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A NEW MULTILEVEL MODELING APPROACH FOR CLUSTERED SURVIVAL DATA*

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In multilevel modeling of clustered survival data, to account for the differences among different clusters, a commonly used approach is to introduce cluster effects, either random or fixed, into the model. Modeling with random effects may lead to difficulties in the implementation of the estimation procedure for the unknown parameters of interest because the numerical computation of multiple integrals may become unavoidable when the cluster effects are not scalars. On the other hand, if fixed effects are used, there is a danger of having estimators with large variances because there are too many nuisance parameters involved in the model. In this article, using the idea of the homogeneity pursuit, we propose a new multilevel modeling approach for clustered survival data. The proposed modeling approach does not have the potential computational problem as modeling with random effects, and it also involves far fewer unknown parameters than modeling with fixed effects. We also establish asymptotic properties to show the advantages of the proposed model and conduct intensive simulation studies to demonstrate the performance of the proposed method. Finally, the proposed method is applied to analyze a dataset on the second-birth interval in Bangladesh. The most interesting finding is the impact of some important factors on the length of the second-birth interval variation over clusters and its homogeneous structure.

1. INTRODUCTION

This article analyses a real dataset from Bangladesh on the second-birth interval, which is the time interval between the first birth and the second birth. The data come from the Bangladesh Demographic and Health Survey of 1996–1997 (Mitra et al., 1997), a cross-sectional, nationally representative survey. The analysis is based on a sample of 7,464 women nested within 125 primary sampling units or

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clusters, with sample sizes ranging from 17 to 242 women. Some women had not had their second child when the survey took place; therefore, their second-birth intervals are censored. The dataset is a typical clustered survival dataset. What we are interested in is how the covariates, which are commonly associated with the second-birth interval affect the length of the second-birth interval. It is well known that a failure to take into account clustering in an analysis of clustered survival data typically leads to the underestimation of the standard errors since clustering reduces the effective sample size. In the case of survival data, clustering, if ignored, can also lead to substantial bias. Hence, multilevel modeling (see Harvey, 2003), has to be employed when analyzing clustered survival data.

To facilitate statistical modeling for the dataset mentioned above, let y_{ij}, $i = 1, \ldots, n_j, j = 1, \ldots, J$, be the length of the second-birth interval of the ith respondent in the jth primary sampling unit in the survey. X_{ij}, a p dimensional vector, is the vector of individual-level covariates of interest corresponding to y_{ij}. In addition, the vector of the covariates, defined at the cluster level, are denoted by a q-dimensional vector $W_j = (w_{j1}, \ldots, w_{jq})^{\mathrm{T}}$. The censoring times, the lengths of the time intervals between the first birth and the time when the survey took place are denoted by c_{ij}s. The observed data are

$$\left(t_{ij},\ (X_{ij}^T,\ W_j^T),\ \delta_{ij}\right), \quad i = 1, \ldots, n_j, \quad j = 1, \ldots, J,$$

where

$$t_{ij} = \min(y_{ij},\ c_{ij}), \quad \delta_{ij} = I(y_{ij} > c_{ij}).$$

For this dataset, the cluster-level variables w_{jk}, $k = 1, \ldots, q$, are all categorical. Suppose variable w_{jk} has $c_k + 1$ categories. To model the effects of w_{jk}, we create c_k (0, 1) dummy variables, $(w_{jk,1}, \ldots, w_{jk,c_k})$. We denote the coefficients of these dummy variables by $(\lambda_{k,1}, \ldots, \lambda_{k,c_k})$.

1.1. The commonly used multilevel modeling strategy

In multilevel modeling for clustered survival data, to account for the difference in the impacts of the covariates of interest among different clusters, a commonly used approach is to introduce cluster effects, either random or fixed, in the modeling, (see Harvey, 2003 and Zhang and Steele, 2004 and the references therein). If random effects are used for our case, when Cox models (see David, 1972) are employed, we have the following conditional proportional hazard function:

$$\begin{aligned} h(t|X_{ij}, W_j, \mathbf{e}_j) &= h_0(t) \exp\left\{ X_{ij}^T(\boldsymbol{\beta} + \mathbf{e}_j) + \sum_{k=1}^{q} \sum_{l=1}^{c_k} \lambda_{k,l} w_{jk,l} \right\} \\ &= h_0(t) \exp\left(\sum_{k=1}^{q} \sum_{l=1}^{c_k} \lambda_{k,l} w_{jk,l} \right) \exp\left(X_{ij}^T \boldsymbol{\beta} + X_{ij}^T \mathbf{e}_j \right), \end{aligned}$$

for the jth cluster, where the $\mathbf{e}_j$s are random effects. Denoting the resulting conditional partial likelihood function, given the X_{ij}s, W_js and $\mathbf{e}_j$s, by

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$L(\boldsymbol{\beta}|\mathbf{e}_1, \ldots, \mathbf{e}_J)$, this typical multilevel modeling problem would lead the estimator of $\boldsymbol{\beta}$ to be the maximizer of

$$E\{L(\boldsymbol{\beta}|\mathbf{e}_1, \ldots, \mathbf{e}_J)\}, \tag{1.1}$$

where the expectation is taken with respect to $\mathbf{e}_1, \ldots, \mathbf{e}_J$. When the dimension of $\mathbf{e}_j$ is not 1, which is often the case, numerical computation of multiple integrals may become unavoidable in the computation of the expectation in (1.1); hence, in the computation of the estimator of $\boldsymbol{\beta}$, it is well known that numerical computation for multiple integrals can cause serious problems even for a moderate number of dimensions. Therefore, this approach is not practical when the dimension of $\mathbf{e}_j$ is not 1.

On the other hand, if we use fixed cluster effects, and still employ Cox models, the estimator of $\boldsymbol{\beta}$ would be the maximizer of $L(\boldsymbol{\beta}|\mathbf{e}_1, \ldots, \mathbf{e}_J)$, and the maximization is with respect to $(\boldsymbol{\beta}, \mathbf{e}_1, \ldots, \mathbf{e}_J)$ under the condition $\sum_{j=1}^{J} \mathbf{e}_j = 0$. Apparently, this approach involves too many nuisance parameters, 744 nuisance parameters in our case; therefore, the resulting estimators may have large variances.

It is clear that when the cluster effects are not scalars, the commonly used multilevel modeling strategy has some problems. In this article, we propose a new multilevel modeling strategy that does not involve any numerical computation for multiple integrals, and the number of unknown parameters involved is also reasonable. Furthermore, every parameter has meaning, and none of them is a nuisance parameter.

1.2. The proposed multilevel modeling strategy

The proposed multilevel modeling strategy is based on the idea of the homogeneity pursuit rather than cluster effects. There is a rich literature about the homogeneity pursuit: see Ke et al. (2015), Ke et al. (2016), Su et al. (2016), Su and Ju (2018), Wang et al. (2018), Wang and Su (2019), Su and Jin (2019), Ando and Bai (2017), Bonhomme and Manresa (2015), and the references therein. To make the description of the proposed methodology more generic, from now on, y_{ij} does not have to be the length of the second-birth interval; it is a survival time in the generic sense. Similarly, c_{ij}, X_{ij}, W_j, n_j, and J are the censoring time, individual-level covariates, cluster-level covariates, the cluster size and the number of clusters, respectively.

We do not employ cluster effects in the proposed multilevel modeling strategy. For each j, $j = 1, \ldots, J$, we apply Cox models to fit the data from the jth cluster, which is the conditional hazard function $h(t|X_{ij}, W_j)$ for the jth cluster and is assumed to be

$$\begin{aligned} h(t|X_{ij}, W_j) &= h_0(t) \exp\left(X_{ij}^T \boldsymbol{\beta}_j + \sum_{k=1}^{q} \sum_{l=1}^{c_k} \lambda_{k,l} w_{jk,l} \right\} \\ &= h_0(t) \exp\left(\sum_{k=1}^{q} \sum_{l=1}^{c_k} \lambda_{k,l} w_{jk,l} \right) \exp\left(X_{ij}^T \boldsymbol{\beta}_j \right), \end{aligned} \tag{1.2}$$

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where $h_0(\cdot)$ is the common baseline hazard function. We embed an unknown homogeneity structure into $\boldsymbol{\beta}_j$s in the modeling to account for the information provided by different clusters about the same unknowns and reduce the number of unknown parameters; that is, we assume $\boldsymbol{\beta}_j = (\beta_{1,j}, \ldots, \beta_{p,j})^{\mathrm{T}}$ have the following homogeneity structure

$$\beta_{\ell,j} = \begin{cases} \beta_{(1)} & \text{when } (\ell, j) \in \mathcal{B}_1, \\ \vdots & \vdots \\ \beta_{(H)} & \text{when } (\ell, j) \in \mathcal{B}_H, \end{cases} \tag{1.3}$$

$\{\mathcal{B}_k : k = 1, \ldots, H\}$ is a partition of set $\{(\ell, j) : \ell = 1, \ldots, p; j = 1, \ldots, J\}$. The model (1.2) together with the homogeneity structure (1.3) is the proposed multilevel modeling strategy for clustered survival data, in which $h_0(\cdot)$, H, $\beta_{(i)}$, $i = 1, \ldots, H$, the partition $\{\mathcal{B}_k : k = 1, \ldots, H\}$, and $\lambda_{k,l}$, $l = 1, \ldots, c_k$, $k = 1, \ldots, q$, are unknown and must be estimated. We also assume the partition $\{\mathcal{B}_k : k = 1, \ldots, H\}$ is independent of the covariates.

The advantages of the proposed multilevel modeling over the commonly used ones are (i) there is no numerical computation for any multiple integrals needed in the estimation of the unknown parameters, which makes the implementation of the estimation much easier; (ii) there are no nuisance parameters involved, and the number of unknown parameters is reasonable, which avoids the danger of having final estimators with large variances; and (iii) cluster level attributes of the impacts of the covariates are better accounted for and are well estimated.

The reason for us to impose a homogeneity structure on the components of $\boldsymbol{\beta}_j$s rather than on $\boldsymbol{\beta}_j$s is to reduce the number of unknown parameters by as much as possible. Two different vectors may have some components in common, which represents a kind of homogeneity, and such homogeneity cannot be detected by the vector-based homogeneity pursuit. Therefore, the vector-based homogeneity pursuit would result in more unknown parameters than the component-based homogeneity pursuit, such as in (1.3).

Although the proposed multilevel modeling strategy is for Cox models, the idea of modeling applies to other kinds of survival models.

The rest of the article is organized as follows. We begin in Section 2 with a description of an estimation procedure for the unknown parameters in the proposed model. In Section 3, we present the asymptotic properties of the proposed estimators. The performance of the proposed estimation procedure is assessed by a simulation study in Section 4. In Section 5, we explore how the covariates, which are commonly found to be associated with the second-birth interval, affect the length of the second-birth interval, based on the proposed modeling strategy and estimation procedure. All the technical conditions and the theoretical proofs of all the theoretical results are left to the Appendix.

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2. ESTIMATION PROCEDURE

In this section, we present an estimation procedure for the unknown parameters in the proposed model (1.2) and its homogeneity structure (1.3).

We first introduce some notation: for the jth cluster, we denote the distinct event times by $t_{(1),j} < \cdots < t_{(T_j),j}$ and the number of events at time $t_{(\ell),j}$ by $d_{\ell,j}$. The set of indices for the individuals at risk up to time $t_{(\ell),j}$ is denoted by $R_{\ell,j}$, and the set of indices for the events at $t_{(\ell),j}$ by $\mathcal{D}_{\ell,j}$.

2.1. Estimation of the impacts (β_js) of individual-level variables

The procedure for estimating $\boldsymbol{\beta}_j$ consists of three stages. In the first stage, an initial estimator for $\boldsymbol{\beta}_j$ is obtained for each cluster by the partial likelihood method (David, 1972), where Peto's (Breslow, 1972) approximation for ties is used. We then conduct the homogeneity pursuit to identify which $\beta_{i,j}$s are the same and which are different. Finally, we reparametrize the models by replacing the $\beta_{i,j}$s, which are identified to have the same value, by a single parameter and apply the partial likelihood method to estimate the unknown parameters in the models.

Explicitly,

Stage 1 (*Initial Estimation*). For each j ($j = 1, \ldots, J$) based on the observations from the jth cluster, the partial log-likelihood function for (1.2) is

$$\mathcal{L}_j(\boldsymbol{\beta}_j) = \sum_{\ell=1}^{T_j} \left\{ \sum_{i \in \mathcal{D}_{\ell,j}} \left(X_{ij}^T \boldsymbol{\beta}_j - \log \left\{ \sum_{k \in R_{\ell,j}} \exp\left(X_{kj}^T \boldsymbol{\beta}_j \right) \right\} \right) \right\}. \quad \textbf{(2.1)}$$

Let $\tilde{\boldsymbol{\beta}}_j = (\tilde{\beta}_{1,j} \cdots \tilde{\beta}_{p,j})$ maximize (2.1). $\tilde{\boldsymbol{\beta}}_j$ is an initial estimator of $\boldsymbol{\beta}_j$.

Stage 2 (*Homogeneity Pursuit*). Let $\tilde{\beta}_{i,j}$ be the ith component of $\tilde{\boldsymbol{\beta}}_j$. We sort $\tilde{\beta}_{i,j}$, $i = 1, \ldots, p, j = 1, \ldots, J$, in ascending order, and denote them by

$$b_{(1)} \le \cdots \le b_{(Jp)}.$$

We use r_{ij} to denote the rank of $\tilde{\beta}_{i,j}$. Identifying the homogeneity among $\tilde{\beta}_{i,j}, i = 1, \ldots, p, j = 1, \ldots, J$, is equivalent to detecting the change points among $b_{(l)}$, $l = 1, \ldots, Jp$. To this end, we apply the binary segmentation algorithm (Bai, 1997; Vostrikova, 1981; Venkatraman, 1993) as follows.

For any $1 \le i < j \le Jp$, let

$$\Delta_{ij}(\kappa) = \sqrt{\frac{(j-\kappa)(\kappa - i + 1)}{j - i + 1}} \left(\frac{\sum_{l=\kappa+1}^{j} b_{(l)}}{j - \kappa} - \frac{\sum_{l=i}^{\kappa} b_{(l)}}{\kappa - i + 1} \right).$$

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Given a threshold δ, in practice, the binary segmentation algorithm to detect the change points is as follows.

(1) Find $\hat{k}_1$ such that

$$\Delta_{1,Jp}(\hat{k}_1) = \max_{1\le\kappa<Jp} \Delta_{1,Jp}(\kappa).$$

If $\Delta_{1,Jp}(\hat{k}_1) \le \delta$, there is no change point among $b_{(l)}$, $l = 1,\ldots,Jp$, and the process of detection ends. Otherwise, add $\hat{k}_1$ to the set of change points and divide the region $\{\kappa : 1 \le \kappa \le Jp\}$ into two subregions: $\{\kappa : 1 \le \kappa \le \hat{k}_1\}$ and $\{\kappa : \hat{k}_1 + 1 \le \kappa \le Jp\}$.

(2) Detect the change points in the two subregions obtained in (1). Let us address the region $\{\kappa : 1 \le \kappa \le \hat{k}_1\}$ first. Find $\hat{k}_2$ such that

$$\Delta_{1,\hat{k}_1}(\hat{k}_2) = \max_{1\le\kappa<\hat{k}_1} \Delta_{1,\hat{k}_1}(\kappa).$$

If $\Delta_{1,\hat{k}_1}(\hat{k}_2) \le \delta$, there is no change point in the region $\{\kappa : 1 \le \kappa \le \hat{k}_1\}$. Otherwise, add $\hat{k}_2$ to the set of change points and divide the region $\{\kappa : 1 \le \kappa \le \hat{k}_1\}$ into two subregions: $\{\kappa : 1 \le \kappa \le \hat{k}_2\}$ and $\{\kappa : \hat{k}_2 + 1 \le \kappa \le \hat{k}_1\}$. For the region $\{\kappa : \hat{k}_1 + 1 \le \kappa \le Jp\}$, we find $\hat{k}_3$ such that

$$\Delta_{\hat{k}_1+1,Jp}(\hat{k}_3) = \max_{\hat{k}_1+1\le\kappa<Jp} \Delta_{\hat{k}_1+1,Jp}(\kappa).$$

If $\Delta_{\hat{k}_1+1,Jp}(\hat{k}_3) \le \delta$, there is no change point in the region $\{\kappa : \hat{k}_1 + 1 \le \kappa \le Jp\}$. Otherwise, add $\hat{k}_3$ to the set of change points and divide the region $\{\kappa : \hat{k}_1 + 1 \le \kappa \le Jp\}$ into two subregions: $\{\kappa : \hat{k}_1 + 1 \le \kappa \le \hat{k}_3\}$ and $\{\kappa : \hat{k}_3 + 1 \le \kappa \le Jp\}$.

(3) For each subregion obtained in (2), we do exactly the same as that for subregion $\{\kappa : 1 \le \kappa \le \hat{k}_1\}$ or $\{\kappa : \hat{k}_1 + 1 \le \kappa \le Jp\}$ in (2), and continue doing so until no subregion contains a change point.

We sort the estimated change points in ascending order and denote them by

$$\hat{k}_{(1)} < \hat{k}_{(2)} < \cdots < \hat{k}_{(\hat{H}_{-1})},$$

where $\hat{H}_{-1}$ is the number of change points detected. In addition, we denote $\hat{k}_{(0)} = 0$, $\hat{H} = \hat{H}_{-1} + 1$, and $\hat{k}_{(\hat{H})} = Jp$. We use $\hat{H}$ to estimate H. Let

$$\hat{\mathcal{B}}_\ell = \{(i,j) : \hat{k}_{(\ell-1)} < r_{ij} \le \hat{k}_{(\ell)}\}, \quad 1 \le \ell \le \hat{H},$$

we use $\{\hat{\mathcal{B}}_\ell : 1 \le \ell \le \hat{H}\}$ to estimate the partition $\{\mathcal{B}_\ell : 1 \le \ell \le H\}$. We consider all the $\beta_{i,j}$s with the subscript (i,j) in the same estimated partition having the same value.

