

INFERENCE UNDER RIGHT CENSORING FOR TRANSFORMATION MODELS WITH A CHANGE-POINT BASED ON A COVARIATE THRESHOLD

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We consider linear transformation models applied to right censored survival data with a change-point in the regression coefficient based on a covariate threshold. We establish consistency and weak convergence of the nonparametric maximum likelihood estimators. The change-point parameter is shown to be n -consistent, while the remaining parameters are shown to have the expected root- n consistency. We show that the procedure is adaptive in the sense that the non-threshold parameters are estimable with the same precision as if the true threshold value were known. We also develop Monte-Carlo methods of inference for model parameters and score tests for the existence of a change-point. A key difficulty here is that some of the model parameters are not identifiable under the null hypothesis of no change-point. Simulation studies establish the validity of the proposed score tests for finite sample sizes.

1. Introduction. The linear transformation model states that a continuous outcome U , given a d -dimensional covariate vector Z , has the form

$$(1) \quad H(U) = -\beta'Z + \varepsilon,$$

where H is an increasing, unknown transformation function, $\beta \in \mathbb{R}^d$ are the unknown regression parameters of interest, and ε has a known distribution F . This model is readily applied to a failure time T by letting $U = \log T$ and $H(u) = \log A(e^u)$, where A is an unspecified integrated baseline hazard. Setting $F(s) = 1 - \exp(-e^s)$ results in the Cox model, while setting $F(s) = e^s/(1 + e^s)$ results in the proportional odds model. More generally, the transformation model for a survival time T conditionally on a time-

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dependent covariate $\tilde{Z}(t) = \{Z(s), 0 \leq s \leq t\}$, takes the form

$$(2) \quad \mathbb{P}[T > t | \tilde{Z}(t)] = S_Z(t) \equiv \Lambda \left(\int_0^t e^{\beta' Z(s)} dA(s) \right),$$

where Λ is a known decreasing function with $\Lambda(0) = 1$. The model (2) is model (1) when the covariates are time-independent and $F(s) = 1 - \Lambda(e^s)$.

In data analysis, the assumption of linearity of the regression effect in (2) is not always satisfied over the whole range of the covariate, and the fit may be improved with a two-phase transformation model having a change-point at an unknown threshold of a one-dimensional covariate Y . Let $Z = (Z_1, Z_2)$, where Z_1 and Z_2 are possibly time-dependent covariates in $\mathbb{R}^p$ and $\mathbb{R}^q$, respectively, where $p + q = d$ and $q \geq 1$. The new model is obtained by replacing $\beta' Z(s)$ in (2) with

$$(3) \quad r_\xi(s; Z, Y) \equiv \beta' Z(s) + [\alpha + \eta' Z_2(s)] \mathbf{1}\{Y > \zeta\},$$

where α is a scalar, $\eta \in \mathbb{R}^q$, $\mathbf{1}\{B\}$ is the indicator of B , and ξ denotes the collected parameters $(\alpha, \beta, \eta, \zeta)$. We also require Y to be time-independent but allow it to be one of the covariates in $Z(t)$. The goal of this paper is to develop methods of inference for this model applied to right censored data.

We note that for the special case when $\alpha = 0$ and $\Lambda(t) = e^{-t}$, the model (3) becomes the Cox model considered by [28] under a slightly different parameterization. Permitting a nonzero α allows the possibility of a “bent-line” covariate effect. Suppose, for example, that Z_2 is one-dimensional and time-independent, while $Z_1 \in \mathbb{R}^{d-1}$ may be time-dependent. If we set $Y = Z_2$ and $\beta = (\beta'_1, \beta'_2)'$, where $\beta_1 \in \mathbb{R}^{d-1}$ and $\beta_2 \in \mathbb{R}$, the model (3) becomes $r_\xi(s; Z, Y) = \beta'_1 Z_1(s) + \beta_2 Z_2 + (\alpha + \eta Z_2) \mathbf{1}\{Z_2 > \zeta\}$. When $\alpha = -\eta\zeta$, the covariate effect for Z_2 consists of two connected linear segments. In many biological settings, such a bent-line effect is realistic and can be much easier to interpret than a quadratic or more complex nonlinear effect [9]. Hence including the intercept term α is useful for applications.

Linear transformation models of the form (1) have been widely used and studied (see, for example, [3, 5, 7, 8, 10–12, 14, 25]). Efficient methods of estimation in the uncensored setting were rigorously studied by [6], among others. The model (2) for right-censored data has also been studied rigorously for a variety of specific choices of Λ [23, 26, 29, 30]; for general but known Λ [31]; and for certain parameterized families of Λ [17].

Change-point models have also been studied extensively and have proven to be popular in clinical research. Several researchers have considered a nonregular Cox model involving a two-phase regression on time-dependent covariates, with a change-point at an unknown time [19, 21, 22]. As mentioned above, [28] considered the Cox model with a change-point at an unknown threshold of a covariate. These authors studied the maximum partial likelihood estimators of the parameters and the estimator of the baseline hazard function. They show that the estimator of the threshold parameter is n -consistent, while the regression parameters are $\sqrt{n}$ -consistent. This happens because the likelihood function is not differentiable with respect to the threshold parameter, and hence the usual Taylor expansion is not available. In this paper, we focus on the covariate threshold setting. While time threshold models are also interesting, we will not pursue them further in this paper because the underlying techniques for estimation and inference are quite distinct from the covariate threshold setting.

The contribution of our paper builds on [28] in three important ways. Firstly, we extend to general transformation models. This results in a significant increase in complexity over the Cox model since estimation of the baseline hazard can no longer be avoided through the use of the partial-profile likelihood. Secondly, we study nonparametric maximum likelihood inference for all model parameters. As part of this, we show that the estimation procedure is adaptive in the sense that the non-threshold parameters—including the infinite-dimensional parameter A —are estimable with the same precision as if the true threshold parameter were known. Thirdly, we develop hypothesis tests for the existence of a change-point. This is quite challenging since some of the model parameters are no longer identifiable under the null hypothesis of no change-point. [1] considers similar nonstandard testing problems when the model is fully parametric and establishes asymptotic null and local alternative distributions of a number of likelihood-based test procedures. Unfortunately, Andrews' results are not directly applicable to our setting because of the presence of an infinite dimensional nuisance parameter, the baseline integrated hazard A , and new methods are required.

The next section, section 2, presents the data and model assumptions. The nonparametric maximum log-likelihood estimation (NPMLE) procedure is presented in section 3. In section 4, we establish the consistency of

the estimators. Score and information operators of the regular parameters are given in section 5. Results on the convergence rates of the estimators are established in section 6. Section 7 presents weak convergence results for the estimators, including the asymptotic distribution of the change-point estimator and the asymptotic normality of the other parameters. This section also establishes the adaptive semiparametric efficiency mentioned above. Monte Carlo inference for the parameters is discussed in section 8. Methods for testing the existence of a change-point are then presented in section 9. A brief discussion on implementation and a small simulation study evaluating the moderate sample size performance of the proposed change-point tests are given in section 10. Proofs are given in section 11. For an expanded version of this paper, with several additional details and results, please see [18].

2. The data set-up and model assumptions. The data $X_i = (V_i, \delta_i, Z_i, Y_i)$, $i = 1, \dots, n$, consists of n i.i.d. realizations of $X = (V, \delta, Z, Y)$, where $V = T \wedge C$, $\delta = 1(T \leq C)$, and C is a right censoring time. The analysis is restricted to the interval $[0, \tau]$, where $\tau < \infty$. The covariate $Y \in \mathbb{R}$ and $Z \equiv \{Z(t), t \in [0, \tau]\}$ is assumed to be a caglad (left-continuous with right-hand limits) process with $Z(t) = (Z'_1(t), Z'_2(t))' \in \mathbb{R}^p \times \mathbb{R}^q$, for all $t \in [0, \tau]$, where $q \geq 1$ but $p = 0$ is allowed.

We assume that conditionally on Z and Y , the survival function is

$$(4) \quad t \mapsto S_{Z,Y}(t) \equiv \Lambda \left(\int_0^t e^{r_\xi(u; Z, Y)} dA(u) \right),$$

where Λ is known, thrice differentiable and decreasing, with $\Lambda(0) = 1$, $r_\xi(s; Z, Y)$ is as in (3), and A is unknown, increasing and restricted to $[0, \tau]$.

Let $G \equiv -\log \Lambda$, and define the derivatives $\dot{\Lambda} \equiv \partial \Lambda(t)/(\partial t)$, $\ddot{\Lambda} \equiv \partial \dot{\Lambda}(t)/(\partial t)$, $\dot{G} \equiv \partial G(t)/(\partial t)$, $\ddot{G} \equiv \partial \dot{G}(t)/(\partial t)$, and $\ddot{\ddot{G}} \equiv \partial \ddot{G}/(\partial t)$. We also define the collected parameters $\gamma \equiv (\alpha, \eta, \beta)$, $\psi \equiv (\gamma, A)$, and $\theta \equiv (\psi, \zeta)$. We use P to denote the true probability measure, while the true parameter values are indicated with a subscript 0.

We now make the following additional assumptions:

- A1 : $P[C = 0] = 0$, $P[C \geq \tau | Z, Y] = P[C = \tau | Z, Y] > 0$ almost surely, and censoring is independent of T given (Z, Y) and uninformative.
- A2 : The total variation of $Z(\cdot)$ on $[0, \tau]$ is $\leq m_0 < \infty$ almost surely.
- B1 : $\zeta_0 \in (a, b)$, for some known $-\infty < a < b < \infty$ with $P[Y < a] > 0$ and $P[Y > b] > 0$.

B2 : For some neighborhood $\tilde{V}(\zeta_0)$ of ζ_0 :

- (i) the density of Y , $\tilde{h}$, exists and is strictly positive, bounded and continuous for all $y \in \tilde{V}(\zeta_0)$; and
- (ii) the conditional law of (C, Z) given $Y = y$, $\mathcal{L}_y$, is left-continuous with right-hand limits over $\tilde{V}(\zeta_0)$.

B3 : For some $t_1, t_2 \in (0, \tau]$, both $\text{var}[Z(t_1)|Y = \zeta_0]$ and $\text{var}[Z(t_2)|Y = \zeta_0 +]$ are positive definite.

B4 : For some $t_3, t_4 \in (0, \tau]$, both $\text{var}[Z(t_3)|Y < a]$ and $\text{var}[Z(t_4)|Y > b]$ are positive definite.

C1 : $\alpha_0 \in \Upsilon \subset \mathbb{R}$, $\beta_0 \in B_1 \subset \mathbb{R}^d$, $\eta_0 \in B_2 \subset \mathbb{R}^q$, where $d \geq q \geq 1$, and Υ , B_1 and B_2 are open, convex, bounded and known.

C2 : Either $\alpha_0 \neq 0$ or $\eta_0 \neq 0$.

C3 : $A_0 \in \mathcal{A}$, where $\mathcal{A}$ is the set of all increasing functions $A : [0, \tau] \mapsto [0, \infty)$ with $A(0) = 0$ and $A(\tau) < \infty$; and A_0 has derivative a_0 satisfying $0 < a_0(t) < \infty$ for all $t \in [0, \tau]$.

D1 : $G : [0, \infty) \mapsto [0, \infty)$ is thrice continuously differentiable, $G(0) = 0$, and, for all $u \in [0, \infty)$, $0 < \dot{G}(u)$, $\ddot{G}(u) < \infty$ and $\sup_{s \in [0, u]} |\ddot{G}(s)| < \infty$.

D2 : For some $c_0 > 0$, $\sup_{u \geq 0} |u^{c_0} \Lambda(u)| < \infty$ and $\sup_{u \geq 0} |u^{1+c_0} \dot{\Lambda}(u)| < \infty$.

Conditions A1, A2, C1 and C3 are commonly used for NPMLE consistency and identifiability in right-censored transformation models, while conditions B1, B2, B3 and C2 are needed for change-point identifiability. As pointed out by a referee, the use of a time-dependent covariate will require that $Z_i(V_j)$ be observed for each individual i and for every j such that $\delta_1 = 1$ and $V_j \leq V_i$. While this is often assumed in theoretical contexts, it can be unrealistic in practice, where missing values of $Z_i(t)$ are not unusual (see [20]). Frequently, data analysts will simply carry the last observation of $Z_i(t)$ forward to avoid the missingness problem. Unfortunately, this simple solution is not necessarily valid. However, addressing this issue thoroughly is beyond the scope of this paper, and we will only mention it again briefly in section 9, where we develop a test of the null hypothesis that there is no change-point ($H_0 : \alpha_0 = 0$ and $\eta_0 = 0$). Also in section 9, we will relax condition C2 to allow for a sequence of contiguous alternative hypotheses that includes H_0 . Condition B2(ii) is also needed to obtain weak convergence for the NPMLE of ζ_0 . The continuity requirements at each point y can be restated in the following way: $\mathcal{L}_\zeta$ converges weakly to $\mathcal{L}_y$, as $\zeta \uparrow y$; and $\mathcal{L}_\zeta$

converges weakly to $\mathcal{L}_{y+}$, as $\zeta \downarrow y$, for some law $\mathcal{L}_{y+}$. It would require a fairly pathological relationship among the variables (C, Z, Y) for this not to hold. Condition B4 is needed for the change-point test developed in section 9.

