normal distribution with mean vector
 97 $\boldsymbol{\mu}_{\mathbf{X}_k}$ and covariance matrix $\boldsymbol{\Sigma}_{\mathbf{X}_k}$, $k = 1, \dots, K$. Thus, the expected values,
 98 variances and covariances of $\mathbf{X}_i|\Omega_k$ are equal for all observations coming from
 99 group Ω_k , while they are different for observations belonging to other groups.
 100 As far as $\mathbf{Y}_i|(\mathbf{X}_i = \mathbf{x}_i, \Omega_k)$ is concerned, its distribution is modelled using a
 101 D -variate normal distribution with conditional expected vector given by some
 102 linear transformation of \mathbf{x}_i and covariance matrix $\boldsymbol{\Sigma}_{\mathbf{Y}_k}$. Thus, variances and
 103 covariances of $\mathbf{Y}_i|(\mathbf{X}_i = \mathbf{x}_i, \Omega_k)$ are equal for observations coming from the same
 104 group; the expected values of $\mathbf{Y}_i|(\mathbf{X}_i = \mathbf{x}_i, \Omega_k)$ for such observations vary with
 105 the observations. Furthermore, different correlation structures among both the
 106 covariates and the responses across the K groups are assumed.

107 In order to describe how a cluster-weighted model with a different vector
 108 of covariates for each response can be obtained, the following additional no-
 109 tation is required. Suppose that only P_d of the P covariates ($P_d \leq P$) are
 110 considered to be relevant for the prediction of the d th response. Thus, let
 111 $\mathbf{x}_{id} = (x_{i,d_1}, x_{i,d_2}, \dots, x_{i,d_{P_d}})'$ be the vector composed of the values of such
 112 P_d covariates for the i th observation and $\mathbf{x}_{id}^* = (1, \mathbf{x}_{id}')'$. Furthermore, let
 113 $\boldsymbol{\beta}_{kd} = (\beta_{kd_1}, \beta_{kd_2}, \dots, \beta_{kd_{P_d}})'$ be the P_d -dimensional vector of regression coeffi-
 114 cients capturing the linear effect of these P_d covariates on the d th response in the
 115 k th group, and $\boldsymbol{\beta}_{kd}^* = (\beta_{kd0}, \boldsymbol{\beta}_{kd}')'$. Then, the vector containing all linear effects
 116 on the D responses in the k th group is given by $\boldsymbol{\beta}_k^* = (\boldsymbol{\beta}_{k1}^*, \dots, \boldsymbol{\beta}_{kd}^*, \dots, \boldsymbol{\beta}_{kD}^*)'$;
 117 the length of this vector is $(P^* + D)$, where $P^* = \sum_{d=1}^D P_d$. Finally, the following
 118 $(P^* + D) \times D$ partitioned matrix is required:

$$119 \quad \mathcal{X}_i = \begin{bmatrix} \mathbf{x}_{i1}^* & \mathbf{0}_{P_1+1} & \dots & \mathbf{0}_{P_1+1} \\ \mathbf{0}_{P_2+1} & \mathbf{x}_{i2}^* & \dots & \mathbf{0}_{P_2+1} \\ \vdots & \vdots & & \vdots \\ \mathbf{0}_{P_D+1} & \mathbf{0}_{P_D+1} & \dots & \mathbf{x}_{iD}^* \end{bmatrix},$$

120 with $\mathbf{0}_{P_d+1}$ denoting the $(P_d + 1)$ -dimensional null vector. With this notation,

the conditional expected vector of $\mathbf{Y}_i | (\mathbf{X}_i = \mathbf{x}_i, \Omega_k)$ is given by

$$\boldsymbol{\mu}_{\mathbf{Y}_k}(\mathbf{x}_i; \boldsymbol{\beta}_k^*) = \mathcal{X}_i' \boldsymbol{\beta}_k^* = (\mathbf{x}_{i1}^{*'} \boldsymbol{\beta}_{k1}^*, \dots, \mathbf{x}_{id}^{*'} \boldsymbol{\beta}_{kd}^*, \dots, \mathbf{x}_{iD}^{*'} \boldsymbol{\beta}_{kD}^*)'. \quad (2)$$

According to this equation, the conditional expected value of the d th response within the k th group is given by the linear term $\mathbf{x}_{id}^{*'} \boldsymbol{\beta}_{kd}^*$, which only depends on the P_d covariates included in the vector \mathbf{x}_{id} . It is worth noting that the regression coefficients vary across groups, which means that the effect of the covariates on the responses changes with the groups. Embedding all these assumptions into model (1) leads to

$$f(\mathbf{x}_i, \mathbf{y}_i; \boldsymbol{\psi}) = \sum_{k=1}^K \pi_k \phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}_k}, \boldsymbol{\Sigma}_{\mathbf{X}_k}) \phi_D(\mathbf{y}_i | \mathbf{x}_i; \mathcal{X}_i' \boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k}), \quad (3)$$

where ϕ_P (ϕ_D) represents the p.d.f. of a P -variate (D -variate) Gaussian random vector, $\boldsymbol{\psi} = \{\pi_1, \dots, \pi_K, \boldsymbol{\mu}_{\mathbf{X}_1}, \dots, \boldsymbol{\mu}_{\mathbf{X}_K}, \boldsymbol{\Sigma}_{\mathbf{X}_1}, \dots, \boldsymbol{\Sigma}_{\mathbf{X}_K}, \boldsymbol{\beta}_1^*, \dots, \boldsymbol{\beta}_K^*, \boldsymbol{\Sigma}_{\mathbf{Y}_1}, \dots, \boldsymbol{\Sigma}_{\mathbf{Y}_K}\}$ denotes the set of all model parameters and $\boldsymbol{\Psi}$ is the parameter space. The number of free parameters in $\boldsymbol{\psi}$ is $K - 1 + K(P + P^* + D) + K[P(P + 1)/2 + D(D + 1)/2]$, which is the sum of the unknown mixture weights, expected values, variances and covariances.

It is worth stressing that the model in equation (3) differs from the model proposed by Dang et al. (2017) because of a different definition of the linear term for the conditional expected value of $\mathbf{Y}_i | (\mathbf{X}_i = \mathbf{x}_i, \Omega_k)$. If all the P covariates are considered to be relevant for the prediction of all responses, that is $\mathbf{x}_{id} = \mathbf{x}_i \forall d$, then $\mathbf{x}_{id}^* = \mathbf{x}_i^* \forall d$, where $\mathbf{x}_i^* = (1, \mathbf{x}_i')'$, and the following equality holds:

$$\mathcal{X}_i = \mathbf{I}_D \otimes \mathbf{x}_i^*,$$

where \mathbf{I}_D is the identity matrix of order D and \otimes denotes the Kronecker product operator (see, e.g., Magnus and Neudecker, 1988). Then, equation (2) can be rewritten as

$$\boldsymbol{\mu}_{\mathbf{Y}_k}(\mathbf{x}_i; \boldsymbol{\beta}_k^*) = (\mathbf{I}_D \otimes \mathbf{x}_i^*)' \boldsymbol{\beta}_k^* = \mathbf{B}_k' \mathbf{x}_i^*, \quad k = 1, \dots, K,$$

where $\mathbf{B}_k = [\boldsymbol{\beta}_{k1}^* \cdots \boldsymbol{\beta}_{kd}^* \cdots \boldsymbol{\beta}_{kD}^*]$, thus leading to the multivariate Gaussian cluster-weighted model introduced by Dang et al. (2017). As illustrated in Section 1, seemingly unrelated regression models can be considered as multivariate

149 regression models in which prior information about the absence of certain covari-
 150 ates for the prediction of certain responses is explicitly taken into consideration
 151 (Srivastava and Giles, 1987). Thus, equation (3) can also be seen as a multivari-
 152 ate Gaussian cluster-weighted model in which some regression coefficients are
 153 constrained to be a priori equal to zero. To the best of the authors' knowledge,
 154 the inclusion of such constraints in the multivariate Gaussian cluster-weighted
 155 model framework has not been addressed yet.

156 2.2. Relationships with linear clusterwise regression models

157 Under suitable conditions, it is possible to establish some relationships be-
 158 tween the multivariate seemingly unrelated Gaussian linear cluster-weighted
 159 models just introduced and some Gaussian linear clusterwise regression models.

160 In Section 2.1 it has been highlighted that models (3) assume that $\mathbf{X}_i|\Omega_k \sim$
 161 $N_P(\boldsymbol{\mu}_{\mathbf{X}_k}, \boldsymbol{\Sigma}_{\mathbf{X}_k})$, for $k = 1, \dots, K$. If the p.d.f of $\mathbf{X}_i|\Omega_k$ does not depend on
 162 group Ω_k , i.e., $\phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}_k}, \boldsymbol{\Sigma}_{\mathbf{X}_k}) = \phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}}, \boldsymbol{\Sigma}_{\mathbf{X}})$ for every $k = 1, \dots, K$,
 163 then equation (3) can also be written as

$$164 \quad f(\mathbf{x}_i, \mathbf{y}_i; \boldsymbol{\psi}) = \phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}}, \boldsymbol{\Sigma}_{\mathbf{X}}) \sum_{k=1}^K \pi_k \phi_D(\mathbf{y}_i | \mathbf{x}_i; \boldsymbol{\mathcal{X}}'_i \boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k}), \quad (4)$$

165 where

$$166 \quad f(\mathbf{y}_i | \mathbf{x}_i; \tilde{\boldsymbol{\psi}}) = \sum_{k=1}^K \pi_k \phi_D(\mathbf{y}_i | \mathbf{x}_i; \boldsymbol{\mathcal{X}}'_i \boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k}), \quad (5)$$

167 with $\tilde{\boldsymbol{\psi}} = \{\pi_1, \dots, \pi_K, \boldsymbol{\beta}_1^*, \dots, \boldsymbol{\beta}_K^*, \boldsymbol{\Sigma}_{\mathbf{Y}_1}, \dots, \boldsymbol{\Sigma}_{\mathbf{Y}_K}\}$, is the seemingly unrelated
 168 Gaussian clusterwise linear regression model described in Galimberti and Sof-
 169 fritti (2020). This means that the assignment of the data points to the groups is
 170 independent of the covariates; such a condition is also known as assignment inde-
 171 pendence (see, e.g., Hennig, 2000). Furthermore, if the researcher sets $\mathbf{x}_{id} = \mathbf{x}_i$
 172 $\forall d$ (i.e., all the P covariates are assumed to be relevant for the prediction of
 173 all responses), then equation (5) leads to the traditional multivariate Gaussian
 174 clusterwise linear regression models (Jones and McLachlan, 1992). Thus, when
 175 in equation (3) the following conditions hold true: $\boldsymbol{\mu}_{\mathbf{X}_k} = \boldsymbol{\mu}_{\mathbf{X}}$, $\boldsymbol{\Sigma}_{\mathbf{X}_k} = \boldsymbol{\Sigma}_{\mathbf{X}}$ for
 176 $k = 1, \dots, K$, then the information about the K disjoint groups $\Omega_1, \dots, \Omega_K$

177 that compose the population Ω can be equivalently obtained either from the
 178 analysis of the conditional p.d.f. $f(\mathbf{y}_i|\mathbf{x}_i; \tilde{\boldsymbol{\psi}})$ through seemingly unrelated linear
 179 clusterwise models or from the analysis of the joint p.d.f. $f(\mathbf{x}_i, \mathbf{y}_i; \boldsymbol{\psi})$ through
 180 seemingly unrelated linear cluster-weighted models.

181 Furthermore, when the following conditions hold true: *i*) the conditional dis-
 182 tribution of $Y_{id}|\mathbf{X}_i = \mathbf{x}_i$ changes with K_d disjoint groups $\Omega_{d1}, \dots, \Omega_{dk_d}, \dots, \Omega_{dK_d}$
 183 that compose the population Ω for $d = 1, \dots, D$; *ii*) these D partitions of Ω as-
 184 sociated with the D responses are mutually independent (i.e., the population
 185 is characterised by D independent cluster structures) (Galimberti and Soffritti,
 186 2007); *iii*) the assignment independence condition holds true for each of these
 187 groupings, then the following model can be defined:

$$188 \quad f(\mathbf{x}_i, \mathbf{y}_i; \boldsymbol{\psi}) = \phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}}, \boldsymbol{\Sigma}_{\mathbf{X}}) \prod_{d=1}^D \sum_{k_d=1}^{K_d} \pi_{k_d} \phi_1(y_{id}|\mathbf{x}_i; \mathbf{x}_{id}^{*'} \boldsymbol{\beta}_{k_d}^*, \sigma_{k_d}^2), \quad (6)$$

189 where y_{id} is the d th element of \mathbf{y}_i , $\mathbf{x}_{id}^{*'} \boldsymbol{\beta}_{k_d}^*$ and $\sigma_{k_d}^2$ are the conditional expected
 190 value and the variance of $Y_{id}|\mathbf{X}_i = \mathbf{x}_i$ within the group Ω_{dk_d} , respectively. Thus,
 191 under conditions *i*)–*iii*), model (6) holds true and the information about the D
 192 independent partitions of the sample observations should be obtained from D
 193 univariate seemingly unrelated linear clusterwise regression models.

194 In the light of the relationships just illustrated, it is possible to conclude
 195 that multivariate seemingly unrelated linear cluster-weighted models will be
 196 more effective than multivariate seemingly unrelated linear clusterwise regres-
 197 sion models when the assignment independence condition does not hold true.
 198 Furthermore, an analysis based on the proposed models should be carried out
 199 rather than D separate analyses, based on D univariate seemingly unrelated
 200 linear clusterwise regression models, whenever either the condition of D inde-
 201 pendent cluster structures or the assignment independence condition do not
 202 hold for the examined population.

203 2.3. Model identifiability

204 Identifiability is essential for parameter estimation and represents a prelim-
 205 inary requirement for the consistency and other asymptotic properties of the

ML estimator. Generally speaking, several types of non-identifiability can affect finite mixture models. A first type is due to invariance to relabeling the components (also known as label-switching). Furthermore, non-identifiability is caused by potential overfitting associated with empty components or equal components (see, e.g., Frühwirth-Schnatter, 2006, p. 15). Thus, identifiability of finite mixture models may be achieved after imposing suitable constraints on the parameter space. As far as multivariate Gaussian cluster-weighted models are concerned, conditions ensuring their identifiability have been defined by Dang et al. (2017). Those conditions can be easily modified in order to hold true also for the seemingly unrelated Gaussian linear cluster-weighted models defined according to equation (3).

The constraints to be imposed on the parameters are $\pi_k > 0 \ \forall \ k$ and $(\beta_k^*, \Sigma_{\mathbf{Y}_k}) \neq (\beta_h^*, \Sigma_{\mathbf{Y}_h})$ for $k \neq h$. These constraints make it possible to avoid the two types of non-identifiability illustrated above. Thus, in order to ensure identifiability, the following class of seemingly unrelated cluster-weighted models has to be considered:

$$\mathfrak{F} = \left\{ f(\mathbf{x}, \mathbf{y}; \bar{\psi}) : f(\mathbf{x}, \mathbf{y}; \bar{\psi}) = \sum_{k=1}^K \pi_k \phi_P(\mathbf{x}; \mu_{\mathbf{X}_k}, \Sigma_{\mathbf{X}_k}) \phi_D(\mathbf{y}|\mathbf{x}; \mathcal{X}'\beta_k^*, \Sigma_{\mathbf{Y}_k}), \right. \\ \left. (\mathbf{x}, \mathbf{y}) \in \mathbb{R}^{P+D}, \bar{\psi} \in \bar{\Psi}, K \in \mathbb{N} \right\},$$

where $\bar{\Psi}$ is the constrained parameter space, defined as follows:

$$\bar{\Psi} = \left\{ \bar{\psi} \in \Psi : \pi_k > 0, \sum_{k=1}^K \pi_k = 1, (\beta_k^*, \Sigma_{\mathbf{Y}_k}) \neq (\beta_h^*, \Sigma_{\mathbf{Y}_h}) \text{ for } k \neq h \right\}.$$

An additional condition for the class \mathfrak{F} to be identifiable is the existence of a set $\mathcal{W} \subseteq \mathbb{R}^P$ having probability equal to one according to the P -dimensional Gaussian distribution such that the following clusterwise regression model

$$\sum_{k=1}^K \phi_M(\mathbf{y}|\mathbf{x}; \mathcal{X}'\beta_k^*, \Sigma_{\mathbf{Y}_k}) \alpha_k(\mathbf{x}), \mathbf{y} \in \mathbb{R}^D,$$

is identifiable for each fixed $\mathbf{x} \in \mathcal{W}$, where $\alpha_1(\mathbf{x}), \dots, \alpha_K(\mathbf{x})$ are positive weights summing to one for each $\mathbf{x} \in \mathcal{W}$. Under this condition, it is possible to prove that the class \mathfrak{F} results to be identifiable in $\mathcal{W} \times \mathbb{R}^D$. The proof of this result can be

233 easily obtained from the proof of the analogous result for multivariate Gaussian
 234 cluster-weighted models (see Dang et al., 2017, Appendix A), by simply changing
 235 the linear term for the conditional expected value of $\mathbf{Y} | (\mathbf{X} = \mathbf{x}, \Omega_k)$.