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Stage 3 (*Final Estimation*). Let $\mathcal{L}(\xi_1, \ldots, \xi_{\hat{H}})$ be

$$\sum_{j=1}^{J} \mathcal{L}_j(\boldsymbol{\beta}_j)$$

with $\beta_{i,j}$ $(i = 1, \ldots, p, j = 1, \ldots, J)$ being replaced by ξ_k if $(i, j) \in \hat{\mathcal{B}}_k$. Let $(\hat{\xi}_1, \ldots, \hat{\xi}_{\hat{H}})$ maximize $\mathcal{L}(\xi_1, \ldots, \xi_{\hat{H}})$. The final estimator $\hat{\beta}_{i,j}$ of $\beta_{i,j}$ is $\hat{\xi}_k$ if $(i, j) \in \hat{\mathcal{B}}_k$.

Remark. The threshold δ used in Stage 2 can be selected by Bayesian information criterion (BIC), see Volinsky and Raftery (2000) because the selection of δ is equivalent to the selection of the number of elements in the partition, namely, the H in (1.3), which is the number of unknown parameters. Therefore, BIC becomes a natural choice, which is why we use BIC to select δ.

2.2. Estimation of the common cumulative baseline hazard function and the impacts ($\lambda_{k,l}$s) of the cluster-level variables

After obtaining the estimator for $\boldsymbol{\beta}_j$ in (1.2), we estimate $\lambda_{k,l}$, $l = 1, \ldots, c_k$; $k = 1, \ldots, q$, the impact of the categorical cluster-level variables and the common cumulative baseline hazard function.

Define the baseline hazard function for the jth cluster as

$$h_{1,j}(t) = h_0(t) \exp\left(\sum_{k=1}^{q} \sum_{l=1}^{c_k} \lambda_{k,l} w_{jk,l} \right) \tag{2.2}$$

and the cumulative baseline hazard function as

$$\Lambda_{1,j}(t) = \int_0^t h_{1,j}(u) du.$$

Breslow's estimator for $\Lambda_{1,j}(t_{(\ell),j})$ is

$$\hat{\Lambda}_{1,j}(t_{(\ell),j}) = \sum_{m=1}^{\ell} \left\{ \sum_{k \in R_{m,j}} \exp\left(X_{kj}^T \hat{\boldsymbol{\beta}}_j \right) \right\}^{-1}. \tag{2.3}$$

Let

$$L_{1,j}(t) = \log\big(\Lambda_{1,j}(t)\big), \quad \Lambda_0(t) = \int_0^t h_0(u) du, \quad L_0(t) = \log\Big(\Lambda_0(t)\Big);$$

we have

$$L_{1,j}(t) = L_0(t) + \sum_{k=1}^{q} \sum_{\ell=1}^{c_k} \lambda_{k,\ell} w_{jk,\ell}.$$

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This equation leads to the following synthetic regression model:

$$\hat{L}_{1,j}(t_{(\ell),j}) = L_0(t_{(\ell),j}) + \sum_{k=1}^{q}\sum_{l=1}^{c_k}\lambda_{k,l}w_{jk,l} + \epsilon_{\ell,j}, \quad \ell = 1,\ldots,T_j, \quad j = 1,\ldots,J, \tag{2.4}$$

where $\hat{L}_{1,j}(t_{(\ell),j}) = \log\left(\hat{\Lambda}_{1,j}(t_{(\ell),j})\right)$.

Next, we consider the estimation of (2.4). Let $t_{(1)} < t_{(2)} < \cdots < t_{(N)}$ be the distinct values of $t_{(\ell),j}$, where $\ell = 1, \ldots, T_j$ and $j = 1, \ldots, J$. For each $t_{(m)}$, $m = 1, \ldots, N$, applying local linear modeling, we obtain the following the local least squares procedure

$$\sum_{j=1}^{J}\sum_{\ell=1}^{T_j}\left\{\hat{L}_{1,j}(t_{(\ell),j}) - a - b(t_{(\ell),j} - t_{(m)}) - \sum_{k=1}^{q}\sum_{l=1}^{c_k}\lambda_{k,l}w_{jk,l}\right\}^2 K_h(t_{(\ell),j} - t_{(m)}), \tag{2.5}$$

where $K_h(\cdot) = K(\cdot/h)/h$, $K(\cdot)$ is a kernel function, usually taken to be the Epanechnikov kernel, $K(u) = 0.75(1-u^2)_+$. h is a bandwidth.

Let

$$\left(\tilde{a}(t_{(m)}), \tilde{b}(t_{(m)}), \tilde{\lambda}_{1,1}(t_{(m)}), \cdots, \tilde{\lambda}_{1,c_1}(t_{(m)}), \cdots, \tilde{\lambda}_{q,1}(t_{(m)}), \cdots, \tilde{\lambda}_{q,c_q}(t_{(m)})\right)$$

be the minimizer of (2.5). The estimators for $\lambda_{k,l}$ are taken to be

$$\hat{\lambda}_{k,l} = \frac{1}{N}\sum_{m=1}^{N}\tilde{\lambda}_{k,l}(t_{(m)}), \quad l = 1, \cdots, c_k, \quad k = 1, \cdots, q. \tag{2.6}$$

The estimator for $L_0(t_{(m)})$, $m = 1, \ldots, N$, is taken to be $\tilde{a}(t_{(m)})$, which leads to the following initial estimator for the common cumulative baseline hazard function at $t_{(m)}$

$$\tilde{\Lambda}_0(t_{(m)}) = \exp\left\{\tilde{a}(t_{(m)})\right\}, \quad m = 1, \ldots, N.$$

Viewing $\left(t_{(m)}, \tilde{\Lambda}_0(t_{(m)})\right)$, $m = 1, \ldots, N$, as a sample from the nonparametric regression model

$$\eta = \Lambda_0(t) + \varepsilon,$$

and using local linear modeling, we obtain the estimator $\hat{\Lambda}_0(\cdot)$ of $\Lambda_0(\cdot)$.

3. ASYMPTOTIC PROPERTIES

In this section, we present the asymptotic properties of the proposed estimators. First, we introduce some notation. We assume H is fixed and let $\mathcal{N} = \sum_{j=1}^{J} n_j$. For the ith subject in the jth cluster, let $N_{ij}(t) = I(t_{ij} \le t, \delta_{ij} = 1)$ and $Y_{ij}(t) = I(t_{ij} \ge t)$ be the counting process and the at-risk process, respectively. We use τ

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to denote the study ending time as in Bradic et al. (2011). Let the σ-filtration $\mathcal{F}_t = \sigma\{N_{ij}(s), Y_{ij}(s), s \le t, i = 1, \ldots, n_j, j = 1, \ldots, J\}$. Denote β_j^* as the true value of β_j and $\Lambda_{ij}(t) = \int_0^t Y_{ij}(u) \exp(X_{ij}^T \beta^*) h_{1,j}(u) du$. With respect to the filtration $\{\mathcal{F}_t, t \ge 0\}$, $M_{ij}(t) = N_{ij}(t) - \int_0^t Y_{ij}(u) \exp(X_{ij}^T \beta^*) h_{1,j}(u) du$, $i = 1, \ldots, n_j$, $j = 1, \ldots, J$, $t \ge 0$ are (local) martingales with predictable variation/covariation processes

$$< M_{ij}, M_{ij} > (t) = \Lambda_{ij}(t) \quad \text{and} \quad < M_{ij}, M_{i'j'} > (t) = 0, \text{ when } i \ne i' \text{ or } j \ne j'.$$

Let $\otimes$ denote the outer product. Define

$$S_j^{(\ell)}(t, \beta) = n_j^{-1} \sum_{i=1}^{n_j} X_{ij}^{\otimes \ell} Y_{ij}(t) \exp(\beta^T X_{ij}), \ \ell = 0, 1, 2,$$

$$E_j(t, \beta) = \frac{S_j^{(1)}(t, \beta)}{S_j^{(0)}(t, \beta)},$$

and

$$V_j(t, \beta) = \frac{S_j^{(2)}(t, \beta)}{S_j^{(0)}(t, \beta)} - E_j(t, \beta)^{\otimes 2}.$$

By differentiation and the rearrangement of terms, it can be shown as in Andersen and Gill (1982) that the gradient of $\mathcal{L}_j(\boldsymbol{\beta})$ is

$$\dot{\mathcal{L}}_j(\boldsymbol{\beta}) \equiv \frac{\partial \mathcal{L}_j(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} = \sum_{i=1}^{n_j} \int_0^t [X_{ij} - E_j(u, \boldsymbol{\beta})] dN_{ij}(u),$$

and the Hessian matrix of $\mathcal{L}_j(\boldsymbol{\beta})$ is

$$\ddot{\mathcal{L}}_j(\boldsymbol{\beta}) \equiv \frac{\partial^2 \mathcal{L}(\boldsymbol{\beta})}{\partial \boldsymbol{\beta} \partial \boldsymbol{\beta}^T} = -\sum_{i=1}^{n_j} \int_0^t V_j(u, \boldsymbol{\beta}) dN_{ij}(u).$$

Let $n = \min_{1 \le j \le J} n_j$ and $\Delta = \min_{2 \le k \le H} |\boldsymbol{\beta}_{(k)} - \boldsymbol{\beta}_{(k-1)}|$. Assume that $n \to \infty$. Suppose K is a sufficiently large positive constant. Next, we list the following regularity conditions.

Condition 1. (i) For any $1 \le j \le J$, the unknown parameter β_j belongs to a compact subset of $\mathcal{R}^p$, the true parameter value β_j^* lies in its interior, and $\|\lambda\| \le K$. (ii) The covariates satisfy

$$\max_{1 \le j \le J} \max_{i < i' \le n_j} \max_{1 \le k \le p} |X_{ijk} - X_{i'jk}| \le K,$$

and $\max_j \|W_j\| \le K$.

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(iii) There exists a positive constant c_0, and with probability tending to 1,

$$\inf_{1\le j\le J}\inf_{\|b\|=1,\, b\in R^p}\int_0^{t_{(T_j),j}} b^T V_j(u,\boldsymbol{\beta}_j^*)S_j^{(0)}(u,\boldsymbol{\beta}_j^*)bh_0(u)du \ge c_0.$$

(iv) We assume

$$\frac{\log J}{n} = o(\Delta^2).$$

Remark 1. Condition 1(i)–(iii) is standard for asymptotic analyses and 1(iv) allows the number of clusters to diverge at a rate slower than the polynomial rate of the minimum cluster size.

Condition 2. (i) Assume that $Jp\log(Jp) = o(\sqrt{n})$.

(ii) There exists a positive constant c_0 such that $\min_{1\le i,\, j\le H}\frac{s_i}{s_j} \ge c_0$.

(iii) $\Delta = \min_{2\le \ell\le H}(\beta_{(\ell)} - \beta_{(\ell-1)}) > \frac{1}{K}$.

(iv) $\delta \ge \frac{1}{K}$ and $\delta = o(\sqrt{Jp})$.

Remark 2. Condition 2(i) allows both the number of covariates p and the number of clusters J to diverge, at a rate more stringent than Condition 1(iv) but still reasonable in most applications. Condition 2(ii) assumes that the sizes of the clusters have about the same magnitude to ensure that the limiting distribution will not be dominated by the information from a subset of the clusters with dominating sizes, for the ease of the exposition of asymptotic results. Condition 2(iii) is similar to the separability condition in K-means or hierarchical clustering, requiring that the true H distinct values of the regression coefficients are separable by $1/K$. Condition 2(iv) specifies the range for the rate of δ.

Condition 3. Assume that $\mathcal{I}_n(u) = \mathcal{N}^{-1}\sum_{j=1}^J\sum_{i=1}^{n_j} Y_{ij}\Psi_j^T V_j(u,\Psi_j\boldsymbol{\xi}^*)\Psi_j \exp(X_{ij}^T\Psi_j^T\boldsymbol{\xi}^* + \lambda^T W_j) \to \mathcal{I}(u)$, in probability, for almost all u in $[0,\, \tau]$ and that $\mathcal{I} = \int_0^\tau \mathcal{I}(u)h_0(u)du$ is positive definite.

Condition 4. There exist functions $s_j^{(0)}(t,\beta_j)$ and $e_j(t,\ \beta_j)$, $1 \le j \le J$, such that

$$\max_{1\le j\le J}\sup_{0\le t\le\tau}|S_j^{(0)}(t,\Psi_j\boldsymbol{\xi}^*) - s_j^{(0)}(t,\Psi_j\boldsymbol{\xi}^*)| \to 0$$

in probability as $n\to\infty$, and

$$\max_{1\le j\le J}\sup_{0\le t\le\tau}|E_j(t,\Psi_j\boldsymbol{\xi}^*) - e_j(t,\Psi_j\boldsymbol{\xi}^*)| \to 0$$

in probability as $n\to\infty$.

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Denote the condition survival function of C_{ij} given the cluster effect by $\bar{G}_{ij}(t) = P(C_{ij} > t|W_j)$ and the conditional density function of t_{ij} by $f_{ij}(t) = dP(t_{ij} \le t|W_j)/dt$.

Condition 5. (i) Let $K(\cdot)$ be a symmetric and bounded kernel density function with a bounded support.

(ii) $h \to 0$ and $\mathcal{N}h^2 \to \infty$.

(iii) f_{ij} and $\bar{G}_{ij}$ have continuous derivatives in $[0, \tau]$.

(iv) As $n \to \infty$,

$$\sup_{0\le t\le\tau} \left| \frac{1}{\mathcal{N}} \sum_{j=1}^{J} \sum_{i=1}^{n_j} f_{ij}(t)\bar{G}_{ij}(t)\tilde{W}_j\tilde{W}_j^T - \Omega(t) \right| \to 0$$

in probability, where for any t, $\Omega(t)$ is a $(c+1) \times (c+1)$ symmetric and positive definite matrix.

(v) Assume that for any $0 \le t_1, t_2 \le \tau$,

$$\mathcal{N}^{-1} \sum_{j=1}^{J} n_j \tilde{W}_j \tilde{W}_j^T s_j^{(0)}(t_1, \Psi_j\boldsymbol{\xi}^*) \int_0^{t_1} [s_j^{(0)}(u, \Psi_j\boldsymbol{\xi}^*)]^{-1} h_{1,j}(u) du s_j^{(0)}(t_2, \Psi_j\boldsymbol{\xi}^*)$$
$$\times \int_0^{t_2} [s_j^{(0)}(v, \Psi_j\boldsymbol{\xi}^*)]^{-1} h_{1,j}(v) dv \to \zeta(t_1, t_2),$$

and

$$\mathcal{N}^{-1} \left(\sum_{j=1}^{J} n_j \tilde{W}_j s_j^{(0)}(t_1, \Psi_j\boldsymbol{\xi}^*) \int_0^{t_1} e_j^T(u, \Psi_j\boldsymbol{\xi}^*) h_{1,j}(u) du \Psi_j^T \right) \to \Upsilon(t_1),$$

where $\zeta(t_1, t_2)$ and $\Upsilon(t_1)$ are $(c+1) \times (c+1)$ and $(c+1) \times H$ matrices, respectively.

Remark 3. Conditions 3, 4, and 5(iii)–(v) are standard regularity conditions for Cox modeling and Condition5(i) and (ii) are standard for kernel smoothing.

We assume that H is fixed. Let $\mathcal{N} = \sum_{j=1}^{J} n_j$.

THEOREM 1. *Under the Conditions 1–3, for any given j, we have*

$$\mathcal{N}^{1/2} \left(\hat{\boldsymbol{\beta}}_j - \boldsymbol{\beta}_j \right) \xrightarrow{D} N\left(0_p, \Psi_j \mathcal{I}^{-1} \Psi_j^T\right).$$

Theorem 1 shows that the proposed estimator $\hat{\boldsymbol{\beta}}_j$ is asymptotically normal and has a convergence rate of order $\mathcal{N}^{-1/2}$, which is a higher order of $n_j^{-1/2}$. In fact, it is the highest order an estimator can achieve even for the case where there is no clustering, which implies the homogeneity pursuit in the estimation procedure significantly improves the accuracy of the estimators of the $\boldsymbol{\beta}_j$s.

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THEOREM 2. *Under Conditions 1–5, when* $\mathcal{N}h^4 \to 0$*, we have*

$$\mathcal{N}^{1/2}\left(\hat{\lambda}_{k,l} - \lambda_{k,l}\right) \xrightarrow{D} N\left(0, e_{k,\ell}^T \bar{\Omega}_{11}^{-2} \bar{v}_{22} e_{k,\ell}\right).$$

Theorem 2 shows that the proposed estimator $\hat{\lambda}_{k,l}$ is also asymptotically normal and has a convergence rate of order $\mathcal{N}^{-1/2}$.

THEOREM 3. *Under Conditions 1–5, when* $\mathcal{N}h^4 \to 0$*, for any given t, we have*

$$\mathcal{N}^{1/2}\left(\hat{\Lambda}_0(t) - \Lambda_0(t)\right) \xrightarrow{D} N\left(0,\ \Lambda_0^2(t) v_{11}(t,t)\right).$$

Theorem 3 shows that the proposed estimator $\hat{\Lambda}_0(t)$ for the common cumulative baseline hazard function is asymptotically normal and has a convergence rate of order $\mathcal{N}^{-1/2}$, which is the highest order an estimator of a monotonic function can achieve.

4. SIMULATION STUDIES

In this section, we use a simulated example to assess the performance of the proposed estimation procedure. As the homogeneity pursuit in the estimation procedure is of importance in its own right, we are also going to examine the accuracy of the proposed homogeneity pursuit in identifying the true homogeneity structure.