Conditions D1 and D2 are also needed for asymptotic normality. Condition D1 is quite similar to conditions (G.1) through (G.4) in [31] who use the condition for developing asymptotic theory for transformation models without a change-point. Condition D2 is slightly weaker than conditions D2 and D3 of [17] who use the condition to obtain asymptotic theory for frailty regression models without a change-point. The following are several instances that satisfy conditions D1 and D2:

1. $\Lambda(u) = e^{-u}$ corresponds to the Cox model.
2. $\Lambda(u) = (1 + cu)^{-1/c}$, for any $c \in (0, \infty)$, corresponds to the family of log-Pareto distributions and results in the odds-rate family.
3. $\Lambda(u) = E[e^{-Wu}]$, where W is a positive frailty with $E[W^{-c}] < \infty$, for some $c > 0$, and $E[W^4] < \infty$, corresponds to the family of frailty transformations. In addition to the odds-rate family, these conditions are satisfied by the inverse Gaussian and log-normal families (see [17]).
4. $\Lambda(u) = [1 + 2cu + u^2]^{-1}$, where $c \in (1/2, 1)$. Because this is the Laplace transform of $t \mapsto e^{-ct} \times \sin(t\sqrt{1-c^2})/\sqrt{1-c^2}$, it is not the Laplace transform of a density and is thus not a member of the frailty family.

Verification of these conditions is routine for examples 1, 2 and 4 above, but verification for example 3 is slightly more involved:

LEMMA 1. *Conditions D1 and D2 are satisfied for example 3 above.*

3. Nonparametric Maximum log-likelihood estimation. The nonparametric log-likelihood has the form $L_n(\psi, \zeta) \equiv$

$$(5) \quad \mathbb{P}_n \left\{ \delta \log(a(V)) + l_1^\psi(V, \delta, Z) \mathbf{1}\{Y \leq \zeta\} + l_2^\psi(V, \delta, Z) \mathbf{1}\{Y > \zeta\} \right\},$$

where

$$\begin{aligned} l_1^\psi(V, \delta, Z) &\equiv \int_0^\tau \left[\log \dot{G}(H_1^\psi(s)) + \beta' Z(s) \right] dN(s) - G(H_1^\psi(V)), \\ l_2^\psi(V, \delta, Z) &\equiv \int_0^\tau \left[\log \dot{G}(H_2^\psi(s)) + \beta' Z(s) + \alpha + \eta' Z_2(s) \right] dN(s) \\ &\quad - G(H_2^\psi(V)), \end{aligned}$$

where $N(t) \equiv \mathbf{1}\{V \leq t\}\delta$, $\tilde{Y}(s) \equiv \mathbf{1}\{V \geq s\}$, $a \equiv dA/dt$, $H_1^\psi(t) \equiv \int_0^t \tilde{Y}(s)e^{\beta'Z(s)}dA(s)$, $H_2^\psi(t) \equiv \int_0^t \tilde{Y}(s)e^{\beta'Z(s)+\alpha+\eta'Z_2(s)}dA(s)$, and $\mathbb{P}_n$ is the empirical probability measure.

As discussed by [23], the maximum likelihood estimator for a does not exist, since any unrestricted maximizer of (5) puts mass only at observed failure times and is thus not a continuous hazard. We replace $a(u)$ in $L_n(\psi, \zeta)$ with $n\Delta A(u)$ as suggested in [24] who remarked that this form of the empirical log-likelihood function is asymptotically equal to the true log-likelihood function in certain instances. Let $\tilde{L}_n(\psi, \zeta)$ be this modified log-likelihood. Note that the maximum likelihood estimator for ζ is not unique, since the likelihood is constant in ζ over the intervals $[Y_{(r)}, Y_{(r+1)})$, where $Y_{(1)} < \dots < Y_{(r)} < \dots < Y_{(n)}$ are the order statistics of Y . For this reason, we only need to consider ζ at the values of the Y order statistics.

The estimators are obtained in the following way: For fixed ζ , we maximize the fully nonparametric log-likelihood over ψ , to obtain the profile log-likelihood $pL_n(\zeta) \equiv \sup_\psi \tilde{L}_n(\psi, \zeta)$. We then maximize $pL_n(\zeta)$ over ζ , to obtain $\hat{\zeta}_n$; and then compute $\hat{\psi}_n = \operatorname{argmax}_\psi \tilde{L}_n(\psi, \hat{\zeta}_n)$. This yields the NPMLE $\hat{\theta}_n = (\hat{\psi}_n, \hat{\zeta}_n)$. Hence we obtain an estimator for A_0 but not for a_0 .

4. Consistency. To study consistency, we first characterize the NPMLE $\hat{\theta}_n$. Consider the following one-dimensional submodels for A :

$$t \mapsto A_t \equiv \int_0^{(\cdot)} (1 + tg(s))dA(s),$$

where g is an arbitrary non-negative bounded function. A score function for A , defined as the derivative of $\tilde{L}_n(\xi, A_t)$ with respect to t at $t = 0$, is

$$(6) \mathbb{P}_n \left\{ \delta g(X) - \left[\dot{G}(H^\theta(V)) - \delta \frac{\ddot{G}(H^\theta(V))}{\dot{G}(H^\theta(V))} \right] \int_0^\tau \tilde{Y}(s)e^{r_\xi(s; Z, Y)} g(s) dA(s) \right\},$$

where $H^\theta(t) \equiv \int_0^t \tilde{Y}(s)e^{r_\xi(s; Z, Y)} dA(s)$. For any fixed ξ , let $\hat{A}_\xi$ denote the maximizer of $A \mapsto \tilde{L}_n(\xi, A)$, and let $\hat{\theta}_\xi \equiv (\xi, \hat{A}_\xi)$. Then the score function (6) is equal to zero when evaluated at $\hat{\theta}_\xi$. We select $g(u) = \mathbf{1}\{u \leq t\}$, insert this into (6), and equate the resulting expression to zero. Hence $\hat{A}_\xi(u) =$

$$(7) \quad \int_0^u \left(\mathbb{P}_n \left[\tilde{Y}(s)e^{r_\xi(s; Z, Y)} \left(\dot{G}\{H^{\hat{\theta}_\xi}(V)\} - \delta \frac{\ddot{G}\{H^{\hat{\theta}_\xi}(V)\}}{\dot{G}\{H^{\hat{\theta}_\xi}(V)\}} \right) \right] \right)^{-1} \mathbb{P}_n\{dN(s)\} \\ \equiv \int_0^u \{\mathbb{P}_n W(s; \hat{\theta}_\xi)\}^{-1} \mathbb{P}_n\{dN(s)\}.$$

Now the profile likelihood has the form $pL_n(\zeta) = \operatorname{argmax}_{\gamma} \tilde{L}_n((\gamma, \hat{A}_{(\gamma, \zeta)}), \zeta)$.

The above characterization facilitates the following consistency results:

LEMMA 2. *Under the regularity conditions of section 2, the transformation model with a covariate threshold change-point is identifiable.*

LEMMA 3. *Under the regularity conditions of section 2, $\hat{A}_n$ is asymptotically bounded, and thus the NPMLE $\hat{\theta}_n$ exists.*

Using these results, we can establish the uniform consistency of $\hat{\theta}_n$:

THEOREM 1. *Under the regularity conditions of section 2, $\hat{\theta}_n$ converges outer almost surely to θ_0 in the uniform norm.*

5. Score and information operators for regular parameters. In this section, we derive the score and information operators for the collected parameters ψ . We refer to these parameters as the regular parameters because, as we will see in section 6, these parameters converge at the $\sqrt{n}$ rate. On the other hand, $\hat{\zeta}_n$ converges at the n rate and thus the parameter ζ is not regular. The score and information operators for ψ are needed for the convergence rate and weak limit results of sections 6 and 7.

Let $\mathcal{H}$ denote the space of the elements $h = (h_1, h_2, h_3, h_4)$ such that $h_1 \in \mathbb{R}$, $h_2 \in \mathbb{R}^q$, $h_3 \in \mathbb{R}^d$, and $h_4 \in D[0, \tau]$, where $D[0, \tau]$ is the space of cadlag functions (right-continuous with left-hand limits) on $[0, \tau]$. We denote by BV the subspace of $D[0, \tau]$ consisting of functions that are of bounded variation over the interval $[0, \tau]$. Define, for future use, the following linear functional for each $\theta = (\psi, \zeta)$ and each $t \in [0, \tau]$:

$$(8) \quad R_{\zeta, \psi}^t(f) \equiv \int_0^t f(u) \tilde{Y}(u) e^{r_{\zeta}(u; Z, Y)} dA(u),$$

where f is an element or vector of elements in BV . Also let $\rho_1(h) \equiv (|h_1|^2 + \|h_2\|^2 + \|h_3\|^2 + \|h_4\|_v^2)^{1/2}$ and $\mathcal{H}_r \equiv \{h \in \mathcal{H} : \rho_1(h) \leq r\}$, where $\|\cdot\|_v$ is the total variation norm on BV and $r \in (0, \infty)$.

The parameter $\psi \in \Psi \equiv \Upsilon \times B_2 \times B_1 \times \mathcal{A}$ can be considered a linear functional on $\mathcal{H}_r$ by defining $\psi(h) \equiv h_1\alpha + h_2'\eta + h_3'\beta + \int_0^\tau h_4(u) dA(u)$, $h \in \mathcal{H}_r$. Viewed this way, Ψ is a subset of $\ell^\infty(\mathcal{H}_r)$ with uniform norm $\|\psi\|_{(r)} \equiv \sup_{h \in \mathcal{H}_r} |\psi(h)|$, where $\ell^\infty(B)$ is the space of bounded functionals on B . Note that $\mathcal{H}_1$ is rich enough to extract all components of ψ . This is easy to see for the Euclidean components; and, for the A component, it works by using the elements $\{h : h_1 = 0, h_2 = 0, h_3 = 0, h_4(u) = \mathbf{1}\{u \leq t\}, t \in [0, \tau]\} \subset \mathcal{H}_1$.

In section 5.1, we derive the score operator; while in section 5.2 we derive the information operator and establish its continuous invertibility.

5.1. *The score operator.* Using the one-dimensional submodel

$$t \rightarrow \psi_t \equiv \psi + t(h_1, h_2, h_3, \int_0^{(\cdot)} h_4(u) dA(u)), \quad h \in \mathcal{H}_r,$$

the score operator takes the form

$$U_{n\zeta}^\tau(\psi)(h) \equiv \frac{\partial}{\partial t} L_n(\psi_t, \zeta) \Big|_{t=0} = \mathbb{P}_n U_\zeta^\tau(\psi)(h),$$

where $U_\zeta^\tau(\psi)(h) \equiv U_{\zeta,1}^\tau(\psi)(h_1) + U_{\zeta,2}^\tau(\psi)(h_2) + U_{\zeta,3}^\tau(\psi)(h_3) + U_{\zeta,4}^\tau(\psi)(h_4)$,

$$\begin{aligned} U_{\zeta,1}^\tau(\psi)(h_1) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \int_0^\tau h_1 dN(u) - \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(h_1) \right\}, \\ U_{\zeta,2}^\tau(\psi)(h_2) &\equiv \mathbf{1}(Y > \zeta) \left\{ \int_0^\tau Z'_2(u) h_2 dN(u) - \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z'_2 h_2) \right\}, \\ U_{\zeta,3}^\tau(\psi)(h_3) &\equiv \int_0^\tau Z'(u) h_3 dN(u) - \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z' h_3), \\ U_{\zeta,4}^\tau(\psi)(h_4) &\equiv \int_0^\tau h_4(u) dN(u) - \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(h_4), \\ \hat{\Xi}_\theta^{(0)}(\tau) &\equiv \mathbf{1}\{Y \leq \zeta\} \hat{\Xi}_{\psi,1}^{(0)}(\tau) + \mathbf{1}\{Y > \zeta\} \hat{\Xi}_{\psi,2}^{(0)}(\tau), \end{aligned}$$

and where, for $j = 1, 2$,

$$\hat{\Xi}_{\psi,j}^{(0)}(\tau) \equiv \left[\dot{G}(H_j^\psi(V \wedge \tau)) - \delta \frac{\ddot{G}(H_j^\psi(V \wedge \tau))}{\dot{G}(H_j^\psi(V \wedge \tau))} \right].$$

The dependence in the notation on τ will prove useful in later developments.