236 2.4. Parameter estimation

237 Given a sample $\mathcal{S} = \{(\mathbf{x}_1, \mathbf{y}_1), \dots, (\mathbf{x}_I, \mathbf{y}_I)\}$ of I independent observations
 238 from model (3), ML estimation of the model parameters ψ can be carried out
 239 by means of an ECM algorithm developed under a general framework dealing
 240 with incomplete-data problems (Dempster et al., 1977; Meng and Rubin, 1993).
 241 The missing information is the specific component of the mixture from which
 242 the sample observations come from; such information can be described by the
 243 K -dimensional vectors $(\mathbf{z}_1, \dots, \mathbf{z}_I)$, where $\mathbf{z}_i = (z_{i1}, \dots, z_{iK})'$ with $z_{ik} = 1$ if the
 244 i th observation comes from the k th component and $z_{ik} = 0$ otherwise, for $k =$
 245 $1, \dots, K$. Then, the complete data would be $\mathcal{S}_c = \{(\mathbf{x}_1, \mathbf{y}_1, \mathbf{z}_1), \dots, (\mathbf{x}_I, \mathbf{y}_I, \mathbf{z}_I)\}$.
 246 Thus, the likelihood functions derived from the incomplete data and the com-
 247 plete data are

$$\begin{aligned} 248 \quad L(\psi | \mathcal{S}) &= \prod_{i=1}^I \left[\sum_{k=1}^K \pi_k \phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}_k}, \boldsymbol{\Sigma}_{\mathbf{X}_k}) \phi_D(\mathbf{y}_i | \mathbf{x}_i; \boldsymbol{\mathcal{X}}'_i \boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k}) \right], \\ 249 \quad L(\psi | \mathcal{S}_c) &= \prod_{i=1}^I \prod_{k=1}^K \left[\pi_k \phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}_k}, \boldsymbol{\Sigma}_{\mathbf{X}_k}) \phi_D(\mathbf{y}_i | \mathbf{x}_i; \boldsymbol{\mathcal{X}}'_i \boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k}) \right]^{z_{ik}}, \end{aligned}$$

250 respectively; the complete-data log-likelihood function employed in the ECM
 251 algorithm for the computation of the parameter estimates is

$$\begin{aligned} 252 \quad \ell(\psi | \mathcal{S}_c) &= \sum_{i=1}^I \sum_{k=1}^K z_{ik} \left[\ln \pi_k + \ln \phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}_k}, \boldsymbol{\Sigma}_{\mathbf{X}_k}) \right. \\ 253 \quad &\quad \left. + \ln \phi_D(\mathbf{y}_i | \mathbf{x}_i; \boldsymbol{\mathcal{X}}'_i \boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k}) \right]. \end{aligned} \quad (7)$$

254 The h th iteration of the E-step in the ECM algorithm consists in calculating
 255 the conditional expectation of the complete-data log-likelihood (7) on the basis
 256 of the current estimate $\hat{\psi}^{(h)}$ of the model parameters ψ :

$$\begin{aligned} 257 \quad \mathbb{E}_{\hat{\psi}^{(h)}} [\ell(\psi | \mathcal{S}_c)] &= \sum_{i=1}^I \sum_{k=1}^K \hat{\tau}_{ik}^{(h)} \left[\ln \hat{\pi}_k^{(h)} + Q_1(\boldsymbol{\mu}_{\mathbf{X}_k}, \boldsymbol{\Sigma}_{\mathbf{X}_k} | \hat{\psi}^{(h)}) \right. \\ 258 \quad &\quad \left. + Q_2(\boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k} | \hat{\psi}^{(h)}) \right], \end{aligned} \quad (8)$$

259 where

$$\begin{aligned}
260 \quad Q_1(\boldsymbol{\mu}_{\mathbf{X}_k}, \boldsymbol{\Sigma}_{\mathbf{X}_k} | \hat{\boldsymbol{\psi}}^{(h)}) &= \frac{1}{2} \left[-P \ln(2\pi) - \ln |\hat{\boldsymbol{\Sigma}}_{\mathbf{X}_k}^{(h)}| \right. \\
261 \quad &\quad \left. - (\mathbf{x}_i - \hat{\boldsymbol{\mu}}_{\mathbf{X}_k}^{(h)})' \hat{\boldsymbol{\Sigma}}_{\mathbf{X}_k}^{(h)(-1)} (\mathbf{x}_i - \hat{\boldsymbol{\mu}}_{\mathbf{X}_k}^{(h)}) \right], \\
262 \quad Q_2(\boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k} | \hat{\boldsymbol{\psi}}^{(h)}) &= \frac{1}{2} \left[-D \ln(2\pi) - \ln |\hat{\boldsymbol{\Sigma}}_{\mathbf{Y}_k}^{(h)}| \right. \\
263 \quad &\quad \left. - (\mathbf{y}_i - \mathcal{X}_i' \hat{\boldsymbol{\beta}}_k^{*(h)})' \hat{\boldsymbol{\Sigma}}_{\mathbf{Y}_k}^{(h)(-1)} (\mathbf{y}_i - \mathcal{X}_i' \hat{\boldsymbol{\beta}}_k^{*(h)}) \right],
\end{aligned}$$

264 and $\hat{\tau}_{ik}^{(h)}$ provides the posterior probability (evaluated using the current estimate
265 $\hat{\boldsymbol{\psi}}^{(h)}$) that $(\mathbf{x}_i, \mathbf{y}_i)$ is generated from the k th component of the mixture, that is

$$\begin{aligned}
266 \quad \hat{\tau}_{ik}^{(h)} &= \mathbb{E}_{\hat{\boldsymbol{\psi}}^{(h)}} [Z_{ik} | \mathbf{x}_i, \mathbf{y}_i] = \mathbb{P}_{\hat{\boldsymbol{\psi}}^{(h)}} \{Z_{ik} = 1 | \mathbf{x}_i, \mathbf{y}_i\} \\
267 \quad &= \frac{\hat{\pi}_k^{(h)} \phi_P(\mathbf{x}_i; \hat{\boldsymbol{\mu}}_{\mathbf{X}_k}^{(h)}, \hat{\boldsymbol{\Sigma}}_{\mathbf{X}_k}^{(h)}) \phi_D(\mathbf{y}_i | \mathbf{x}_i; \mathcal{X}_i' \hat{\boldsymbol{\beta}}_k^{*(h)}, \hat{\boldsymbol{\Sigma}}_{\mathbf{Y}_k}^{(h)})}{\sum_{k'=1}^K \hat{\pi}_{k'}^{(h)} \phi_P(\mathbf{x}_i; \hat{\boldsymbol{\mu}}_{\mathbf{X}_{k'}}^{(h)}, \hat{\boldsymbol{\Sigma}}_{\mathbf{X}_{k'}}^{(h)}) \phi_D(\mathbf{y}_i | \mathbf{x}_i; \mathcal{X}_i' \hat{\boldsymbol{\beta}}_{k'}^{*(h)}, \hat{\boldsymbol{\Sigma}}_{\mathbf{Y}_{k'}}^{(h)})}. \quad (9) \\
268
\end{aligned}$$

269 The $(h+1)$ th update of $\hat{\boldsymbol{\psi}}^{(h)}$ is obtained by a sequence of CM-steps involved
270 in the ECM algorithm. These steps are meant to maximise the conditional
271 expectation of $\ell(\boldsymbol{\psi} | \mathcal{S}_c)$ with respect to $\boldsymbol{\psi}$. This maximisation can be achieved
272 by setting the first order derivatives of $\mathbb{E}[\ell(\boldsymbol{\psi} | \mathcal{S}_c)]$ equal to zero and then solving
273 the resulting system of equations with respect to the parameters of interest.
274 Since this expected value can be decomposed in a sum of three terms, each one
275 depending on a specific set of parameters (see equation (8)), maximisation can
276 be carried out separately for each set of parameters. The resulting updates of
277 $\hat{\pi}_k^{(h)}$, $\hat{\boldsymbol{\mu}}_{\mathbf{X}_k}^{(h)}$, $\hat{\boldsymbol{\Sigma}}_{\mathbf{X}_k}^{(h)}$, $k = 1, \dots, K$ are:

$$278 \quad \hat{\pi}_k^{(h+1)} = \frac{1}{I} \sum_{i=1}^I \hat{\tau}_{ik}^{(h)}, \quad (10)$$

$$279 \quad \hat{\boldsymbol{\mu}}_{\mathbf{X}_k}^{(h+1)} = \frac{\sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \mathbf{x}_i}{\sum_{i=1}^I \hat{\tau}_{ik}^{(h)}}, \quad (11)$$

$$280 \quad \hat{\boldsymbol{\Sigma}}_{\mathbf{X}_k}^{(h+1)} = \frac{\sum_{i=1}^I \hat{\tau}_{ik}^{(h)} (\mathbf{x}_i - \hat{\boldsymbol{\mu}}_{\mathbf{X}_k}^{(h+1)}) (\mathbf{x}_i - \hat{\boldsymbol{\mu}}_{\mathbf{X}_k}^{(h+1)})'}{\sum_{i=1}^I \hat{\tau}_{ik}^{(h)}}. \quad (12)$$

281 Such updates coincide with the ones reported in Dang et al. (2017). The CM-

steps to update the remaining parameters are (see Appendix A for a proof)

$$\hat{\beta}_k^{*(h+1)} = \left[\sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \mathcal{X}_i \left(\hat{\Sigma}_{\mathbf{Y}_k}^{(h)} \right)^{-1} \mathcal{X}_i' \right]^{-1} \left[\sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \mathcal{X}_i \left(\hat{\Sigma}_{\mathbf{Y}_k}^{(h)} \right)^{-1} \mathbf{y}_i \right], \quad (13)$$

$$\hat{\Sigma}_{\mathbf{Y}_k}^{(h+1)} = \frac{\sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \left(\mathbf{y}_i - \mathcal{X}_i' \hat{\beta}_k^{*(h+1)} \right) \left(\mathbf{y}_i - \mathcal{X}_i' \hat{\beta}_k^{*(h+1)} \right)'}{\sum_{i=1}^I \hat{\tau}_{ik}^{(h)}}. \quad (14)$$

It is worth noting that the matrix $\sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \mathcal{X}_i \left(\hat{\Sigma}_{\mathbf{Y}_k}^{(h)} \right)^{-1} \mathcal{X}_i'$ has to be nonsingular in order for the update $\hat{\beta}_k^{*(h+1)}$ in equation (13) to exist. In addition, Appendix B shows that equation (13) is equivalent to the expression reported in Dang et al. (2017) for the updates of the regression coefficient matrix when $\mathbf{x}_{id} = \mathbf{x}_i \forall d$. As a consequence, in this special case the ECM algorithm described in this section reduces to the EM algorithm described in Dang et al. (2017). Finally, once the convergence is reached, the ECM algorithm also provides estimates of the posterior probabilities according to equation (9), which can be used to partition the I observations into K clusters, by assigning each observation to the component showing the highest posterior probability.

Difficulties with this ECM algorithm can arise when matrices $\hat{\Sigma}_{\mathbf{X}_k}^{(h+1)}$ and $\hat{\Sigma}_{\mathbf{Y}_k}^{(h+1)}$ in equations (12) and (14) are singular or nearly singular. Another difficulty with ML estimation of Gaussian mixture models is the unboundedness of the likelihood function (see, e.g. Frühwirth-Schnatter, 2006, p. 173). A way to deal with these problems is to introduce suitable constraints on the parameter space Ψ and to perform the estimation under a constrained Ψ (see, e.g. Ingrassia and Rocci, 2011; Rocci et al., 2018). All the analyses illustrated in this paper have been carried out through an implementation of the proposed ECM algorithm, which also allows the estimation of the multivariate linear cluster-weighted models introduced by Dang et al. (2017), in the R environment. Such an implementation embeds suitable constraints on the eigenvalues of both $\hat{\Sigma}_{\mathbf{X}_k}^{(h+1)}$ and $\hat{\Sigma}_{\mathbf{Y}_k}^{(h+1)}$ for $k = 1, \dots, K$. Namely, following Dang et al. (2017), all estimated covariance matrices have been required to have eigenvalues greater than the conservative bound 10^{-20} ; furthermore, the ratio between the smallest and the largest eigenvalues of such matrices is required to be not lower than 10^{-10} .

Finally, in order to avoid problems associated with the invariance of a mixture distribution to relabeling its components (see, e.g., Frühwirth-Schnatter, 2006, p. 15), the K estimated components of the model (3) have been labeled according to the estimated prior probabilities taken in non-decreasing order.

2.5. Initialisation and convergence of the ECM algorithm

A crucial point of any ECM algorithm is the choice of the starting values for the model parameters (i.e., $\hat{\psi}^{(0)}$). An approach based on multiple random initialisations and multiple executions of the ECM algorithm could be adopted. Approaches based on non-random choices can be employed. A solution could be obtained by resorting to the following two-step strategy. In the first step a mixture of K Gaussian models is estimated for the joint distribution all covariates and responses. This task can be carried out, for example, by resorting to the `mclust` package (Scrucca et al., 2017) for the R environment. The K prior probabilities, mean vectors and covariance matrices for the predictors estimated in this way are used as $\hat{\pi}_k^{(0)}$, $\hat{\mu}_{\mathbf{X}_k}^{(0)}$ and $\hat{\Sigma}_{\mathbf{X}_k}^{(0)}$, for $k = 1, \dots, K$. In the second step $\hat{\beta}_k^{*(0)}$ and $\hat{\Sigma}_{\mathbf{Y}_k}^{(0)}$ are obtained from an estimate of the parameters of the conditional distribution of the responses given the predictors based on the fitting of a seemingly unrelated Gaussian linear regression model to the sample observations that have been assigned to the k th component of the mixture model estimated in the first step. The R package `systemfit` (Henningsen and Hamann, 2007) can be exploited to perform this task. Another way to obtain $\hat{\pi}_k^{(0)}$, $\hat{\mu}_{\mathbf{X}_k}^{(0)}$ and $\hat{\Sigma}_{\mathbf{X}_k}^{(0)}$, for $k = 1, \dots, K$ could be based on the fitting of a mixture of K Gaussian models for the marginal distribution of the covariates in the first step of the previous strategy while keeping the second step unchanged. In all analyses reported in this paper involving either models defined in equation (3) or models introduced by Dang et al. (2017), both these strategies have been simultaneously employed; thus, two different initialisations have been considered for each analysed dataset. Then, the ECM algorithm has been initialised with the strategy leading to the largest value of the incomplete log-likelihood.

In the R function employed for the parameter estimation in all analyses

summarised in this paper, the convergence of the ECM algorithm has been evaluated through a criterion based on the Aitken acceleration (Aitken, 1926) which consists in stopping the ECM algorithm when $\left|l_A^{(h+1)} - \ell(\hat{\psi}^{(h)}|\mathcal{S})\right| < \epsilon$, where $l_A^{(h+1)}$ is the $(h+1)$ th Aitken accelerated estimate of the log-likelihood limit and $\ell(\hat{\psi}^{(h)}|\mathcal{S})$ is the value of the incomplete log-likelihood at the h th iteration (see, e.g., McNicholas, 2010, for more details). Such criterion can avoid premature stops associated with the use of lack of progress stopping criteria, such as the one based on the difference between the log-likelihood values at two consecutive steps of the ECM algorithm. The maximum number of iterations for the ECM algorithm and the value for ϵ have been set equal to 500 and 10^{-8} , respectively.

2.6. Model selection

The ECM algorithm described in Section 2.4 performs the ML estimation for a given value of K . However, in most practical applications, the number of groups is not known and must be determined from the data \mathcal{S} . A common solution to this task is obtained by resorting to model selection criteria which allows to trade-off the fit (measured by $l_M(\hat{\psi}|\mathcal{S})$, the maximum of the incomplete loglikelihood of model M) and complexity (given by $npar_M$, the number of free parameters in model M) (see, e.g., Frühwirth-Schnatter, 2006, subsections 4.4.2-4.4.3). In the context of Gaussian mixture models and Gaussian cluster-weighted models (see, e.g., Fraley and Raftery, 2002; Dang et al., 2017), the Bayesian Information Criterion (BIC) (Schwarz, 1978) has performed well and is commonly employed. It can be computed as follows: $BIC_M = -2l_M(\hat{\psi}|\mathcal{S}) + npar_M \ln I$. Given a collection of competing fitted candidate models, the one that minimises BIC_M is preferred. Model selection criteria that also consider the quality of the estimated partition of the sample observations represent another possible solution (see, e.g., Frühwirth-Schnatter, 2006, subsection 7.1.4).