We set $h_0(t) = 1$, $p = 2$, $q = 1$, $c_q = 2$, and $\boldsymbol{\beta}_j = (1,\ 2)^{\mathrm{T}}$. When j is odd, $\boldsymbol{\beta}_j = (-1,\ -2)^{\mathrm{T}}$; when j is even, $\lambda_{1,1} = 1$, and $\lambda_{1,2} = -2$ in model (1.2), $H = 4$ in the homogeneity structure (1.3), then data are generated from model (1.2). We first generate the X_{ij}s and W_js, then y_{ij}, given X_{ij} and W_j, for each $(X_{ij}^{\mathrm{T}},\ W_j)$, hence, the generated $(y_{ij},\ X_{ij}^{\mathrm{T}},\ W_j)$s. Once $(y_{ij},\ X_{ij}^{\mathrm{T}},\ W_j)$s are generated, we generate the censoring times t_{ij}s, and obtain the generated observations $(t_{ij},\ X_{ij}^{\mathrm{T}},\ W_j,\ \delta_{ij})$. The details about how the data are generated are as follows:

We generate the independent and identically distributed observations X_{ij}, $i = 1, \ldots, n_j$, $j = 1, \ldots, J$, of the individual-level variable from the bivariate normal distribution with mean zero and covariance matrix $\begin{pmatrix} 1.0 & 0.2 \\ 0.2 & 1.0 \end{pmatrix}$. The observations w_{j1}, $j = 1, \ldots, J$, of the cluster-level variable are independently and identically generated from a multinomial distribution with three categories with the probability for each category of 1/3, namely *Multi*(1, 1/3, 1/3, 1/3). Based on the generated w_{j1}s, we can obtain the generated observations $w_{j1,\,1}$ and $w_{j1,\,2}$, $j = 1, \ldots, J$, of the two dummy variables created from the sw_{j1}s by setting the first category as the reference level.

Once the X_{ij}s and W_js are generated, for each $(X_{ij}^{\mathrm{T}},\ W_j)$, y_{ij}, given $(X_{ij}^{\mathrm{T}},\ W_j)$, is generated as follows:
from

$$h(t|X_{ij}, W_j) = h_0(t) \exp\left(X_{ij}^{\mathrm{T}} \boldsymbol{\beta}_j + w_{j1,1}\lambda_{1,1} + w_{j1,2}\lambda_{1,2}\right),$$

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we have

$$\int_0^t h(u|X_{ij}, W_j)du = \Lambda_0(t)\exp\left(X_{ij}^{\mathrm{T}}\boldsymbol{\beta}_j + w_{j1,1}\lambda_{1,1} + w_{j1,2}\lambda_{1,2}\right).$$

Since

$$\int_0^t h(u|X_{ij}, W_j)du = -\log(1 - F_y(t|X_{ij}, W_j)),$$

where $F_y(t|X_{ij}, W_j)$ is the conditional distribution of y_{ij} given (X_{ij}, W_j), we have

$$\Lambda_0(y_{ij})\exp\left(X_{ij}^{\mathrm{T}}\boldsymbol{\beta}_j + w_{j1,1}\lambda_{1,1} + w_{j1,2}\lambda_{1,2}\right) = -\log(1 - F_y(y_{ij}|X_{ij}, W_j)).$$

It is easy to see that $-\log(1 - F_y(y_{ij}|X_{ij}, W_j))$, given X_{ij} and W_j, follows a standard exponential distribution, and $\Lambda_0(y_{ij}) = y_{ij}$ as $h_0(t) = 1$. Therefore, we generate an ϵ_{ij} from a standard exponential distribution, and y_{ij}, given $(X_{ij}^{\mathrm{T}},\ W_j)$, can be generated through

$$y_{ij} = \exp\left(-X_{ij}^{\mathrm{T}}\boldsymbol{\beta}_j - w_{j1,1}\lambda_{1,1} - w_{j1,2}\lambda_{1,2}\right)\epsilon_{ij};$$

therefore, we have the generated $(y_{ij},\ X_{ij}^{\mathrm{T}},\ W_j)$s.

The censoring times (c_{ij}s) are independently and identically generated from the uniform distribution $U(0, 10)$, and the observed survival times t_{ij}s and censoring indicators δ_{ij}s are generated through

$$t_{ij} = \min(y_{ij},\ c_{ij}), \quad \delta_{ij} = I(y_{ij} > c_{ij}).$$

Therefore, we have the generated observations $(t_{ij},\ X_{ij}^{\mathrm{T}},\ W_j,\ \delta_{ij})$.

We use 95% confidence intervals for each component of $\boldsymbol{\beta}_j$ and $\lambda_{1,l}$ and

$$\mathrm{MSE}_\beta = \frac{1}{J}\sum_{j=1}^{J} E\left(\|\hat{\boldsymbol{\beta}}_j - \boldsymbol{\beta}_j\|^2\right), \quad \mathrm{MSE}_\lambda = \frac{1}{2}\sum_{l=1}^{2} E(\hat{\lambda}_{1,l} - \lambda_{1,l})^2$$

to evaluate the estimators ($\hat{\boldsymbol{\beta}}_j$s) and $\hat{\lambda}_{1,l}$s. Furthermore, we use

$$\mathrm{MISE}(\Lambda_0) = E\left\{\int\left(\hat{\Lambda}_0(t) - \Lambda_0(t)\right)^2 dt\right\}$$

to evaluate $\hat{\Lambda}_0(\cdot)$, and the normalized mutual information (NMI), see Ke et al. (2015), to measure how close the estimated homogeneity structure is to the true homogeneity structure. The NMI is defined as follows:

Let $A = \{A_1, A_2, \cdots\}$ and $B = \{B_1, B_2, \cdots\}$ be two partitions of a set of cardinality k. For any set S, we use $|S|$ to denote the cardinality of S. The NMI between A and B is defined as

$$\mathrm{NMI}(A,\ B) = \frac{2I(A,\ B)}{H(A) + H(B)},$$

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where

$$I(A,\ B)=\sum_{i,j}\frac{|A_i\cap B_j|}{k}\log\left(\frac{k|A_i\cap B_j|}{|A_i||B_j|}\right),\quad H(A)=\sum_{i}\frac{|A_i|}{k}\log\left(\frac{k}{|A_i|}\right).$$

The NMI ranges between 0 and 1 with a large value indicating a high degree of similarity between the two partitions, A and B.

In all numerical studies in this article, we use BIC to select the threshold δ needed in the homogeneity pursuit step in the proposed estimation procedure. The Epanechnikov kernel is used, and a rule-of-thumb bandwidth is adopted when estimating $\lambda_{1,1}$, $\lambda_{1,2}$, and $\Lambda_0(\cdot)$.

Our simulation studies are conducted under either a balanced design or an unbalanced design. For the cases with balanced designs, we set the number of clusters to be either 40, 80, or 120, and the cluster size to be either 40, 80, or 120. For the cases with unbalanced designs, we still set the number of clusters to be either 40, 80, or 120, but the cluster sizes, the n_js, to be the absolute values of the integer parts of the random variables generated from the uniform distribution $U(\bar{n}-10,\ \bar{n}+10)$, where $\bar{n}$ is set to be either 40, 80, or 120. In each case, we perform 100 simulations.

The average censoring rate across the 100 simulations for each case is presented in Table 1, which shows that all cases concerned share similar censoring rates.

We first examine the accuracy of the proposed homogeneity pursuit in identifying the true homogeneity structure. We compare our proposed method with the K-means estimation method using the number of clusters $k=4$. The K-means method is executed by the *kmeans* function in R using the algorithm proposed by Hartigan and Wong (1979). For each case, we compute the NMI between the identified homogeneity structure, by the proposed pursuit, and the true homogeneity structure for each of the 100 simulations for that case, and present the median of the obtained 100 NMIs in Table 2. Table 2 shows that there is no large differences between the balanced cases and the unbalanced cases on the accuracy of the proposed homogeneity pursuit, and the proposed homogeneity pursuit works well in any case and performs better than the K-means method. Interestingly, the number of clusters does not have much impact on the accuracy of the proposed homogeneity pursuit.

We now turn to examining the accuracy of the proposed estimation procedure. We are not only interested in the accuracy of the proposed estimation procedure

TABLE 1. The average censoring rate for each case investigated

	Balanced design			Unbalanced design		
	$n_j=40$	$n_j=80$	$n_j=120$	$\bar{n}=40$	$\bar{n}=80$	$\bar{n}=120$
$J=40$	0.300	0.306	0.302	0.304	0.307	0.305
$J=80$	0.301	0.300	0.303	0.307	0.303	0.304
$J=120$	0.303	0.302	0.302	0.304	0.304	0.302

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TABLE 2. The median of the NMIs for each case investigated

	The proposed method					
	Balanced design			Unbalanced design		
	$n_j = 40$	$n_j = 80$	$n_j = 120$	$\bar{n} = 40$	$\bar{n} = 80$	$\bar{n} = 120$
$J = 40$	0.835	0.964	1.000	0.846	0.964	1.000
$J = 80$	0.825	0.964	1.000	0.817	0.961	1.000
$J = 120$	0.817	0.954	0.985	0.809	0.956	1.000
	The K-means method					
	Balanced design			Unbalanced design		
	$n_j = 40$	$n_j = 80$	$n_j = 120$	$\bar{n} = 40$	$\bar{n} = 80$	$\bar{n} = 120$
$J = 40$	0.744	0.802	0.813	0.758	0.804	0.810
$J = 80$	0.738	0.800	0.813	0.744	0.803	0.806
$J = 120$	0.737	0.797	0.808	0.726	0.800	0.801

but also the improvement of the proposed method over the K-means method, the over-fitting method, and the under-fitting method. The over-fitting method is the method without the homogeneity pursuit when estimating the $\boldsymbol{\beta}_j$s, which is basically the initial estimation of the proposed method for estimating the $\boldsymbol{\beta}_j$s. The under-fitting method is the method that assumes that all clusters share the same $\boldsymbol{\beta}_j$ when estimating the $\boldsymbol{\beta}_j$s. The K-means method, over-fitting method, and under-fitting method estimate $\lambda_{1,1}$, $\lambda_{1,2}$, and $\Lambda_0(\cdot)$ in the same way as the proposed method once the estimators of $\boldsymbol{\beta}_j$s are obtained.

For each case, in each of the 100 simulations for that case, we apply either the proposed estimation procedure, the K-means method, the over-fitting method, or the under-fitting method to estimate the $\boldsymbol{\beta}_j$s, $\lambda_{1,1}$, $\lambda_{1,2}$, and $\Lambda_0(\cdot)$. We report the 95% confidence intervals for each component of the $\boldsymbol{\beta}_j$s and the $\lambda_{1,l}$s and compute the MSE $_\beta$, MSE $_\lambda$, and MISE(Λ_0) of the estimators obtained by each of the four methods. The results are presented in Tables 3–7 for balanced design cases and in Tables 8–12 for unbalanced design cases. From these tables, we can see the balanced design cases tell the same story as the unbalanced design cases, and the proposed estimation procedure works well for any of the cases.

Compared with the K-means method, the over-fitting method, and the under-fitting method, the proposed method yields significant improvement in the accuracy of the estimators of the $\boldsymbol{\beta}_j$s, the impact of individual-level variables. However, when it comes to estimate the impact of the cluster-level variables, $\lambda_{1,1}$, $\lambda_{1,2}$, or the common cumulative baseline hazard function $\Lambda_0(\cdot)$, the K-means method and the over-fitting method perform as well as the proposed method because the only problem with the K-means method or the over-fitting method is that the variances of the estimators of $\boldsymbol{\beta}_j$s would be large, and the estimation of $\lambda_{1,1}$, $\lambda_{1,2}$, and $\Lambda_0(\cdot)$, after the estimators of $\boldsymbol{\beta}_j$s are obtained, is essentially a smoothing operation. The effect of the variances of the estimators of the $\boldsymbol{\beta}_j$s can be reduced with smoothing,

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TABLE 3. The 95% confidence intervals for each component of $\boldsymbol{\beta}_j$s for each case under balanced designs

		The proposed method			The K-means method		
J	$\beta_{i,j}$	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	1	(0.932, 1.165)	(0.958, 1.072)	(0.966, 1.047)	(1.002, 1.218)	(1.025, 1.157)	(1.003, 1.113)
	2	(1.825, 2.068)	(1.936, 2.051)	(1.967, 2.016)	(1.535, 1.916)	(1.559, 1.907)	(1.686, 1.974)
	−1	(−1.170, −0.960)	(−1.084, −0.969)	(−1.058, −0.986)	(−1.198, −0.981)	(−1.155, −1.023)	(−1.141, −1.033)
	−2	(−2.087, −1.764)	(−2.043, −1.851)	(−2.037, −1.856)	(−2.032, −1.637)	(−1.909, −1.560)	(−1.896, −1.567)
80	1	(0.995, 1.139)	(0.974, 1.049)	(0.983, 1.022)	(1.038, 1.188)	(1.036, 1.130)	(1.029, 1.102)
	2	(1.865, 2.064)	(1.958, 2.031)	(1.977, 2.015)	(1.666, 1.943)	(1.650, 1.887)	(1.685, 1.903)
	−1	(−1.139, −0.998)	(−1.043, −0.977)	(−1.021, −0.984)	(−1.193, −1.040)	(−1.130, −1.039)	(−1.125, −1.048)
	−2	(−2.062, −1.851)	(−2.029, −1.942)	(−2.016, −1.968)	(−1.913, −1.641)	(−1.866, −1.625)	(−1.831, −1.595)
120	1	(1.000, 1.122)	(0.985, 1.046)	(0.987, 1.011)	(1.038, 1.158)	(1.057, 1.132)	(1.037, 1.096)
	2	(1.881, 2.048)	(1.961, 2.024)	(1.984, 2.015)	(1.716, 1.932)	(1.631, 1.831)	(1.687, 1.869)
	−1	(−1.110, −0.995)	(−1.035, −0.981)	(−1.017, −0.988)	(−1.157, −1.037)	(−1.116, −1.042)	(−1.105, −1.043)
	−2	(−2.036, −1.863)	(−2.024, −1.957)	(−2.012, −1.979)	(−1.899, −1.678)	(−1.86, −1.664)	(−1.853, −1.668)
		Over-fitting method			Under-fitting method		
J	$\beta_{i,j}$	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	1	(0.915, 1.184)	(0.947, 1.116)	(0.950, 1.089)	(−1.250, −0.945)	(−1.119, −0.967)	(−1.086, −0.970)
	2	(1.914, 2.295)	(1.935, 2.188)	(1.937, 2.124)	(−2.336, −1.968)	(−2.210, −1.953)	(−2.123, −1.938)
	−1	(−1.192, −0.916)	(−1.116, −0.943)	(−1.091, −0.957)	(−1.250, −0.945)	(−1.119, −0.967)	(−1.086, −0.970)
	−2	(−2.320, −1.927)	(−2.176, −1.932)	(−2.129, −1.939)	(−2.336, −1.968)	(−2.210, −1.953)	(−2.123, −1.938)
80	1	(0.973, 1.167)	(0.969, 1.089)	(0.971, 1.063)	(−1.164, −0.981)	(−1.077, −0.962)	(−1.058, −0.959)
	2	(1.993, 2.281)	(1.976, 2.149)	(1.968, 2.098)	(−2.215, −1.985)	(−2.144, −1.971)	(−2.062, −1.945)
	−1	(−1.162, −0.972)	(−1.087, −0.966)	(−1.063, −0.970)	(−1.164, −0.981)	(−1.077, −0.962)	(−1.058, −0.959)
	−2	(−2.261, −1.988)	(−2.137, −1.964)	(−2.095, −1.965)	(−2.215, −1.985)	(−2.144, −1.971)	(−2.062, −1.945)
120	1	(0.986, 1.147)	(0.982, 1.081)	(0.977, 1.053)	(−1.154, −0.975)	(−1.060, −0.961)	(−1.050, −0.973)
	2	(2.016, 2.246)	(1.989, 2.130)	(1.983, 2.092)	(−2.173, −1.964)	(−2.143, −2.001)	(−2.070, −1.963)
	−1	(−1.136, −0.975)	(−1.074, −0.976)	(−1.055, −0.979)	(−1.154, −0.975)	(−1.060, −0.961)	(−1.050, −0.973)
	−2	(−2.242, −2.009)	(−2.127, −1.987)	(−2.088, −1.980)	(−2.173, −1.964)	(−2.143, −2.001)	(−2.070, −1.963)

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TABLE 4. The 95% confidence intervals for each component of $\lambda_{1,l}$s for each case under balanced designs

		The proposed method			The K-means method		
J	$\lambda_{1,l}$	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	1	(0.697, 1.083)	(0.804, 1.029)	(0.812, 1.019)	(0.637, 1.070)	(0.720, 1.013)	(0.772, 0.980)
	−2	(−2.162, −1.663)	(−2.092, −1.752)	(−2.072, −1.793)	(−2.142, −1.540)	(−2.040, −1.602)	(−2.049, −1.653)
80	1	(0.784, 1.033)	(0.852, 1.004)	(0.877, 0.995)	(0.716, 1.026)	(0.758, 0.994)	(0.785, 0.984)
	−2	(−2.108, −1.744)	(−2.040, −1.809)	(−2.015, −1.861)	(−2.049, −1.661)	(−2.012, −1.646)	(−2.019, −1.650)
120	1	(0.811, 1.003)	(0.865, 0.988)	(0.890, 0.985)	(0.759, 0.993)	(0.769, 0.974)	(0.796, 0.978)
	−2	(−2.104, −1.769)	(−2.017, −1.853)	(−2.006, −1.875)	(−2.074, −1.680)	(−1.992, −1.679)	(−2.027, −1.663)
		Over-fitting method			Under-fitting method		
J	$\lambda_{1,l}$	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	1	(0.580, 1.227)	(0.707, 1.138)	(0.777, 1.104)	(−0.867, 0.707)	(−0.701, 0.937)	(−0.944, 0.942)
	−2	(−2.440, −1.585)	(−2.255, −1.740)	(−2.192, −1.763)	(−0.939, 0.847)	(−0.969, 1.088)	(−0.936, 0.909)
80	1	(0.752, 1.143)	(0.775, 1.097)	(0.830, 1.050)	(−0.620, 0.532)	(−0.528, 0.544)	(−0.596, 0.644)
	−2	(−2.312, −1.760)	(−2.194, −1.763)	(−2.106, −1.809)	(−0.610, 0.563)	(−0.696, 0.610)	(−0.665, 0.657)
120	1	(0.756, 1.101)	(0.821, 1.049)	(0.860, 1.046)	(−0.503, 0.522)	(−0.482, 0.415)	(−0.469, 0.465)
	−2	(−2.352, −1.771)	(−2.125, −1.853)	(−2.103, −1.835)	(−0.418, 0.458)	(−0.549, 0.555)	(−0.541, 0.413)