5.2. *The information operator.* To obtain the information operator, we can differentiate the expectation of the score operator using the map $t \rightarrow \psi + t\psi_1$, where $\psi, \psi_1 \in \Psi$. The information operator, $\sigma_\theta : \mathcal{H}_\infty \rightarrow \mathcal{H}_\infty$, where $\mathcal{H}_\infty \equiv \{h : h \in \mathcal{H}_r \text{ for some } r < \infty\}$, satisfies

$$(9) \quad \psi_1(\sigma_\theta(h)) = -\frac{\partial}{\partial t} P U_\zeta^\tau(\psi + t\psi_1)(h) \Big|_{t=0},$$

for every $h \in \mathcal{H}_\infty$. Taking the Gâteaux derivative in (9), we obtain $\sigma_\theta(h) =$

$$(10) \quad \begin{pmatrix} \sigma_\theta^{11} & \sigma_\theta^{12} & \sigma_\theta^{13} & \sigma_\theta^{14} \\ \sigma_\theta^{21} & \sigma_\theta^{22} & \sigma_\theta^{23} & \sigma_\theta^{24} \\ \sigma_\theta^{31} & \sigma_\theta^{32} & \sigma_\theta^{33} & \sigma_\theta^{34} \\ \sigma_\theta^{41} & \sigma_\theta^{42} & \sigma_\theta^{43} & \sigma_\theta^{44} \end{pmatrix} \begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{pmatrix} \equiv P \begin{pmatrix} \hat{\sigma}_\theta^{11} & \hat{\sigma}_\theta^{12} & \hat{\sigma}_\theta^{13} & \hat{\sigma}_\theta^{14} \\ \hat{\sigma}_\theta^{21} & \hat{\sigma}_\theta^{22} & \hat{\sigma}_\theta^{23} & \hat{\sigma}_\theta^{24} \\ \hat{\sigma}_\theta^{31} & \hat{\sigma}_\theta^{32} & \hat{\sigma}_\theta^{33} & \hat{\sigma}_\theta^{34} \\ \hat{\sigma}_\theta^{41} & \hat{\sigma}_\theta^{42} & \hat{\sigma}_\theta^{43} & \hat{\sigma}_\theta^{44} \end{pmatrix} \begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{pmatrix}$$

$\equiv P\hat{\sigma}_\theta(h)$, where

$$\begin{aligned}
\hat{\sigma}_\theta^{11}(h_1) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) + \hat{\Xi}_\theta^{(1)}(\tau) H_2^\psi(V \wedge \tau) \right\} R_{\zeta,\psi}^\tau(h_1), \\
\hat{\sigma}_\theta^{12}(h_2) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) + \hat{\Xi}_\theta^{(1)}(\tau) H_2^\psi(V \wedge \tau) \right\} R_{\zeta,\psi}^\tau(Z'_2 h_2), \\
\hat{\sigma}_\theta^{13}(h_3) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) + \hat{\Xi}_\theta^{(1)}(\tau) H_2^\psi(V \wedge \tau) \right\} R_{\zeta,\psi}^\tau(Z' h_3), \\
\hat{\sigma}_\theta^{14}(h_4) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) + \hat{\Xi}_\theta^{(1)}(\tau) H_2^\psi(V \wedge \tau) \right\} R_{\zeta,\psi}^\tau(h_4), \\
\hat{\sigma}_\theta^{21}(h_1) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z_2 h_1) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z_2) R_{\zeta,\psi}^\tau(h_1) \right\} \\
\hat{\sigma}_\theta^{22}(h_2) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z_2 Z'_2 h_2) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z_2) R_{\zeta,\psi}^\tau(Z'_2 h_2) \right\}, \\
\hat{\sigma}_\theta^{23}(h_3) &\equiv \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z_2 Z' h_3) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z_2) R_{\zeta,\psi}^\tau(Z' h_3), \\
\hat{\sigma}_\theta^{24}(h_4) &\equiv \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z_2 h_4) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z_2) R_{\zeta,\psi}^\tau(h_4), \\
\hat{\sigma}_\theta^{31}(h_1) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z h_1) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z) R_{\zeta,\psi}^\tau(h_1) \right\}, \\
\hat{\sigma}_\theta^{32}(h_2) &\equiv \mathbf{1}\{Y > \zeta\} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z Z'_2 h_2) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z) R_{\zeta,\psi}^\tau(Z'_2 h_2) \right\}, \\
\hat{\sigma}_\theta^{33}(h_3) &\equiv \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z Z' h_3) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z) R_{\zeta,\psi}^\tau(Z' h_3), \\
\hat{\sigma}_\theta^{34}(h_4) &\equiv \hat{\Xi}_\theta^{(0)}(\tau) R_{\zeta,\psi}^\tau(Z h_4) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z) R_{\zeta,\psi}^\tau(h_4), \\
\hat{\sigma}_\theta^{41}(h_1)(u) &\equiv \mathbf{1}\{Y > \zeta\} \tilde{Y}(u) e^{r\varepsilon(u;Z,Y)} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) h_1 + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(h_1) \right\}, \\
\hat{\sigma}_\theta^{42}(h_2)(u) &\equiv \mathbf{1}\{Y > \zeta\} \tilde{Y}(u) e^{r\varepsilon(u;Z,Y)} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) Z'_2(u) h_2 + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z'_2 h_2) \right\}, \\
\hat{\sigma}_\theta^{43}(h_3)(u) &\equiv \tilde{Y}(u) e^{r\varepsilon(u;Z,Y)} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) Z'(u) h_3 + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(Z' h_3) \right\}, \\
\hat{\sigma}_\theta^{44}(h_4)(u) &\equiv \tilde{Y}(u) e^{r\varepsilon(u;Z,Y)} \left\{ \hat{\Xi}_\theta^{(0)}(\tau) h_4(u) + \hat{\Xi}_\theta^{(1)}(\tau) R_{\zeta,\psi}^\tau(h_4) \right\},
\end{aligned}$$

and where

$$\hat{\Xi}_\theta^{(1)}(\tau) \equiv \ddot{G}(H^\theta(V \wedge \tau)) - \delta \left[\frac{\ddot{G}(H^\theta(V \wedge \tau))}{\dot{G}(H^\theta(V \wedge \tau))} - \left\{ \frac{\ddot{G}(H^\theta(V \wedge \tau))}{\dot{G}(H^\theta(V \wedge \tau))} \right\}^2 \right].$$

Note that all the above operators are bounded whenever θ is bounded.

The following lemma strengthens the above Gâteaux derivative to a Fréchet derivative. We will need this strong differentiability to obtain weak convergence of our estimators.

LEMMA 4. *Under the regularity conditions of section 2 and for any $\zeta \in [a, b]$ and $\psi_1 \in \Psi$, the operator $\psi \mapsto PU_\zeta^\tau(\psi)$ is Fréchet differentiable at ψ_1 , with derivative $-\psi(\sigma_{\psi_1}(h))$, where h ranges over $\mathcal{H}_r$ and is the index for $P_\zeta^\tau(\psi)(\cdot)$, ψ ranges over the linear span $\text{lin } \Psi$ of Ψ , and $0 < r < \infty$.*

The following lemma gives us the desired continuous invertibility of both σ_{θ_0} and the operator $\psi \mapsto \psi(\sigma_{\theta_0}(\cdot))$. This last operator will be needed for weak convergence of regular parameters.

LEMMA 5. *Under the regularity conditions of section 2, the linear operator $\sigma_{\theta_0} : \mathcal{H}_\infty \rightarrow \mathcal{H}_\infty$ is continuously invertible and onto, with inverse $\sigma_{\theta_0}^{-1}$. Moreover, the linear operator $\psi \mapsto \psi(\sigma_{\theta_0}(\cdot))$, as a map from and to $\text{lin } \Psi$, is also continuously invertible and onto, with inverse $\psi \mapsto \psi(\sigma_{\theta_0}^{-1}(\cdot))$.*

6. The convergence rates of the estimators. To determine the convergence rates of the estimators, we need to study closely the log-likelihood process $\tilde{L}_n(\theta)$ near its maximizer. In the parametric setting, this process can be approximated by its expectation which can be shown to be locally concave. For the Cox model, as in [28], this same procedure can be applied to the partial likelihood which shares the local concavity features of a parametric likelihood. Unfortunately, in our present set-up, studying the expectation of $\tilde{L}_n(\theta)$ will lead to problems since A_0 has a density and thus $\Delta A_0(t) = 0$ for all $t \in [0, \tau]$. Hence $\tilde{L}_n(\theta_0) = -\infty$, and a new approach is needed. The approach we take involves a careful reparameterization of $\hat{A}_n$.

From section 4, we know that the maximizer $\hat{A}_n(t) = \int_0^t \left\{ \mathbb{P}_n W(s; \hat{\theta}_n) \right\}^{-1} \times d\tilde{G}_n(s)$, where $\tilde{G}_n(t) \equiv \mathbb{P}_n N(t)$ and $W(\cdot; \cdot)$ is as defined in (7). It is easy to see that for all n large enough and all θ sufficiently close to θ_0 , $t \mapsto \mathbb{P}_n W(t; \theta)$ is bounded below and above and in total variation, with large probability. Thus, if we use the reparameterization $\Gamma(\cdot) \mapsto A_n^{(\Gamma)}(\cdot) \equiv \int_0^{(\cdot)} \exp\{-\Gamma(s)\} d\tilde{G}_n(s)$, and maximize $\tilde{L}_n(\xi, A_n^{(\Gamma)})$ over ξ and Γ , where $\Gamma \in BV$, we will achieve the same NPMLE as before. Note that the Γ component of the maximizer of $\tilde{L}(\xi, A_n^{(\Gamma)})$ is therefore just $\hat{\Gamma}_n(\cdot) \equiv -\log \mathbb{P}_n W(\cdot; \hat{\theta}_n)$.

Define $\Gamma_0(\cdot) \equiv -\log(PW(\cdot; \theta_0))$ and $\theta_n(\zeta, \gamma, \Gamma) \equiv (\zeta, \gamma, A_n^{(\Gamma)})$, and note that the reparameterized NPMLE $(\hat{\zeta}_n, \hat{\gamma}_n, \hat{\Gamma}_n)$ is the maximizer of the process

$$\begin{aligned} (\zeta, \gamma, \Gamma) \mapsto \tilde{X}_n(\zeta, \gamma, \Gamma) &\equiv \tilde{L}_n(\zeta, \gamma, A_n^{(\Gamma)}) - \tilde{L}_n(\zeta_0, \gamma_0, A_n^{(\Gamma_0)}) \\ &= \mathbb{P}_n \left\{ \int_0^\tau \left[-\Gamma(t) + \Gamma_0(t) + \log \frac{\dot{G}(H^{\theta_n(\zeta, \gamma, \Gamma)}(t))}{\dot{G}(H^{\theta_n(\zeta_0, \gamma_0, \Gamma_0)}(t))} + (r_\xi - r_{\xi_0})(t; Z, Y) \right] \right. \\ &\quad \left. \times dN(t) - (G(H^{\theta_n(\zeta, \gamma, \Gamma)}(V)) - G(H^{\theta_n(\zeta_0, \gamma_0, \Gamma_0)}(V))) \right\}. \end{aligned}$$

We will argue shortly that $\tilde{X}_n$ is uniformly consistent for the function

$$\begin{aligned} (\zeta, \gamma, \Gamma) \mapsto \tilde{X}(\zeta, \gamma, \Gamma) \equiv \\ P \left\{ \int_0^\tau \left[-\Gamma(t) + \Gamma_0(t) + \log \frac{\dot{G}(H^{\theta_0(\zeta, \gamma, \Gamma)}(t))}{\dot{G}(H^{\theta_0}(t))} + (r_\xi - r_{\xi_0})(t; Z, Y) \right] dN(t) \right. \\ \left. - (G(H^{\theta_0(\zeta, \gamma, \Gamma)}(V)) - G(H^{\theta_0}(V))) \right\}, \end{aligned}$$

where $\theta_0(\zeta, \gamma, \Gamma) \equiv (\zeta, \gamma, A_0^{(\Gamma)})$, $A_0^{(\Gamma)}(\cdot) \equiv \int_0^{(\cdot)} \exp\{-\Gamma(s)\} d\tilde{G}_0(s)$, and $\tilde{G}_0(t) \equiv PN(t)$. It will occasionally be useful to use the shorthand $\lambda \equiv (\gamma, \Gamma)$, $\hat{\lambda}_n \equiv (\hat{\gamma}_n, \hat{\Gamma}_n)$ and $\lambda_0 \equiv (\gamma_0, \Gamma_0)$.