2.7. Parsimonious models

As the number of free parameters in equation (3) increases quadratically with both the number of responses and the number of predictors, analyses

based on the proposed models can become unfeasible in practical applications.
 This problem can be overcome by introducing constraints on the elements of
 the covariance matrices $\Sigma_{\mathbf{X}_k}$ and $\Sigma_{\mathbf{Y}_k}$ ($k = 1, \dots, K$) according to the ap-
 proach illustrated in Celeux and Govaert (1995). In this approach, the follow-
 ing eigen-decomposition of the covariance matrix $\Sigma_{\mathbf{X}_k}$ has to be considered:
 $\Sigma_{\mathbf{X}_k} = \alpha_k \mathbf{D}_k \mathbf{A}_k \mathbf{D}_k'$, where $\alpha_k = |\Sigma_{\mathbf{X}_k}|^{1/D}$, \mathbf{A}_k is the diagonal matrix con-
 taining the eigenvalues of $\Sigma_{\mathbf{X}_k}$ (normalised in such a way that $|\mathbf{A}_k| = 1$) and
 \mathbf{D}_k is the matrix of eigenvectors of $\Sigma_{\mathbf{X}_k}$. Thus, variances and covariances in
 $\Sigma_{\mathbf{X}_k}$ can be obtained from α_k , \mathbf{A}_k and \mathbf{D}_k . From a geometrical point of view,
 such parameters determine the volume, shape and orientation of the k th cluster
 of observations with respect to the predictors. By constraining one or more
 of these three parameters to be equal across components, 14 different covari-
 ance structures for the predictors in models (3) with $K > 1$ can be determined
 (see Celeux and Govaert, 1995, for more details). Additional information about
 these parameterisations can be found in Table 1. The application of the same
 approach to the covariance matrices $\Sigma_{\mathbf{Y}_k}$, $k = 1, \dots, K$ leads to a class of 196
 different models for any given $K > 1$. Equations (12) and (14) represent the
 solutions for the model in which the covariance structures of both predictors
 and responses are fully unconstrained. For all other parsimonious models, the
 CM-step updates for the estimation of $\Sigma_{\mathbf{X}_k}$ and $\Sigma_{\mathbf{Y}_k}$ in the ECM algorithm
 have to be modified; these modified updates can be computed either in closed
 form or using iterative procedures, depending on the specific parameterisation
 to be employed (see Celeux and Govaert, 1995, for more details). The CM-step
 updates $\hat{\Sigma}_{\mathbf{X}_k}^{(h+1)}$ and $\hat{\Sigma}_{\mathbf{Y}_k}^{(h+1)}$ associated with the parameterisations **EVE** and **VVE**
 can be computed using the F-G algorithm (Flury and Gautschi, 1986) or one of
 its variants (see, e.g., Lin, 2014). Algorithms which are computationally feasible
 also in high-dimensional situations have been recently introduced (Browne and
 McNicholas, 2014a,b). All the experimental results illustrated here and concern-
 ing the **EVE** and **VVE** parameterisations have been obtained using the algorithms
 given in Browne and McNicholas (2014a). When $K = 1$, only three covariance
 structures for both responses and covariates are possible: diagonal with different

Table 1: Parsimonious parameterisations for the component-covariance matrices

Acronym	Model	Distribution	Volume	Shape	Orientation
EEE	$\alpha \mathbf{DAD}'$	Ellipsoidal	Equal	Equal	Equal
VVV	$\alpha_k \mathbf{D}_k \mathbf{A}_k \mathbf{D}_k'$	Ellipsoidal	Variable	Variable	Variable
EII	$\alpha \mathbf{I}$	Spherical	Equal	Equal	—
VII	$\alpha_k \mathbf{I}$	Spherical	Variable	Equal	—
EEI	$\alpha \mathbf{A}$	Diagonal	Equal	Equal	—
VEI	$\alpha_k \mathbf{A}$	Diagonal	Variable	Equal	—
EVI	$\alpha \mathbf{A}_k$	Diagonal	Equal	Variable	—
VVI	$\alpha_k \mathbf{A}_k$	Diagonal	Variable	Variable	—
EEV	$\alpha \mathbf{D}_k \mathbf{AD}_k'$	Ellipsoidal	Equal	Equal	Variable
VEV	$\alpha_k \mathbf{D}_k \mathbf{AD}_k'$	Ellipsoidal	Variable	Equal	Variable
EVE	$\alpha \mathbf{DA}_k \mathbf{D}'$	Ellipsoidal	Equal	Variable	Equal
VVE	$\alpha_k \mathbf{DA}_k \mathbf{D}'$	Ellipsoidal	Variable	Variable	Equal
VEE	$\alpha_k \mathbf{DAD}'$	Ellipsoidal	Variable	Equal	Equal
EVV	$\alpha \mathbf{D}_k \mathbf{A}_k \mathbf{D}_k'$	Ellipsoidal	Equal	Variable	Variable

entries (VI), diagonal with the same entries (EI) and fully unconstrained (VV).
Thus, nine differentially parameterised one-component cluster-weighted models
can be obtained.

3. Results from Monte Carlo studies

The main purpose of the studies based on simulated datasets illustrated here
is to obtain an evaluation of the effectiveness of the proposed methodology in
comparison with the approach introduced by Dang et al. (2017), where the same
vector of covariates has to be employed for all responses. Thus, cluster-weighted
models belonging to two different classes have been fitted to each simulated
dataset: *i*) models in which all the D responses are assumed to depend on all
the P examined covariates (i.e., the models proposed by Dang et al. (2017));
ii) models defined according to equation (3) in which each response has its

specific predictors. From now on, such models have been denoted as **CW** and **SuCW**, respectively. A hundred datasets of $I = 450$ independent observations have been randomly generated from model (3) with $D = 2$ responses, $P = 3$ predictors and $K = 3$ components in which the elements of the conditional expected vector (2) are defined as follows:

$$E(Y_{i1}|\mathbf{X}_i = \mathbf{x}_i, \Omega_k) = \beta_{k10} + \beta_{k11}x_{i1} + \beta_{k12}x_{i2}, \quad (15)$$

$$E(Y_{i2}|\mathbf{X}_i = \mathbf{x}_i, \Omega_k) = \beta_{k20} + \beta_{k21}x_{i1} + \beta_{k22}x_{i3}. \quad (16)$$

Thus, the model employed to generate the datasets assumes that the first response Y_1 depends on X_1 and X_2 while Y_2 depends on X_1 and X_3 . Furthermore, the component-covariance structures of both the predictors and the responses are defined using the **VVV** parameterisation. The specific values of the parameters for the data-generating model are: $\pi_1 = 0.4$, $\pi_2 = 0.35$, $\pi_3 = 0.25$, $\boldsymbol{\mu}_{\mathbf{X}_1} = (0, 0, 0)'$, $\boldsymbol{\mu}_{\mathbf{X}_2} = (2, 4, -2)'$, $\boldsymbol{\mu}_{\mathbf{X}_3} = \boldsymbol{\mu}_{\mathbf{X}_2} + 2\epsilon \cdot \mathbf{1}_P$, where $\mathbf{1}_P$ is the $P \times 1$ vector having each element equal to 1, $\boldsymbol{\beta}_1^* = (-2, 0.75, 1, 1, 0.5, -2)'$, $\boldsymbol{\beta}_2^* = (0.5, 1.75, 0.25, 1, 1, 1)'$, $\boldsymbol{\beta}_3^* = \boldsymbol{\beta}_2^* + \epsilon \cdot \mathbf{1}_6$, $\boldsymbol{\Sigma}_{\mathbf{X}_1} = \begin{pmatrix} 1.72 & -0.18 & 0.27 \\ -0.18 & 1.89 & 0.27 \\ 0.27 & 0.27 & 2.89 \end{pmatrix}$, $\boldsymbol{\Sigma}_{\mathbf{X}_2} = \begin{pmatrix} 2.33 & -0.52 & -0.06 \\ -0.52 & 0.88 & -0.34 \\ -0.06 & -0.34 & 1.04 \end{pmatrix}$, $\boldsymbol{\Sigma}_{\mathbf{X}_3} = \boldsymbol{\Sigma}_{\mathbf{X}_2}$, $\boldsymbol{\Sigma}_{\mathbf{Y}_1} = \begin{pmatrix} 1.34 & 0.47 \\ 0.47 & 1.66 \end{pmatrix}$, $\boldsymbol{\Sigma}_{\mathbf{Y}_2} = \begin{pmatrix} 0.50 & 0.04 \\ 0.04 & 1.50 \end{pmatrix}$, $\boldsymbol{\Sigma}_{\mathbf{Y}_3} = \boldsymbol{\Sigma}_{\mathbf{Y}_2}$. Since the second and third components of the data-generating model only differ in the values of intercepts and regression coefficients and the expected values of the regressors, the separation between such components depends on ϵ . The simulated datasets have been generated using the following values of ϵ : 0.275, 0.3, 0.325, 0.350 and 0.375; this allows an evaluation of the performances of the approaches based on **SuCW** and **CW** models under different experimental levels of separation between those components. Figures 1 and 2 show the scatterplots for two simulated datasets obtained with $\epsilon = 0.3$ and $\epsilon = 0.375$, respectively.

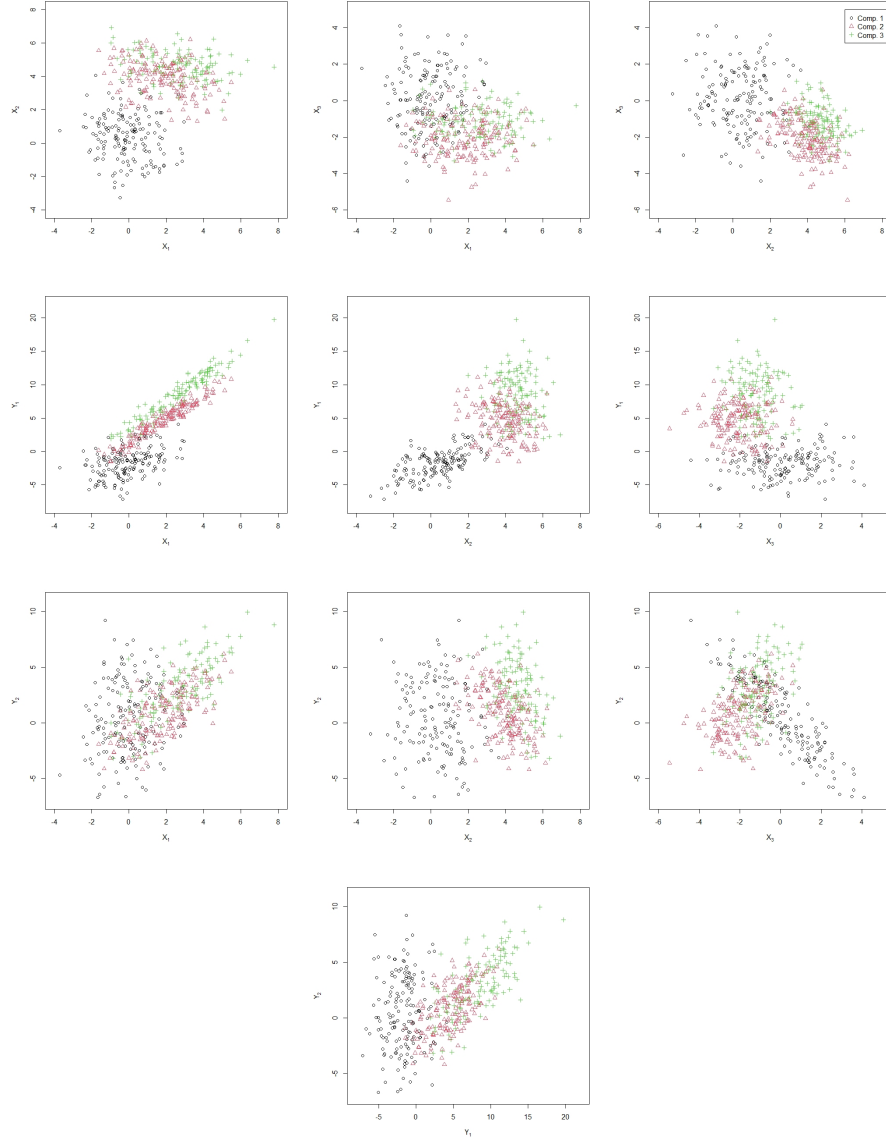


Figure 1: Bivariate scatterplots for pairs of variables in a simulated dataset, $\epsilon = 0.3$.

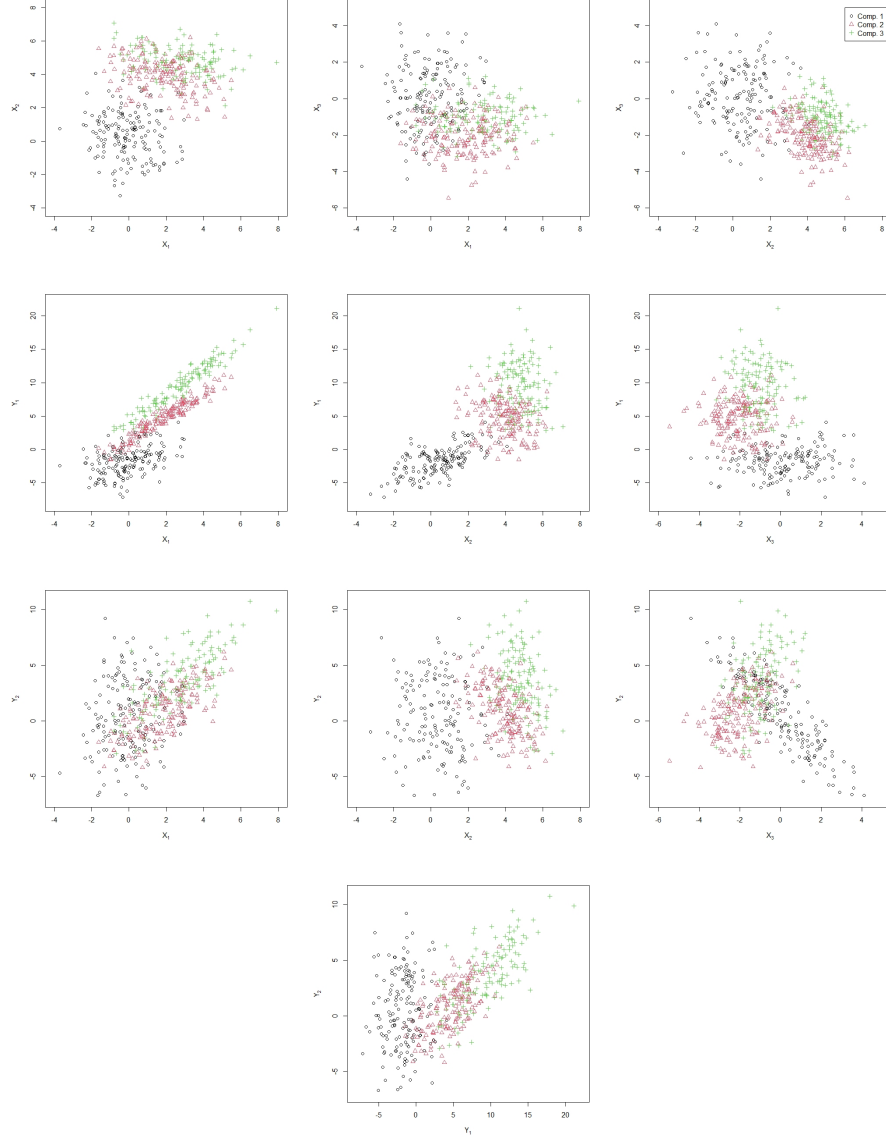


Figure 2: Bivariate scatterplots for pairs of variables in a simulated dataset, $\epsilon = 0.375$.

438 A first analysis has been carried out where the 196 **SuCW** and **CW** models with
 439 $K = 3$ components associated with all the parameterisations for the component-
 440 covariance structures of both the predictors and the responses have been fitted to
 441 each dataset. It is worth noting that using **CW** models leads to non-parsimonious
 442 specifications for such datasets, as six regression coefficients (two for each com-
 443 ponent) have been estimated although in fact they are equal to zero. The
 444 analysis has been run on an IBM x3750 M4 server with 4 Intel Xeon E5-4620
 445 processors with 8 cores and 128GB RAM. The average execution times (over
 446 100 datasets) for **SuCW** models have ranged between 2.698 and 35.309 seconds,
 447 depending on the specific combination of parameterisations for the component
 448 covariance matrices and the value of ϵ . Concerning **CW** models, the minimum
 449 and maximum average execution times have resulted to be equal to 3.382 and
 450 40.710 seconds, respectively. Since the implementation of the ECM algorithm
 451 has not been carried out with the goal of being efficient from a computational
 452 point of view, these CPU times are merely illustrative and can be reduced using
 453 more efficient implementations. For all the models fitted to any dataset, the
 454 value of BIC has been computed and the models with the lowest BIC within
 455 the two collections of fitted models have been selected. The 100 pairs of models
 456 selected as just illustrated, one for each simulated dataset, have been employed
 457 to compare the effectiveness of the two approaches. As expected, **SuCW** models
 458 have resulted to be preferable to **CW** ones. For each dataset $BIC_{\text{SuCW}} < BIC_{\text{CW}}$ for
 459 all the examined values of ϵ with the exception of two datasets when $\epsilon = 0.350$.