TABLE 5. The MSE $_\beta$s for each case under balanced designs

	The proposed method			The K-means method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.088	0.027	0.009	0.180	0.113	0.095
80	0.083	0.016	0.004	0.158	0.117	0.090
120	0.091	0.014	0.003	0.154	0.111	0.092
	Over-fitting method			Under-fitting method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.174	0.058	0.035	5.695	5.243	5.138
80	0.157	0.060	0.036	5.410	5.214	5.196
120	0.158	0.059	0.035	5.677	5.176	5.060

TABLE 6. The MSE $_\lambda$s for each case under balanced designs

	The proposed method			The K-means method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.023	0.014	0.009	0.039	0.031	0.025
80	0.015	0.008	0.005	0.032	0.029	0.022
120	0.011	0.006	0.005	0.025	0.025	0.022
	Over-fitting method			Under-fitting method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.048	0.019	0.014	2.572	2.641	2.653
80	0.018	0.010	0.009	2.544	2.592	2.537
120	0.014	0.007	0.006	2.600	2.554	2.452

TABLE 7. The MISE(Λ_0)s for each case under balanced designs

	The proposed method			The K-means method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.635	0.186	0.119	0.873	0.459	0.430
80	0.362	0.127	0.058	0.620	0.304	0.288
120	0.309	0.129	0.065	0.587	0.433	0.313
	Over-fitting method			Under-fitting method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.719	0.178	0.110	7.579	7.695	7.606
80	0.311	0.106	0.059	7.645	7.695	7.705
120	0.266	0.108	0.066	7.889	7.820	7.856

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TABLE 8. The 95% confidence intervals for each component of $\boldsymbol{\beta}_j$s for each case under unbalanced designs

		The proposed method			The K-means method		
J	$\beta_{i,j}$	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	1	(0.949, 1.156)	(0.950, 1.078)	(0.977, 1.034)	(1.003, 1.205)	(1.014, 1.157)	(1.032, 1.139)
	2	(1.843, 2.080)	(1.924, 2.043)	(1.980, 2.028)	(1.614, 1.993)	(1.587, 1.932)	(1.568, 1.900)
	−1	(−1.179, −0.969)	(−1.081, −0.970)	(−1.049, −0.983)	(−1.208, −0.993)	(−1.154, −1.016)	(−1.122, −1.014)
	−2	(−2.093, −1.753)	(−2.047, −1.850)	(−2.050, −1.873)	(−2.015, −1.605)	(−1.933, −1.599)	(−1.951, −1.630)
80	1	(0.998, 1.156)	(0.977, 1.042)	(0.987, 1.023)	(1.034, 1.202)	(1.032, 1.116)	(1.046, 1.119)
	2	(1.840, 2.061)	(1.953, 2.027)	(1.986, 2.017)	(1.671, 1.958)	(1.668, 1.894)	(1.627, 1.862)
	−1	(−1.135, −0.996)	(−1.036, −0.972)	(−1.019, −0.986)	(−1.191, −1.047)	(−1.114, −1.023)	(−1.123, −1.045)
	−2	(−2.065, −1.843)	(−2.029, −1.946)	(−2.014, −1.979)	(−1.880, −1.604)	(−1.902, −1.672)	(−1.846, −1.616)
120	1	(1.003, 1.127)	(0.984, 1.043)	(0.990, 1.018)	(1.060, 1.188)	(1.056, 1.131)	(1.053, 1.114)
	2	(1.871, 2.046)	(1.960, 2.024)	(1.991, 2.015)	(1.635, 1.863)	(1.634, 1.830)	(1.647, 1.837)
	−1	(−1.119, −1.007)	(−1.033, −0.983)	(−1.015, −0.988)	(−1.170, −1.052)	(−1.109, −1.037)	(−1.095, −1.035)
	−2	(−2.050, −1.880)	(−2.019, −1.945)	(−2.016, −1.980)	(−1.903, −1.677)	(−1.873, −1.683)	(−1.875, −1.695)
		Over-fitting method			Under-fitting method		
J	$\beta_{i,j}$	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	1	(0.927, 1.187)	(0.938, 1.109)	(0.956, 1.086)	(−1.096, −0.874)	(−1.121, −0.961)	(−1.093, −0.933)
	2	(1.932, 2.314)	(1.931, 2.177)	(1.948, 2.132)	(−2.246, −1.880)	(−2.184, −1.966)	(−2.190, −1.952)
	−1	(−1.203, −0.919)	(−1.112, −0.941)	(−1.083, −0.951)	(−1.096, −0.874)	(−1.121, −0.961)	(−1.093, −0.933)
	−2	(−2.336, −1.932)	(−2.164, −1.928)	(−2.134, −1.946)	(−2.246, −1.880)	(−2.184, −1.966)	(−2.190, −1.952)
80	1	(0.972, 1.177)	(0.968, 1.084)	(0.973, 1.065)	(−1.217, −0.988)	(−1.094, −0.976)	(−1.078, −0.989)
	2	(1.987, 2.285)	(1.969, 2.135)	(1.972, 2.104)	(−2.401, −2.075)	(−2.157, −1.980)	(−2.086, −1.956)
	−1	(−1.163, −0.961)	(−1.080, −0.962)	(−1.065, −0.972)	(−1.217, −0.988)	(−1.094, −0.976)	(−1.078, −0.989)
	−2	(−2.286, −1.993)	(−2.141, −1.968)	(−2.100, −1.968)	(−2.401, −2.075)	(−2.157, −1.980)	(−2.086, −1.956)
120	1	(0.986, 1.154)	(0.980, 1.078)	(0.981, 1.057)	(−1.140, −0.985)	(−1.060, −0.962)	(−1.030, −0.955)
	2	(2.004, 2.244)	(1.989, 2.127)	(1.987, 2.095)	(−2.336, −2.048)	(−2.100, −1.955)	(−2.055, −1.936)
	−1	(−1.146, −0.987)	(−1.074, −0.977)	(−1.054, −0.978)	(−1.140, −0.985)	(−1.060, −0.962)	(−1.030, −0.955)
	−2	(−2.251, −2.017)	(−2.120, −1.979)	(−2.092, −1.981)	(−2.336, −2.048)	(−2.100, −1.955)	(−2.055, −1.936)

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TABLE 9. The 95% confidence intervals for each component of $\lambda_{1,l}$s for each case under unbalanced designs

		The proposed method			The K-means method		
J	$\lambda_{1,l}$	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	1	(0.734, 1.060)	(0.806, 1.030)	(0.829, 1.026)	(0.708, 1.032)	(0.729, 1.010)	(0.751, 1.005)
	−2	(−2.153, −1.638)	(−2.102, −1.744)	(−2.061, −1.789)	(−2.157, −1.522)	(−2.084, −1.627)	(−2.035, −1.631)
80	1	(0.804, 1.014)	(0.839, 1.003)	(0.873, 0.987)	(0.743, 0.999)	(0.754, 0.999)	(0.771, 0.972)
	−2	(−2.114, −1.721)	(−2.046, −1.816)	(−2.033, −1.854)	(−2.063, −1.620)	(−2.045, −1.658)	(−2.009, −1.671)
120	1	(0.818, 1.014)	(0.866, 0.993)	(0.896, 0.978)	(0.732, 1.001)	(0.784, 0.972)	(0.789, 0.978)
	−2	(−2.084, −1.770)	(−2.013, −1.838)	(−2.018, −1.881)	(−2.037, −1.682)	(−1.998, −1.680)	(−2.018, −1.684)
		Over-fitting method			Under-fitting method		
J	$\lambda_{1,l}$	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	1	(0.619, 1.285)	(0.732, 1.163)	(0.777, 1.112)	(−0.797, 0.918)	(−0.844, 0.998)	(−0.947, 0.874)
	−2	(−2.440, −1.566)	(−2.266, −1.657)	(−2.189, −1.764)	(−0.89, 0.863)	(−0.862, 0.906)	(−0.940, 0.811)
80	1	(0.723, 1.167)	(0.779, 1.062)	(0.825, 1.063)	(−0.554, 0.604)	(−0.504, 0.496)	(−0.630, 0.628)
	−2	(−2.360, −1.709)	(−2.193, −1.787)	(−2.108, −1.827)	(−0.625, 0.627)	(−0.617, 0.534)	(−0.640, 0.598)
120	1	(0.790, 1.119)	(0.823, 1.056)	(0.834, 1.055)	(−0.395, 0.503)	(−0.547, 0.438)	(−0.542, 0.507)
	−2	(−2.299, −1.748)	(−2.152, −1.801)	(−2.132, −1.832)	(−0.471, 0.426)	(−0.559, 0.489)	(−0.504, 0.470)

TABLE 10. The MSE $_\beta$s for each case under unbalanced designs

	The proposed method			The K-means method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.088	0.024	0.006	0.164	0.112	0.099
80	0.097	0.015	0.004	0.163	0.095	0.105
120	0.093	0.014	0.004	0.172	0.106	0.110
	Over-fitting method			Under-fitting method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.167	0.058	0.036	5.432	5.176	5.031
80	0.180	0.060	0.036	5.258	5.203	5.107
120	0.170	0.061	0.036	5.394	5.210	5.122

TABLE 11. The MSE $_\lambda$s for each case under unbalanced designs

	The proposed method			The K-means method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.021	0.013	0.007	0.034	0.031	0.026
80	0.013	0.007	0.005	0.032	0.023	0.025
120	0.010	0.006	0.005	0.025	0.023	0.025
	Over-fitting method			Under-fitting method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.034	0.019	0.014	2.578	2.561	2.646
80	0.019	0.009	0.007	2.577	2.513	2.548
120	0.017	0.008	0.005	2.551	2.547	2.499

TABLE 12. The MISE(Λ_0)s for each case under unbalanced designs

	The proposed method			The K-means method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.620	0.176	0.097	0.666	0.415	0.344
80	0.335	0.112	0.062	0.596	0.360	0.344
120	0.360	0.115	0.058	0.658	0.397	0.362
	Over-fitting method			Under-fitting method		
J	$n_j = 40$	$n_j = 80$	$n_j = 120$	$n_j = 40$	$n_j = 80$	$n_j = 120$
40	0.520	0.177	0.110	7.348	7.727	7.695
80	0.328	0.104	0.070	7.813	7.881	7.839
120	0.296	0.114	0.060	7.755	7.933	7.864

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so that the variances of the estimators of the $\boldsymbol{\beta}_j$s do not have much effect on the estimation of $\lambda_{1,1}$, $\lambda_{1,2}$, and $\Lambda_0(\cdot)$, which is why the K-means method and the over-fitting method perform as well as the proposed method when estimating $\lambda_{1,1}$, $\lambda_{1,2}$, and $\Lambda_0(\cdot)$. The under-fitting method performs poorly irrespective of the parameter being estimated because under-fitting comes with a large bias, and the bias cannot be reduced by smoothing.

5. ANALYSIS OF THE SECOND-BIRTH INTERVAL IN BANGLADESH

In this section, we apply the proposed multilevel modeling together with the proposed estimation procedure to analyse the dataset that motivates this article. The data are extracted from the Bangladesh Demographic and Health Survey conducted by the government of the People's Republic of Bangladesh. The sample is nationally representative and is based on 7,464 women nested within 125 primary sampling clusters, with sample sizes ranging from 17 to 242 women.

The second-birth interval is an important indicator for family planning. The effects of the covariates that are commonly found to be associated with the second-birth interval on the length of the second-birth interval is of great importance. In this section, we explore these effects based on the data extracted.

Let y_{ij} be the duration in months between the first birth and the second birth for the ith woman in the jth cluster. As 19.35% of the women in the sample had not given second birth by the time of the survey, 19.35% of the y_{ij}s are censored. The important covariates have been identified as potential explanatory variables based on previous research (see Zhang and Steele, 2004). They are year of marriage (continuous), women's level of education (categorized as none, primary, and secondary or higher; "none" is taken to be the reference in the modeling), religion (Muslim or other; "Muslim" is taken to be the reference in the modeling), and sex or survival status of the first child (girl, boy, or deceased; and "girl" is taken to be the reference in the modeling). In addition, we also consider two cluster level covariates: region of residence (rural and urban; "rural" is taken to be the reference in the modeling) and administrative division (Barisal, Chittagong, Dhaka, Kulna, Rajshahi, and Sylhet; "Barisal" is taken to be the reference in the modeling).

We apply the proposed model (1.2) together with the homogeneity structure (1.3) to fit the data. The proposed estimation procedure is used to construct the estimates of the unknown parameters; the threshold δ used in the homogeneity pursuit is set to 4, the bandwidth for producing the estimates of the coefficients of the cluster level variables is set to 25% of the range of the second-birth interval across all the clusters, and the kernel function involved is the Epanechnikov kernel. Figure 1 shows the graph of the sorted initial estimates for each individual-level variable. It is very interesting that the range of initial estimates for year of marriage is much smaller than the estimates for other variables. The obtained final results are presented in Table 13.

To explain Table 13, we use the category "Primary" of the covariate "Education" as an example. The 28.08% in the brackets following "Primary" means 28.08% of

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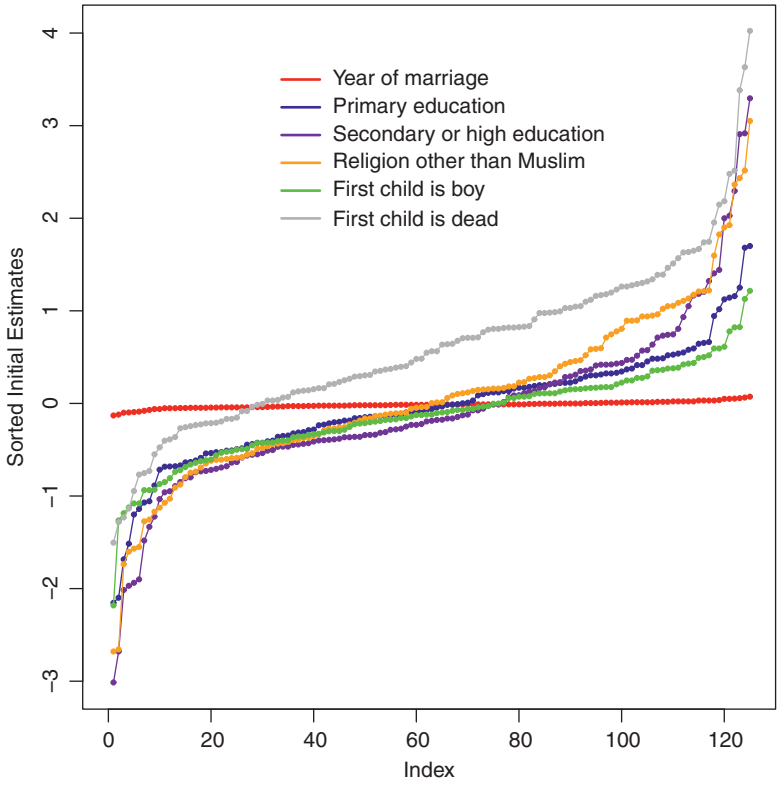


FIGURE 1. Plot of the sorted initial estimates for each individual-level variable.

the women in the data have primary school education. In the column "Estimate," there are two values corresponding to "Primary," which means, as far as the coefficient of the dummy variable, which takes value 1 when the woman of interest has a primary school education, 0 otherwise, is concerned, the clusters in the data are grouped into two groups by the homogeneity pursuit in the proposed estimation procedure, and the clusters in the same group share the same coefficient. Specifically, the coefficient is −0.280 for Group 1 and 0.251 for Group 2. The entries in the column "Standard Error" are the standard errors of the corresponding estimates. The corresponding entry in the column "% of sample," say, for example, 57.06, means Group 1 accounts for 57.06% of the total number of clusters in the data.