Define the modified parameter space $\Theta^* \equiv (a, b) \times \Upsilon \times B_2 \times B_1 \times BV$; and, for each $h = (h_1, h_2, h_3, h_4, h_5) \in \mathbb{R} \times \mathcal{H}_\infty$, define the metric $\rho_2(h) \equiv (|h_1| + |h_2|^2 + \|h_3\|^2 + \|h_4\|^2 + \|h_5\|_\infty^2)^{1/2}$, where $\|\cdot\|_\infty$ is the uniform norm. Note that $|h_1|$ is deliberately not squared. For each $\epsilon > 0$ and $k < \infty$, define $B_\epsilon^{*k} \equiv \{(\zeta, \lambda) \in \Theta^* : \rho_2((\zeta, \lambda) - (\zeta_0, \lambda_0)) < \epsilon, \|\Gamma\|_v \leq k\}$. Note that for some $k_0 < \infty$ and any $\epsilon > 0$, $(\hat{\zeta}_n, \hat{\lambda}_n)$ is eventually in $B_\epsilon^{*k_0}$ for all n large enough by theorem 1 above combined with lemma 6 below:

LEMMA 6. *There exists a $k_0 < \infty$ such that $\limsup_{n \rightarrow \infty} \|\hat{\Gamma}_n\|_v \leq k_0$ and $\lim_{n \rightarrow \infty} \|\hat{\Gamma}_n - \Gamma_0\|_\infty = 0$ outer almost surely.*

Now we study the local behavior of $\tilde{X}$. First fix $\zeta \in (a, b)$. Since, for any $g \in BV$, $\partial A_0^{(\Gamma+tg)}(\cdot)/(\partial t)|_{t=0} = -\int_0^{(\cdot)} g(s) dA_0^{(\Gamma)}(s)$, we obtain that the first derivative of $(\gamma, \Gamma) \mapsto \tilde{X}(\zeta, \gamma, \Gamma)$ in the direction $h \in \mathcal{H}_\infty$, is precisely $-PU_\zeta^\tau(\gamma, A_0^{(\Gamma)})(h)$. Moreover, by definition of the score and information op-

erators, the second derivative in the same direction is $-\psi_\Gamma^h \left(\sigma_{(\zeta, \gamma, A_0^{(\Gamma)})}(h) \right)$,

where $\psi_\Gamma^h \equiv (h_1, h_2, h_3, \int_0^{(\cdot)} h_4(s) dA_0^{(\Gamma)}(s))$. At the point $(\zeta, \gamma, \Gamma) = (\zeta_0, \gamma_0, \Gamma_0)$, the first derivative is 0, while the second derivative is < 0 , by lemma 5. By the smoothness of the score and information operators ensured by condition D1 and D2, and by the arbitrariness of h , we now have that the function $(\gamma, \Gamma) \mapsto \tilde{X}(\zeta, \gamma, \Gamma)$ is concave for all $(\zeta, \gamma, \Gamma) \in B_\epsilon^{*k_0}$, for small enough ϵ .

Now note that $\tilde{X}(\zeta, \gamma, \Gamma) = Pl^*(\zeta, \gamma, \Gamma) - Pl^*(\zeta_0, \gamma_0, \Gamma_0)$, where $l^*(\zeta, \gamma, \Gamma) \equiv$

$$(11) \quad - \int_0^\tau \Gamma(t) dN(t) + l_1^{\psi(\gamma, \Gamma)}(V, \delta, Z) \mathbf{1}\{Y \leq \zeta\} + l_2^{\psi(\gamma, \Gamma)}(V, \delta, Z) \mathbf{1}\{Y > \zeta\},$$

and where l_j^ψ , $j = 1, 2$, are as defined in section 3, and $\psi(\gamma, \Gamma) \equiv (\gamma, A_0^{(\Gamma)})$. By condition B2, we now have that for small enough $\epsilon > 0$, $\zeta \mapsto \tilde{X}(\zeta, \gamma, \Gamma)$

is right and left continuously differentiable for all $(\zeta, \gamma, \Gamma) \in B_{\epsilon}^{*k_0}$, with left partial derivative $\dot{X}_{\zeta}^{-}(\gamma, \Gamma) \equiv P \left\{ l_1^{\psi(\gamma, \Gamma)}(V, \delta, Z) - l_2^{\psi(\gamma, \Gamma)}(V, \delta, Z) \middle| Y = \zeta \right\}$ and right partial $\dot{X}_{\zeta}^{+}(\gamma, \Gamma) \equiv P \left\{ l_1^{\psi(\gamma, \Gamma)}(V, \delta, Z) - l_2^{\psi(\gamma, \Gamma)}(V, \delta, Z) \middle| Y = \zeta + \right\}$.

We now have the following lemmas on the local behavior of $\tilde{X}$ over ζ :

LEMMA 7. $\dot{X}_{\zeta_0}^{-}(\gamma_0, \Gamma_0) > 0$ and $\dot{X}_{\zeta_0}^{+}(\gamma_0, \Gamma_0) < 0$.

LEMMA 8. *There exists $\epsilon_1, k_1 > 0$ such that $\tilde{X}(\zeta, \gamma, \Gamma) \leq -k_1|\zeta - \zeta_0|$ for all $(\zeta, \gamma, \Gamma) \in B_{\epsilon_1}^{*k_0}$.*

To these lemmas we add lemma 9 below to obtain $\sqrt{n}$ consistency:

LEMMA 9. *There exists an $\epsilon_2 > 0$ such that $D_n \equiv \sqrt{n}(\tilde{X}_n - \tilde{X})$ converges weakly to a tight mean zero Gaussian process D_0 , in $\ell^\infty(B_{\epsilon_2}^{*k_0})$, for which $D_0(\zeta, \gamma, \Gamma) \rightarrow 0$ in probability, as $\rho_2((\zeta, \gamma, \Gamma) - (\zeta_0, \gamma_0, \Gamma_0)) \rightarrow 0$.*

THEOREM 2. $\sqrt{n}|\hat{\zeta}_n - \zeta_0| = O_P(1)$, $\sqrt{n}\|\hat{\psi}_n - \psi_0\|_\infty = O_P(1)$, and $\sqrt{n}\|\hat{\Gamma}_n - \Gamma_0\|_\infty = O_P(1)$.

To refine the rate for $\hat{\zeta}_n$, we need two additional lemmas, lemmas 10 and 11 below.

LEMMA 10. $0 \leq \tilde{X}_n(\hat{\zeta}_n, \hat{\lambda}_n) - \tilde{X}_n^*(\hat{\zeta}_n) \leq O_P(n^{-1})$, where $\zeta \mapsto \tilde{X}_n^*(\zeta) \equiv$

$$\mathbb{P}_n \left\{ \int_0^\tau \left[\log \frac{\dot{G}(H^{\theta_0(\zeta, \gamma_0, \Gamma_0)}(t))}{\dot{G}(H^{\theta_0}(t))} + (r_{(\zeta, \gamma_0)} - r_{\xi_0})(t; Z, Y) \right] dN(t) - (G(H^{\theta_0(\zeta, \gamma_0, \Gamma_0)}(V)) - G(H^{\theta_0}(V))) \right\}.$$

LEMMA 11. *There exists an $\epsilon_3 > 0$ and $k_2 < \infty$ such that, for all $0 \leq \epsilon \leq \epsilon_3$ and $n \geq 1$, $E \left[\sup_{|\zeta - \zeta_0| \leq \epsilon} |\tilde{D}_n(\zeta)| \right] \leq k_2 \sqrt{\epsilon}$, where $\tilde{D}_n(\zeta) \equiv \sqrt{n}(\tilde{X}_n^*(\zeta) - \tilde{X}(\zeta, \lambda_0))$.*

THEOREM 3. $n|\hat{\zeta}_n - \zeta_0| = O_P(1)$.

Proof. The method of proof involves a “peeling device” (see, for example, the proof of theorem 5.1 of [15], or the proof of theorem 2 of [28]). Fix $\epsilon > 0$. By consistency and lemma 6, $P((\hat{\zeta}_n, \hat{\lambda}_n) \in B_{\epsilon_4}^{*k_0}) \geq 1 - \epsilon$ for all n large enough, where $\epsilon_4 = \epsilon_1 \wedge \epsilon_2 \wedge \epsilon_3$. By lemma 10, there exists an $M_1^* < \infty$ such

that $P(\tilde{X}_n(\hat{\zeta}_n, \hat{\lambda}_n) - \tilde{X}_n^*(\hat{\zeta}_n) > M_1^*/n) \leq \epsilon$. For integers $k \geq 1$, let $m_k \equiv k^4$. We now have, for any integer $k \geq 1$, that $\limsup_{n \rightarrow \infty} P(n|\hat{\zeta}_n - \zeta_0| > m_k)$

$$\begin{aligned}
&\leq \limsup_{n \rightarrow \infty} P\left(n|\hat{\zeta}_n - \zeta_0| > m_k, (\hat{\zeta}_n, \hat{\lambda}_n) \in B_{\epsilon_4}^{*k_0}, \right. \\
&\quad \left. \tilde{X}_n(\hat{\zeta}_n, \hat{\lambda}_n) - \tilde{X}_n^*(\hat{\zeta}_n) \leq \frac{M_1^*}{n}\right) + 2\epsilon \\
&\leq \limsup_{n \rightarrow \infty} P\left(\sup_{\zeta: m_k/n < |\zeta - \zeta_0| \leq \epsilon_4} \tilde{X}_n^*(\zeta) \geq -\frac{M_1^*}{n}\right) + 2\epsilon \\
(12) \quad &\leq \limsup_{n \rightarrow \infty} \sum_{j=k}^{k_{\epsilon_4}} P\left(\sup_{\zeta: m_j/n < |\zeta - \zeta_0| \leq (m_{j+1}/n) \wedge \epsilon_4} \tilde{D}_n(\zeta) \right. \\
&\quad \left. \geq \sqrt{n} \left(\frac{k_1 m_j}{n} - \frac{M_1^*}{n}\right)\right) + 2\epsilon,
\end{aligned}$$

by lemma 8, where $k_{\epsilon_4} = \min\{k : m_{k+1} \geq n\epsilon_4\}$. But, by lemma 11,

$$(12) \leq \limsup_{n \rightarrow \infty} \sum_{j=k}^{k_{\epsilon_4}} \frac{k_2 \sqrt{m_{j+1}}}{k_1 m_j - M_1^*} + 2\epsilon \leq \sum_{j=k}^{\infty} \frac{k_2 (j+1)^2}{k_1 j^4 - M_1^*} + 2\epsilon.$$

We can now choose $k < \infty$ large enough so that this last term $\leq 3\epsilon$. Since $\epsilon > 0$ was arbitrary, we now have that $\lim_{m \rightarrow \infty} \limsup_{n \rightarrow \infty} P(n|\hat{\zeta}_n - \zeta_0| > m) = 0$, and the desired conclusion follows. $\square$

7. Weak convergence of the estimators.

7.1. *The asymptotic distribution of the change-point estimator.* Denote $\mathbb{U}_{n,M} \equiv \{u = n(\zeta - \zeta_0) : \zeta \in [a, b], |u| \leq M\}$ and $\zeta_{n,u} \equiv \zeta_0 + u/n$. The limiting distribution of $n(\hat{\zeta}_n - \zeta_0)$ will be deduced from the behavior of the restriction of the process $u \rightarrow n[\tilde{L}_n(\hat{\psi}_n, \zeta_{n,u}) - \tilde{L}_n(\hat{\psi}_n, \zeta_0)]$ to the compact set $\mathbb{U}_{n,M}$, for M sufficiently large.

THEOREM 4. *The following holds for all $M > 0$, as $n \rightarrow \infty$: $u \mapsto n[\tilde{L}_n(\hat{\psi}_n, \zeta_{n,u}) - \tilde{L}_n(\hat{\psi}_n, \zeta_0)] = Q_n(u) + o_P^{n,M}(1)$, where $o_P^B(1)$ denotes a term going to zero in probability uniformly over the set B and $Q_n(u) \equiv n\mathbb{P}_n\left\{(\mathbf{1}\{\zeta_{n,u} < Y \leq \zeta_0\} - \mathbf{1}\{\zeta_0 < Y \leq \zeta_{n,u}\}) \left[l_2^{\psi_0}(V, \delta, Z) - l_1^{\psi_0}(V, \delta, Z)\right]\right\}$.*

Let $Q_n(u) = Q_n^+(u)\mathbf{1}\{u > 0\} - Q_n^-(u)\mathbf{1}\{u < 0\}$. We now study the weak convergence of Q_n as a random variable on the space of cadlag functions D with the Skorohod topology, and on its restriction to the space

D_M of cadlag functions on $[-M, M]$, for any $M > 0$, similar to the approach taken in [28]. In order to describe the asymptotic distribution of Q_n , let ν^+ and ν^- be two independent jump processes on $\mathbb{R}$ such that $\nu^+(s)$ is a Poisson variable with parameter $s^+ \tilde{h}(\zeta_0)$ and $\nu^-(s)$ is a Poisson variable with parameter $(-s)^+ \tilde{h}(\zeta_0)$. Here, u^+ denotes $u \vee 0$. Let $(\check{V}_k^+)_{k \geq 1}$ and $(\check{V}_k^-)_{k \geq 1}$ be independent sequences of i.i.d. random variables with characteristic functions $\phi^+(t) = P[e^{it\check{V}_k^+}] = P\left[e^{it\left\{l_1^{\psi_0}(V, \delta, Z) - l_2^{\psi_0}(V, \delta, Z)\right\}} \middle| Y = \zeta_0^+\right]$, and $\phi^-(t) = P[e^{it\check{V}_k^-}] = P\left[e^{it\left\{l_1^{\psi_0}(V, \delta, Z) - l_2^{\psi_0}(V, \delta, Z)\right\}} \middle| Y = \zeta_0\right]$, respectively, where $(\check{V}_k^+)_{k \geq 1}$ and $(\check{V}_k^-)_{k \geq 1}$ are independent of ν^+ and ν^- .