460 A further evaluation of the two approaches has been performed by examining
 461 their ability to recover the true values of the unknown parameters (i.e., param-
 462 eter recovery). In particular, the attention has been focused on the bias and
 463 the root mean squared error (RMSE) for the regression coefficients in equations

464 (15) and (16). Namely, the following quantities have been computed

$$\begin{aligned}
465 \quad Bias\left(\hat{\beta}_{kdp}\right) &= \left| \beta_{kdp} - \frac{\sum_{r=1}^{100} \hat{\beta}_{kdp}^{(r)}}{100} \right|, \quad k = 1, 2, 3, \quad d = 1, 2, \quad p = 1, 2, \\
466 \quad RMSE\left(\hat{\beta}_{kdp}\right) &= \sqrt{\frac{\sum_{r=1}^{100} \left(\beta_{kdp} - \hat{\beta}_{kdp}^{(r)}\right)^2}{100}}, \quad k = 1, 2, 3, \quad d = 1, 2, \quad p = 1, 2,
\end{aligned}$$

467 where $\hat{\beta}_{kdp}^{(r)}$ is the ML estimate of β_{kdp} obtained from the r th dataset ($r =$
468 $1, \dots, 100$). Note that **CW** models contain additional regression coefficients as-
469 sociated with the equation-specific irrelevant regressors. The bias and RMSE
470 have been computed also for these additional coefficients, using 0 as their true
471 value. Tables 2 and 3 report the values of bias and RMSE, respectively, ob-
472 tained for each value of ϵ . Overall, both approaches tend to provide acceptable
473 results in terms of recovering the true values of the regression coefficients. This
474 is evident for the parameters of the first component. As far as the second and
475 third components are concerned, there seems to be a tendency for **SuCW** models
476 to perform slightly better than **CW** models, especially considering the RMSE for
477 low values of ϵ . It is also worth noting that **CW** models appear to be capable of
478 recognising the presence of irrelevant regressors, as the corresponding estimated
479 regression coefficients are on average very close to 0. However, the RMSE of
480 some of these estimates tend to be large, suggesting a low precision in the
481 estimation of the effect of some irrelevant regressors. This precision seems to
482 improve as the separation among components increases.

483 The performance of the two approaches has also been evaluated by their abil-
484 ity to properly estimate the true classification of the sample observations (i.e.,
485 classification recovery). This task has been carried out by means of the adjusted
486 Rand index (*ARI*) (Hubert and Arabie, 1985). Some summary statistics of this
487 index (over the 100 datasets) for both approaches by the five examined levels
488 of separation are reported in Table 4. These results show that the classification
489 recovery associated with the use of both approaches increases with the level of
490 separation between the second and third components (see the mean and me-
491 dian values of *ARI* in Table 4); on the contrary, the interquartile range and

Table 2: Bias for the regression coefficients under SuCW and CW models in the first study.

	$\epsilon = 0.275$		$\epsilon = 0.3$		$\epsilon = 0.325$		$\epsilon = 0.350$		$\epsilon = 0.375$	
	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW
$\beta_{111} = 0.75$	0.005	0.003	0.005	0.004	0.006	0.005	0.007	0.005	0.006	0.005
$\beta_{112} = 1$	0.003	0.001	0.002	0.003	0.003	0.003	0.002	0.005	0.002	0.003
$\beta_{121} = 0.5$	0.010	0.013	0.005	0.007	0.005	0.008	0.002	0.006	0.005	0.008
$\beta_{122} = -2$	0.000	0.005	0.002	0.004	0.002	0.004	0.002	0.004	0.002	0.004
$\beta_{211} = 1.75$	0.027	0.090	0.011	0.023	0.001	0.010	0.037	0.002	0.003	0.002
$\beta_{212} = 0.25$	0.067	0.160	0.023	0.040	0.009	0.022	0.010	0.023	0.000	0.002
$\beta_{221} = 1$	0.028	0.039	0.019	0.011	0.013	0.009	0.007	0.008	0.009	0.007
$\beta_{222} = 1$	0.004	0.026	0.028	0.042	0.027	0.023	0.027	0.053	0.028	0.028
$\beta_{311} = 1.75 + \epsilon$	0.002	0.005	0.002	0.003	0.001	0.002	0.003	0.003	0.002	0.003
$\beta_{312} = 0.25 + \epsilon$	0.052	0.100	0.014	0.034	0.010	0.016	0.012	0.016	0.004	0.017
$\beta_{321} = 1 + \epsilon$	0.023	0.065	0.022	0.028	0.013	0.012	0.017	0.018	0.009	0.009
$\beta_{322} = 1 + \epsilon$	0.004	0.020	0.013	0.015	0.016	0.007	0.009	0.011	0.020	0.021
Irrelevant regressors										
$\beta_{113} = 0$	—	0.007	—	0.003	—	0.003	—	0.001	—	0.003
$\beta_{123} = 0$	—	0.022	—	0.021	—	0.021	—	0.022	—	0.021
$\beta_{213} = 0$	—	0.060	—	0.016	—	0.015	—	0.006	—	0.002
$\beta_{223} = 0$	—	0.001	—	0.011	—	0.005	—	0.004	—	0.003
$\beta_{313} = 0$	—	0.067	—	0.040	—	0.028	—	0.023	—	0.019
$\beta_{323} = 0$	—	0.082	—	0.011	—	0.002	—	0.007	—	0.003

Table 3: RMSE for the regression coefficients under SuCW and CW models in the first study.

	$\epsilon = 0.275$		$\epsilon = 0.3$		$\epsilon = 0.325$		$\epsilon = 0.350$		$\epsilon = 0.375$	
	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW
$\beta_{111} = 0.75$	0.058	0.059	0.058	0.059	0.059	0.059	0.060	0.060	0.058	0.060
$\beta_{112} = 1$	0.075	0.075	0.068	0.069	0.069	0.069	0.069	0.069	0.068	0.069
$\beta_{121} = 0.5$	0.096	0.094	0.075	0.077	0.075	0.077	0.077	0.078	0.075	0.077
$\beta_{122} = -2$	0.055	0.063	0.054	0.057	0.054	0.057	0.054	0.057	0.054	0.057
$\beta_{211} = 1.75$	0.264	0.374	0.087	0.121	0.058	0.088	0.487	0.135	0.045	0.045
$\beta_{212} = 0.25$	0.182	0.316	0.116	0.166	0.090	0.127	0.131	0.142	0.073	0.074
$\beta_{221} = 1$	0.211	0.339	0.096	0.120	0.080	0.105	0.111	0.117	0.067	0.073
$\beta_{222} = 1$	0.437	0.548	0.126	0.181	0.113	0.130	0.440	0.341	0.103	0.111
$\beta_{311} = 1.75 + \epsilon$	0.089	0.176	0.083	0.100	0.074	0.089	0.074	0.085	0.059	0.063
$\beta_{312} = 0.25 + \epsilon$	0.185	0.252	0.130	0.167	0.117	0.152	0.125	0.153	0.104	0.127
$\beta_{321} = 1 + \epsilon$	0.112	0.275	0.103	0.115	0.083	0.113	0.086	0.099	0.076	0.088
$\beta_{322} = 1 + \epsilon$	0.149	0.197	0.131	0.150	0.125	0.176	0.132	0.145	0.119	0.135
Irrelevant regressors										
$\beta_{113} = 0$	—	0.057	—	0.048	—	0.048	—	0.052	—	0.048
$\beta_{123} = 0$	—	0.082	—	0.081	—	0.081	—	0.080	—	0.080
$\beta_{213} = 0$	—	0.179	—	0.106	—	0.099	—	0.081	—	0.062
$\beta_{223} = 0$	—	0.214	—	0.200	—	0.156	—	0.126	—	0.125
$\beta_{313} = 0$	—	0.353	—	0.139	—	0.108	—	0.101	—	0.089
$\beta_{323} = 0$	—	0.294	—	0.163	—	0.172	—	0.162	—	0.163

Table 4: Summary statistics of the *ARI* index under **SuCW** and **CW** models in the first study: mean, median, interquartile range (IQR) and standard deviation (SD). The p-values in the last row refer to the paired samples Wilcoxon test for the hypothesis of equality between *ARIs* for each ϵ .

	$\epsilon = 0.275$		$\epsilon = 0.3$		$\epsilon = 0.325$		$\epsilon = 0.350$		$\epsilon = 0.375$	
	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW
Mean	0.852	0.806	0.901	0.887	0.927	0.920	0.936	0.936	0.956	0.956
Median	0.878	0.862	0.911	0.901	0.930	0.929	0.945	0.947	0.959	0.960
IQR	0.062	0.192	0.035	0.043	0.030	0.034	0.026	0.028	0.020	0.023
SD	0.083	0.121	0.037	0.070	0.026	0.048	0.057	0.053	0.018	0.019
p-value	$< 10^{-5}$		0.0717		0.573		0.262		0.935	

Table 5: Distributions of the number of components for the best **SuCW** and **CW** models in the second study.

	$\epsilon = 0.275$		$\epsilon = 0.3$		$\epsilon = 0.325$		$\epsilon = 0.350$		$\epsilon = 0.375$	
	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW
$K = 2$	48	99	7	84	1	39	1	10	0	1
$K = 3$	52	1	93	16	99	61	98	90	100	99
$K = 4$	0	0	0	0	0	0	1	0	0	0

the standard deviation of *ARI* seem to show a decreasing trend. Furthermore, **SuCW** models tend to be characterised by a greater ability to properly estimate the true classification of the sample observations for each examined value of ϵ , even though the differences in terms of mean and median values of *ARI* seem to vanish for larger values of ϵ . This pattern is confirmed by the results of the paired samples Wilcoxon test, suggesting that the difference between the mean values of *ARI* with the two approaches appears to be statistically significant only when the degree of separation is low (see the p-values in the last row of Table 4). This behaviour might be connected to the fact that, as the value of ϵ increases, not only the differences between the two approaches in recovering the actual values of the parameters tend to vanish, but also there is an improvement in the ability of **CW** models to recognise the presence of irrelevant regressors.

504 A second analysis has been carried out, where the performance of the two
 505 approaches has been evaluated without exploiting the knowledge of neither the
 506 number of components nor the parameterisation of the component-covariance
 507 matrices of \mathbf{X} and \mathbf{Y} employed to generate the datasets. Thus, 597 different
 508 SuCW models have been estimated for each simulated dataset: 196 differentially
 509 parameterised models for each $K = 2, 3, 4$ and 9 models with $K = 1$. The same
 510 task has been carried out by employing CW models. Then, the best SuCW and CW
 511 models fitted to each dataset have been selected according to the *BIC*. Table 5
 512 summarises the results of this procedure in terms of recovery of the true K .
 513 The impact of the value of ϵ on this aspect is evident. Generally speaking, the
 514 ability to select the correct value of K improves as the separation increases.
 515 By focusing the attention on the distributions of the number of components
 516 for the best CW models fitted to the 100 datasets, it emerges that with such an
 517 approach the true number of components tends to be severely underestimated
 518 with the two lowest levels of separation ($\epsilon = 0.275, 3$). On the contrary, using
 519 SuCW models leads to the selection of the correct number of components for the
 520 majority of the simulated datasets with all levels of separation; furthermore, the
 521 proportion of datasets for which the selected SuCW model has three components
 522 increases quickly with ϵ , reaching 93% when $\epsilon = 0.3$ and approaching nearly
 523 100% for larger values of ϵ .

524 In order to assess the possible consequences of a wrong choice of K on
 525 the ability of CW models to recognise the presence of equation-specific irrelevant
 526 regressors, the biases of the estimates of the effects of these regressors have been
 527 computed for CW models with K equal to 1, 2 and 4. According to the values
 528 reported in Table 6, it appears that the estimates of the regression coefficients for
 529 the irrelevant regressors can be severely biased when the number of components
 530 is lower than the true one. On the contrary, when the number of components
 531 exceeds the true K , the results are comparable with those obtained in the first
 532 analysis using models with $K = 3$ components (see the lower part of Table 2).
 533 It is also worth noting that for some coefficients the bias seems to show a trend
 534 which increases with the separation among components.

Table 6: Bias for the regression coefficients for equation-specific irrelevant regressors under **CW** models in the second study.

		$\epsilon = 0.275$	$\epsilon = 0.3$	$\epsilon = 0.325$	$\epsilon = 0.350$	$\epsilon = 0.375$
$K = 1$	$\beta_{113} = 0$	0.047	0.065	0.084	0.105	0.127
	$\beta_{123} = 0$	0.525	0.504	0.483	0.462	0.440
$K = 2$	$\beta_{113} = 0$	0.003	0.003	0.003	0.003	0.003
	$\beta_{123} = 0$	0.022	0.022	0.022	0.022	0.022
	$\beta_{213} = 0$	0.377	0.428	0.479	0.529	0.578
	$\beta_{223} = 0$	0.110	0.128	0.147	0.166	0.186
$K = 4$	$\beta_{113} = 0$	0.011	0.024	0.023	0.008	0.032
	$\beta_{123} = 0$	0.034	0.047	0.043	0.035	0.027
	$\beta_{213} = 0$	0.017	0.012	0.004	0.014	0.013
	$\beta_{223} = 0$	0.095	0.015	0.011	0.093	0.065
	$\beta_{313} = 0$	0.056	0.017	0.010	0.011	0.012
	$\beta_{323} = 0$	0.009	0.056	0.004	0.011	0.004
	$\beta_{413} = 0$	0.070	0.017	0.026	0.024	0.018
	$\beta_{423} = 0$	0.057	0.024	0.013	0.013	0.000

As far as the classification recovery is concerned, the obtained results demonstrates that the ability to estimate the true classification of the sample observations with both approaches increases with ϵ . However, the gap between the two approaches in terms of mean and median *ARI* is quite large and statistically significant for the three smallest values of ϵ (see the Table 7). It is worth noting that the behaviour of the variability of the *ARI* index is strictly related to the variability in the distribution of the optimal value of K selected according to the *BIC*. In summary, the obtained results seem to suggest that the inclusion of the regressor X_3 in the equation (15) and the regressor X_2 in the equation (16) has a negative impact both on the choice of the correct number of components and on the reconstruction of the true classification of the sample observations. However, the consequences of including these irrelevant regressors seem to become negligible as the separation among components increases. A possible explanation of this behaviour could be related to the fact that the clustering task is eased when the components are well-separated. In such situations, even if **CW** models are non-parsimonious, they can lead to the correct choice of K . As a consequence, they are able to provide estimates for the regression coefficients of irrelevant regressors that are sufficiently close to zero, so that the inclusion of such regressors has little effect on the estimated posterior probabilities employed to classify the sample observations.

4. Results from the analysis of real data

Two real situations have been examined to evaluate the practical usefulness of **SuCW** models in comparison with **CW** models. For both these model classes, models have been estimated for K from 1 to 9. For each of these values, all possible parsimonious **CW** and **SuCW** models have been fitted (see Section 2.7). Analyses of the examined real datasets have been carried out also through the clusterwise regression models described in Section 2.2. Namely, the comparison with models (5) allows to assess the adequacy of the assignment independence assumption. Furthermore, from the comparison with models (6) it is possi-

Table 7: Summary statistics of the *ARI* index for the best model **SuCW** and **CW** model in the second study: mean, median, interquartile range (IQR) and standard deviation (SD). The p-values in the last row refer to the paired samples Wilcoxon test for the hypothesis of equality between *ARIs* for each ϵ .

	$\epsilon = 0.275$		$\epsilon = 0.3$		$\epsilon = 0.325$		$\epsilon = 0.350$		$\epsilon = 0.375$	
	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW	SuCW	CW
Mean	0.766	0.644	0.885	0.687	0.924	0.820	0.939	0.916	0.956	0.953
Median	0.785	0.644	0.905	0.652	0.929	0.904	0.945	0.945	0.959	0.960
IQR	0.236	0.036	0.041	0.048	0.030	0.273	0.026	0.030	0.020	0.023
SD	0.120	0.034	0.071	0.103	0.035	0.138	0.038	0.087	0.018	0.036
p-value	$< 10^{-10}$		$< 10^{-15}$		$< 10^{-8}$		0.022		0.851	

564 ble to establish whether fitting multivariate cluster-weighted models based on
 565 seemingly unrelated linear regression for D responses leads to an improvement
 566 over an approach based on D univariate seemingly unrelated linear clusterwise
 567 regression models. From now on, models (5) and (6) are denoted as **SuCR** and
 568 **uSuCR**, respectively. Models from equations (5) and (6) have been estimated
 569 also using the same vector of covariates for all responses (i.e., with $\mathbf{x}_{id} = \mathbf{x}_i$
 570 $\forall d$); in the following, they are denoted as **CR** and **uCR**, respectively. All these
 571 clusterwise regression models have been fitted for a number of components from
 572 1 to 9 through a specific function developed in the R environment which also
 573 allows the estimation of seemingly unrelated linear parsimonious clusterwise
 574 models (for more details see Galimberti and Soffritti, 2020). Parameters $\boldsymbol{\mu}_{\mathbf{X}}$
 575 and $\boldsymbol{\Sigma}_{\mathbf{X}}$ of the Gaussian distribution for the covariates in models (5) and (6)
 576 have been estimated under three possible structures of $\boldsymbol{\Sigma}_{\mathbf{X}}$: fully unconstrained
 577 (**VV**), diagonal with P unequal variances (**VI**) and diagonal with equal variances
 578 (**EI**). As far as the variances $\sigma_{k_d d}$, $k_d = 1, \dots, K_d$, in the univariate clusterwise
 579 regression models are concerned, the estimation has been carried out under both
 580 an homoscedastic (**E**) and heteroscedastic (**V**) assumption.