From Table 13, we can see that, compared with women with no education, women who were educated at a primary school level or beyond have a longer second-birth interval for more than half of the clusters. This finding can be interpreted as educated women tend to be more devoted to their careers and are, therefore, more likely to delay giving birth to their second child. However, we can

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Table 13. Results of the analysis of the second-birth interval in Bangladesh

Covariate of interest	Estimate	Standard error	% of sample
Individual level			
Year of marriage	−0.013	0.002	100.00
Education			
None (54.11%)	0.000	–	100.00
Primary (28.08%)	−0.280	0.042	57.06
	0.251	0.047	42.94
Secondary or higher (17.81%)	−0.936	0.189	5.03
	−0.286	0.048	68.23
	0.475	0.089	23.46
	1.874	0.367	3.28
Religion			
Muslim (88.21%)	0.000	–	100.00
Other (11.79%)	−1.068	0.179	7.00
	−0.200	0.054	65.68
	0.725	0.092	27.32
Sex or survival status of the first child			
Girl (42.43%)	0.000	–	100.00
Boy (43.18%)	−0.429	0.051	31.74
	0.059	0.034	68.26
Deceased (14.39%)	0.784	0.051	52.66
	0.974	0.058	44.37
	1.994	0.310	2.97
Cluster level			
Type of region of residence			
Rural (83.99%)	0.000	–	100.00
Urban (16.01%)	−0.063	0.042	100.00
Administrative division			
Barisal (10.61%)	0.000	–	100.00
Chittagong (15.11%)	0.126	0.070	100.00
Dhaka (27.80%)	−0.078	0.099	100.00
Kulna (11.78%)	−0.111	0.080	100.00
Rajshahi (24.96%)	−0.152	0.061	100.00
Sylhet (9.74%)	0.046	0.143	100.00

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also see from Table 13 that there is a small number of clusters in which women who were educated at a primary school level have shorter second-birth intervals. For most of the clusters, Muslims have shorter second-birth intervals. However, there are some clusters where Muslims have longer second-birth intervals. This finding indicates that there may be some cultural difference between these clusters and others. Compared with the first child being a girl, if the first child is a boy, the second-birth interval becomes significantly longer for some clusters, and it does not have a significant difference for the remaining clusters. This finding reflects the culture of favoring boys in some parts of Bangladesh. When the first child is deceased, the second-birth interval becomes even shorter for all of the clusters. It is also noticeable that women in urban areas tend to have longer second-birth intervals than those in rural areas, which is logical because the use of contraceptives in rural areas is lower than in urban areas. The second-birth intervals are shorter in Chittagong than in the other divisions. This regional effect is as expected because Chittagong is in the most religiously conservative part of Bangladesh, where the use of contraceptives is rare.

6. CONCLUDING REMARKS

In this article, we propose a new multilevel modeling strategy for clustered survival data. The methodological advantage of the proposed modeling strategy is that it successfully avoids the computation of multiple integrals and the abundance of nuisance parameters, which makes the implementation of the proposed modeling much easier than that of traditional methods. In applications, the proposed modeling strategy enables investigators to explore individual/subgroup attributes of covariates, which traditional methods cannot do because they assume that the impact of covariates is constant over clusters and they only use cluster effects to account for differences among clusters. Our application to second-birth intervals shows that the impact of some factors on the birth interval is homogeneous within each cluster and varies across clusters, thereby revealing cultural differences among some clusters. Such findings cannot be obtained by the traditional multilevel modeling strategy. In conclusion, the proposed multilevel modeling strategy facilitates implementation and offers the advantage of distinguishing cluster coefficients in applications.

REFERENCES

Andersen, P.K. & R.D. Gill (1982) Cox's regression model for counting processes: A large sample study. *Annals of Statistics* 10, 1100–1120.

Ando, T. & J. Bai (2017) Clustering huge number of financial time series: A panel data approach with high-dimensional predictors and factor structures. *Journal of the American Statistical Association* 112, 1182–1198.

Azuma, K. (1967) Weighted sums of certain dependent random variables. *Tohoku Mathematical Journal, Second Series* 19, 357–367.

Bai, J. (1997) Estimating multiple breaks one at a time. *Econometric Theory* 13, 315–352.

https://doi.org/10.1017/S0266466619000343 Published online by Cambridge University Press

Bonhomme, S. & E. Manresa (2015) Grouped patterns of heterogeneity in panel data. *Econometrica* 83, 1147–1184.
Bradic, J., J. Fan, & J. Jiang (2011) Regularization for Cox's proportional hazards model with np-dimensionality. *Annals of Statistics* 39, 3092–3210.
Breslow, N. (1972) Comment on "regression and life tables" by DR Cox. *Journal of the Royal Statistical Society, Series B* 34, 216–217.
David, C.R. (1972) Regression models and life tables (with discussion). *Journal of the Royal Statistical Society, Series B* 34, 187–220.
Fleming, T.R. & D.P. Harrington (2011) *Counting Processes and Survival Analysis.* Wiley.
Hartigan, J.A. & M.A. Wong (1979) Algorithm as 136: A k-means clustering algorithm. *Journal of the Royal Statistical Society, Series C* 28, 100–108.
Harvey, G. (2003) *Multilevel Statistical Models*. 3rd edition. Arnold, London, UK.
Hoeffding, W. (1963) *Probability Inequalities for Sums of Bounded Random Variables*. Vol. 58. Taylor & Francis, pp. 13–30.
Ke, Y., J. Li, & W. Zhang (2016) Structure identification in panel data analysis. *Annals of Statistics* 44, 1193–1233.
Ke, Z.T., J. Fan, & Y. Wu (2015) Homogeneity pursuit. *Journal of the American Statistical Association* 110, 175–194.
Mitra, S., A. Al-Sabir, A.R. Cross, & K. Jamil (1997) *Bangladesh Demographic and Health Survey 1996–1997*. National Institute of Population Research and Training (NIPORT), Mitra and Associates, and Macro International Inc., Dhakaand Calverton, MD.
Ortega, J.M. & W.C. Rheinboldt (1970) *Iterative Solution of Nonlinear Equations in Several Variables*. Academic Press, San Diego, CA.
Su, L. & G. Ju (2018) Identifying latent grouped patterns in panel data models with interactive fixed effects. *Journal of Econometrics* 206, 554–573.
Su, L., Z. Shi, & P.C. Phillips (2016) Identifying latent structures in panel data. *Econometrica* 84, 2215–2264.
Su, L., W.X. Liangjun, & S. Jin (2019) Sieve estimation of time-varying panel data models with latent structures. *Journal of Business & Economic Statistics* 37, 334–349.
Venkatraman, E.S. (1993) Consistency results in multiple change-point problems. Ph.D. thesis, Stanford Univ., ProQuest LLC, Ann Arbor, MI.
Volinsky, C.T. & A.E. Raftery (2000) Bayesian information criterion for censored survival models. *Biometrics* 56, 256–262.
Vostrikova, L. (1981) Detection of the disorder in multidimensional random-processes. *Doklady Akademii Nauk SSSR* 259, 270–274.
Wang, W., P.C. Phillips, & L. Su (2018) Homogeneity pursuit in panel data models: Theory and application. *Journal of Applied Econometrics* 33, 797–815.
Wang, W., & L. Su (2019) Identifying latent group structures in nonlinear panels. *Journal of Econometrics* (in press).
Zhang, W., & F. Steele (2004) A semiparametric multilevel survival model. *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 53, 387–404.

APPENDIX A

We first prove three lemmas and then prove Theorems 1–3.

LEMMA 1. *Assume that Condition 1 holds. Then,* $\max_{1\le j\le J}\|n_j^{1/2}(\tilde{\boldsymbol{\beta}}_j - \boldsymbol{\beta}_j^*)\| = O_p((\log J)^{1/2})$.

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Proof. We prove the statement in the following three steps:

(i) We first show that $\max_{1\le j\le J} n_j^{-1/2}\dot{\mathcal{L}}_j(\boldsymbol{\beta}_j^*) = O_P((\log J)^{1/2})$. By definition, $\dot{\mathcal{L}}_j(\boldsymbol{\beta}_j^*) = \sum_{i=1}^{n_j}\int_0^\tau [X_{ij} - E_j(u,\boldsymbol{\beta}_j^*)]dN_{ij}(u) = \sum_{i=1}^{n_j}\int_0^\tau [X_{ij} - E_j(u,\boldsymbol{\beta}_j^*)]dM_{ij}(u)$. Let $a_{ijk}(u) = X_{ijk} - E_{jk}(u,\boldsymbol{\beta}_j^*), k = 1,\ldots,p$. For the jth cluster, let $t_{(0),j} = 0$ and denote the distinct event times by $t_{(1),j} < \cdots < t_{(T_j),j}$. Then, $t_{(\ell),j}$ are stopping times. For $\ell = 0,\ldots,T_j$, define

$$Z_{\ell,jk} = \sum_{i=1}^{n_j}\int_0^{t_{(\ell),j}} a_{ijk}(u)dN_{ij}(u) = \sum_{i=1}^{n_j}\int_0^{t_{(\ell),j}} a_{ijk}(u)dM_{ij}(u).$$

Note that $\dot{\mathcal{L}}_{jk}(\boldsymbol{\beta}_j^*) = Z_{T_j,jk}$. Since the $M_{ij}(u)$s are martingales and the $a_{ijk}(u)$s are predictable, $\{Z_{\ell,jk},\ \ell = 0,\ 1,\ldots\}$ is a martingale with a difference $|Z_{\ell,jk} - Z_{\ell-1,jk}| \le \max_{i,j,k,u}|a_{ijk}(u)| \le K$. By the martingale version of the Hoeffding (1963) inequality (Azuma, 1967), for any $x > 0$,

$$P(|Z_{T_j,jk}| > n_j x) \le 2\exp(-n_j^2x^2/(2K^2T_j)) \le 2e^{-n_jx^2/(2K^2)}.$$

For any $1 \le k \le p$ and for any $C > 0$,

$$P\Big(\max_{1\le j\le J} n_j^{-1/2}|\dot{\mathcal{L}}_{jk}(\boldsymbol{\beta}_j^*)| \ge CK(\log J)^{1/2}\Big) \le 2Je^{-C^2(\log J)/2} = 2J^{1-C^2/2}.$$

For sufficiently large C, $2J^{1-C^2/2}$ tends to 0. Hence, $\max_{1\le j\le J} n_j^{-1/2}\dot{\mathcal{L}}_j(\boldsymbol{\beta}_j^*) = O_P((\log J)^{1/2})$.

(ii) We prove that with probability tending to 1,

$$\inf_{1\le j\le J}\inf_{\|b\|=1,\,b\in R^p} b^T(-n_j^{-1}\ddot{\mathcal{L}}_j(\boldsymbol{\beta}_j^*))b \ge c_0e^{-K^2}/2.$$

Let $a_{jkm}(u) = (V_j(u,\beta_j^*))_{(km)} = \sum_{i=1}^{n_j} w_{ij}(u,\beta_j^*)\{X_{ijk} - E_{jk}(u,\beta_j^*)\}\{X_{ijm} - E_{jm}(u,\beta_j^*)\}$, where $w_{ij}(u,\boldsymbol{\beta}) = Y_{ij}(u)\exp(X_{ij}^T\boldsymbol{\beta})/[n_jS_j^{(0)}(u,\boldsymbol{\beta})]$. Note that

$$-n_j^{-1}\ddot{\mathcal{L}}_j(\boldsymbol{\beta}_j^*) = n_j^{-1}\sum_{i=1}^{n_j}\int_0^t V_j(u,\boldsymbol{\beta}_j^*)dN_{ij}(u),$$

and

$$\sum_{i=1}^{n_j}\int_0^t V_j(u,\boldsymbol{\beta}_j^*)(dN_{ij}(u) - Y_{ij}(u)\exp(X_{ij}^T\boldsymbol{\beta}_j^*)h_{1,j}(u)du)$$

is a martingale. By the Azuma–Hoeffding inequality, for any $x > 0$,

$$P\left(\max_{1\le j\le J} n_j^{-1}\left|\sum_{i=1}^{n_j}\int_0^{t_{(T_j),j}} a_{jkm}(u,\boldsymbol{\beta}_j^*)(dN_{ij}(u)\right.\right.$$
$$\left.\left. - Y_{ij}(u)\exp(X_{ij}^T\boldsymbol{\beta}_j^*)h_{1,j}(u)du)\right| > K^2x\right) \le 2Je^{-nx^2}.$$

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It follows that with probability less than $2Je^{-n(c_0e^{-K^2}/(2K^2))^2}$,

$$\sup_{\|b\|=1, b\in R^p} \left| b^T \left[-n_j^{-1}\ddot{\mathcal{L}}_j - n_j^{-1}\sum_{i=1}^{n_j}\int_0^t V_j(u,\boldsymbol{\beta}_j^*)Y_{ij}(u)\exp(X_{ij}^T\boldsymbol{\beta}_j^*)h_{1,j}(u)du \right] b \right| \le c_0e^{-K^2}/2.$$

By Condition 1(i)–(iv), we have, with probability tending to 1,

$$\inf_{1\le j\le J}\inf_{\|b\|=1, b\in R^p} b^T(-n_j^{-1}\ddot{\mathcal{L}}_j(\boldsymbol{\beta}_j^*))b \ge c_0e^{-K^2}/2.$$

(iii) We prove that for any $\epsilon > 0$, there exists a constant $C > 0$ such that for all sufficiently large n,

$$P\left(\cap_{j=1}^J \left\{ \sup_{\|\boldsymbol{\beta}_j-\boldsymbol{\beta}_j^*\|=C(\frac{\log J}{n_j})^{1/2}} (\boldsymbol{\beta}_j-\boldsymbol{\beta}_j^*)^T\dot{\mathcal{L}}_j(\boldsymbol{\beta}_j) < 0 \right\} \right) > 1-\epsilon. \tag{A.1}$$

By the concavity of $\mathcal{L}_j(\cdot)$ and Thm. 6.3.4 of Ortega and Rheinboldt (1970), Condition (A.1) is sufficient to show that $\max_{1\le j\le J}\|n_j^{1/2}(\tilde{\boldsymbol{\beta}}_j-\boldsymbol{\beta}_j^*)\| = O_p((\log J)^{1/2})$. For any $\boldsymbol{\beta}_j$ satisfying $\|\boldsymbol{\beta}_j-\boldsymbol{\beta}_j^*\| = C\left(\frac{\log J}{n_j}\right)^{1/2}$, let $b_j = \boldsymbol{\beta}_j-\boldsymbol{\beta}_j^*$, $a_{ij} = a_{ij}(u) = b_j^T\{X_{ij}-E_j(u,\boldsymbol{\beta}_j^*),\}$, $w_{ij} = w_{ij}(u) = Y_{ij}(u)\exp(X_{ij}^T\boldsymbol{\beta}_j^*)$, $c_j = c_j(u) = (\max_i a_{ij}(u)+\min_i a_{ij}(u))/2$, and $\eta_j = KC(\frac{\log J}{n_j})^{1/2}$. Note that $\max_i|a_{ij}(u)-c_j(u)| \le \frac{\eta_j}{2}$ and

$$\begin{aligned}
&b_j^T\{E_j(u,\boldsymbol{\beta}_j^*+b_j)-E_j(u,\boldsymbol{\beta}_j^*)\}\\
&= \left(\sum_{i=1}^{n_j}a_{ij}w_{ij}e^{a_{ij}}\right)\Big/\left(\sum_{i=1}^{n_j}w_{ij}e^{a_{ij}}\right) - \left(\sum_{i=1}^{n_j}a_{ij}w_{ij}\right)\Big/\left(\sum_{i=1}^{n_j}w_{ij}\right)\\
&= \left(\sum_{i,k=1}^{n_j}(a_{ij}-a_{kj})(e^{a_{ij}-c_j}-e^{a_{kj}-c_j})w_{ij}w_{kj}\right)\Big/\left(\sum_{i,k=1}^{n_j}2w_{ij}w_{kj}e^{a_{ij}-c_j}\right)\\
&\ge \exp(-2\max_i|a_{ij}-c_j|)\left(\sum_{i,k=1}^{n_j}(a_{ij}-a_{kj})^2w_{ij}w_{kj}\right)\Big/\left(\sum_{i,k=1}^{n_j}2w_{ij}w_{kj}\right)\\
&\ge \exp(-\eta_j)\left(\sum_{i}^{n_j}w_{ij}a_{ij}^2\right)\Big/\left(\sum_{i}^{n_j}w_{ij}\right),
\end{aligned}$$

where the first inequality comes from $(e^y-e^x)/(y-x) \ge e^{-(|y|\vee|x|)}$ and the second inequality comes from $\sum_i^{n_j}w_{ij}a_{ij} = 0$ and $\sum_{i,k=1}^{n_j}w_{ij}w_{kj}(a_{ij}-a_{kj})^2 = \left(2\sum_{i,k=1}^{n_j}w_{ij}a_{ij}^2\right)\left(\sum_{i,k=1}^{n_j}w_{ij}\right)$. It follows that

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$$b_j^T[\dot{\mathcal{L}}_j(\boldsymbol{\beta}_j)-\dot{\mathcal{L}}_j(\boldsymbol{\beta}_j^*)] \le -e^{-\eta_j}\sum_i^{n_j}\int_0^\tau \left(\sum_i^{n_j} w_{ij}a_{ij}^2\right)\left(\sum_i^{n_j} w_{ij}\right)^{-1} dN_{ij}(u)$$

$$= e^{-\eta_j} b_j^T \ddot{\mathcal{L}}(\boldsymbol{\beta}_j^*) b_j.$$

Hence, by (i) and (ii), uniformly for all j, we have

$$\left(\boldsymbol{\beta}_j-\boldsymbol{\beta}_j^*\right)^T \dot{\mathcal{L}}_j\left(\boldsymbol{\beta}_j\right) = \left(\boldsymbol{\beta}_j-\boldsymbol{\beta}_j^*\right)^T \dot{\mathcal{L}}_j\left(\boldsymbol{\beta}_j^*\right) + \left(\boldsymbol{\beta}_j-\boldsymbol{\beta}_j^*\right)^T \left[\dot{\mathcal{L}}_j\left(\boldsymbol{\beta}_j\right)-\dot{\mathcal{L}}_j\left(\boldsymbol{\beta}_j^*\right)\right]$$

$$\le n_j\left[O_P\left(\left(\frac{\log J}{n_j}\right)^{1/2}\right)KC\left(\frac{\log J}{n_j}\right)^{1/2} - K^2C^2\frac{\log J}{n_j}e^{-\eta_j}c_0e^{-K^2}/2\right].$$

Since $\log J/n \to 0$ is $n \to \infty$, it is easy to see that (A.1) holds, and this completes the proof. Without loss of generality, assume $\boldsymbol{\beta}_{(1)} < \cdots < \boldsymbol{\beta}_{(H)}$. Write $s_0 = 0$. Let $s_k = |\mathcal{B}_k|$ be the size of $\mathcal{B}_k$ and $r_k = \sum_{\ell=1}^k s_\ell, k = 0, \ldots, H$. Define $\tilde{\mathcal{B}}_k := \{(i,j), \sum_\ell^{k-1} s_\ell + 1 \le r_{ij} \le \sum_{\ell=1}^k s_\ell\}, k = 1, \ldots, H$. The following lemma shows that with probability tending to 1, the homogeneity structure in the estimated coefficients is identical to that in Section 2.2.