Let $Q(s) = Q^+(s)\mathbf{1}\{s > 0\} - Q^-(s)\mathbf{1}\{s < 0\}$ be a right-continuous jump process with $Q^+(s) = \sum_{0 \leq k \leq \nu^+(s)} \check{V}_k^+$ and $Q^-(s) = \sum_{0 \leq k \leq \nu^-(s)} \check{V}_k^-$, where $\check{V}_0^+ = \check{V}_0^- = 0$. Using a modification of the arguments in [28], we obtain:

THEOREM 5. *Under the regularity conditions of section 2, the process Q_n converges weakly to Q in D_M , for every $M > 0$; $n(\hat{\zeta}_n - \zeta_0) = \operatorname{argmax}_u Q_n(u) + o_p(1)$ which converges weakly to $\hat{v}_Q \equiv \operatorname{argmin}\{|v| : Q(v) = \operatorname{argmax} Q\}$; and $n(\hat{\zeta}_n - \zeta_0)$ and $\sqrt{n}\mathbb{P}_n U_{\zeta_0}^T(\psi_0)(h)$ are asymptotically independent for all $h \in \mathcal{H}_\infty$.*

7.2. Asymptotic normality of the regular parameters. We use Hoffmann-Jørgensen weak convergence as described in [33]. We have the following result:

THEOREM 6. *Under the conditions of theorem 1, $\sqrt{n}(\hat{\psi}_n - \psi_0)$ is asymptotically linear, with influence function $\tilde{l}(h) = U_{\zeta_0}^T(\psi_0)(\sigma_{\theta_0}^{-1}(h))$, $h \in \mathcal{H}_1$, converging weakly in the uniform norm to a tight, mean zero Gaussian process $\mathbb{Z}$ with covariance $E[\tilde{l}(g)\tilde{l}(h)]$, for all $g, h \in \mathcal{H}_1$. Thus $n(\hat{\zeta}_n - \zeta_0)$ and $\sqrt{n}(\hat{\psi}_n - \psi_0)$ are asymptotically independent.*

REMARK 1. *Since $\sqrt{n}(\hat{\psi}_n - \psi_0)$ is asymptotically linear, with influence function contained in the closed linear span of the tangent space (since σ_{θ_0} is continuously invertible), $\hat{\psi}_n$ is regular and hence as efficient as if ζ_0 were known, by Theorem 5.2.3 and Theorem 5.2.1 of [4].*

8. Inference when $\alpha_0 \neq 0$ or $\eta_0 \neq 0$. In this section we develop Monte Carlo methods for inference for the parameter estimators when it is known that either $\alpha_0 \neq 0$ or $\eta_0 \neq 0$, i.e., it is known that condition C2 is satisfied. In section 9, we develop a hypothesis testing procedure to assess

whether $H_0 : \alpha_0 = 0 = \eta_0$ holds (i.e., that C2 does not hold). When it is known that H_0 holds, the model reduces to the usual transformation model (see [31]), and thus validity of the bootstrap will follow from arguments similar to those used in the proof of corollary 1 of [17].

8.1. *Inference for the change-point.* One possibility for inference for ζ is to use the subsampling bootstrap [27] which is guaranteed to work, provided the subsample sizes ℓ_n satisfy $\ell_n \rightarrow \infty$ and $\ell_n/n \rightarrow 0$. However, this approach is very computationally intense since, for each subsample, the likelihood must be maximized over the entire parameter space. To ameliorate the computational strain, we propose as an alternative the following specialized parametric bootstrap. Let $\tilde{F}_+$ and $\tilde{F}_-$ be the distribution functions corresponding to the moment generating functions ϕ^+ and ϕ^- , respectively. We need to make the following additional assumption:

B5: Both $\tilde{F}_+$ and $\tilde{F}_-$ are continuous.

Now let $\tilde{m}_n$ be the minimum of the number of Y observations in the sample $> \hat{\zeta}_n$ and the number of Y observations $< \hat{\zeta}_n$. Now choose sequences of possibly data dependent integers $1 \leq C_{1,n} < C_{2,n} \leq \tilde{m}_n$ such that $C_{1,n} \rightarrow \infty$, $C_{2,n} - C_{1,n} \rightarrow \infty$, and $C_{2,n}/n \rightarrow 0$, in probability, as $n \rightarrow \infty$. Note that if one chooses $C_{1,n}$ to be the closest integer to $\tilde{m}_n^{1/4}$ and $C_{2,n}$ to be the closest integer to $\tilde{m}_n^{3/4}$, the given requirements will be satisfied since $\tilde{m}_n \rightarrow \infty$, in probability, by assumption B1. Let $X_{(1)}, \dots, X_{(n)}$ be the complete data observations corresponding to the order statistics $Y_{(1)}, \dots, Y_{(n)}$ of the Y observations. Also let $\tilde{k}_n \equiv C_{2,n} - C_{1,n} + 1$, and define $\tilde{l}_n$ to be the integer satisfying $\hat{\zeta}_n = Y_{(\tilde{l}_n)}$, whose existence follows from the form of the MLE.

Now, for $j = 1, \dots, \tilde{k}_n$, and any $\psi \in \Psi$, define

$$\begin{aligned} \tilde{V}_{j,\psi}^+ &\equiv l_1^\psi(V_{(\tilde{l}_n+C_{1,n}+j-1)}, \delta_{(\tilde{l}_n+C_{1,n}+j-1)}, Z_{(\tilde{l}_n+C_{1,n}+j-1)}) \\ &\quad - l_2^\psi(V_{(\tilde{l}_n+C_{1,n}+j-1)}, \delta_{(\tilde{l}_n+C_{1,n}+j-1)}, Z_{(\tilde{l}_n+C_{1,n}+j-1)}), \\ \tilde{V}_{j,\psi}^- &\equiv l_1^\psi(V_{(\tilde{l}_n-C_{1,n}-j)}, \delta_{(\tilde{l}_n-C_{1,n}-j)}, Z_{(\tilde{l}_n-C_{1,n}-j)}) \\ &\quad - l_2^\psi(V_{(\tilde{l}_n-C_{1,n}-j)}, \delta_{(\tilde{l}_n-C_{1,n}-j)}, Z_{(\tilde{l}_n-C_{1,n}-j)}), \end{aligned}$$

$Y_j^+ \equiv Y_{(\tilde{l}_n+C_{1,n}+j-1)}$, and $Y_j^- \equiv Y_{(\tilde{l}_n-C_{1,n}-j)}$. Also let $\hat{F}_+^n$ be the data-dependent distribution function for a random variable drawn with replacement from $\{\tilde{V}_{1,\hat{\psi}_n}^+, \dots, \tilde{V}_{\tilde{k}_n,\hat{\psi}_n}^+\}$, and let $\hat{F}_-^n$ be the data-dependent distribution function for a random variable drawn with replacement from $\{\tilde{V}_{1,\hat{\psi}_n}^-, \dots,$

$\check{V}_{\tilde{k}_n, \hat{\psi}_n}^- \}$. By the smoothness of the terms involved, it is easy to verify that both $\sup_{1 \leq j \leq \tilde{k}_n} |\check{V}_{j, \hat{\psi}_n}^+ - \check{V}_{j, \psi_0}^+| = o_P(1)$ and $\sup_{1 \leq j \leq \tilde{k}_n} |\check{V}_{j, \hat{\psi}_n}^- - \check{V}_{j, \psi_0}^-| = o_P(1)$. Moreover, by assumption B2(i), the fact that $n(\hat{\zeta}_n - \zeta_0) = O_P(1)$, and the conditions on $C_{1,n}$ and $C_{2,n}$, we have that both $P(Y_1^- < \zeta_0 < Y_1^+) \rightarrow 1$ and $Y_{\tilde{k}_n}^+ - Y_{\tilde{k}_n}^- = o_P(1)$. Thus, by assumption B2(ii), the collection $\{\check{V}_{1, \psi_0}^+, \dots, \check{V}_{\tilde{k}_n, \psi_0}^+\}$ converges in distribution to an i.i.d. sample of random variables with characteristic function ϕ^+ , while the collection $\{\check{V}_{1, \psi_0}^-, \dots, \check{V}_{\tilde{k}_n, \psi_0}^-\}$ is independent of the first collection and converges in distribution to an i.i.d. sample of random variables with characteristic function ϕ^- . By assumption B5 and the fact that $\tilde{k}_n \rightarrow \infty$, in probability, we now have that both $\sup_{v \in \mathbb{R}} |\hat{F}_+^n(v) - \tilde{F}_+(v)| = o_P(1)$ and $\sup_{v \in \mathbb{R}} |\hat{F}_-^n(v) - \tilde{F}_-(v)| = o_P(1)$.

Now let $\hat{h}_n$ be a consistent estimator of $\tilde{h}(\zeta_0)$. Such an estimator can be obtained from a kernel density estimator of $\tilde{h}$ based on the Y observations and evaluated at $\hat{\zeta}_n$. The basic idea of our parametric bootstrap is to create a stochastic process $\hat{Q}_n$ defined similarly to the process Q described in section 7.1. To this end, let $\hat{\nu}^+$ and $\hat{\nu}^-$ be two independent jump processes defined on the interval $\tilde{B}_n \equiv [-n(\hat{\zeta}_n - a), n(b - \hat{\zeta}_n)]$ such that $\hat{\nu}^+(s)$ is Poisson with parameter $s^+ \hat{h}_n$ and $\hat{\nu}^-(s)$ is Poisson with parameter $(-s)^+ \hat{h}_n$. Also let $(\check{V}_{*,k}^+)_{k \geq 1}$ and $(\check{V}_{*,k}^-)_{k \geq 1}$ be two independent sequences of i.i.d. random variables drawn from $\hat{F}_+^n$ and $\hat{F}_-^n$ and independent of the Poisson processes. Now construct $u \mapsto \hat{Q}_n(u) \equiv \hat{Q}_n^+(u) \mathbf{1}\{u > 0\} - \hat{Q}_n^-(u) \mathbf{1}\{u < 0\}$ on the interval $\tilde{B}_n$, where $\hat{Q}_n^+(u) \equiv \sum_{0 \leq k \leq \hat{\nu}^+(u)} \check{V}_{*,k}^+$ and $\hat{Q}_n^-(u) \equiv \sum_{0 \leq k \leq \hat{\nu}^-(u)} \check{V}_{*,k}^-$. Finally, we compute $\hat{v}_* \equiv \operatorname{argmin}_{\tilde{B}_n} \left\{ |v| : \hat{Q}_n(v) = \operatorname{argmax}_{\tilde{B}_n} \hat{Q}_n \right\}$. The next proposition follows since $P(K \in \tilde{B}_n) \rightarrow 1$ for all compact $K \subset \mathbb{R}$:

PROPOSITION 1. *The conditional distribution of $\hat{v}_*$ given the data is asymptotically equal to the distribution of $\hat{v}_Q$ defined in theorem 5.*

8.2. Inference for regular parameters. Because $\hat{\zeta}_n$ is n -consistent for ζ_0 , ζ_0 can be treated as known in constructing inference for the regular parameters. Accordingly, we propose bootstrapping the likelihood and maximizing over ψ while holding ζ fixed at $\hat{\zeta}_n$. This will significantly reduce the computational demands of the bootstrap. Also, to avoid the occurrence of ties during resampling, we suggest the following weighted bootstrap alternative to the usual nonparametric bootstrap. First generate n i.i.d. positive random variables $\kappa_1, \dots, \kappa_n$, with mean $0 < \mu_\kappa < \infty$, variance $0 < \sigma_\kappa^2 < \infty$, and with $\int_0^\infty \sqrt{P(\kappa_1 > u)} du < \infty$. Divide each weight by the sample average of

the weights $\bar{\kappa}$, to obtain “standardized weights” $\kappa_1^\circ, \dots, \kappa_n^\circ$ which sum to n . For a real, measurable function f , define the weighted empirical measure $\mathbb{P}_n^\circ f \equiv n^{-1} \sum_{i=1}^n \kappa_i^\circ f(X_i)$. Recall that the nonparametric bootstrap empirical measure $\mathbb{P}_n^\bullet f \equiv n^{-1} \sum_{i=1}^n \kappa_i^\bullet f(X_i)$ uses multinomial weights $\kappa_1^\bullet, \dots, \kappa_n^\bullet$, where $E[\kappa_i^\bullet] = 1$, $i = 1, \dots, n$, and $\sum_{i=1}^n \kappa_i^\bullet = n$ almost surely.