581 4.1. Canned tuna sales in USA

582 Data taken from Chevalier et al. (2003) and available within the R package
583 **bayesm** (Rossi, 2012) provides information about seven of the top 10 U.S. brands
584 in the canned tuna product category for $I = 338$ weeks between September
585 1989 and May 1997 (**tuna** dataset). The available information is the volume
586 of weekly sales (**Move**), a measure of the display activity (**Nsale**) and the log
587 price (**Lprice**) of each brand. Analyses illustrated here have been focused on
588 $D = 2$ products: Bumble Bee Chunk 6.12 oz. (BBC) and Bumble Bee Solid
589 6.12 oz. (BBS). A previous study about the effect of prices and promotional
590 activities on sales for these two products, based on clusterwise linear regression
591 models (Galimberti and Soffritti, 2020), demonstrated that the effect of log price
592 on log unit sales is not homogeneous during the examined period of time for
593 both products. Furthermore, a search for the predictors to be employed in the
594 two regression equations showed that models including only the log unit prices
595 should be preferred. Thus, the analysis here has been focused on four variables:
596 $\mathbf{Y} = (\text{Lmove BBC}, \text{Lmove BBS})'$, $\mathbf{X} = (\text{Lprice BBC}, \text{Lprice BBS})'$, where **Lmove**
597 denotes the logarithm of **Move**. As typically happens with food prices, also
598 prices of BBC and BBS appear to change according to an almost discrete grid of
599 values (see the scatterplot on the left part of Figure 3). Although the Pearson's
600 correlation coefficient between the two responses is low (0.1844), according to
601 the Student's t test the hypothesis of linear independence between **Lmove BBC**
602 and **Lmove BBS** has to be rejected; **Lmove BBC** results to be negatively and
603 strongly correlated with **Lprice BBC**; there is also a negative and significant
604 linear dependence between **Lmove BBS** and the logarithm of the prices for both
605 products (see Table 8).

606 By assuming that prices for each of the two examined products can only
607 affect sales of the same product, **SuCW**, **SuCR** and **uSuCR** models have been spec-
608 ified by using **Lprice BBS** as regressor in the equation for **Lmove BBS**, **Lprice**
609 **BBC** as regressor for **Lmove BBC**. Table 9 reports the models which best fit the
610 **tuna** dataset according to the BIC for each combination of the nine examined
611 values of K and each of the model types **SuCW** and **CW**. All these models have

Table 8: Pearson's correlation matrix (lower diagonal part) and p-values of the Student's t test for the hypothesis of linear independence between variables (upper diagonal part) from the **tuna** dataset.

	Lmove BBC	Lmove BBS	Lprice BBC	Lprice BBS
Lmove BBC	1.0000	0.0007	$< 10^{-67}$	0.2678
Lmove BBS	0.1844	1.0000	0.0011	$< 10^{-8}$
Lprice BBC	-0.7727	-0.1767	1.0000	0.4420
Lprice BBS	-0.0604	-0.3172	0.0420	1.0000

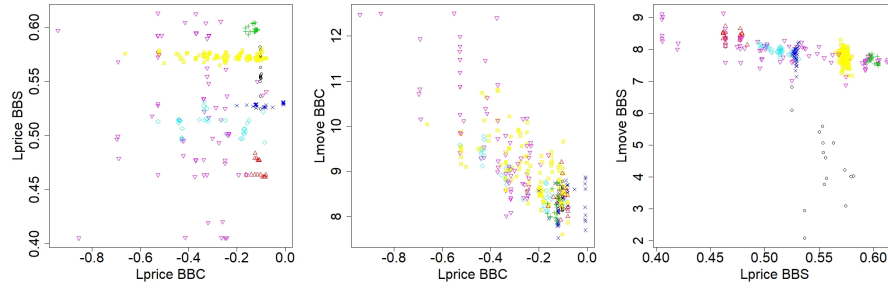


Figure 3: Scatterplots for three pairs of variables from the analysis of the **tuna** dataset. Observations are pictured with seven different colours and symbols according to the classification obtained from the best model.

Table 9: Best models fitted to the **tuna** dataset within some given model classes and their BIC values. Columns $acr.X$ and $acr.Y$ report the acronyms of the parsimonious paramaterisations for the component-covariance matrices of \mathbf{X} and \mathbf{Y} , respectively.

Model	K	$acr.X$	$acr.Y$	BIC_M	Model	K	$acr.X$	$acr.Y$	BIC_M
SuCW	1	EEI	EEI	-18.9	CW	1	EEI	EEI	-18.1
SuCW	2	VVE	EVV	-812.2	CW	2	VVE	EVV	-794.2
SuCW	3	VVI	EVV	-929.1	CW	3	VEV	VVE	-922.3
SuCW	4	VVE	VVE	-1195.0	CW	4	VVE	VVE	-1157.4
SuCW	5	VVI	VEV	-1282.0	CW	5	VVI	VVE	-1267.1
SuCW	6	VVI	VEV	-1355.2	CW	6	VVI	VVE	-1333.7
SuCW	7	VVI	VEV	-1389.8	CW	7	VVI	VVE	-1331.4
SuCW	8	VVI	VEV	-1387.2	CW	8	VVI	VVE	-1341.3
SuCW	9	VVI	VEV	-1371.1	CW	9	VVI	VVI	-1326.4

612 been estimated within a limit of 237 iterations of the ECM algorithm. Figure 4
613 shows the values of the BIC for the best CW and SuCW models by K . As far
614 as the clusterwise regression models are concerned, Table 10 summarises some
615 information about the best fitted models within each of the model classes SuCR,
616 CR, uSuCR and uCR obtained from equations (5) and (6). Overall, it seems that
617 the best trade-off between the fit and complexity can be obtained using the SuCW
618 model with $K = 7$ clusters of weeks. The convergence of the ECM algorithm for
619 the parameter estimation has been reached after 53 iterations. For the clusters
620 detected by this model, the distributions of the two regressors are diagonal with
621 variable volumes and shapes. As far as the joint conditional distributions of
622 the two responses given the corresponding regressors are concerned, clusters are
623 characterized by ellipsoidal distributions with variable volumes and orientations
624 and equal shape.

625 The first cluster is composed of 16 consecutive weeks corresponding to the
626 period from end-October 1990 to mid-February 1991 (see the additional in-
627 formation about this dataset available at the University of Chicago website
628 <http://research.chicagobooth.edu/kilts/marketing-databases/dominicks>). In that

Table 10: Best models fitted to the **tuna** dataset within the model classes defined from equations (5) and (6) and their BIC values.

Model	Best fitted model	BIC_M
$\phi_P(\mathbf{x}_i; \boldsymbol{\mu}_X, \boldsymbol{\Sigma}_X)$	$M_a: \text{acr}.X = \mathbf{VI}$	-1408.0
$\sum_{k=1}^K \pi_k \phi_D(\mathbf{y}_i \mathbf{x}_i; \mathcal{X}'_i \boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{Y_k})$	$M_b: K = 3, \text{acr}.Y = \mathbf{EVV}$	652.5
$\sum_{k=1}^K \pi_k \phi_D(\mathbf{y}_i \mathbf{x}_i; \mathbf{B}'_k \mathbf{x}_i^*, \boldsymbol{\Sigma}_{Y_k})$	$M_c: K = 3, \text{acr}.Y = \mathbf{VVE}$	683.4
$\sum_{k=1}^K \pi_k \phi_1(y_{i1} \mathbf{x}_i; \mathbf{x}_{i1}^* \boldsymbol{\beta}_{k1}^*, \sigma_{k1}^2)$	$M_d: K = 2, \text{acr}.Y = \mathbf{V}$	496.1
$\sum_{k=1}^K \pi_k \phi_1(y_{i1} \mathbf{x}_i; \boldsymbol{\beta}_{k1}^* \mathbf{x}_i^*, \sigma_{k1}^2)$	$M_e: K = 2, \text{acr}.Y = \mathbf{V}$	505.4
$\sum_{k=1}^K \pi_k \phi_1(y_{i2} \mathbf{x}_i; \mathbf{x}_{i2}^* \boldsymbol{\beta}_{k2}^*, \sigma_{k2}^2)$	$M_f: K = 2, \text{acr}.Y = \mathbf{V}$	162.0
$\sum_{k=1}^K \pi_k \phi_1(y_{i2} \mathbf{x}_i; \boldsymbol{\beta}_{k2}^* \mathbf{x}_i^*, \sigma_{k2}^2)$	$M_g: K = 2, \text{acr}.Y = \mathbf{V}$	164.7
SuCR	M_a and M_b	-755.5
CR	M_a and M_c	-724.6
uSuCR	M_a, M_d and M_f	-749.9
uCR	M_a, M_e and M_g	-737.9

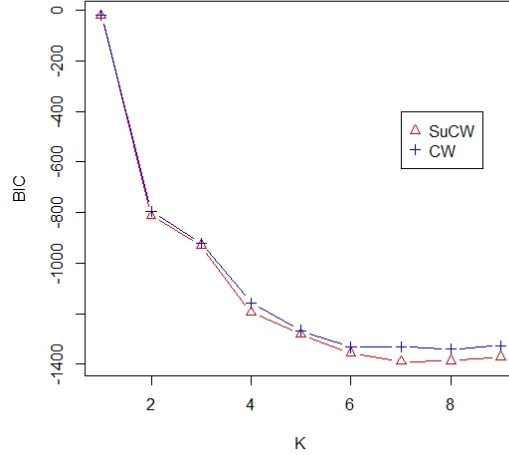


Figure 4: **Tuna** dataset: BIC values of the best CW and SuCW models by number of components.

Table 11: Estimated π_k , $\mu_{\mathbf{x}_k}$ and β_k^* of the best model fitted to the **tuna** dataset. $\mathbf{a}[l]$ denotes the l th element of vector \mathbf{a} .

k	1	2	3	4	5	6	7
$\hat{\pi}_k$	0.047	0.063	0.080	0.098	0.104	0.254	0.354
$\hat{\mu}_{\mathbf{x}_k}[1]$	-0.103	-0.106	-0.130	-0.085	-0.297	-0.366	-0.245
$\hat{\mu}_{\mathbf{x}_k}[2]$	0.554	0.468	0.599	0.528	0.511	0.520	0.573
$\hat{\beta}_{k1}^*[1]$	7.946	8.506	8.925	8.203	7.844	7.751	8.239
$\hat{\beta}_{k1}^*[2]$	-4.493	0.801	5.187	-0.421	-3.544	-5.090	-3.173
$\hat{\beta}_{k2}^*[1]$	17.051	8.820	16.503	-4.040	13.142	10.504	20.766
$\hat{\beta}_{k2}^*[2]$	-22.692	-0.855	-14.724	22.436	-10.115	-4.920	-22.712

629 period a worldwide boycott campaign (promoted by the U.S. nongovernmental
 630 organisation Earth Island Institute) encouraged consumers not to buy Bumble
 631 Bee tuna because Bumble Bee was found to be buying yellow-fin tuna caught
 632 by dolphin-unsafe techniques (Baird and Quastel, 2011). The negative impact
 633 of such a campaign on Bumble Bee tuna sales appears to be evident for BBS
 634 (see the black points in the scatterplot of Figure 3 for this product). The mean
 635 prices of both products in the weeks of this cluster are quite high (see the first
 636 column in Table 11). Furthermore, prices of BBC in this cluster are highly
 637 homogeneous, as suggested by the low variance of `Lprice BBC` (not reported
 638 here). Finally, the effect of prices on sales in the same weeks is negative and
 639 particularly strong for BBS (see Table 11). The second cluster comprises 22
 640 weeks (red points in the scatterplots of Figure 3), some of which are in close
 641 correspondence with Easter 1990 and 1991, Christmas 1993, Presidents day and
 642 Labor day 1994. They are mainly characterized by the lowest mean price of BBS
 643 and a negligible impact of prices on sales for both products. Furthermore, prices
 644 of BBS in such weeks result to be quite homogeneous. Cluster 3 is composed
 645 of 27 weeks (green points in Figure 3) with the highest mean price of BBS. In
 646 this cluster, the effects of prices on sales are negative for BBS and positive for
 647 BBC; furthermore, prices of both products are homogeneous. The special events
 648 corresponding to the weeks of cluster 3 are: Memorial days 1994 and 1995, 4th

649 of July 1994 and 1995, Halloween and Thanksgiving 1994. Cluster 4 is mainly
 650 composed of weeks from end-November 1995 to end-April 1997; two distinctive
 651 features of this cluster (34 weeks, dark blue points) are that it shows the highest
 652 mean price of BBC and highly homogeneous prices of BBS; furthermore, the
 653 estimated effect of prices on sales of BBS is positive and particularly strong.
 654 Labor day 1991, January 1992, Memorial days 1992 and 1993 are the events
 655 and periods associated with the weeks in cluster 5 (37 weeks, sky-blue points),
 656 which is characterized by intermediate mean prices and mild negative effects
 657 of prices on sales for both products. As far as clusters 6 and 7 are concerned,
 658 they contain 78 (purple points) and 124 (yellow points) weeks, respectively. The
 659 main distinctive feature of cluster 6 is that the variances of `Lprice BBC` and
 660 `Lprice BBS` (not reported here) are extremely large; furthermore, this cluster
 661 registers the lowest mean price of BBC. Cluster 6 mainly comprises weeks from
 662 mid-September 1991 to end-December 1991, January 1993, and the periods as-
 663 sociated with Christmas 1992, Presidents day 1992 and 1993, Easter 1992, 1993
 664 and 1995. Weeks belonging to cluster 7 are characterized by high and highly
 665 homogeneous prices of BBS; furthermore, the effect of prices on sales of BBS in
 666 these weeks is negative and particularly strong. In summary, by focusing the
 667 attention on the estimated regression coefficients of the seven clusters of weeks
 668 detected by the model, the main interesting findings are a clear evidence of dif-
 669 ferential effects of the log prices on the log unit sales for both products and the
 670 identification of two clusters in which such effects are positive for either BBS
 671 or BBC. The overall agreement between this partition and the one produced
 672 by the best `CW` model, which is composed of 8 clusters (see Table 12), is high
 673 ($ARI = 0.8293$): weeks have been classified in almost the same way by the two
 674 approaches; some exceptions mainly involve the sixth cluster of the partition
 675 illustrated above.

676 The comparison between these results and those produced from the best
 677 fitted linear clusterwise regression model (see the `SuCR` model in Table 10) shows
 678 that in the analysed dataset there is an additional source of heterogeneity over
 679 time, which appears to lie mainly in the prices of BBC tuna. Thus, when

Table 12: Cross-classification of the observations from the `tuna` dataset, based on the maximum posterior probabilities estimated from the best `CW` and `SuCW` fitted models. Labels for clusters reported in rows and columns refer to `CW` and `SuCW`, respectively.

k	1	2	3	4	5	6	7
1	0	0	0	0	0	6	0
2	16	0	0	0	0	0	0
3	0	21	0	0	0	0	0
4	0	0	27	0	0	0	0
5	0	0	0	33	0	1	0
6	0	1	0	1	36	21	0
7	0	0	0	0	1	48	2
8	0	0	0	0	0	2	122

modelling the joint distribution of prices and sales for both products, more clusters have been detected (7 instead of 3). A further difference between the results obtained from these two approaches is that all the effects of log prices on the log unit sales for both products results to be negative within each cluster identified by the best linear clusterwise regression model. It is also worth noting that there is an almost perfect correspondence between one of the three clusters identified through the best linear clusterwise regression model and the first cluster described above (see Galimberti and Soffritti, 2020, for more details on the results obtained from the analysis of these data through the clusterwise regression approach).