LEMMA 2. *If Condition 1 holds, then*

$$\lim_{n\to\infty} P(\cap_{k=1}^H\{\tilde{\mathcal{B}}_k = \mathcal{B}_k\}) = 1.$$

Proof. Let $\Delta = \min_{2\le k\le H}|\boldsymbol{\beta}_{(k)} - \boldsymbol{\beta}_{(k-1)}|$. Let $\epsilon = \Delta/2$. By Lemma 1 and Condition 1(iv), as n goes to ∞, with probability tending to 1, $\max_{1\le j\le J}\|\tilde{\boldsymbol{\beta}}_j - \boldsymbol{\beta}_j\| < \Delta/3$, and hence, $\max_{1\le j\le J, 1\le i\le p}\|\tilde{\beta}_{ij} - \beta_{ij}\| < \Delta/2$. It is sufficient to show that for any $(i_1, j_1) \ne (i_2, j_2)$ satisfying $\beta_{i_1j_1} \ne \beta_{i_2j_2}$, $(\tilde{\beta}_{i_1j_1} - \tilde{\beta}_{i_2j_2})(\beta_{i_1j_1} - \beta_{i_2j_2}) > 0$. This property easily follows since

$$(\beta_{i_1j_1} - \beta_{i_2j_2})(\tilde{\beta}_{i_1j_1} - \tilde{\beta}_{i_2j_2}) \ge (|\beta_{i_1j_1} - \beta_{i_2j_2}|)(|\beta_{i_1j_1} - \beta_{i_2j_2}| - 2\Delta/3) = \Delta^2/3 > 0.$$

Next, we prove the consistency of the binary segmentation procedure in identifying the homogeneity structure.

LEMMA 3. *If Conditions 1 and 2 hold, then*

$$\lim_{n\to\infty} P(\cap_{\ell=1}^{\hat{H}-1}\{\hat{k}_{(\ell)} = r_\ell\} \cap \{\hat{H} = H\}) = 1.$$

Proof. Let $b_{(\ell)}^0$ be the true coefficient associated with $b_{(\ell)}$, $\ell = 1, \ldots, Jp$. By Lemma 2, with probability tending to 1, $b_{(\ell)}^0 = \beta_{(d)}$ for $\sum_{k=1}^{d-1} s_k + 1 \le \ell \le \sum_{k=1}^d s_k, d = 1, \ldots, H$. Write $b_{(\ell)} = b_{(\ell)}^0 + e_{(\ell)}$. By definition,

$$\Delta_{1,Jp}(\hat{k}_1) = \max_{1\le\kappa<Jp}\Delta_{1,Jp}(\kappa),$$

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where

$$\Delta_{ij}(\kappa)=\sqrt{\frac{(j-\kappa)(\kappa-i+1)}{j-i+1}}\left(\frac{\sum_{l=\kappa+1}^{j}b_{(l)}}{j-\kappa}-\frac{\sum_{l=i}^{\kappa}b_{(l)}}{\kappa-i+1}\right).$$

First, we prove by contradiction that with probability tending to 1, $\hat{k}_1=r_k$ for some $1\le k\le H-1$. Otherwise, there exist a k and m such that $\hat{k}_1=r_k+m$, where $0\le k\le H-1$ and $1\le m<s_{k+1}$. There are three cases, and we will consider them one by one.

Case 1: $k=0$ and $\hat{k}_1=m<s_1=r_1$.

Let $\bar{\beta}_1=\frac{\sum_{l=1}^{m}b^0_{(l)}}{m}$ and $\bar{\beta}_2=\frac{\sum_{l=r_1+1}^{Jp}b^0_{(l)}}{Jp-r_1}$. We have $\bar{\beta}_1<\bar{\beta}_2$,

$$\Delta_{1,Jp}(\hat{k}_1)=\sqrt{\frac{m}{Jp(Jp-m)}}(Jp-r_1)(\bar{\beta}_2-\bar{\beta}_1)+\sqrt{\frac{(Jp-m)m}{Jp}}\left(\frac{\sum_{l=m+1}^{Jp}e_{(l)}}{Jp-m}-\frac{\sum_{l=1}^{m}e_{(l)}}{m}\right),$$

and

$$\Delta_{1,Jp}(r_1)=\sqrt{\frac{r_1(Jp-r_1)}{Jp}}(\bar{\beta}_2-\bar{\beta}_1)+\sqrt{\frac{(Jp-r_1)r_1}{Jp}}\left(\frac{\sum_{l=r_1+1}^{Jp}e_{(l)}}{Jp-r_1}-\frac{\sum_{l=1}^{r_1}e_{(l)}}{r_1}\right).$$

By Lemma 2,

$$\Delta_{1,Jp}(r_1)-\Delta_{1,Jp}(\hat{k}_1)=\left[\sqrt{\frac{r_1(Jp-r_1)}{Jp}}-\sqrt{\frac{m}{Jp(Jp-m)}}(Jp-r_1)\right](\bar{\beta}_2-\bar{\beta}_1)+O_p\left(\sqrt{Jp}\frac{\log Jp}{\sqrt{n}}\right).$$

By Condition (i),

$$\Delta_{1,Jp}(r_1)-\Delta_{1,Jp}(\hat{k}_1)=\left[\sqrt{\frac{r_1(Jp-r_1)}{Jp}}-\sqrt{\frac{m}{Jp(Jp-m)}}(Jp-r_1)\right](\bar{\beta}_2-\bar{\beta}_1)+o_p\left(\frac{1}{\sqrt{Jp}}\right).$$

By calculation, uniformly for $1\le m<r_1$,

$$\sqrt{r_1(Jp-r_1)}-\sqrt{\frac{m}{(Jp-m)}}(Jp-r_1)=(Jp-r_1)\left[\sqrt{\frac{r_1}{(Jp-r_1)}}-\sqrt{\frac{m}{(Jp-m)}}\right]$$

$$\ge(Jp-r_1)\left[\sqrt{\frac{r_1}{(Jp-r_1)}}-\sqrt{\frac{r_1-1}{(Jp-r_1+1)}}\right]$$

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$$\geq (Jp-r_1)\frac{\frac{r_1}{(Jp-r_1)}-\frac{r_1-1}{(Jp-r_1+1)}}{2\sqrt{\frac{r_1}{(Jp-r_1)}}} = \frac{Jp}{2(Jp-r_1+1)}\sqrt{\frac{Jp-r_1}{r_1}}$$
$$= \frac{Jp(Jp-r_1)}{2(Jp-r_1+1)}\frac{1}{Jp-r_1}\sqrt{\frac{Jp-r_1}{r_1}}$$
$$\geq \frac{1}{4}\frac{Jp}{\sqrt{(Jp-r_1)r_1}} \geq \frac{1}{2}.$$

Thus, with probability tending to 1,

$$\Delta_{1,Jp}(r_1) - \Delta_{1,Jp}(\hat{k}_1) > 0$$

which yields the contradiction.

Case 2: $k = H-1$ and $\hat{k}_1 = r_{H-1}+m$, where $1 \leq m < s_H$.

Let $\bar{\beta}_1 = \frac{\sum_{l=1}^{r_{H-1}} b_{(l)}^0}{r_{H-1}}$ and $\bar{\beta}_2 = \frac{\sum_{l=r_{H-1}+1}^{Jp} b_{(l)}^0}{Jp-r_{H-1}}$. We have $\bar{\beta}_1 < \bar{\beta}_2$,

$$\Delta_{1,Jp}(\hat{k}_1) = \sqrt{\frac{(s_H-m)(Jp-s_H+m)}{Jp}}\left(\frac{\sum_{l=r_{H-1}+m+1}^{Jp} b_{(l)}^0}{s_H-m} - \frac{\sum_{l=1}^{r_{H-1}+m} b_{(l)}^0}{Jp-s_H+m}\right)$$
$$+\sqrt{\frac{(s_H-m)(Jp-s_H+m)}{Jp}}\left(\frac{\sum_{l=r_{H-1}+m+1}^{Jp} e_{(l)}^0}{s_H-m} - \frac{\sum_{l=1}^{r_{H-1}+m} e_{(l)}^0}{Jp-s_H+m}\right)$$
$$= \sqrt{\frac{s_H-m}{Jp(Jp-s_H+m)}}(\bar{\beta}_2-\bar{\beta}_1)r_{H-1} + o_p\left(\frac{1}{\sqrt{Jp}}\right),$$

and

$$\Delta_{1,Jp}(r_{H-1}) = \sqrt{\frac{r_{H-1}(Jp-r_{H-1})}{Jp}}(\bar{\beta}_2-\bar{\beta}_1) + o_p\left(\frac{1}{\sqrt{Jp}}\right).$$

Hence,

$$\Delta_{1,Jp}(r_{H-1}) - \Delta_{1,Jp}(\hat{k}_1)$$
$$= \frac{1}{\sqrt{Jp}}\left\{r_{H-1}\left[\sqrt{\frac{s_H}{Jp-s_H}} - \sqrt{\frac{s_H-m}{Jp-s_H+m}}\right](\bar{\beta}_2-\bar{\beta}_1) + o_p(1)\right\}$$

Since

$$r_{H-1}\left[\sqrt{\frac{s_H}{Jp-s_H}} - \sqrt{\frac{s_H-m}{Jp-s_H+m}}\right] \geq (Jp-s_H)\left[\sqrt{\frac{s_H}{Jp-s_H}} - \sqrt{\frac{s_H-1}{Jp-s_H+1}}\right]$$
$$\geq (Jp-s_H)\frac{\frac{s_H}{Jp-s_H}-\frac{s_H-1}{Jp-s_H+1}}{2\sqrt{\frac{s_H}{Jp-s_H}}} = \frac{Jp}{Jp-S_H+1}\frac{1}{2\sqrt{\frac{s_H}{Jp-s_H}}} \geq 1/2,$$

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uniformly for $1 \le m < s_H$, it follows that with probability tending to 1, $\Delta_{1,Jp}(r_{H-1}) > \Delta_{1,Jp}(\hat{k}_1)$, which yields the contradiction.

Case 3: $1 \le k \le H-2$. Let

$$\bar{\beta}_1 = \frac{\sum_{i=1}^{k} s_i b^0_{(i)}}{r_k}, \quad \bar{\beta}_2 = \frac{\sum_{i=k+2}^{H} s_i b^0_{(i)}}{Jp - r_{k+1}}, \quad \bar{\beta} = b^0_{(r_k+1)}.$$

We have $\bar{\beta}_2 > \bar{\beta} > \bar{\beta}_1$,

$$\Delta_{1,Jp}(\hat{k}_1) = \sqrt{\frac{(Jp-r_k-m)(r_k+m)}{Jp}} \left(\frac{\sum_{l=r_k+m+1}^{Jp} b^0_{(l)}}{Jp-r_k-m} - \frac{\sum_{l=1}^{r_k+m} b^0_{(l)}}{r_k+m} \right)$$

$$+ \sqrt{\frac{(Jp-r_k-m)(r_k+m)}{Jp}} \left(\frac{\sum_{l=r_k+m+1}^{Jp} e^0_{(l)}}{Jp-r_k-m} - \frac{\sum_{l=1}^{r_k+m} e^0_{(l)}}{r_k+m} \right)$$

$$= \sqrt{\frac{(Jp-r_k-m)(r_k+m)}{Jp}} \left(\frac{(s_{k+1}-m)\bar{\beta} + (Jp-r_{k+1})\bar{\beta}_2}{Jp-r_k-m} \right.$$

$$\left. - \frac{r_k\bar{\beta}_1 + m\bar{\beta}}{r_k+m} \right) + o_p\left(\frac{1}{\sqrt{Jp}}\right),$$

$$\Delta_{1,Jp}(r_k) = \sqrt{\frac{(Jp-r_k)(r_k)}{Jp}} \left(\frac{s_{k+1}\bar{\beta} + (Jp-r_{k+1})\bar{\beta}_2}{Jp-r_k} - \bar{\beta}_1 \right) + o_p\left(\frac{1}{\sqrt{Jp}}\right),$$

and

$$\Delta_{1,Jp}(r_{k+1}) = \sqrt{\frac{(Jp-r_{k+1})(r_{k+1})}{Jp}} \left(\bar{\beta}_2 - \frac{r_k\bar{\beta}_1 + s_{k+1}\bar{\beta}}{r_{k+1}} \right) + o_p\left(\frac{1}{\sqrt{Jp}}\right).$$

Define the function

$$f(u) = (Jp-r_{k+1})(\bar{\beta}_2 - \bar{\beta})\sqrt{u} + r_k(\bar{\beta} - \bar{\beta}_1)\frac{1}{\sqrt{u}},$$

for any $u > 0$. Let $u_m = \frac{r_k+m}{Jp-r_k-m}$, $u_1 = \frac{r_k}{Jp-r_k}$, $u_2 = \frac{r_{k+1}}{Jp-r_{k+1}}$, $u_3 = \frac{r_k+1}{Jp-r_k-1}$, and $u_4 = \frac{r_{k+1}-1}{Jp-r_{k+1}+1}$. By Condition (ii), $\frac{c_0}{H} \le \frac{kc_0}{(H-k)} \le u_1 < u_3 \le u_m \le u_4 < u_2 \le \frac{(k+1)}{(H-k-1)c_0} \le \frac{H}{c_0}$. By Lemma 2 and Condition (i), $\Delta_{1,Jp}(\hat{k}_1) = \frac{1}{\sqrt{Jp}}(f(u_m) + o_p(1))$, $\Delta_{1,Jp}(r_k) = \frac{1}{\sqrt{Jp}}(f(u_1) + o_p(1))$, $\Delta_{1,Jp}(r_{k+1}) = \frac{1}{\sqrt{Jp}}(f(u_2) + o_p(1))$, $\Delta_{1,Jp}(r_k + 1) = \frac{1}{\sqrt{Jp}}(f(u_3) + o_p(1))$, and $\Delta_{1,Jp}(r_{k+1} - 1) = \frac{1}{\sqrt{Jp}}(f(u_4) + o_p(1))$.

(i) If

$$\sqrt{u_1 u_2} \ge \frac{r_k(\bar{\beta} - \bar{\beta}_1)}{(Jp-r_{k+1})(\bar{\beta}_2 - \bar{\beta})},$$

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then

$$u_2 - \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{(Jp-r_{k+1})(\bar{\beta}_2-\bar{\beta})} > \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{(Jp-r_{k+1})(\bar{\beta}_2-\bar{\beta})} - u_1.$$

Since $u_2-u_1 = \frac{r_{k+1}}{Jp-r_{k+1}} - \frac{r_k}{Jp-r_k} = \frac{Jp(r_{k+1}-r_k)}{(Jp-r_{k+1})(Jp-r_k)} \geq \frac{s_k}{Jp} \geq \frac{c_0}{H}$,

$$\sqrt{u_2u_4} - \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{(Jp-r_{k+1})(\bar{\beta}_2-\bar{\beta})} > \sqrt{u_2u_4} - u_2 + \frac{c_0}{2H}.$$

By calculation,

$$\begin{aligned} f(u_2)-f(u_m) &= \left((Jp-r_{k+1})(\bar{\beta}_2-\bar{\beta}) - \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{\sqrt{u_2u_m}}\right)(\sqrt{u_2}-\sqrt{u_m}) \\ &\geq \left(\frac{r_k(\bar{\beta}-\bar{\beta}_1)}{\sqrt{u_2u_1}} - \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{\sqrt{u_2u_m}}\right)(\sqrt{u_2}-\sqrt{u_m}) \\ &\geq \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{\sqrt{u_2u_1u_m}}(\sqrt{u_m}-\sqrt{u_1})(\sqrt{u_2}-\sqrt{u_m}) \\ &\geq \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{u_2u_m\sqrt{u_1}}(u_m-u_1)(u_2-u_m) \\ &\geq \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{2u_2u_m\sqrt{u_1}}(u_2-u_1)\min(u_3-u_1, u_2-u_4). \end{aligned}$$

By Condition 2(ii),

$$r_k(u_3-u_1) = r_k\left(\frac{r_k+1}{Jp-r_k-1} - \frac{r_k}{Jp-r_k}\right) \geq \frac{r_k(Jp)}{(Jp)^2} \geq \frac{c_0}{H},$$

and

$$r_k(u_2-u_4) = r_k\left(\frac{r_{k+1}}{Jp-r_{k+1}} - \frac{r_{k+1}-1}{Jp-r_{k+1}+1}\right) \geq \frac{r_k(Jp)}{(Jp)^2} \geq \frac{c_0}{H}.$$

Thus,

$$f(u_2)-f(u_m) \geq \frac{c_0^2(\bar{\beta}-\bar{\beta}_1)}{2H^2}\frac{H^{5/2}}{c_0^{5/2}} = \frac{(\bar{\beta}-\bar{\beta}_1)H^{1/2}}{2c_0^{1/2}}.$$

It follows that with probability tending to $1, \Delta_{1,Jp}(\hat{k}_1) < \Delta_{1,Jp}(r_{k+1})$ which yields the contradiction.