The proposed weighted bootstrap estimate $\hat{\psi}_n^\circ$ is obtained by maximizing $\tilde{L}_n^\circ(\psi, \hat{\zeta}_n)$ over $\psi \in \Psi$, where $\tilde{L}_n^\circ$ is obtained by replacing $\mathbb{P}_n$ with $\mathbb{P}_n^\circ$ in the definition of $\tilde{L}_n$ from section 3. We can similarly define a modified nonparametric bootstrap $\hat{\psi}_n^\bullet$ as the argmax of $\psi \mapsto \tilde{L}_n^\bullet(\psi, \hat{\zeta}_n)$, where $\tilde{L}_n^\bullet$ is obtained by replacing $\mathbb{P}_n$ with $\mathbb{P}_n^\bullet$ in the definition of $\tilde{L}_n$. The following corollary establishes the validity of both kinds of bootstraps:

COROLLARY 1. *Under the conditions of theorem 6, the conditional bootstrap of $\hat{\psi}_n$, based on either $\hat{\psi}_n^\bullet$ or $\hat{\psi}_n^\circ$, is asymptotically consistent for the limiting distribution $\mathbb{Z}$ in the following sense: Both $\sqrt{n}(\hat{\psi}_n^\bullet - \hat{\psi}_n)$ and $\sqrt{n}(\mu_\kappa/\sigma_\kappa)(\hat{\psi}_n^\circ - \hat{\psi}_n)$ are asymptotically measurable, and both*

$$\begin{aligned} (i) \quad & \sup_{g \in BL_1} \left| E_\bullet g \left(\sqrt{n}(\hat{\psi}_n^\bullet - \hat{\psi}_n) \right) - Eg(\mathbb{Z}) \right| \rightarrow 0 \text{ and} \\ (ii) \quad & \sup_{g \in BL_1} \left| E_\circ g \left(\sqrt{n}(\mu_\kappa/\sigma_\kappa)(\hat{\psi}_n^\circ - \hat{\psi}_n) \right) - Eg(\mathbb{Z}) \right| \rightarrow 0, \end{aligned}$$

in outer probability, where BL_1 is the space of functions mapping $\mathbb{R}^{d+q+1} \times \ell^\infty[0, \tau] \mapsto \mathbb{R}$ which are bounded in absolute value by 1 and have Lipschitz norm ≤ 1 . Here, $E_\bullet$ and $E_\circ$ are expectations that are taken over the multinomial and standardized weights, respectively, conditional on the data.

9. Test for the presence of a change-point. Constructing a valid test of the null hypothesis that there is no change-point, $H_0 : \alpha_0 = 0 = \eta_0$, poses an interesting challenge. Since the location of the change-point is no longer identifiable under H_0 , this is an example of the issue studied in [1]. The test statistic we propose is a functional of the α and η components of the score process, $\zeta \mapsto \hat{S}_1(\zeta) \equiv \sqrt{n} \mathbb{P}_n(U_{\zeta,1}^\tau(\hat{\psi}_0), U_{\zeta,2}^\tau(\hat{\psi}_0)')'$, where $\zeta \in [a, b]$, $\hat{\psi}_0 \equiv (0, 0, \hat{\beta}_0, \hat{A}_0)$, and where $(\hat{\beta}_0, \hat{A}_0)$ is the restricted MLE of (β_0, A_0) under the assumption that $\alpha = 0$ and $\eta = 0$. This MLE is relatively easy to compute since estimation of ζ is not needed. Specifically, we have from section 3, that $\hat{\psi}_0$ is the maximizer of

$$(13) \quad \psi \mapsto \mathbb{P}_n \left\{ \delta \log(n\Delta A(V)) + l_1^\psi(V, \delta, Z) \right\}.$$

We also define for future use $h \mapsto \hat{S}_2(h) \equiv \sqrt{n} \mathbb{P}_n(U_{\zeta,3}^\tau(\hat{\psi}_0)(h_3), U_{\zeta,4}^\tau(\hat{\psi}_0)(h_4))'$, where $h \in \mathcal{H}_1$. The statistic we propose using is $\hat{T}_n \equiv \sup_{\zeta \in [a,b]} \left\{ \hat{S}_1'(\zeta) \hat{V}_n^{-1}(\zeta) \right\}$

$\times \hat{S}_1(\zeta)\}$, where $\hat{V}_n(\zeta)$ is a consistent estimator of the covariance of $\hat{S}_1(\zeta)$.

There are several reasons for us to consider the sup functional of score statistics instead of wald or likelihood ratio statistics. Firstly, the score statistic is much less computational intense which makes the bootstrap implementation feasible. Secondly, we choose the sup functional because of its guarantee to have some power under local alternatives, as argued in [13] and which we prove below. We note, however, that [2] argue that certain weighted averages of score statistics are optimal tests in some settings. A careful analysis of the relative merits of the two approaches in our setting is beyond the scope of the current paper but is an interesting topic for future research. However, as a step in this direction, we will compare $\hat{T}_n$ with the integrated statistic $\tilde{T}_n \equiv \int_{[a,b]} \{\hat{S}'_1(\zeta)\hat{V}_n^{-1}(\zeta)\hat{S}_1(\zeta)\} d\zeta$.

In this section, we first discuss a Monte Carlo technique which enables computation of $\hat{V}_n(\zeta)$, so that $\hat{T}_n$ and $\tilde{T}_n$ can be calculated in the first place, as well as computation of critical values for hypothesis testing. We then discuss the asymptotic properties of the statistics under a sequence of contiguous alternatives so that power can be verified. Specifically, we assume that all the conditions of section 2 hold except for C2 which we replace with

C2': For each $n \geq 1$, $\alpha_0 = \alpha_*/\sqrt{n}$ and $\eta_0 = \eta_*/\sqrt{n}$, for some fixed $\alpha_* \in \mathbb{R}$, $\eta_* \in \mathbb{R}^q$. The joint distribution of (C, Z, Y) does not change with n .

Note that when $\alpha_* \neq 0$ or $\eta_* \neq 0$, condition C2' will cause the distribution of the failure time T , given the covariates (Z, Y) , to change with n , and the value of ζ_0 will affect this distribution.

9.1. Monte Carlo computation and inference. While the nonparametric bootstrap may be a reasonable approach, it is unclear how to verify its theoretical properties in this context. We will use instead the weighted bootstrap, based on the multipliers $\kappa_1^\circ, \dots, \kappa_n^\circ$ defined in section 8.2. Let $\mathbb{P}_n^\circ$ be the corresponding weighted empirical measure, and define $\hat{\psi}_0^\circ$ to be the maximizer of (13) after replacing $\mathbb{P}_n$ with $\mathbb{P}_n^\circ$. Also let $\hat{S}_1^\circ(\zeta) \equiv \sqrt{n}\mathbb{P}_n^\circ(U_{\zeta,1}^\tau(\hat{\psi}_0^\circ), U_{\zeta,2}^\tau(\hat{\psi}_0^\circ)')'$. Note that the same sample of weights $\kappa_1^\circ, \dots, \kappa_n^\circ$ are used for computing both $\hat{\psi}_0^\circ$ and the process $\{\hat{S}_1^\circ(\zeta), \zeta \in [a, b]\}$, so that the proper dependence between the score statistic and $\hat{\psi}_0$ will be captured. The structure of the set-up only requires considering values of ζ in the set $\{Y_{(1)}, \dots, Y_{(n)}\} \cap [a, b]$, since $\zeta \mapsto \hat{S}_1^\circ(\zeta)$ does not change over the intervals $[Y_{(j)}, Y_{(j+1)})$, $1 \leq j \leq n-1$. Now repeat the bootstrap procedure

a large number of times $\tilde{M}_n$, to obtain the bootstrapped score processes $\hat{S}_{1,1}^\circ, \dots, \hat{S}_{1,\tilde{M}_n}^\circ$. Note that we are allowing the number of bootstraps to depend on n . Define $\zeta \mapsto \hat{\mu}_n(\zeta) \equiv \tilde{M}_n^{-1} \sum_{k=1}^{\tilde{M}_n} \hat{S}_{1,k}^\circ(\zeta)$ and let $\zeta \mapsto \hat{V}_n(\zeta) \equiv \tilde{M}_n^{-1} \sum_{k=1}^{\tilde{M}_n} \left\{ \hat{S}_{1,k}^\circ(\zeta) - \hat{\mu}_n(\zeta) \right\} \left\{ \hat{S}_{1,k}^\circ(\zeta) - \hat{\mu}_n(\zeta) \right\}'$. Now we can compute the test statistics $\hat{T}_n$ and $\tilde{T}_n$ with this choice for $\hat{V}_n$.

To estimate critical values, we compute the standardized bootstrap test statistics $\hat{T}_{n,k}^\circ \equiv \sup_{\zeta \in [a,b]} \left\{ \left[\hat{S}_{1,k}^\circ(\zeta) - \hat{\mu}_n(\zeta) \right]' \hat{V}_n^{-1}(\zeta) \left[\hat{S}_{1,k}^\circ(\zeta) - \hat{\mu}_n(\zeta) \right] \right\}$ and $\tilde{T}_{n,k}^\circ \equiv \int_{[a,b]} \left\{ \left[\hat{S}_{1,k}^\circ(\zeta) - \hat{\mu}_n(\zeta) \right]' \hat{V}_n^{-1}(\zeta) \left[\hat{S}_{1,k}^\circ(\zeta) - \hat{\mu}_n(\zeta) \right] \right\} d\zeta$, for $1 \leq k \leq \tilde{M}_n$. For a test of size π , we compare the test statistics with the $(1 - \pi)$ th quantile of the corresponding $\tilde{M}_n$ standardized bootstrap statistics. The reason we subtract off the sample mean when computing the bootstrapped test statistics is to make sure that we are approximating the null distribution even when the null hypothesis may not be true. What is a little unusual about this procedure is that the bootstrap must be performed before the statistics $\hat{T}_n$ and $\tilde{T}_n$ can be calculated in the first place. We also reiterate again that we are assuming the covariates $Z_i(\cdot)$ are observed at all time points $V_j \leq V_i$ for which $\delta_j = 1$. As noted in section 2, we are aware that this is not necessarily valid in practice. As pointed out by a referee this is an important issues and it would be worth investigating whether the bootstrap weighting scheme could be modified to perform and account for imputation of the missing covariate values. Nevertheless, this issue is beyond the scope of this paper and we do not pursue it further here.

9.2. Asymptotic properties. In this section we establish the asymptotic validity of the proposed test procedure. Let P denote the fixed probability distribution under the null hypothesis H_0 , and let P_n be the sequence of probability distributions under the contiguous sequence of alternatives H_1^n defined in C2'. Note that P and P_n can be equal if $\alpha_* = 0 = \eta_*$. We need to study the proposed procedure under general P_n to determine both its size under the null and its power under the alternative. We will use the notation $\overset{P_n}{\rightsquigarrow}$ to denote weak convergence under P_n . We need the following lemmas and theorem, where we let $\psi_0^* \equiv (0, 0, \beta_0, A_0)$.

LEMMA 12. *The sequence of probability measures P_n satisfies*

$$(14) \quad \int \left[\sqrt{n}(dP_n^{1/2} - dP^{1/2}) - \frac{1}{2} \left(U_{\zeta_0,1}^\tau(\psi_0^*)(\alpha_*) + U_{\zeta_0,2}^\tau(\psi_0^*)(\eta_*) \right) dP^{1/2} \right]^2 \rightarrow 0.$$

LEMMA 13. $\|\hat{\psi}_0 - \psi_0^*\|_\infty \rightarrow 0$ in probability under P_n .

THEOREM 7. Under the conditions of section 2, with condition C2 replaced by C2', $\hat{S}_1$ converges under P_n in distribution in $l^\infty([a, b]^{q+1})$ to the $(q+1)$ -vector process $\zeta \mapsto \mathbb{Z}_*(\zeta) + \nu_*(\zeta)$, where $\mathbb{Z}_*$ is a tight, mean zero Gaussian $(q+1)$ -vector process with $\text{cov}[\mathbb{Z}_*(\zeta_1), \mathbb{Z}_*(\zeta_2)] = \Sigma_*(\zeta_1, \zeta_2) \equiv \sigma_*^{11}(\zeta_1 \vee \zeta_2) - \sigma_*^{12}(\zeta_1)[\sigma_*^{22}]^{-1}\sigma_*^{21}(\zeta_2)$, for all $\zeta_1, \zeta_2 \in [a, b]$, where,

$$\begin{aligned} \nu_*(\zeta) &\equiv \left\{ \sigma_*^{11}(\zeta \vee \zeta_0) - \sigma_*^{12}(\zeta)[\sigma_*^{22}]^{-1}\sigma_*^{21}(\zeta_0) \right\} \begin{pmatrix} \alpha_* \\ \eta_* \end{pmatrix}, \\ \sigma_*^{11}(\zeta) &\equiv \begin{pmatrix} \sigma_{\psi_0^*, \zeta}^{11} & \sigma_{\psi_0^*, \zeta}^{12} \\ \sigma_{\psi_0^*, \zeta}^{21} & \sigma_{\psi_0^*, \zeta}^{22} \end{pmatrix}, \quad \sigma_*^{12}(\zeta) \equiv \begin{pmatrix} \sigma_{\psi_0^*, \zeta}^{13} & \sigma_{\psi_0^*, \zeta}^{14} \\ \sigma_{\psi_0^*, \zeta}^{23} & \sigma_{\psi_0^*, \zeta}^{24} \end{pmatrix}, \\ \sigma_*^{21}(\zeta) &\equiv \begin{pmatrix} \sigma_{\psi_0^*, \zeta}^{31} & \sigma_{\psi_0^*, \zeta}^{32} \\ \sigma_{\psi_0^*, \zeta}^{41} & \sigma_{\psi_0^*, \zeta}^{42} \end{pmatrix}, \quad \sigma_*^{22} \equiv \begin{pmatrix} \sigma_{\psi_0^*, \zeta_0}^{33} & \sigma_{\psi_0^*, \zeta_0}^{34} \\ \sigma_{\psi_0^*, \zeta_0}^{43} & \sigma_{\psi_0^*, \zeta_0}^{44} \end{pmatrix}, \end{aligned}$$

for $\zeta \in [a, b]$, and where σ_θ^{jk} , for $1 \leq j, k \leq 4$, is as defined in section 5.2.