As illustrated in Section 2.1, an underlying assumption of the best fitted model is that both $\mathbf{X}|\Omega_k$ and $\mathbf{Y}|\mathbf{X}=\mathbf{x}, \Omega_k$ follow a multivariate normal distribution for $k = 1, \dots, K$. An evaluation of the adequacy of such an assumption for the examined dataset has been carried out by resorting to some measures of multivariate skewness and kurtosis (Mardia, 1970, 1974); by exploiting their asymptotic distribution derived under the hypothesis of multivariate normality, those measures can also be employed as statistics for testing the hypothesis of multivariate normality. Namely, the function `mult.norm` of the R

Table 13: P-values of Mardia’s skewness and kurtosis statistics for the residuals $\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}_k}$ and $\mathbf{y} - \mathcal{X}'\boldsymbol{\beta}_k$, $k = 1, \dots, K$, computed from the best model fitted to the **tuna** dataset.

k	1	2	3	4	5	6	7
$\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}_k}$							
skewness	0.2654	0.1887	0.0124	0.0370	0.7230	0.0013	0.0000
kurtosis	0.9963	0.3052	0.6470	0.3134	0.0510	0.0777	0.0371
$\mathbf{y} - \mathcal{X}'\boldsymbol{\beta}_k$							
skewness	0.0086	0.3526	0.7434	0.0829	0.8385	0.0002	0.0185
kurtosis	0.1308	0.5668	0.2121	0.3235	0.0483	0.0008	0.3927

698 package **QuantPsych** (Fletcher, 2012) has been employed to compute the values
699 of such measures within each cluster detected by the best model from the es-
700 timated residuals $\mathbf{x}_i - \hat{\boldsymbol{\mu}}_{\mathbf{x}_k}$ and $\mathbf{y}_i - \mathcal{X}'_i \hat{\boldsymbol{\beta}}_k \forall (i, k) \in \{(i, k), i \in \{1, \dots, I\}, k =$
701 $\arg \max_h \{\hat{\tau}_{ih}, h = 1, \dots, K\}\}$; the p-values associated with the so obtained re-
702 sults are summarised in Table 13. Based on these findings, in the first five
703 clusters the null hypothesis of multivariate normality should not be rejected
704 at a Bonferroni-corrected $0.05/7 = 0.0071$ significance level. On the contrary,
705 both types of residuals clearly deviate from the multivariate normality within
706 the sixth cluster. As far as the seventh cluster is concerned, the null hypothesis
707 should be rejected only for the residuals $\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}_k}$.

708 4.2. Regional tourism in Italy

709 In line with studies aiming at evaluating the link between tourism flows and
710 attendance at museums and monuments (see, e.g., Cellini and Cuccia, 2013), the
711 data analysed here provides information about tourist arrivals (denoted **Arriv**),
712 tourist overnights (**Overn**) and visits to State museums, monuments and mu-
713 seum networks (**Visit**) with a monthly frequency over the period January 1999
714 to December 2017 in two Italian regions: Emilia Romagna (**ER**) and Veneto (**Ve**).
715 Data concerning **Visit** has been obtained from the website of the Italian Min-

istry of Cultural Heritage¹; the sources for **Arriv** and **Overn** are the websites of the two regional governments². In this dataset the average stays (**AvStay**), computed as the ratio between **Overn** and **Arriv**, are also provided. Thus, the dataset is composed of $I = 228$ monthly observations for eight variables; from now on, it has been denoted as **RtI**. The goal of the analysis is to study the effect of the tourist arrivals and average stays on the visits to State museums, monuments and museum networks in Emilia-Romagna and Veneto. Thus, in this analysis $\mathbf{Y} = (\text{Visit ER}, \text{Visit Ve})'$, $\mathbf{X} = (\text{Arriv ER}, \text{AvStay ER}, \text{Arriv Ve}, \text{AvStay Ve})'$. The analysis has been performed using data in thousands. Figure 5 shows the bivariate scatterplots for pairs of regressors and pairs composed of one response and one regressor; month abbreviations are used as labels for the observations. Visits to to State museums, monuments and museum networks in the two regions result to be highly linearly dependent (see Table 14); high and positive pairwise correlations also characterise tourist arrivals and average stays in either region; the hypothesis of linear independence is not rejected between **Visit ER** and the average stays; the same result holds true also for **Visit Ve**.

Table 14: Pearson's correlation matrix (lower diagonal part) and p-values of the Student's t test for the hypothesis of linear independence between variables (upper diagonal part) from the **RtI** dataset.

	Visit ER	Visit Ve	Arriv ER	AvStay ER	Arriv Ve	AvStay Ve
Visit ER	1.0000	$< 10^{-66}$	0.0002	0.3684	0.0003	0.3879
Visit VE	0.8562	1.0000	$< 10^{-8}$	0.7807	$< 10^{-9}$	0.9572
Arriv ER	0.2421	0.3722	1.0000	$< 10^{-53}$	$< 10^{-166}$	$< 10^{-47}$
AvStay ER	-0.0598	0.0185	0.8081	1.0000	$< 10^{-45}$	$< 10^{-175}$
Arriv Ve	0.2394	0.4015	0.9826	0.7696	1.0000	$< 10^{-40}$
AvStay Ve	-0.0575	-0.0036	0.7833	0.9856	0.7456	1.0000

¹<http://www.statistica.beniculturali.it>.

²<https://statistica.regione.emilia-romagna.it/turismo>,
<https://www.veneto.eu/web/area-operatori/statistiche>.

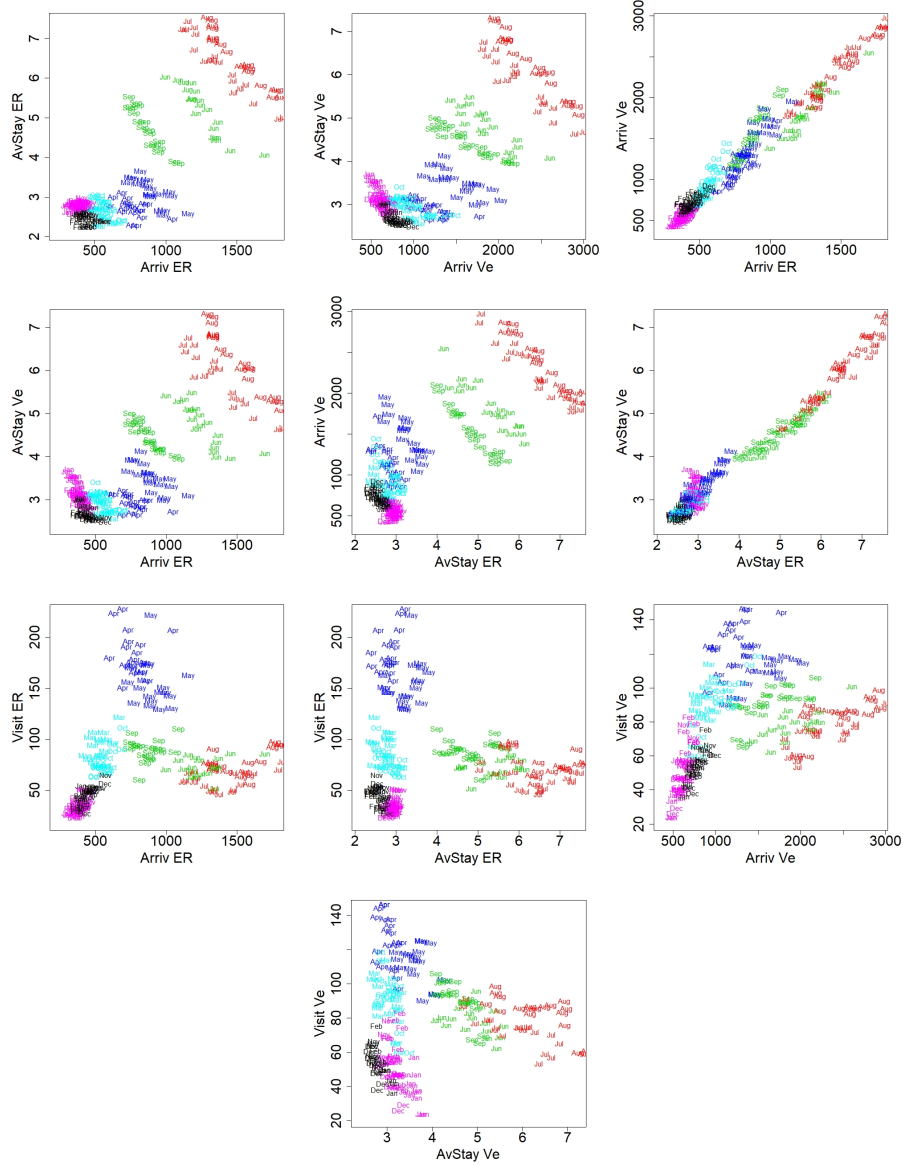


Figure 5: Bivariate scatterplots for pairs of variables in the analysis of the RtI dataset. Month abbreviations are used as labels. Observations are coloured according to the classification obtained from the best model.

Table 15: Best models fitted to the **RtI** dataset within some given model classes and their *BIC* values. Columns *acr.X* and *acr.Y* report the acronyms of the parsimonious paramaterisations for the component-covariance matrices of **X** and **Y**, respectively.

Model	<i>K</i>	<i>acr.X</i>	<i>acr.Y</i>	<i>BIC_M</i>	Model	<i>K</i>	<i>acr.X</i>	<i>acr.Y</i>	<i>BIC_M</i>
SuCW	1	EEE	EEE	10948.6	CW	1	EEE	EEE	10965.7
SuCW	2	VVV	EEV	10223.8	CW	2	VVV	EEV	10146.2
SuCW	3	VVV	VVV	9991.5	CW	3	VVV	VVE	9934.6
SuCW	4	VVV	VEV	9898.8	CW	4	VVV	VEE	9886.6
SuCW	5	EVV	VEE	9822.3	CW	5	VVV	VII	9751.2
SuCW	6	VVV	VVI	9716.5	CW	6	VVV	VEE	9788.3
SuCW	7	VVV	VEV	9736.9	CW	7	VVV	VEE	9799.4
SuCW	8	EVV	VEV	9796.0	CW	8	EVV	VEE	9861.2
SuCW	9	VVV	VEV	9815.0	CW	9	VVV	VEE	9917.1

732 A first analysis has been performed by assuming that arrivals and average
 733 stays in each of the two regions can only affect attendance at museums and
 734 monuments of the same region. Thus, SuCW models have been specified by using
 735 **Arriv ER** and **AvStay ER** as regressors in the equation for **Visit ER**, **Arriv Ve**
 736 and **AvStay Ve** as regressors for **Visit Ve**. However, since Emilia-Romagna
 737 and Veneto are neighboring regions, arrivals and average stays in one region
 738 could also have an impact on the visits to State museums and monuments of
 739 the other region, hence the second analysis has been carried out through CW
 740 models. Table 15 provides information about the models which best fit the **RtI**
 741 dataset according to the *BIC* for each combination of the nine examined values
 742 of *K* and the two fitted model types. The convergence of the ECM algorithm for
 743 the estimation of these models has been reached within a limit of 161 iterations.
 744 Figure 6 shows the values of the *BIC* for the best CW and SuCW models by *K*.
 745 Table 16 provides a summary of the results obtained from the best fitted models
 746 within each of the model classes defined by equations (5) and (6). Overall,
 747 the model with the best trade-off between the fit and complexity seems to be
 748 the SuCW model with $K = 6$ clusters of months. The ECM algorithm for the

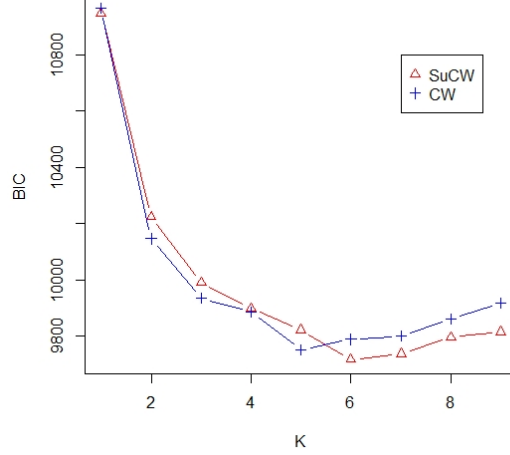


Figure 6: **RtI** dataset: BIC values of the best CW and SuCW models by number of components.

estimation of this model has reached the convergence after 47 iterations. For the resulting clusters, the four regressors have ellipsoidal distributions with variable volumes, shapes and orientations. As far as the joint conditional distributions of the two responses given the corresponding regressors are concerned, clusters show diagonal distributions with variable volumes and shapes, suggesting that **Visit Ve** and **Visit ER** are independent, conditionally on the regressors and cluster membership.

Four clusters are perfectly related to some months (see Table 17). They are:
cluster 2: observations in July and August;
cluster 3: observations in June and September;
cluster 4: observations in April and May;
cluster 5: observations in March and October.

As far as the months from November to February are concerned, observations from January 1999 to November 2010 and those of January 2011 and February 2012 have been assigned to cluster 6; cluster 1 comprises all the remaining observations in such months. The obtained cluster structure clearly reflects

765 seasonal patterns characterising tourism flows. Observations in cluster 2 (July
 766 and August) are characterized by the highest mean values of tourist arrivals
 767 and average stays in both regions, followed by those in cluster 3 (June and
 768 September) and cluster 4 (April and May) (see Table 18). From the comparison
 769 between clusters 1 and 6 it emerges that wintertime tourism flows have changed
 770 in both regions, showing an increase in the mean number of arrivals and a
 771 decrease in the mean number of stays in recent years (cluster 1). In all clusters,
 772 Veneto is characterised by mean values of both regressors which are higher than
 773 those of Emilia-Romagna except for the average stays from June to September.
 774 As far as the estimated regression coefficients are concerned (see Table 18), the
 775 first interesting finding is that the effects of both the tourist arrivals and the
 776 average stays on the number of visits result to be not homogeneous during the
 777 examined period of time. In both regions, such effects are positive in July and
 778 August; in Emilia-Romagna, this result also holds true in the months belonging
 779 to cluster 6. In the other clusters of months the effect of tourist arrivals are
 780 generally positive in both regions, while the average number of stays seem to
 781 have a negative impact on the number of visits. This latter impact in Veneto
 782 appears to be stronger than that in Emilia-Romagna in April, May, June and
 783 September; the opposite result holds true for all the other months.

784 The comparison between this partition and the one based on the maximum
 785 posterior probabilities estimated from the best **CW** fitted model (see Table 19)
 786 suggests that they are quite similar ($ARI = 0.8014$); the main difference is
 787 that according to the approach based on **CW** models all the observations in the
 788 months from November to February should be grouped into the same cluster.
 789 This latter result mainly depends on the fact that, in the best model fitted to the
 790 **RtI** dataset within the class of **CW** models with $K = 6$, the effects of both **Arriv**
 791 **Ve** on **Visit ER** and **Arriv ER** on **Visit Ve** in two clusters have been estimated
 792 to be quite similar (detailed results are not reported) and, thus, a better trade-
 793 off between the fit and the complexity is reached by the best fitted **CW** model with
 794 $K = 5$. Furthermore, the comparison between the results obtained through **SuCW**
 795 models and those produced from linear clusterwise regression analyses (see Table

Table 16: Best models fitted to the **RtI** dataset within the model classes defined from equations (5) and (6) and their BIC values.