(ii) If

$$\sqrt{u_1u_2} < \frac{r_k(\bar{\beta}-\bar{\beta}_1)}{(Jp-r_{k+1})(\bar{\beta}_2-\bar{\beta})},$$

$$f(u_1)-f(u_m) = \left(\frac{r_k(\bar{\beta}-\bar{\beta}_1)}{\sqrt{u_1u_m}} - (Jp-r_{k+1})(\bar{\beta}_2-\bar{\beta})\right)(\sqrt{u_m}-\sqrt{u_1})$$

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$$\geq \left(\frac{r_k(\bar{\beta} - \bar{\beta}_1)}{\sqrt{u_m u_1}} - \frac{r_k(\bar{\beta} - \bar{\beta}_1)}{\sqrt{u_1 u_2}} \right) (\sqrt{u_m} - \sqrt{u_1})$$

$$\geq \frac{r_k(\bar{\beta} - \bar{\beta}_1)}{\sqrt{u_2 u_1 u_m}} (\sqrt{u_m} - \sqrt{u_1})(\sqrt{u_2} - \sqrt{u_m})$$

$$\geq \frac{r_k(\bar{\beta} - \bar{\beta}_1)}{u_2 u_m \sqrt{u_1}} (u_m - u_1)(u_2 - u_m)$$

$$\geq \frac{r_k(\bar{\beta} - \bar{\beta}_1)}{2u_2 u_m \sqrt{u_1}} (u_2 - u_1) \min(u_3 - u_1, u_2 - u_4) \geq \frac{(\bar{\beta} - \bar{\beta}_1) H^{1/2}}{2c_0^{1/2}}.$$

It follows that with probability tending to 1, $\Delta_{1,Jp}(\hat{k}_1) < \Delta_{1,Jp}(r_k)$, which yields the contradiction.

Hence, with probability tending to 1, $\hat{k}_1 = r_k$ for some k. Inductively, for $\ell = 2, \ldots, H-1$, with probability tending to 1, there exists a k such that $\hat{k}_\ell = r_k$. Next, we show that with probability tending to 1, $\hat{H} = H$. For any $0 \leq k_1 < k_2 \leq H$, if $k_1 + 1 < k_2$, then with probability tending to 1, there exists $k_1 < \tilde{k} < k_2$ and

$$\Delta_{r_{k_1}+1, r_{k_2}}(r_{\tilde{k}}) = \max_{r_{k_1}+1 \leq \kappa \leq r_{k_2}} \Delta_{r_{k_1}+1, r_{k_2}}(\kappa) \geq \frac{\sqrt{Jp}}{H^2 K^2} \left[\frac{1}{K} + o_P\left(\frac{1}{\sqrt{Jp}}\right) \right].$$

By Condition 2(iv), the change point $r_{\tilde{k}}$ will be detected by the algorithm. If $k_2 = k_1 + 1$, then

$$\max_{r_{k_1}+1 \leq \kappa \leq r_{k_2}} \Delta_{r_{k_1}+1, r_{k_2}}(\kappa) = \frac{\sqrt{Jp}}{H^2 K^2} o_P\left(\frac{1}{\sqrt{Jp}}\right) = o_P(1).$$

Again, by Condition 2(iv), with probability tending to 1, the algorithm will stop, which completes the proof.

Proof of Theorem 1. Let $\Psi_j = (\psi_{ik,j})$ be a $p \times H$ matrix, where $\psi_{ik,j} = I(\beta_{i,j} \in \mathcal{B}_k)$, $1 \leq i \leq p$, $1 \leq k \leq H$, $1 \leq j \leq J$. By Lemma 3, with probability tending to 1, $\hat{\boldsymbol{\xi}} = (\hat{\xi}_1, \ldots, \hat{\xi}_H)^T$ maximizes

$$\mathcal{L}(\boldsymbol{\xi}) = \sum_{j=1}^{J} \mathcal{L}_j(\Psi_j \boldsymbol{\xi}),$$

and $\hat{\boldsymbol{\beta}}_j = \Psi_j \hat{\boldsymbol{\xi}}$. Let $\boldsymbol{\xi}^*$ denote the true parameter values of $\boldsymbol{\xi}$ and $\boldsymbol{\beta}_j = \Psi_j \boldsymbol{\xi}^*$. For any s in a compact set of $\mathcal{R}^H$, define

$$G(s) = \mathcal{L}(\boldsymbol{\xi}^* + s/\sqrt{\mathcal{N}}) - \mathcal{L}(\boldsymbol{\xi}^*)$$

$$= \sum_{j=1}^{J} \sum_{i=1}^{n_j} \int_0^\tau \{\mathcal{N}^{-1/2} X_{ij}^T s - \log S_j^{(0)}(u, \Psi_j \boldsymbol{\xi}^* + \mathcal{N}^{-1/2} \Psi_j s)$$

$$+ \log S_j^{(0)}(u, \Psi_j \boldsymbol{\xi}^*)\} dN_{ij}(u).$$

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Write

$$\log S_j^{(0)}(u, \Psi_j\xi^* + \mathcal{N}^{-1/2}\Psi_j s) - \log S_j^{(0)}(u, \Psi_j\xi^*) =$$

$$\mathcal{N}^{-1/2}s^T\Psi_j^T E_j(u, \Psi_j\xi^*) + \frac{1}{2\mathcal{N}}s^T\Psi_j^T V_j(u, \Psi_j\xi^*)\Psi_j s + v_j(s,u).$$

Some analysis reveals that $|v_j(s,u)| \le \frac{4}{3}\mathcal{N}^{-3/2}\max_{1\le i\le n_j}|s^T\Psi_j^T(X_{ij} - E_j(u, \Psi_j\xi^*))|^3 = O(\mathcal{N}^{-3/2})$. It follows that

$$G_n(s) = U_n^T s - \frac{1}{2}s^T\mathcal{I}_n^* s - r_n(s),$$

where

$$U_n = \mathcal{N}^{-1/2}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau \Psi_j^T\{X_{ij} - E_j(u, \Psi_j\xi^*)\}dN_{ij}(u),$$

$$\mathcal{I}_n^* = \mathcal{N}^{-1}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau \Psi_j^T V_j(u, \Psi_j\xi^*)\Psi_j dN_{ij}(u),$$

and

$$r_n(s) = \sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau v_j(s,u)dN_{ij}(u).$$

Note that

$$U_n = \mathcal{N}^{-1/2}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau \Psi_j^T\{X_{ij} - E_j(u, \Psi_j\xi^*)\}dM_{ij}(u)$$

and

$$\mathcal{I}_n^* = \mathcal{N}^{-1}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau Y_{ij}\Psi_j^T V_j(u, \Psi_j\xi^*)\Psi_j \exp(X_{ij}^T\Psi_j^T\xi^* + \lambda^T W_j)h_0(u)du$$

$$+\mathcal{N}^{-1}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau \Psi_j^T V_j(u, \Psi_j\xi^*)\Psi_j dM_{ij}(u).$$

By the boundedness of the integrand, the first term of $\mathcal{I}_n^*$ goes to $\mathcal{I}$ in probability. Since then,

$$E\left\{\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau \Psi_j^T V_j(u, \Psi_j\xi^*)\Psi_j dM_{ij}(u)\right\}^2$$

$$= E\sum_{j=1}^{J}\sum_{i=1}^{n_j}\left\{\Psi_j^T V_j(u, \Psi_j\xi^*)\Psi_j\right\}^{\otimes 2} d < M_{i,j}, M_{i,j} > (u),$$

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by the boundedness of the covariates, the second term of $\mathcal{I}_n^*$ is $O_p(\mathcal{N}^{-1/2})$. For any $\epsilon > 0$, let

$$U_n^\epsilon(t) = \mathcal{N}^{-1/2} \sum_{j=1}^{J} \sum_{i=1}^{n_j} \int_0^t \Psi_j^T \{X_{ij} - E_j(u, \Psi_j \boldsymbol{\xi}^*)\} I\{\mathcal{N}^{-1/2} |\Psi_j^T (X_{ij} - E_j(u, \Psi_j \boldsymbol{\xi}^*)| \geq \epsilon\} dM_{ij}(u).$$

The predictable variation/covariation processes of $U_n(\cdot)$ and $U_n^\epsilon(\cdot)$ are

$$< U_n, U_n > (t) = \mathcal{N}^{-1} \sum_{j=1}^{J} \sum_{i=1}^{n_j} \int_0^t \Psi_j^T \{X_{ij} - E_j(u, \Psi_j \boldsymbol{\xi}^*))\}^{\otimes 2} \Psi_j d < M_{ij}, M_{ij} > (u)$$

$$= \int_0^s \mathcal{I}_n(u) h_0(u) du \xrightarrow{p} \int_0^s \mathcal{I}(u) h_0(u) du,$$

and

$$< U_n^\epsilon, U_n^\epsilon > (t) = \mathcal{N}^{-1} \sum_{j=1}^{J} \sum_{i=1}^{n_j} \int_0^t Y_{ij} \Psi_j^T \{X_{ij} - E_j(u, \Psi_j \boldsymbol{\xi}^*)\}^{\otimes 2} \Psi_j$$

$$I\{\mathcal{N}^{-1/2} |\Psi_j^T (X_{ij} - E_j(u, \Psi_j \boldsymbol{\xi}^*)| \geq \epsilon\} \exp(X_{ij}^T \Psi_j^T \boldsymbol{\xi}^* + \lambda^T W_j) h_0(u) du \xrightarrow{p} 0,$$

by the martingale central limit theorem (Fleming and Harrington, 2011), $U_n \to U \sim N_H(0_H, \mathcal{I})$. To summarize, for any s in a compact set S of $\mathcal{R}^H$, we have

$$G_n(s) \xrightarrow{p} G(s) = U^T s - \frac{1}{2} s^T \mathcal{I} s.$$

By the concavity of $G_n(s)$ and $G(s)$ and the concavity lemma (Andersen and Gill, 1982, p. 1116), it follows that

$$\sup_{s \in S} |G_n(s) - G(s)| \xrightarrow{p} 0.$$

We now prove that $\mathcal{N}^{1/2}(\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}^*) \to N(0_H, \mathcal{I}^{-1})$. Let $\gamma_n = \mathcal{N}^{1/2}(\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}^*)$ and $\alpha_n = \mathcal{I}^{-1} U$, which maximize $G_n(s)$ and $G(s)$, respectively. It is sufficient to show that for any $\delta > 0$,

$$P(|\gamma_n - \alpha_n| > \delta) \to 0.$$

For any $|s - \alpha_n| = \delta$, $G(\alpha_n) - G(s) \geq \frac{1}{2} \delta^2 \lambda_{\min}(\mathcal{I})$. If $|\gamma_n - \alpha_n| = l > \delta$, then let $\eta_n = \alpha_n + (\gamma_n - \alpha_n) \frac{\delta}{l}$. By the concavity of G_n,

$$G_n(\eta_n) \geq \left(1 - \frac{\delta}{l}\right) G_n(\alpha_n) + \frac{\delta}{l} G_n(\gamma_n).$$

Hence,

$$0 \leq [G_n(\gamma_n) - G_n(\alpha_n) \leq \frac{l}{\delta} \left[2 \sup_{|s - \alpha_n| = \delta} |G_n(s) - G(s)| - \frac{1}{2} \delta^2 \lambda_{\min}(\mathcal{I}) \right].$$

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It follows that

$$P(|\gamma_n - \alpha_n| > \delta) \le P\left(\sup_{|s-\alpha_n|=\delta} |G_n(s) - G(s)| \ge \frac{1}{4}\delta^2 \lambda_{\min}(\mathcal{I})\right) \to 0.$$

Note that $\boldsymbol{\beta}_j = \Psi_j \boldsymbol{\xi}^*$ and consequently, for any $1 \le j \le J$, we have $\mathcal{N}^{-1/2}(\hat{\boldsymbol{\beta}}_j - \boldsymbol{\beta}_j^*) \to N(0_p, \Psi_j \mathcal{I}^{-1} \Psi_j^T)$. This completes the proof of Theorem 1. ■

Proof of Theorem 2. Let $y_{\ell j} = \hat{L}_{1,j}(t_{(\ell),j})$, $\alpha_{\ell j} = L_0(t_{(\ell),j})$. Hence, (3.4) can be written as

$$y_{\ell j} = \alpha_{\ell j} + W_j^T \lambda + \epsilon_{\ell j},$$

where $W_j = (W_{j11,\ldots,jqc_q})^T$ and $\lambda = (\lambda_{11}, \ldots, \lambda_{qc_q})^T$. Let $\Gamma_j = \mathbf{1}_{T_j} \otimes W_j^T$, where $\mathbf{1}_d$ is a d-dimensional vector with each component for which each component is 1. Write $y_j = (y_{1j}, \ldots, y_{T_j j})^T$ and $\epsilon_j = (\epsilon_{1j}, \ldots, \epsilon_{T_j j})^T$. We have

$$y_j = \alpha_j + \Gamma_j \lambda + \epsilon_j.$$

Write $y = (y_1^T, \ldots, y_J^T)^T$, $\alpha = (\alpha_1^T, \ldots, \alpha_J^T)^T$, $\Gamma = (\Gamma_1^T, \ldots, \Gamma_J^T)^T$, and $\epsilon = (\epsilon_1^T, \ldots, \epsilon_J^T)^T$. Hence,

$$y = \alpha + \Gamma\lambda + \epsilon.$$

Let $c = c_1 + \cdots + c_q$, $\mathcal{W}(t) = \text{diag}(K_h(t_{(1),1} - t), \ldots, K_h(t_{(T_J),J} - t))$, $u(t) = (t_{(1),1} - t), \ldots, t_{(T_J),J} - t)^T$, and $X(t) = (\mathbf{1}_N, \Gamma, u(t))$. We estimate $L_0(t), L_0'(t) = \frac{h_0(t)}{\Lambda_0(t)}$ and λ by $\tilde{a}(t), \tilde{b}(t)$, and $\tilde{\lambda}(t)$, which minimize

$$\mathcal{M}_t(a, \lambda, b) = (y - a1_N - \Gamma\lambda - bu(t))^T \mathcal{W}(t)(y - a1_N - \Gamma\lambda - bu(t)).$$

It follows that

$$\tilde{\lambda}(t) = (0_{c\times 1}, I_c, 0_{c\times 1})(X(t)^T \mathcal{W}(t) X(t))^{-1} X(t)^T \mathcal{W}(t) y,$$

$$\tilde{a}(t) = (1, 0_{c+1}^T)(X(t)^T \mathcal{W}(t) X(t))^{-1} X(t)^T \mathcal{W}(t) y,$$

and

$$\tilde{b}(t) = (0_{c+1}^T, 1)(X(t)^T \mathcal{W}(t) X(t))^{-1} X(t)^T \mathcal{W}(t) y.$$

Let $\alpha = (L_0(t_{(1),1}), \ldots, L_0(t_{(T_J),J})^T$. Thus,

$$\begin{aligned}\tilde{\lambda}(t) - \lambda = {} & (0_{c\times 1}, I_c, 0_{c\times 1})(X(t)^T \mathcal{W}(t) X(t))^{-1} X(t)^T \mathcal{W}(t)\epsilon \\ & + (0_{c\times 1}, I_c, 0_{c\times 1})(X(t)^T \mathcal{W}(t) X(t))^{-1} X(t)^T \mathcal{W}(t)[\alpha - L_0(t)1_{\mathcal{N}} - L_0'(t)u(t)].\end{aligned}$$

To derive the limiting distribution of $\tilde{\lambda}(t) - \lambda$, we first show that the first term is asymptotically normal with a mean of zero and then evaluate the magnitude of the second term to yield the bias. Let $W_0 = 1$, $\tilde{W}_j = (W_0, W_j^T)^T$. For $m = 0, 1, 2$ and $\ell = 0, 1, \ldots, c$, let $\mu_m = \int u^m K(u) du$. Write

$$\Omega = \begin{pmatrix} \Omega_{11} & \Omega_{21}^T \\ \Omega_{21} & \Omega_{22} \end{pmatrix},$$

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where Ω_{11}, Ω_{21}, and Ω_{22} are 1×1, $c\times 1$, and $c\times c$ matrices, respectively. Let $\Omega_{1\ell}$ denote the ℓth element in the first row of Ω. Define

$$S^n_{\ell,m}(t)=\frac{1}{\mathcal{N}}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\delta_{ij}(h^{-1}(t_{ij}-t))^m K_h(t_{ij}-t)\tilde{W}_{j,\ell}.$$

Then,

$$ES^n_{\ell,m}(t)=\frac{\mu_m}{\mathcal{N}}\sum_{j=1}^{J}\sum_{i=1}^{n_j}f_{ij}(t)\bar{G}_{ij}(t)\tilde{W}_{j,\ell}(1+o_p(1))=\mu_m\Omega_{1\ell}(t)(1+o_p(1)).$$

As $K(\cdot)$ is a bounded function with a bounded support, for any $0\le m\le 4$, $|u^mK(u)|$ is bounded. By Jensen's inequality,

$$\mathrm{var}(S^n_{\ell,m}(t))\le\mathcal{N}^{-2}\sum_{j=1}^{J}n_j\sum_{i=1}^{n_j}[\delta_{ij}(h^{-1}(t_{ij}-t))^m K_h(t_{ij}-t)\tilde{W}_{j,\ell}]^2=O((\mathcal{N}h^2)^{-1}).$$

It follows that

$$S^n_{\ell,m}(t)=ES^n_{\ell,m}(t)+O_p\left(\sqrt{\mathrm{var}(S^n_{\ell,m}(t))}\right)=\mu_m\Omega_{1\ell}(t)(1+o_p(1)).$$

Hence,

$$\frac{1}{\mathcal{N}}X(t)^T\mathcal{W}(t)X(t)=H\begin{Bmatrix}\mu_0\Omega(t) & 0\\ 0 & \mu_2\Omega_{11}(t)\end{Bmatrix}H(1+o_p(1)),$$

where $H=\begin{Bmatrix}I_{c+1} & 0\\ 0 & h\end{Bmatrix}$. Now, we derive the limiting distribution of

$$\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau W_jK_h(u-t)[\hat{L}_{1,j}(u)-L_{1,j}(u)]dN_{ij}(u),$$

$$\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau (u-t)K_h(u-t)[\hat{L}_{1,j}(u)-L_{1,j}(u)]dN_{ij}(u),$$

and

$$\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau K_h(u-t)[\hat{L}_{1,j}(u)-L_{1,j}(u)]dN_{ij}(u).$$