The following is the main result on the limiting distribution of the test statistics. For the remainder of this section, we require condition B4 to hold. As will be shown in the proof of corollary 2, condition B4 implies that $V_*(\zeta) \equiv \Sigma_*(\zeta, \zeta)$ is positive definite for all $\zeta \in [a, b]$. Note that we will establish consistency of $\hat{V}_n$ after we verify bootstrap validity.

COROLLARY 2. Assume B4 holds and $\hat{V}_n(\zeta) \rightarrow V_*(\zeta)$ in probability under P_n , uniformly over $\zeta \in [a, b]$. Then $\hat{T}_n \xrightarrow{P_n} \sup_{\zeta \in [a, b]} \left\{ [\mathbb{Z}_*(\zeta) + \nu_*(\zeta)]' \times V_*^{-1}(\zeta) [\mathbb{Z}_*(\zeta) + \nu_*(\zeta)] \right\}$ and $\tilde{T}_n \xrightarrow{P_n} \int_{[a, b]} \left\{ [\mathbb{Z}_*(\zeta) + \nu_*(\zeta)]' V_*^{-1}(\zeta) [\mathbb{Z}_*(\zeta) + \nu_*(\zeta)] \right\} d\zeta$. Thus the limiting null distributions of $\hat{T}_n$ and $\tilde{T}_n$ are $\hat{\mathbb{T}}_* \equiv \sup_{\zeta \in [a, b]} \left\{ \mathbb{Z}'_*(\zeta) V_*^{-1}(\zeta) \mathbb{Z}_*(\zeta) \right\}$ and $\tilde{\mathbb{T}}_* \equiv \int_{[a, b]} \left\{ \mathbb{Z}'_*(\zeta) V_*^{-1}(\zeta) \mathbb{Z}_*(\zeta) \right\} d\zeta$, respectively.

REMARK 2. Note that $\nu_*(\zeta_0)$ equals the matrix $\Sigma_*(\zeta_0, \zeta_0)$ times $(\alpha_*, \eta'_*)'$. By arguments in the proof of lemma 5, we know that $\Sigma_*(\zeta_0, \zeta_0)$ is positive definite. Thus $\nu_*(\zeta_0)$ will be strictly nonzero whenever $(\alpha_*, \eta'_*)' \neq 0$. Thus both $\hat{T}_n$ and $\tilde{T}_n$ will have power to reject H_0 under strictly non-null contiguous alternatives H_1^n .

The following theorem and corollary establish the validity of the bootstrap under the conditions of theorem 7. For brevity, we will use the notation $\xrightarrow[\circ]{P_n}$

to denote conditional convergence of the bootstrap, either weakly in the sense of corollary 1 or in probability, but under P_n rather than P . Also let $\hat{\mathbb{F}}(u) \equiv \tilde{M}_n^{-1} \sum_{k=1}^{\tilde{M}_n} \mathbf{1} \{ \hat{T}_{n,k}^\circ \leq u \}$ and $\tilde{\mathbb{F}}(u) \equiv \tilde{M}_n^{-1} \sum_{k=1}^{\tilde{M}_n} \mathbf{1} \{ \tilde{T}_{n,k}^\circ \leq u \}$.

THEOREM 8. $\hat{S}_1^\circ - \hat{S}_1 \xrightarrow[\circ]{P_n} \mathbb{Z}_*$ in $\ell^\infty([a, b]^{q+1})$.

COROLLARY 3. *There exists a sequence $\tilde{M}_n \rightarrow \infty$, as $n \rightarrow \infty$, such that $\hat{V}_n \xrightarrow[\circ]{P_n} \Sigma_*$, $\hat{V}_n \xrightarrow[\circ]{P_n} \Sigma_*$, and both $\sup_{u \in \mathbb{R}} \left| \hat{\mathbb{F}}(u) - P \{ \hat{\mathbb{T}}_* \leq u \} \right| \xrightarrow[\circ]{P_n} 0$ and $\sup_{u \in \mathbb{R}} \left| \tilde{\mathbb{F}}(u) - P \{ \tilde{\mathbb{T}}_* \leq u \} \right| \xrightarrow[\circ]{P_n} 0$.*

10. Implementation and simulation study. We have implemented the proposed estimation and inference procedures for both the proportional hazards and proportional odds models. The maximum likelihood estimates were computed using the profile likelihood $pL_n(\zeta)$ defined in section 4. A line search over the order statistics of Y is used to maximize over ζ , while Newton's method is used to maximize over ψ . The stationary point equation (7) can be used to profile over A for each value of ζ and γ . In our experience, the computational time of the entire procedure is reasonable. A thorough simulation study to validate the moderate sample size performance of this procedure and the proposed bootstrap procedures of section 8 is underway and will be presented elsewhere.

Because of the unusual form of the statistical tests proposed in section 9, we feel it is worthwhile at this point to present a small simulation study evaluating their moderate sample size performance. Both the proportional hazards and proportional odds models were considered. A single time-independent covariate Z with a standard normal distribution was used, so that $d = q = 1$, and the change-point $Y \perp Z$ also had a standard normal distribution. The parameter values were set at $\zeta_0 = 0$, $\alpha_0 = 0$, $\beta_0 = 1$, $\eta_0 \in \{0, -0.5, -1, -2, -3\}$, and $A_0(t) = t$. The range of η_0 values includes the null hypothesis H_0 (when $\eta_0 = 0$) and several alternative hypotheses. The censoring time was exponentially distributed with rate 0.1 and truncated at 10. This resulted in a censoring rate of about 25%. The sample size for each simulated data set was 300. For each simulated data set, 250 bootstraps were generated with standard exponential weights truncated at 5, to compute $\hat{V}_n$ and the critical values for the two test statistics, $\hat{T}_n$ (the “sup score test”) and $\tilde{T}_n$ (the “mean score test”). The range for ζ was restricted to the inner 80% of the Y values. Each scenario was replicated 250 times.

The results of the simulation study are presented in table 1 on page 23.

TABLE 1

Results from the simulation study of the sup and mean score test statistics in the proportional hazards and proportional odds models. The sample size is 300, the level of censoring approximately 25%, and the nominal type I error is 0.05. 250 replicates were generated for each configuration. The parameters were set at $\zeta_0 = 0$, $\alpha_0 = 0$, $\beta_0 = 1$, and $A_0(t) = t$, with the value of η_0 varying. The worst-case Monte Carlo standard error for the power estimates is $0.03 = 0.50/\sqrt{250}$.

Proportional hazards model					
Sup score test statistic	Null $\eta_0 = 0$	$\eta_0 = -0.5$	$\eta_0 = -1$	$\eta_0 = -2$	$\eta_0 = -3$
mean	5.078	5.590	7.874	13.524	35.507
Standard Deviation	2.728	2.859	3.919	6.992	11.337
power	0.044	0.076	0.180	0.536	0.980
Mean score test statistic	Null $\eta_0 = 0$	$\eta_0 = -0.5$	$\eta_0 = -1$	$\eta_0 = -2$	$\eta_0 = -3$
mean	1.403	1.694	2.560	5.412	5.529
Standard Deviation	1.206	1.104	1.597	2.492	2.683
power	0.040	0.050	0.120	0.236	0.304
Proportional odds model					
Sup score test statistic	Null $\eta_0 = 0$	$\eta_0 = -0.5$	$\eta_0 = -1$	$\eta_0 = -2$	$\eta_0 = -3$
mean	3.950	4.762	5.693	8.327	13.956
Standard Deviation	2.390	1.610	1.255	2.901	4.244
power	0.043	0.068	0.112	0.364	0.660
Mean score test statistic	Null $\eta_0 = 0$	$\eta_0 = -0.5$	$\eta_0 = -1$	$\eta_0 = -2$	$\eta_0 = -3$
mean	1.177	1.912	2.848	3.265	4.349
Standard Deviation	0.946	1.078	1.360	1.498	1.718
power	0.048	0.056	0.116	0.167	0.285

The type I error (the $\eta_0 = 0$ column) is quite close to the targeted 0.05 level, and the power increases with the magnitude of η_0 . Also, the sup test is notably more powerful than the mean test for all alternatives. We also tried the nonparametric bootstrap and found that it did not work nearly as well. While it is difficult to make sweeping generalizations with this small of a numerical study, it appears as if the proposed test statistics match the theoretical predictions and have reasonable power. More simulation studies into the properties of these statistics is needed, including studies of the impact of time-dependent covariates.

11. Proofs. *Proof of lemma 1.* Verification of D1 is straightforward.

For D2, we have for all $u \geq 0$, $|\ddot{\Lambda}(u)/\dot{\Lambda}(u)| = \mathbb{E}[W^2 e^{-uW}] / \mathbb{E}[W e^{-uW}] \leq \mathbb{E}[W^2] / \mathbb{E}[W] < \infty$. The second-to-last inequality requires some justification (see [18]). This proves the first part. For the second part, take $c_0 = c$, and note that $|u^c \Lambda(u)| = \mathbb{E}[u^c e^{-uW}] = \mathbb{E}[W^{-c}(uW)^c e^{-uW}] \leq k \mathbb{E}[W^{-c}]$, where $k = \sup_{x \geq 0} x^c e^{-x} = c^c e^{-c} < \infty$. Also, $|u^{1+c} \dot{\Lambda}(u)| = \mathbb{E}[u^{1+c} W e^{-uW}] = \mathbb{E}[W^{-c}(uW)^{1+c} e^{-uW}] \leq k' \mathbb{E}[W^{-c}]$, where $k' = \sup_{x \geq 0} x^{1+c} e^{-x} < \infty$. $\square$

Proof of lemma 2. Suppose that

$$(15) \quad G\left(\int_0^t \tilde{Y}(s) e^{r_\xi(u;Z,Y)} dA(u)\right) = G\left(\int_0^t \tilde{Y}(s) e^{r_{\xi_0}(u;Z,Y)} dA_0(u)\right)$$

for all $t \in [0, \tau]$ almost surely under P . The target is to show that (15) implies that $\xi = \xi_0$ and $A = A_0$ on $[0, \tau]$. By condition A1, (15) implies $\int_0^t e^{r_\xi(u;Z,Y)} dA(u) = \int_0^t e^{r_{\xi_0}(u;Z,Y)} dA_0(u)$ for all $t \in [0, \tau]$ almost surely. Taking the Radon-Nikodym derivative of both sides with respect to A_0 , taking logarithms, and letting $\tilde{a} \equiv dA/dA_0$, we obtain that almost surely

$$(16) \quad \beta' Z(t) + (\alpha + \eta' Z_2(t)) \mathbf{1}\{Y > \zeta\} - \beta'_0 Z(t) - (\alpha_0 + \eta'_0 Z_2(t)) \mathbf{1}\{Y > \zeta_0\} + \log(\tilde{a}(t)) = 0.$$

Assume that $\zeta > \zeta_0$. Now choose $y < \zeta_0$ such that $y \in \tilde{V}(\zeta_0)$ and $\text{var}[Z(t_1)|Y = y]$ is positive definite, where t_1 is as defined in B3. Note that this is possible by assumptions B2 and B3. Conditioning the left-hand side of (16) on $Y = y$ and evaluating at $t = t_1$ yields that $\beta = \beta_0$. Now choose $\zeta_0 < y < \zeta$ such that $y \in \tilde{V}(\zeta_0)$ and $\text{var}[Z(t_2)|Y = y]$ is positive definite. Conditioning the left-hand side of (16) on $Y = y$, and evaluating at $t = t_2$ yields that $\eta_0 = 0$. Because the density of Y is positive in $\tilde{V}(\zeta_0)$, we also see that $\alpha_0 = 0$. But this is not possible by condition C2. A similar argument can be used to show that $\zeta < \zeta_0$ is impossible. Thus $\zeta = \zeta_0$. Now it is not hard to argue that condition B3 forces $\beta = \beta_0$, $\eta = \eta_0$ and $\alpha = \alpha_0$. Hence $\log(\tilde{a}(t)) = 0$ for all $t \in [0, \tau]$, and the proof is complete. $\square$

Proof of lemma 3. Note that for each n , maximizing the log-likelihood over A is equivalent to maximizing over a fixed number of parameters since the number of jumps $K \leq n$. Thus maximizing over θ involves maximizing an empirical average of functions that are smooth over ψ and cadlag over ζ . Also note $\|\hat{A}_n - A_0\|_{[0,\tau]} = \max_{1 \leq j \leq K} \left(\left| \hat{A}_n(T_j-) - A_0(T_j) \right| \vee \left| \hat{A}_n(T_j) - A_0(T_j) \right| \right)$, where $\|\cdot\|_B$ is the uniform norm over the set B , and thus $\|\hat{A}_n - A_0\|_{[0,\tau]}$ is measurable. Hence the uniform distance between $\hat{\theta}_n$ and θ_0 is also measurable. Thus almost sure convergence of $\hat{\theta}_n$ is equivalent to outer almost sure convergence. Now we return to the proof. Assume $\limsup_{n \rightarrow \infty} \hat{A}_n(\tau) = \infty$,

with probability > 0 . Using arguments similar to those used in the proof of proposition 2 of [17], we can show that this leads to a contradiction. The details can be found in [18]. Thus, $\limsup_{n \rightarrow \infty} \hat{A}_n(\tau) < \infty$ almost surely. $\square$