Model	Best fitted model	BIC_M
$\phi_P(\mathbf{x}_i; \boldsymbol{\mu}_{\mathbf{X}}, \boldsymbol{\Sigma}_{\mathbf{X}})$	M_a : $acr.X = \mathbf{V}\mathbf{V}$	6808.1
$\sum_{k=1}^K \pi_k \phi_D(\mathbf{y}_i \mathbf{x}_i; \boldsymbol{\chi}'_i \boldsymbol{\beta}_k^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k})$	M_b : $K = 4$, $acr.Y = \mathbf{V}\mathbf{E}\mathbf{V}$	3943.3
$\sum_{k=1}^K \pi_k \phi_D(\mathbf{y}_i \mathbf{x}_i; \mathbf{B}'_k \mathbf{x}_i^*, \boldsymbol{\Sigma}_{\mathbf{Y}_k})$	M_c : $K = 3$, $acr.Y = \mathbf{V}\mathbf{E}\mathbf{V}$	3920.2
$\sum_{k=1}^K \pi_k \phi_1(y_{i1} \mathbf{x}_i; \mathbf{x}_{i1}^* \boldsymbol{\beta}_{k1}^*, \sigma_{k1}^2)$	M_d : $K = 4$, $acr.Y = \mathbf{V}$	2166.6
$\sum_{k=1}^K \pi_k \phi_1(y_{i1} \mathbf{x}_i; \boldsymbol{\beta}_{k1}^{*'} \mathbf{x}_i^*, \sigma_{k1}^2)$	M_e : $K = 3$, $acr.Y = \mathbf{V}$	2183.4
$\sum_{k=1}^K \pi_k \phi_1(y_{i2} \mathbf{x}_i; \mathbf{x}_{i2}^* \boldsymbol{\beta}_{k2}^*, \sigma_{k2}^2)$	M_f : $K = 4$, $acr.Y = \mathbf{E}$	1987.2
$\sum_{k=1}^K \pi_k \phi_1(y_{i2} \mathbf{x}_i; \boldsymbol{\beta}_{k2}^{*'} \mathbf{x}_i^*, \sigma_{k2}^2)$	M_g : $K = 2$, $acr.Y = \mathbf{V}$	1987.1
SuCR	M_a and M_b	10751.4
CR	M_a and M_c	10728.3
uSuCR	M_a , M_d and M_f	10962.0
uCR	M_a , M_e and M_g	10978.6

Table 17: Cross-classification of the observations from the **RtI** dataset, based on their variable time identified by month and maximum posterior probability estimated from the best fitted model.

k	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	6	6	0	0	0	0	0	0	0	0	7	8
2	0	0	0	0	0	0	19	19	0	0	0	0
3	0	0	0	0	0	19	0	0	19	0	0	0
4	0	0	0	19	19	0	0	0	0	0	0	0
5	0	0	19	0	0	0	0	0	0	19	0	0
6	13	13	0	0	0	0	0	0	0	0	12	11

Table 18: Estimated π_k , $\boldsymbol{\mu}_{\mathbf{X}_k}$ and $\boldsymbol{\beta}_k^*$ of the best model fitted to the **RtI** dataset. $\mathbf{a}[l]$ denotes the l th element of vector \mathbf{a} .

k	1	2	3	4	5	6
$\hat{\pi}_k$	0.121	0.167	0.167	0.167	0.167	0.213
$\hat{\boldsymbol{\mu}}_{\mathbf{X}_k}[1]$	377.1	1389.8	1001.0	767.7	487.4	316.5
$\hat{\boldsymbol{\mu}}_{\mathbf{X}_k}[2]$	2.350	6.304	4.847	2.823	2.572	2.694
$\hat{\boldsymbol{\mu}}_{\mathbf{X}_k}[3]$	665.5	2248.1	1639.0	1251.5	867.7	502.5
$\hat{\boldsymbol{\mu}}_{\mathbf{X}_k}[4]$	2.588	5.894	4.511	3.119	2.836	3.039
$\hat{\boldsymbol{\beta}}_{k1}^*[1]$	34.063	-263.846	143.648	278.219	163.170	-68.964
$\hat{\boldsymbol{\beta}}_{k1}^*[2]$	0.117	0.116	-0.028	-0.095	0.008	0.090
$\hat{\boldsymbol{\beta}}_{k1}^*[3]$	-15.948	26.302	-7.994	-14.227	-34.080	25.994
$\hat{\boldsymbol{\beta}}_{k2}^*[1]$	29.502	-43.971	183.051	179.415	106.489	-6.196
$\hat{\boldsymbol{\beta}}_{k2}^*[2]$	0.071	0.035	-0.006	0.003	0.032	0.132
$\hat{\boldsymbol{\beta}}_{k2}^*[3]$	-9.889	6.876	-20.067	-21.422	-16.044	-4.297

16) demonstrates that there is some clear evidence of seasonal heterogeneity not only in attendance at museums and monuments but also in tourism flows. Finally, a joint analysis for the two examined Italian regions based on seemingly unrelated cluster-weighted models results to be more effective than two separate linear clusterwise regression analyses.

As in the previous application, the `mult.norm` function of the R package **QuantPsych** has been employed to obtain an evaluation of the adequacy of the normality assumption within each cluster detected by the best model, based on the p-values of Mardia's measures of multivariate skewness and kurtosis computed from the estimated residuals $\mathbf{x}_i - \hat{\boldsymbol{\mu}}_{\mathbf{X}_k}$ and $\mathbf{y}_i - \mathcal{X}'_i \hat{\boldsymbol{\beta}}_k \forall (i, k) \in \{(i, k), i \in \{1, \dots, I\}, k = \arg \max_h \{\hat{\tau}_{ih}, h = 1, \dots, K\}\}$ (see Table 20). The obtained results suggest that the null hypothesis of multivariate normality should not be rejected at a Bonferroni-corrected $0.05/6 = 0.0083$ significance level in any cluster.

Table 19: Cross-classification of the observations from the **RtI** dataset, based on the maximum posterior probabilities estimated from the best **CW** and **SuCW** fitted models. Labels for clusters reported in rows and columns refer to **CW** and **SuCW**, respectively.

k	1	2	3	4	5	6
1	0	0	34	0	0	0
2	0	0	0	38	0	0
3	0	0	0	0	38	0
4	0	38	4	0	0	0
5	27	0	0	0	0	49

Table 20: P-values of Mardia’s skewness and kurtosis statistics for the residuals $\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}_k}$ and $\mathbf{y} - \boldsymbol{\chi}'\boldsymbol{\beta}_k$, $k = 1, \dots, K$, computed from the best model fitted to the **RtI** dataset.

k	1	2	3	4	5	6
$\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}_k}$						
skewness	0.4513	0.3886	0.1150	0.4504	0.0422	0.0317
kurtosis	0.0171	0.0375	0.6161	0.4693	0.4039	0.8658
$\mathbf{y} - \boldsymbol{\chi}'\boldsymbol{\beta}_k$						
skewness	0.6053	0.6263	0.5742	0.2526	0.6386	0.0212
kurtosis	0.0369	0.3261	0.9268	0.3922	0.1747	0.7168

810 5. Conclusions

811 The proposed multivariate seemingly unrelated Gaussian linear cluster-weighted
812 models can account for heterogeneous regression data with multivariate corre-
813 lated responses, each one depending on its own set of covariates. This latter
814 feature represents the main novelty of the models proposed here in reference
815 with the ones introduced by Dang et al. (2017), thus leading to a more flex-
816 ible modelling of data in applications where prior information concerning the
817 absence of certain covariates from the linear term employed in the prediction
818 of a certain response has to be conveyed into the model, and different covari-
819 ates are expected to be relevant in the prediction of different responses. The
820 distribution of the covariates is also explicitly incorporated in the model for-
821 mulation. The resulting approach encompasses the models introduced by Dang
822 et al. (2017) as well as other Gaussian mixture-based linear regression models
823 with random covariates. Details about identifiability, ML estimation and model
824 selection have been provided. Furthermore, models with a reduced number of
825 variance-covariance parameters have been specified. The comparisons among
826 some cluster-weighted models and clusterwise linear regression models based on
827 the analyses of the `tuna` and `RtI` datasets have highlighted the effectiveness of
828 the proposed models in detecting the presence of unobserved heterogeneity; such
829 models have been proved to be useful also to establish the relevance of a multi-
830 variate regression analysis and the inadequacy of the assignment independence
831 assumption in both applications. From the Monte Carlo studies it appears that
832 including irrelevant regressors in a cluster-weighted model can lead to a wrong
833 choice of the number of components and a sub-optimal reconstruction of the
834 true classification of the sample observations, especially when the components
835 are not well-separated. The approach introduced here is able to avoid some
836 drawbacks due to the presence of irrelevant regressors in a multivariate Gaus-
837 sian linear cluster-weighted model. This happens because the proposed models
838 are multivariate Gaussian linear cluster-weighted models in which some regres-
839 sion coefficients are set a priori equal to zero. Thus, the proposed approach also

840 represents a framework for multivariate linear cluster-weighted analysis under
841 such constraints.

842 As far as the development of inferential methods for the parameters of the
843 proposed models is concerned, an assessment of the sample variability of the pa-
844 rameter estimates is required. Since the ECM algorithm does not automatically
845 produce any estimate of the covariance matrix of the ML estimator, additional
846 computations are necessary. To this end, several approaches commonly em-
847 ployed under finite mixture models could be exploited (see, e.g., McLachlan
848 and Peel, 2000). For example, estimates of the asymptotic covariance matrix
849 of the ML estimator can be computed through an approach which is based on
850 the gradient vector and the second-order derivative matrix of the incomplete
851 data log-likelihood, and makes also use of a sandwich estimator. This approach
852 has been successfully applied to Gaussian mixture models (Boldea and Magnus,
853 2009), t mixture models (Wang and Lin, 2016), clusterwise Gaussian linear re-
854 gression models (Galimberti et al., 2021) and Gaussian linear cluster-weighted
855 models (Soffritti, 2021). In addition, given the critical role played by the initial-
856 isation in any ECM algorithm, further investigation might be needed in order
857 to confirm the encouraging results described in Section 3. In particular, this ad-
858 ditional investigation should focus on the performance of the proposed strategy
859 in presence of high dimensional data.

860 Another crucial aspect associated with the adoption of the proposed models
861 in practical applications is the assessment of their adequacy. For finite mixtures
862 of linear regression models with a univariate response and fixed, concomitant or
863 random covariates, Ingrassia and Punzo (2020) have recently introduced some
864 indices able to measure the association between the response variable and the
865 latent groups, the model goodness-of-fit, and the proportion of the total varia-
866 tion in the response which remains unexplained by the fitted model. Local and
867 overall coefficients of determination have also been described. After suitable
868 modifications, those indices could also be employed to assess the adequacy of
869 the multivariate cluster-weighted models based on seemingly underlated linear
870 regression illustrated here.

871 Multivariate seemingly unrelated linear cluster-weighted analyses based on
872 the proposed models implicitly require that the researcher has prior information
873 on the specific covariates that have to be included in the linear term employed in
874 the prediction of each response in the model. In practical applications in which
875 the choice of the regressors to be used for different responses is questionable, the
876 relevant regressors for each response can be detected through strategies (e.g.,
877 stepwise techniques, genetic algorithms) that allow to perform variable selec-
878 tion in a multivariate regression framework. To this end, the optimal model for
879 the given dataset should be determined from a model class which also includes
880 the cluster-weighted models based on seemingly unrelated linear regression il-
881 lustrated in this paper.

882 Finally, it is worth noting that the new multivariate seemingly unrelated
883 cluster-weighted models described here have been specified under the follow-
884 ing assumptions: *i)* the joint conditional distribution of the P covariates given
885 the group Ω_k is Gaussian $\forall k$; *ii)* the joint conditional distribution of the D
886 responses given the covariates and the group Ω_k is Gaussian $\forall k$; *iii)* the con-
887 ditional expected value of the D responses given the covariates and the group
888 Ω_k is a linear transformation of the covariates $\forall k$. These assumptions could
889 be relaxed by resorting to the approaches developed by Punzo (2014), Punzo
890 and McNicholas (2017), Gallagher et al. (2021) or Sahin and Czado (2021)
891 so as to obtain multivariate seemingly unrelated cluster-weighted models which
892 could be more effectively employed in the analysis of real datasets composed of
893 unknown clusters of observations characterised by skewed distributions, outliers
894 or non-linear relationships.

895 **Appendix A. Derivation of $\hat{\beta}_k^{*(h+1)}$ and $\hat{\Sigma}_{Y_k}^{(h+1)}$**

896 The CM-steps to update the estimates of the model parameters β_k^* and Σ_{Y_k}
897 at the $(h+1)$ th iteration in the ECM algorithm, as illustrated in equations (13)

and (14), can be obtained as follows.

$$\begin{aligned}
\frac{\partial}{\partial \beta_k^{*'}} Q(\psi | \psi^{(h)}) &= \frac{\partial}{\partial \beta_k^{*'}} \sum_{i=1}^I \sum_{k=1}^K \hat{\tau}_{ik}^{(h)} Q_2(\beta_k^*, \Sigma_{\mathbf{Y}_k} | \psi^{(h)}) \\
&= \frac{\partial}{\partial \beta_k^{*'}} \left[-\frac{1}{2} \sum_{i=1}^I \hat{\tau}_{ik}^{(h)} (\mathbf{y}_i - \mathcal{X}_i' \beta_k^*)' \Sigma_{\mathbf{Y}_k}^{(h)(-1)} (\mathbf{y}_i - \mathcal{X}_i' \beta_k^*) \right] \\
&= -\frac{1}{2} \sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \frac{\partial}{\partial \beta_k^{*'}} \left(-2 \mathbf{y}_i' \Sigma_{\mathbf{Y}_k}^{(h)(-1)} \mathcal{X}_i' \beta_k^* + \beta_k^{*'} \mathcal{X}_i' \Sigma_{\mathbf{Y}_k}^{(h)(-1)} \mathcal{X}_i' \beta_k^* \right) \\
&= -\frac{1}{2} \sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \left(-2 \mathbf{y}_i' \Sigma_{\mathbf{Y}_k}^{(h)(-1)} \mathcal{X}_i' + 2 \beta_k^{*'} \mathcal{X}_i' \Sigma_{\mathbf{Y}_k}^{(h)(-1)} \mathcal{X}_i' \right) \\
&= \sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \mathbf{y}_i' \Sigma_{\mathbf{Y}_k}^{(h)(-1)} \mathcal{X}_i' - \sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \beta_k^{*'} \mathcal{X}_i' \Sigma_{\mathbf{Y}_k}^{(h)(-1)} \mathcal{X}_i'. \quad (\text{A.1})
\end{aligned}$$

Setting (A.1) equal to the null vector, $\Sigma_{\mathbf{Y}_k}^{(h)}$ equal to $\hat{\Sigma}_{\mathbf{Y}_k}^{(h)}$ and solving the so obtained system with respect to β_k^* leads to the solution reported in equation (13).

$$\begin{aligned}
\frac{\partial}{\partial \Sigma_{\mathbf{Y}_k}^{-1}} Q(\psi | \psi^{(h)}) &= \frac{\partial}{\partial \Sigma_{\mathbf{Y}_k}^{-1}} \sum_{i=1}^I \sum_{k=1}^K \hat{\tau}_{ik}^{(h)} Q_2(\beta_k^*, \Sigma_{\mathbf{Y}_k} | \psi^{(h)}) \\
&= \frac{\partial}{\partial \Sigma_{\mathbf{Y}_k}^{-1}} \left\{ \frac{1}{2} \sum_{i=1}^I \hat{\tau}_{ik}^{(h)} [\ln |\Sigma_{\mathbf{Y}_k}^{-1}| \right. \\
&\quad \left. - (\mathbf{y}_i - \mathcal{X}_i' \beta_k^{*(h+1)})' \Sigma_{\mathbf{Y}_k}^{-1} (\mathbf{y}_i - \mathcal{X}_i' \beta_k^{*(h+1)})] \right\} \\
&= \frac{1}{2} \sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \frac{\partial}{\partial \Sigma_{\mathbf{Y}_k}^{-1}} [\ln |\Sigma_{\mathbf{Y}_k}^{-1}| \\
&\quad - \text{tr}(\Sigma_{\mathbf{Y}_k}^{-1} (\mathbf{y}_i - \mathcal{X}_i' \beta_k^{*(h+1)}) (\mathbf{y}_i - \mathcal{X}_i' \beta_k^{*(h+1)})')] \\
&= \frac{1}{2} \left[\sum_{i=1}^I \hat{\tau}_{ik}^{(h)} \Sigma_{\mathbf{Y}_k} - \sum_{i=1}^I \hat{\tau}_{ik}^{(h)} (\mathbf{y}_i - \mathcal{X}_i' \beta_k^{*(h+1)}) (\mathbf{y}_i - \mathcal{X}_i' \beta_k^{*(h+1)})' \right]
\end{aligned}$$

where the second and third equalities are obtained using properties of trace and transpose and differentiation rules of functions of matrices. Setting (A.2) equal to the null matrix, $\beta_k^{*(h+1)}$ equal to $\hat{\beta}_k^{*(h+1)}$ and solving the resulting system with respect to $\Sigma_{\mathbf{Y}_k}$ gives the update in equation (14).