Let

$$\hat{\Lambda}_{1,j}(t)=\int_0^t\sum_{i=1}^{n_j}\frac{1}{n_jS^{(0)}_j\left(u,\Psi_j^T\hat{\xi}\right)}dN_{ij}(u),$$

$$\tilde{\Lambda}_{1,j}(t)=\int_0^t\left\{\sum_{i=1}^{n_j}Y_{ij}(u)e^{X_{ij}^T\Psi_j^T\xi^*}\right\}^{-1}d\left[\sum_{i=1}^{n_j}N_{ij}(u)\right],$$

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and

$$\Lambda^*_{1,j}(t) = \int_0^t I\left(\sum_{i=1}^{n_j} Y_{ij}(u) > 0\right) h_{1,j}(u)du.$$

We have

$$n_j^{1/2}(\hat{\Lambda}_{1,j}(t) - \Lambda_{1,j}(t)) = n_j^{1/2}(\hat{\Lambda}_{1,j}(t) - \tilde{\Lambda}_{1,j}(t)) + n_j^{1/2}(\tilde{\Lambda}_{1,j}(t) - \Lambda^*_{1,j}(t)) + n_j^{1/2}(\Lambda^*_{1,j}(t) - \Lambda_{1,j}(t)).$$

It is easy to see that $n_j^{1/2}(\Lambda^*_{1,j}(t) - \Lambda_{1,j}(t))$ is asymptotically negligible, $n_j^{1/2}(\tilde{\Lambda}_{1,j}(t) - \Lambda^*_{1,j}(t))$ converges to a mean of zero and an incremental Gaussian process with variance function

$$\int_0^t \left[s_j^{(0)}(u, \Psi_j\boldsymbol{\xi}^*)\right]^{-1} h_{1,j}(u)du,$$

and

$$\begin{aligned} &n_j^{1/2}(\hat{\Lambda}_{1,j}(t) - \tilde{\Lambda}_{1,j}(t)) \\ &= \left[-\int_0^t n_j^{-1} \frac{S_j^{(1)}(u, \Psi_j\boldsymbol{\xi}^*)}{\left\{S_j^{(0)}(u, \Psi_j\boldsymbol{\xi}^*)\right\}^2} d\sum_{i=1}^{n_j} N_{ij}(u) + o_p(1)\right]\left[n_j^{1/2}\Psi_j^T(\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}^*)\right] \\ &= \left[-\int_0^t e_j(u, \Psi_j\boldsymbol{\xi}^*)h_{1,j}(u)du + o_p(1)\right]\left[n_j^{1/2}\Psi_j^T(\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}^*)\right]. \end{aligned}$$

Note that

$$\mathcal{N}^{1/2}(\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}^*) = \mathcal{I}^{-1}\mathcal{N}^{-1/2}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau \Psi_j^T\{X_{ij} - E_j(u, \Psi_j\boldsymbol{\xi}^*)\}dM_{ij}(u) + o_p(1),$$

and for any $1 \le j \le J$,

$$n_j^{1/2}(\tilde{\Lambda}_{1,j}(t) - \Lambda^*_{1,j}(t)) = n_j^{-1/2}\sum_{i=1}^{n_j}\int_0^t \left\{S_j^{(0)}(u, \Psi_j\boldsymbol{\xi}^*)\right\}^{-1} dM_{ij}(u) + o_p(1).$$

Because

$$\begin{aligned} &<\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau \Psi_j^T\{X_{ij} - E_j(u, \Psi_j\boldsymbol{\xi}^*)\}dM_{ij}(u), \sum_{i=1}^{n_j}\int_0^t \left\{S_j^{(0)}(u, \Psi_j\boldsymbol{\xi}^*)\right\}^{-1} dM_{ij}(u)>(t) \\ &= \sum_{i=1}^{n_j}\int_0^t \Psi_j^T\{X_{ij} - E_j(u, \Psi_j\boldsymbol{\xi}^*)\}\{S_j^{(0)}(u, \Psi_j\boldsymbol{\xi}^*)\}^{-1} Y_{ij}(u)\exp\left(X_{ij}^T\Psi_j\boldsymbol{\xi}^*\right)h_{1,j}(u)du \\ &= 0, \end{aligned}$$

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it follows that $n_j^{1/2}(\tilde{\Lambda}_{1,j}(t) - \Lambda^*_{1,j}(t)), j = 1, \ldots, J$ and $(\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}^*)$ are asymptotically independent. Furthermore,

$$\sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau K_h(u-t)[\hat{L}_{1,j}(u) - L_{1,j}(u)]dN_{ij}(u)$$

$$= \sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau Y_{ij}(u)\exp\left(X_{ij}^T\Psi_j\boldsymbol{\xi}^*\right)K_h(u-t)[\hat{L}_{1,j}(u) - L_{1,j}(u)]h_{1,j}(u)du$$

$$+ \sum_{j=1}^{J}\sum_{i=1}^{n_j}\int_0^\tau K_h(u-t)[\hat{L}_{1,j}(u) - L_{1,j}(u)]dM_{ij}(u)$$

$$= \left\{\sum_{j=1}^{J}\int_0^\tau n_j[\hat{L}_{1,j}(u) - L_{1,j}(u)]K_h(u-t)h_{1,j}(u)s_j^{(0)}(u,\Psi_j\boldsymbol{\xi}^*)du\right\}(1+o_p(1))$$

$$= \left\{\sum_{j=1}^{J}\int_0^\tau n_j[\hat{\Lambda}_{1,j}(u) - \Lambda_{1,j}(u)]K_h(u-t)s_j^{(0)}(u,\Psi_j\boldsymbol{\xi}^*)du\right\}(1+o_p(1)).$$

By calculation,

$$\begin{aligned}
&\mathrm{Var}\left(\sum_{j=1}^{J}\int_0^\tau n_j[\hat{\Lambda}_{1,j}(u) - \Lambda_{1,j}(u)]K_h(u-t)s_j^{(0)}(u,\Psi_j\boldsymbol{\xi}^*)du\right)\\
&= \left\{\sum_{j=1}^{J} n_j[s_j^{(0)}(t,\Psi_j\boldsymbol{\xi}^*)]^2\int_0^t[s_j^{(0)}(u,\Psi_j\boldsymbol{\xi}^*)]^{-1}h_{1,j}(u)du\right.\\
&\quad + \mathcal{N}^{-1}\left(\sum_{j=1}^{J} n_j s_j^{(0)}(t,\Psi_j\boldsymbol{\xi}^*)\int_0^t e_j^T(u,\Psi_j\boldsymbol{\xi}^*)h_{1,j}(u)du\Psi_j^T\right)\\
&\quad \left.\times\mathcal{I}^{-1}\left(\sum_{j=1}^{J} n_j s_j^{(0)}(t,\Psi_j\boldsymbol{\xi}^*)\times\Psi_j\int_0^t e_j(u,\Psi_j\boldsymbol{\xi}^*)h_{1,j}(u)du\right)\right\}(1+o_p(1)).
\end{aligned}$$

By the Lindeberg–Feller Central Limit Theorem, Slutsky's theorem, and similar calculations as above, we have that

$$\mathcal{N}^{-1/2}(I_{c+1},0_{c+1})H^{-1}X^T\mathcal{W}(t)\epsilon$$

is asymptotically normal with the covariance function

$$\zeta(t,t) + \Upsilon(t)\mathcal{I}^{-1}\Upsilon(t)^T,$$

and hence,

$$\mathcal{N}^{1/2}(I_{c+1},0_{c+1})(X(t)^T\mathcal{W}(t)X(t))^{-1}X(t)^T\mathcal{W}(t)\epsilon$$

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is asymptotically normal with a mean of zero with the covariance function

$$\Omega(t)^{-1}[\zeta(t,t)+\Upsilon(t)\mathcal{I}^{-1}\Upsilon(t)^T]\Omega(t)^{-1}.$$

Define

$$\nu(t_1,t_2)=\Omega(t_1)^{-1}[\zeta(t_1,t_2)+\Upsilon(t_1)\mathcal{I}^{-1}\Upsilon(t_2)^T]\Omega(t_2)^{-1},$$

and write

$$\nu(t_1,t_2)=\begin{pmatrix} \nu_{11}(t_1,t_2) & \nu_{12}(t_1,t_2) \\ \nu_{12}^T(t_1,t_2) & \nu_{22}(t_1,t_2) \end{pmatrix},$$

where $\nu_{11}(t_1,t_2)$, $\nu_{12}(t_1,t_2)$, and $\nu_{22}(t_1,t_2)$ are 1×1, $1\times c$, and $c\times c$ matrices, respectively.

Next, we evaluate the bias term

$$\begin{aligned}
&\mathcal{N}^{1/2}(I_{c+1},0_{c+1})(X(t)^T\mathcal{W}(t)X(t))^{-1}X(t)^T\mathcal{W}(t)[\alpha-L_0(t)1_N-L_0^{'}(t)u(t)] \\
&\quad=2^{-1}L_0^{''}(t)\mathcal{N}^{1/2}(I_{c+1},0_{(c+1)\times 1})(X(t)^T\mathcal{W}(t)X(t))^{-1}X(t)^T\mathcal{W}(t)u^2(t)[1+o_p(1)] \\
&\quad=\mathcal{N}^{1/2}2^{-1}L_0^{''}(t)\mu_2h^2\Omega^{-1}(t)\begin{pmatrix}\Omega_{11}(t)\\ \Omega_{21}(t)\end{pmatrix}[1+o_p(1)].
\end{aligned}$$

When $\mathcal{N}h^4$ is bounded, we have

$$\sqrt{\mathcal{N}}\{(\tilde{a}(t),\tilde{\lambda}^T)^T-(L_0(t),\lambda^T)^T-\frac{h^2\mu_2L_0^{''}(t)}{2}(1,0_c^T)^T\}\to N(0_{(c+1)\times 1},\nu(t,t)).$$

Now, we proceed to obtain the limiting distribution of $\hat{\lambda}$. By definition,

$$\begin{aligned}
\hat{\lambda}&=\frac{1}{N}\sum_{m=1}^{N}\tilde{\lambda}(t_{(m)}) \\
&=\frac{1}{N}\sum_{j=1}^{J}\sum_{i=1}^{T_j}(0_{c\times 1},I_c,0_{c\times 1})(X^T(t_{(i),j})\mathcal{W}(t_{(i),j})X(t_{(i),j}))^{-1}X^T(t_{(i),j})\mathcal{W}(t_{(i),j})y.
\end{aligned}$$

By straightforward but tedious calculation and the law of large numbers, we have

$$\begin{aligned}
&\mathrm{Var}(N\hat{\lambda}) \\
&=E\sum_{j=1}^{J}\sum_{i=1}^{T_j}\sum_{r=1}^{J}\sum_{\ell=1}^{T_r}(0_{c\times 1},I_c,0_{c\times 1})(X^T(t_{(i),j})\mathcal{W}(t_{(i),j})X(t_{(i),j}))^{-1}X^T(t_{(i),j})\mathcal{W}(t_{(i),j})\epsilon \\
&\quad\times\epsilon^T\mathcal{W}(t_{(\ell),r})X(t_{(\ell),r})(X^T(t_{(\ell),r})\mathcal{W}(t_{(\ell),r})X(t_{(\ell),r}))^{-1}(0_{c\times 1},I_c,0_{c\times 1})^T \\
&=(1+o(1))E\mathcal{N}^{-1}\sum_{j=1}^{J}\sum_{i=1}^{T_j}\sum_{r=1}^{J}\sum_{\ell=1}^{T_r}\nu_{22}(t_{(i),j},t_{(\ell),r}) \\
&=(1+o(1))E\mathcal{N}^{-1}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\sum_{r=1}^{J}\sum_{\ell=1}^{n_r}\delta_{ij}\delta_{\ell r}\nu_{22}(t_{ij},t_{\ell r}),
\end{aligned}$$

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and

$$\text{Bias}(\hat{\lambda}) = E\hat{\lambda} - \lambda$$

$$= (1 + o_p(1))E\frac{1}{N}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\frac{h^2\mu_2\delta_{ij}L_0^{''}(t_{ij})}{2}.$$

Define

$$\bar{\Omega}_{11} = \int_0^\tau \Omega_{11}(u)du,$$

$$\bar{\nu}_{22} = \int_0^\tau \int_0^\tau \nu_{22}(u,v)\Omega_{11}(u)\Omega_{11}(v)dudv,$$

and

$$\Phi = \int_0^\tau L_0^{''}(u)\Omega_{11}(u)du.$$

By the law of large numbers,

$$\mathcal{N}^{-1}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\delta_{ij} \to \bar{\Omega}_{11},$$

$$\mathcal{N}^{-2}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\sum_{r=1}^{J}\sum_{\ell=1}^{n_r}\delta_{ij}\delta_{\ell r}\nu_{22}(t_{ij},t_{\ell r}) \to \bar{\nu}_{22},$$

and

$$\mathcal{N}^{-1}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\delta_{ij}L_0^{''}(t_{ij}) \to \Phi.$$

It follows that when $\mathcal{N}h^4$ is bounded,

$$\sqrt{\mathcal{N}}\left[\hat{\lambda} - \lambda - \frac{\Phi h^2\mu_2}{2\bar{\Omega}_{11}}(1, 0_c^T)^T\right] \to N(0_c, \bar{\Omega}_{11}^{-2}\bar{\nu}_{22}).$$

Hence, when $\mathcal{N}h^4 \to 0$,

$$\sqrt{\mathcal{N}}(\hat{\lambda} - \lambda) \to N(0_c, \bar{\Omega}_{11}^{-2}\bar{\nu}_{22}).$$

Let $e_{k,\ell}$ denote the unit vector of length c with 1 at the position corresponding to $\lambda_{k,\ell}$. Thus, for any $k = 1, \ldots c_q; \ell = 1, \ldots, q$,

$$\sqrt{\mathcal{N}}(\hat{\lambda}_{k,\ell} - \lambda_{k,\ell}) \to N(0, e_{k,\ell}^T\bar{\Omega}_{11}^{-2}\bar{\nu}_{22}e_{k,\ell}).$$

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Proof of Theorem 3. We establish the limiting distribution for $\hat{\Lambda}_0(t)$. Write

$$\Xi_1(t) = \frac{1}{N}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\delta_{ij}h^{-1}(t_{ij}-t)K_h(t_{ij}-t) \times \exp\{(1_{1\times 1}, 0_{(c+1)\times 1})(X^T(t_{ij})\mathcal{W}(t_{ij})X(t_{ij}))^{-1}X^T(t_{ij})\mathcal{W}(t_{ij})y\},$$

$$\Xi_0(t) = \frac{1}{N}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\delta_{ij}K_h(t_{ij}-t) \times \exp\{(1_{1\times 1}, 0_{(c+1)\times 1})(X^T(t_{ij})\mathcal{W}(t_{ij})X(t_{ij}))^{-1}X^T(t_{ij})\mathcal{W}(t_{ij})y\},$$

and for $\ell = 0, 1, 2$,

$$\Theta_\ell(t) = \frac{1}{N}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\delta_{ij}h^{-\ell}(t_{ij}-t)^\ell K_h(t_{ij}-t).$$

By the law of large numbers and Condition 5(iv),

$$\Theta_\ell(t) = \mu_\ell(1+o_p(1)).$$

Thus,

$$\hat{\Lambda}_0(t) = (1,0)\begin{pmatrix}\Theta_0(t) & \Theta_1(t)\\ \Theta_1(t) & \Theta_2(t)\end{pmatrix}^{-1}\begin{pmatrix}\Xi_0(t)\\ \Xi_1(t)\end{pmatrix} = \Xi_0(t)(1+o_p(1)).$$

By similar arguments as in the Proof of Theorem 2, it can be shown that

$$\begin{aligned}\mathrm{Var}(\mathcal{N}^{1/2}\Xi_0(t)) &= (1+o(1))EN^{-2}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\sum_{r=1}^{J}\sum_{\ell=1}^{n_r}\delta_{ij}\delta_{r\ell}K_h(t_{ij}-t)\\ &\quad\times K_h(t_{r\ell}-t)\nu_{11}(t_{ij},t_{r\ell})\Lambda_0(t_{ij})\Lambda_0(t_{r\ell})\\ &= (1+o(1))\Lambda_0^2(t)\nu_{11}(t,t).\end{aligned}$$

Write

$$\mathrm{Bias}(\Xi_0(t)) = E[\Xi_0(t)] - \Lambda_0(t) = \mathrm{Bias}_1 + \mathrm{Bias}_2,$$

where

$$\mathrm{Bias}_1 = E[\Xi_0(t)] - E\sum_{j=1}^{J}\sum_{i=1}^{n_j}N^{-1}\delta_{ij}K_h(t_{ij}-t)\Lambda_0(t_{ij}),$$

and

$$\mathrm{Bias}_2 = E\sum_{j=1}^{J}\sum_{i=1}^{n_j}N^{-1}\delta_{ij}K_h(t_{ij}-t)\Lambda_0(t_{ij}) - \Lambda_0(t).$$

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By Theorem 2,

$$\text{Bias}_1 = \frac{\mu_2 h^2}{2}\Lambda_0(t)L_0^{''}(t),$$

and it is easy to see that

$$\text{Bias}_2 = \frac{\mu_2 h^2}{2}h_0^{'}(t).$$

Hence,

$$\text{Bias}(\Xi_0(t)) = \frac{\mu_2 h^2}{2}[\Lambda_0(t)L_0^{''}(t) + h_0^{'}(t)](1+o(1)).$$

It follows that when $\mathcal{N}h^4 \to 0$,

$$\mathcal{N}^{1/2}(\hat{\Lambda}_0(t) - \Lambda_0(t)) \to N(0, \Lambda_0^2(t)\nu_{11}(t,t)).$$

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