916 **Appendix B. Expression of $\hat{\beta}_k^{*(h+1)}$ when $\mathbf{x}_{id} = \mathbf{x}_i \forall d$**

917 Similarly to Park (1993), equation (13) can be rewritten as

$$918 \quad \hat{\beta}_k^* = \left\{ \mathcal{X} \left[\text{diag}(\hat{\tau}_k) \otimes \hat{\Sigma}_{\mathbf{Y}_k}^{-1} \right] \mathcal{X}' \right\}^{-1} \mathcal{X} \left[\text{diag}(\hat{\tau}_k) \otimes \hat{\Sigma}_{\mathbf{Y}_k}^{-1} \right] \mathbf{y}, \quad (\text{B.1})$$

919 where the superscripts (h) and $(h+1)$ have been dropped to ease notation,
 920 $\mathcal{X} = [\mathcal{X}_1, \mathcal{X}_2, \dots, \mathcal{X}_I]$ is a $(P^* + D) \times (D \cdot I)$ matrix, $\text{diag}(\hat{\tau}_k)$ is a diag-
 921 onal matrix whose diagonal elements are the values $\hat{\tau}_{ik}$ ($i = 1, \dots, I$) and
 922 $\mathbf{y} = (\mathbf{y}'_1, \mathbf{y}'_2, \dots, \mathbf{y}'_I)'$. Consider now the vectors $\mathbf{v}_d = (y_{1d}, y_{2d}, \dots, y_{Id})'$, con-
 923 taining the values of the d th response on the I observations ($d = 1, \dots, D$), and
 924 the vector $\mathbf{v} = (\mathbf{v}'_1, \dots, \mathbf{v}'_D)'$. It is evident that \mathbf{v} and \mathbf{y} contain the same values
 925 but in a different order. As shown in Park (1993), by exchanging the rows of
 926 the identity matrix of order $D \cdot I$, it is possible to define a matrix \mathbf{L} such that

$$927 \quad \mathbf{L}\mathbf{L}' = \mathbf{L}'\mathbf{L} = \mathbf{I}_{D \cdot I}$$

928 and

$$929 \quad \mathbf{L}\mathbf{y} = \mathbf{v}.$$

930 Matrix \mathbf{L} can also be used to reorder the columns of \mathcal{X} and the rows and columns
 931 of $\left[\text{diag}(\hat{\tau}_k) \otimes \hat{\Sigma}_{\mathbf{Y}_k}^{-1} \right]$. Namely,

$$932 \quad \mathcal{X}\mathbf{L}' = \mathcal{Z} = \begin{bmatrix} \mathbf{Z}_1 & \mathbf{0}_{(P_1+1) \times I} & \dots & \mathbf{0}_{(P_1+1) \times I} \\ \mathbf{0}_{(P_2+1) \times I} & \mathbf{Z}_2 & \dots & \mathbf{0}_{(P_2+1) \times I} \\ \vdots & \vdots & & \vdots \\ \mathbf{0}_{(P_D+1) \times I} & \mathbf{0}_{(P_D+1) \times I} & \dots & \mathbf{Z}_D \end{bmatrix},$$

933 where $\mathbf{Z}_d = [\mathbf{x}_{1d}^*, \mathbf{x}_{2d}^*, \dots, \mathbf{x}_{Id}^*]$ is a $(P_d + 1) \times I$ matrix ($d = 1, \dots, D$), and

$$934 \quad \mathbf{L} \left[\text{diag}(\hat{\tau}_k) \otimes \hat{\Sigma}_{\mathbf{Y}_k}^{-1} \right] \mathbf{L}' = \left[\hat{\Sigma}_{\mathbf{Y}_k}^{-1} \otimes \text{diag}(\hat{\tau}_k) \right].$$

935 Thus, an equivalent expression for $\hat{\beta}_k^*$ is given by

$$\begin{aligned} 936 \quad \hat{\beta}_k^* &= \left\{ \mathcal{X}\mathbf{L}'\mathbf{L} \left[\text{diag}(\hat{\tau}_k) \otimes \hat{\Sigma}_{\mathbf{Y}_k}^{-1} \right] \mathbf{L}'\mathbf{L}\mathcal{X}' \right\}^{-1} \mathcal{X}\mathbf{L}'\mathbf{L} \left[\text{diag}(\hat{\tau}_k) \otimes \hat{\Sigma}_{\mathbf{Y}_k}^{-1} \right] \mathbf{L}'\mathbf{L}\mathbf{y} \\ 937 &= \left\{ \mathcal{Z} \left[\hat{\Sigma}_{\mathbf{Y}_k}^{-1} \otimes \text{diag}(\hat{\tau}_k) \right] \mathcal{Z}' \right\}^{-1} \mathcal{Z} \left[\hat{\Sigma}_{\mathbf{Y}_k}^{-1} \otimes \text{diag}(\hat{\tau}_k) \right] \mathbf{v}. \end{aligned} \quad (\text{B.2})$$

938 If $\mathbf{x}_{id} = \mathbf{x}_i \forall d$, then $\mathbf{Z}_d = [\mathbf{x}_1^*, \mathbf{x}_2^*, \dots, \mathbf{x}_I^*] = \mathbf{Z} \forall d$ and

$$939 \quad \mathcal{Z} = \mathbf{I}_D \otimes \mathbf{Z}. \quad (\text{B.3})$$

940 By exploiting equation (B.3) and the properties of the Kronecker product (see,
941 e.g., Magnus and Neudecker, 1988), equation (B.2) can be simplified as follows:

$$942 \quad \hat{\boldsymbol{\beta}}_k^* = \left\{ \mathbf{I}_D \otimes [\mathbf{Z} \text{diag}(\hat{\boldsymbol{\tau}}_k) \mathbf{Z}']^{-1} \mathbf{Z} \text{diag}(\hat{\boldsymbol{\tau}}_k) \right\} \mathbf{v}. \quad (\text{B.4})$$

944 Firstly, note that equation (B.4) does not depend on $\hat{\boldsymbol{\Sigma}}_{\mathbf{Y}_k}$. Furthermore, the
945 matrix $\left\{ \mathbf{I}_D \otimes [\mathbf{Z} \text{diag}(\hat{\boldsymbol{\tau}}_k) \mathbf{Z}']^{-1} \mathbf{Z} \text{diag}(\hat{\boldsymbol{\tau}}_k) \right\}$ has a block-diagonal structure.
946 By coupling it with the structure of the vector \mathbf{v} , the following expression for
947 the vector $\hat{\boldsymbol{\beta}}_{kd}^*$ containing the estimated coefficients associated with the d th
948 response in the k th group can be obtained:

$$\begin{aligned} 949 \quad \hat{\boldsymbol{\beta}}_{kd}^* &= [\mathbf{Z} \text{diag}(\hat{\boldsymbol{\tau}}_k) \mathbf{Z}']^{-1} \mathbf{Z} \text{diag}(\hat{\boldsymbol{\tau}}_k) \mathbf{v}_d \\ 950 \quad &= \left(\sum_{i=1}^I \hat{\tau}_{ik} \mathbf{x}_i^* \mathbf{x}_i^{*'} \right)^{-1} \left(\sum_{i=1}^I \hat{\tau}_{ik} \mathbf{x}_i^* y_{id} \right), \quad d = 1, \dots, D. \end{aligned} \quad (\text{B.5})$$

951 Apart from differences related to notation, it can be noticed that equation (B.5)
952 coincides with the d th row of the matrix defined in equation (8) in Dang et al.
953 (2017).

954 References

- 955 Aitken AC (1926) A series formula for the roots of algebraic and transcendental
956 equations. Proc. R. Soc. Edinb. 45:14–22
- 957 Baird IG, Quastel N (2011) Dolphin-safe tuna from California to Thailand:
958 localisms in environmental certification of global commodity networks. Ann.
959 Assoc. Am. Geogr. 101:337–355
- 960 Browne RP, McNicholas PD (2014a) Estimating common principal components
961 in high dimensions. Adv. Data Anal. Classif. 8:217–226

- 962 Browne RP, McNicholas PD (2014b) Orthogonal Stiefel manifold optimization
963 for eigen-decomposed covariance parameter estimation in mixture models.
964 Stat. Comput. 24:203–210
- 965 Boldea O, Magnus JR (2009) Maximum likelihood estimation of the multivariate
966 normal mixture model. J. Am. Stat. Assoc. 104:1539–1549
- 967 Cadavez VAP, Henningsen A (2012) The use of seemingly unrelated regression
968 (SUR) to predict the carcass composition of lambs. Meat Sci. 92:548–553
- 969 Celeux G, Govaert G (1995) Gaussian parsimonious clustering models. Pattern
970 Recognit. 28:781–793
- 971 Cellini R, Cuccia T (2013) Museum and monument attendance and tourism
972 flow: a time series analysis approach. Appl. Econ. 45:3473–3482
- 973 Chevalier JA, Kashyap AK, Rossi PE (2003) Why don't prices rise during peri-
974 ods of peak demand? Evidence from scanner data. Am. Econ. Rev. 93:15–37
- 975 Dang UJ, McNicholas PD (2015) Families of parsimonious finite mixtures of
976 regression models. In: Morlini I, Minerva T, Vichi M (eds) Advances in sta-
977 tistical models for data analysis. Springer, Cham, pp 73–84
- 978 Dang UJ, Punzo A, McNicholas PD, Ingrassia S, Browne RP (2017) Multivari-
979 ate response and parsimony for Gaussian cluster-weighted models. J. Classif.
980 34:4–34
- 981 Dempster AP, Laird NM, Rubin DB (1977) Maximum likelihood for incomplete
982 data via the EM algorithm. J. Roy. Statist. Soc. B 39:1–22
- 983 Di Mari R, Bakk Z, Punzo A (2020) A random-covariate approach for distal
984 outcome prediction with latent class analysis. Struct. Equ. Model. 27:351–
985 368
- 986 Disegna M, Osti L (2016) Tourists' expenditure behaviour: the influence of
987 satisfaction and the dependence of spending categories. Tour. Econ. 22:5–30

988 Fletcher TD (2012) **QuantPsyc**: Quantitative psychology tools. R package ver-
989 sion 1.5. URL <http://CRAN.R-project.org/package=QuantPsyc>

990 Flury BN, Gautschi W (1986) An algorithm for simultaneous orthogonal trans-
991 formation of several positive definite symmetric matrices to nearly diagonal
992 form. *J. Sci. Statist. Comput.* 7:169–184

993 Fraley C, Raftery AE (2002) Model-based clustering, discriminant analysis and
994 density estimation. *J. Am. Stat. Assoc.* 97:611–631

995 Frühwirth-Schnatter S (2006) Finite mixture and Markov switching models.
996 Springer, New York

997 Galimberti G., Soffritti G. (2007) Model-based methods to identify multiple
998 cluster structures in a data set. *Comput. Stat. Data Anal.* 52:520–536

999 Galimberti G, Scardovi E, Soffritti G (2016) Using mixtures in seemingly unre-
1000 related linear regression models with non-normal errors. *Stat. Comput.* 26:1025–
1001 1038

1002 Galimberti G, Nuzzi L, Soffritti G (2021) Covariance matrix estimation of the
1003 maximum likelihood estimation in multivariate clusterwise linear regression.
1004 *Stat. Methods Appl.* 30:235–268

1005 Galimberti G, Soffritti G (2020) Seemingly unrelated clusterwise linear regres-
1006 sion. *Adv. Data Anal. Classif.* 14:235–260

1007 Gallagher MPB, Tomarchio SD, McNicholas PD, Punzo A (2021) Multivariate
1008 cluster weighted models using skewed distributions. *Adv. Data Anal. Classif.*
1009 <https://doi.org/10.1007/s11634-021-00480-5>

1010 Gershensfeld N (1997) Nonlinear inference and cluster-weighted modeling. *Ann.*
1011 *N. Y. Acad. Sci.* 808:18–24

1012 Giles S, Hampton P (1984) Regional production relationships during the indus-
1013 trialization of New Zealand, 1935–1948. *Reg. Sci.* 24:519–533

1014 Grün B, Leisch F (2008) FlexMix version 2: finite mixtures with concomitant
1015 variables and varying and constant parameters. *J. Stat. Softw.* 28(4):1–35

1016 Heidari S., Keshavarz S., Mirahmadizadeh A (2017) Application of seemingly
1017 unrelated regression (SUR) in determination of risk factors of fatigue and
1018 general health among the employees of petrochemical companies. *J. Health*
1019 *Sci. Surveillance Sys.* 5:1–8

1020 Hennig C (2000) Identifiability of models for clusterwise linear regression. *J.*
1021 *Classif.* 17:273–296

1022 Henningsen A, Hamann JD (2007) **systemfit**: a package for estimating systems
1023 of simultaneous equations in R. *J. Stat. Softw.* 23(4):1–40

1024 Hubert L, Arabie P (1985) Comparing partitions. *J. Classif.* 2:193–218

1025 Ingrassia S, Minotti SC, Vittadini G (2012) Local statistical modeling via a
1026 cluster-weighted approach with elliptical distributions. *J. Classif.* 29:363–401

1027 Ingrassia S, Minotti SC, Punzo A (2014) Model-based clustering via linear
1028 cluster-weighted models. *Comput. Stat. Data Anal.* 71:159–182

1029 Ingrassia S, Punzo A (2020) Cluster validation for mixtures of regressions via
1030 the total sum of squares decomposition. *J. Classif.* 37:526–547

1031 Ingrassia S, Punzo A, Vittadini G, Minotti SC (2015) The generalized linear
1032 mixed cluster-weighted model. *J. Classif.* 32:85–113

1033 Ingrassia S, Rocci R (2011) Degeneracy of the EM algorithm for the MLE of
1034 multivariate Gaussian mixtures and dynamic constraints. *Comput. Stat. Data*
1035 *Anal.* 55:1715–1725

1036 Jones PN, McLachlan GJ (1992) Fitting finite mixture models in a regression
1037 context. *Aust. J. Stat.* 34:233–240

1038 Keshavarzi S, Ayatollahi SMT, Zare N, Pakfetrat M (2012) Application of seem-
1039 ingly unrelated regression in medical data with intermittently observed time-
1040 dependent covariates. *Comput. Math. Methods Med.* 821643

1041 Keshavarzi S, Ayatollahi SMT, Zare N, Sharif F (2013) Quality of life of child-
1042 bearing age women and its associated factors: an application of seemingly
1043 unrelated regression (SUR) models. *Qual. Life Res.* 22:1255–1263

1044 Lin TI (2014) Learning from incomplete data via parameterized t mixture mod-
1045 els through eigenvalue decomposition. *Comput. Stat. Data Anal.* 71:183–195

1046 Magnus JR, Neudecker H (1988) Matrix differential calculus with applications
1047 in statistics and econometrics. John Wiley & Sons, New York

1048 Mardia KV (1970) Measures of multivariate skewness and kurtosis with appli-
1049 cations. *Biometrika* 57:519–530

1050 Mardia, K.V (1974) Applications of some measures of multivariate skewness and
1051 kurtosis for testing normality and robustness studies. *Sankhya*, 36:115–128

1052 McLachlan GJ, Peel D (2000) Finite mixture models. Wiley, New York

1053 McNicholas PD (2010) Model-based classification using latent Gaussian mixture
1054 models. *J. Stat. Plan. Inference* 140:1175–1181

1055 Meng X, Rubin DB (1993) Maximum likelihood estimation via the ECM algo-
1056 rithm: a general framework. *Biometrika* 80:267–278

1057 Park T (1993) Equivalence of maximum likelihood estimation and iterative two-
1058 stage estimation for seemingly unrelated regression models. *Comm. Statist.:
1059 Theory Meth.* 22:2285–2296

1060 Punzo A (2014) Flexible mixture modeling with the polynomial Gaussian
1061 cluster-weighted model. *Stat. Model.* 14:257–291

1062 Punzo A, Ingrassia S (2013) On the use of the generalized linear exponential
1063 cluster-weighted model to assess local linear independence in bivariate data.
1064 *QdS - J. Methodol. Appl. Stat.* 15:131–144

1065 Punzo A, Ingrassia S (2015) Clustering bivariate mixed-type data via the cluster-
1066 weighted model. *Comput. Stat.* 31:989–1013

1067 Punzo A, McNicholas PD (2017) Robust clustering in regression analysis via
1068 the contaminated Gaussian cluster-weighted model. *J. Classif.* 34:249–293

1069 R Core Team (2020) R: a language and environment for statistical com-
1070 puting. R Foundation for Statistical Computing, Vienna, Austria. URL
1071 <http://www.R-project.org>

1072 Rocci R, Gattone SA, Di Mari R (2018) A data driven equivariant approach to
1073 constrained Gaussian mixture modeling. *Adv. Data Anal. Classif.* 12:235–260

1074 Rossi PE (2012) **bayesm**: Bayesian inference for marketing/micro-econometrics.
1075 R package version 2.2-5. URL <http://CRAN.R-project.org/package=bayesm>

1076 Sahin Ö, Czado C (2021) Vine copula mixture models and clustering for non-
1077 Gaussian data. *Econ. Stat.* <https://doi.org/10.1016/j.ecosta.2021.08.011>

1078 Schwarz G (1978) Estimating the dimension of a model. *Ann. Stat.* 6:461–464

1079 Scrucca L, Fop M, Murphy TB, Raftery AE (2017) **mclust** 5: clustering, clas-
1080 sification and density estimation using Gaussian finite mixture models. *The*
1081 *R Journal* 8/1:205–223

1082 Soffritti G (2021) Estimating the covariance matrix of the maximum likelihood
1083 estimator under linear cluster-weighted models. *J. Classif.* 38:594–625

1084 Soffritti G, Galimberti G (2011) Multivariate linear regression with non-normal
1085 errors: a solution based on mixture models. *Stat. Comput.* 21:523–536

1086 Srivastava VK, Giles DEA (1987) Seemingly unrelated regression equations
1087 models. Marcel Dekker, New York

1088 Subedi S, Punzo A, Ingrassia S, McNicholas PD (2013) Clustering and classifi-
1089 cation via cluster-weighted factor analyzers. *Adv. Data Anal. Classif.* 7:5–40.

1090 Subedi S, Punzo A, Ingrassia S, McNicholas PD (2015) Cluster-weighted t-factor
1091 analyzers for robust model-based clustering and dimension reduction. *Stat.*
1092 *Methods Appl.* 24:623–649

- 1093 Wang WL, Lin TI (2016) Maximum likelihood inference for the multivariate t
1094 mixture model. *J. Multivar. Anal.* 149:54–64
- 1095 White EN, Hewings GJD (1982) Space-time employment modelling: some re-
1096 sults using seemingly unrelated regression estimators. *J. Reg. Sci.* 22:283–302