Proof of theorem 1. By the opening arguments in the proof of lemma 3, we have that outer almost sure convergence is equivalent to the usual almost sure convergence in this instance. Note that $\{\hat{A}_n(\tau)\}$ is bounded almost surely, $\tilde{G}_n \rightarrow \tilde{G}_0$ almost surely, and the class $\mathcal{F}_{(k)} \equiv \{W(t; \theta) : t \in [0, \tau], \xi \in \mathcal{X}, A \in \mathcal{A}_{(k)}\}$, where $\mathcal{A}_{(k)} \equiv \{A \in \mathcal{A} : A(\tau) \leq k\}$, is Donsker (and hence also Glivenko-Cantelli) for every $k < \infty$ by lemma 14 below. By similar arguments to those used in lemma 14, we have that the class $\{G(H^\theta(V)) : \xi \in \mathcal{X}, A \in \mathcal{A}_{(k)}\}$ is also Glivenko-Cantelli for all $k < \infty$. We therefore have the following with probability 1: $\{\hat{A}_n(\tau)\}$ is bounded asymptotically, $\tilde{G}_n \rightarrow \tilde{G}_0$ uniformly, $(\mathbb{P}_n - P)W(\cdot; \hat{\theta}_n) \rightarrow 0$ uniformly, and $(\mathbb{P}_n - P)[G(H^{\hat{\theta}_n}(V)) - G(H^{\theta_n}(V))] \rightarrow 0$. Now, using somewhat standard arguments, we can use the Helly selection theorem and the identifiability of the model to obtain that all convergent subsequences of $\hat{\theta}_n$, on a set of probability 1, converge to θ_0 (see [18]). The desired result now follows. $\square$

LEMMA 14. $\forall k < \infty$, the class $\mathcal{F}_{(k)} \equiv \{W(t; \theta) : t \in [0, \tau], \xi \in \mathcal{X}, A \in \mathcal{A}_{(k)}\}$, is P -Donsker.

Proof. The somewhat routine details can be found in [18]. $\square$

Proof of lemma 4. The results follow from the smoothness assumed in D1 of the involved derivatives. Additional details can be found in [18]. $\square$

Proof of lemma 5. First note that for any $h = (h_1, h_2, h_3, h_4) \in \mathcal{H}_\infty$, $\sigma_{\theta_0}(h) = \mathbb{A}(h) + \mathbb{B}(h)$, where $\mathbb{A}(h) = (h_1, h_2, h_3, g_0 h_4)$, $\mathbb{B}(h) = \sigma_{\theta_n}(h) - \mathbb{A}(h)$, and $g_0(u) = P[\tilde{Y}(u)e^{r\xi_0(u; Z, Y)}\hat{\Xi}_{\theta_0}^{(0)}(\tau)]$. It is not hard to verify that since g_0 is bounded below, $\mathbb{A}$ is one-to-one and onto with continuous inverse defined by $\mathbb{A}^{-1}(h) = (h_1, h_2, h_3, h_4/g_0)$. It is also not hard to verify that the operator $\mathbb{B}$ is compact as an operator on $\mathcal{H}_r$ for any $0 < r < \infty$. Thus the first part of the theorem is proved by lemma 25.93 of [32], if we can show that σ_{θ_0} is one-to-one. This will then imply that for each $r > 0$, there is an $s > 0$ with $\sigma_{\theta_0}^{-1}(\mathcal{H}_s) \subset \mathcal{H}_r$. Now we have $\inf_{\psi \in \text{lin } \Psi} (\|\psi(\sigma_{\theta_0}(\cdot))\|_{(r)} / \|\psi\|_{(r)}) \geq \inf_{\psi \in \text{lin } \Psi} (\sup_{h \in \sigma_{\theta_0}^{-1}(\mathcal{H}_s)} |\psi(\sigma_{\theta_0}(h))| / \|\psi\|_{(r)}) = \inf_{\psi \in \text{lin } \Psi} (\|\psi\|_{(s)} / \|\psi\|_{(r)}) \geq s/(4r)$, since $\|\psi\|_{(r)} \leq 4(r/s)\|\psi\|_{(s)}$. Thus $\psi \mapsto \psi(\sigma_0(\cdot))$ is continuously invertible on its range by proposition A.1.7 of [4]. That it is also onto with inverse $\psi \mapsto \psi(\sigma_{\theta_0}^{-1}(\cdot))$ follows from σ_{θ_0} being onto.

Let $h \in \mathcal{H}_\infty$ such that $\sigma_{\theta_0}(h) = 0$. For the one-dimensional submodel defined by the map $s \rightarrow \psi_{0s} \equiv \psi_0 + s(h_1, h_2, h_3, \int_0^{\cdot} h_4(u) dA_0(u))$, we have

$$(17) \quad P\left\{\frac{\partial}{\partial s} L_1(\psi_{0s}, \zeta_0)|_{s=0}\right\}^2 = P\{U_{\zeta_0}^\tau(\psi_0)(h)\}^2 = 0.$$

Define the random set $\mathcal{S}(n, \tilde{y}, t) \equiv \{(N, \tilde{Y}) : N(u) = n(u), \tilde{Y}(u) = \tilde{y}(u), u \in [t, \tau]\}$. The equality (17) implies that $P\{U_{\zeta_0}^\tau(\psi_0)(h)|\mathcal{S}(n, y, t)\}^2 = 0$ for all $\mathcal{S}$ such that $P\{\mathcal{S}(n, y, t)\} > 0$, which implies that $U_{\zeta_0}^t(\psi_0)(h) = 0$ almost surely for all $t \in [0, \tau]$. Consider the set on which the observation (X, δ, Z, Y) is censored at a time $t \in [0, \tau]$. From (17) and the preceding argument,

$$(18) \quad R_{\zeta_0, \psi_0}^t(h_1 \mathbf{1}(Y > \zeta_0) + h_2' Z_2(t) \mathbf{1}(Y > \zeta_0) + h_3' Z(t) + h_4) = 0.$$

Taking the Radon-Nikodym derivative of (18) with respect to A_0 and dividing throughout by $e^{r_{\zeta_0}(t; Z, Y)}$ yields

$$(19) \quad \tilde{Y}(t)(h_1 \mathbf{1}(Y > \zeta_0) + h_2' Z_2(t) \mathbf{1}(Y > \zeta_0) + h_3' Z(t) + h_4(t)) = 0.$$

Arguments quite similar to those used in the proof of lemma 2 can now be used to verify that (19) forces $h = 0$, and thus σ_{θ_0} is one-to-one. $\square$

Proof of lemma 6. For the first part, note that $t \mapsto \tilde{Y}(t)$ has total variation bounded by 1; and, by the model assumptions, the total variation of $t \mapsto e^{r_\varepsilon(t; Z, Y)}$ is bounded by a universal constant that doesn't depend on θ . Thus there exists a universal constant k_* such that $\|\mathbb{P}_n W(\cdot; \hat{\theta}_n)\|_v \leq k_* \mathbb{P}_n |\hat{\Xi}_{\hat{\theta}_n}^{(0)}|$. By the smoothness of the functions involved, and the fact that $u \mapsto \log(u)$ is Lipschitz on compacts bounded above zero, we obtain the first result of the lemma. The consistency part follows from lemma 14 combined with theorem 1, the continuity of $\theta \mapsto PW(\cdot; \theta)$, and reapplication of the Lipschitz continuity of $u \mapsto \log(u)$. $\square$

Proof of lemma 7. The right-hand derivative of $P(L_1(\psi, \zeta))$ with respect to ζ at $\zeta = \zeta_0$ is: $(\partial^+ / (\partial \zeta)) P(L_1(\psi, \zeta))|_{\zeta=\zeta_0}$

$$\begin{aligned} &= \int \left\{ P[l_1^\psi(V, \delta, Z)|Y = y+] - P[l_2^\psi(V, \delta, Z)|Y = y+] \right\} \tilde{\delta}_{\zeta_0}(y) \tilde{h}(y) dy \\ &= \left(P[l_1^\psi(V, \delta, Z)|Y = \zeta_0+] - P[l_2^\psi(V, \delta, Z)|Y = \zeta_0+] \right) \tilde{h}(\zeta_0), \text{ where the super-} \\ &\text{script } + \text{ denotes differentiating from the right and } \tilde{\delta}_{\zeta_0}(y) \text{ is the Dirac delta} \\ &\text{function assigning measure 1 to the event } \{y = \zeta_0\}. \text{ Now, } P[l_1^\psi(V, \delta, Z)|Y = \\ &\zeta_0+] - P[l_2^\psi(V, \delta, Z)|Y = \zeta_0+] = \int \left[l_1^\psi(v, d, z) - l_2^\psi(v, d, z) \right] \ell_2(v, d, z) \ell_0^+(v, d, z) \\ &\times d\mu(v, d, z) \equiv \tilde{R}^+(\psi), \text{ where } \ell_j(v, d, z) \equiv \exp\{l_j^{\psi_0}(v, d, z)\}, \text{ for } j = 1, 2; \\ &\mu(v, d, z) \text{ is the dominating measure; and } \ell_0^+(v, d, z) \text{ consists of the remain-} \\ &\text{ing components of the conditional distribution of } (V, \delta, Z) \text{ given } Y = \zeta_0+. \end{aligned}$$

Note that under the model, ℓ_0^+ does not depend on the parameters. Thus $\tilde{R}^+(\psi_0) = \int \left[l_1^{\psi_0}(v, d, z) - l_2^{\psi_0}(v, d, z) \right] \ell_2(v, d, z) \ell_0^+(v, d, z) d\mu(v, d, z) = \int \log \left[\ell_1 \ell_0^+ / (\ell_2 \ell_0^+) \right] \ell_2 \ell_0^+ d\mu < \log \int \left[\ell_1 \ell_0^+ / (\ell_2 \ell_0^+) \right] \ell_2 \ell_0^+ d\mu = \log \int \ell_1(v, d, z) \times \ell_0^+(v, d, z) d\mu(v, d, z) = 0$, since the integral of a density is 1. Thus $\dot{X}_{\zeta_0}^+(\gamma_0, \Gamma_0) < 0$. A similar argument [18] is used to conclude $\dot{X}_{\zeta_0}^-(\gamma_0, \Gamma_0) > 0$. $\square$

Proof of lemma 8. This follows from lemma 7, the local concavity of $\tilde{X}$, and the smoothness of the derivatives involved. $\square$

Proof of lemma 9. Note that $\tilde{X}_n(\zeta, \eta, \Gamma)$

$$= \mathbb{P}_n \left[- \int_0^\tau \{ \Gamma(t) - \Gamma_0(t) \} dN(t) + \tilde{W}(\zeta, \eta, A_n^{(\Gamma)}) - \tilde{W}(\zeta_0, \eta_0, A_n^{(\Gamma_0)}) \right],$$

where $\tilde{W}(\zeta, \gamma, A) \equiv l_1^\psi(V, \delta, Z) \mathbf{1}\{Y \leq \zeta\} + l_2^\psi(V, \delta, Z) \mathbf{1}\{Y > \zeta\}$. The classes $\{\int_0^\tau \{ \Gamma(t) - \Gamma_0(t) \} dN(t) : \|\Gamma - \Gamma_0\|_\infty \leq \epsilon, \|\Gamma\|_v \leq k_0\}$, for any $\epsilon > 0$, and $\{\tilde{W}(\zeta, \lambda) : (\zeta, \lambda) \in B_{\epsilon_2}^{*k_0}\}$, for some $\epsilon_2 > 0$, can be shown to be Donsker. The arguments for this are somewhat standard and can be found in [18]. Since we also have that $\sqrt{n}(\tilde{G}_n - \tilde{G}_0)$ converges to a Gaussian process,

$$\sqrt{n}(\mathbb{P}_n - P) \left[- \int_0^\tau \{ \Gamma(t) - \Gamma_0(t) \} dN(t) + \tilde{W}(\zeta, \eta, A_n^{(\Gamma)}) - \tilde{W}(\zeta_0, \eta_0, A_n^{(\Gamma_0)}) \right]$$

converges weakly in $\ell^\infty(B_{\epsilon_2}^{*k_0})$ to the tight Gaussian process

$$\mathbb{G} \left[- \int_0^\tau \{ \Gamma(t) - \Gamma_0(t) \} dN(t) + \tilde{W}(\zeta, \eta, A_0^{(\Gamma)}) - \tilde{W}(\zeta_0, \eta_0, A_0^{(\Gamma_0)}) \right],$$

where $\mathbb{G}$ is the Brownian bridge measure.

By the smoothness of the functions and derivatives involved, we also have $\sqrt{n} \left\{ P \left[- \int_0^\tau \{ \Gamma(t) - \Gamma_0(t) \} dN(t) + \tilde{W}(\zeta, \eta, A_n^{(\Gamma)}) - \tilde{W}(\zeta_0, \eta_0, A_n^{(\Gamma_0)}) \right] - \tilde{X}(\zeta, \eta, \Gamma) \right\} = \sqrt{n} P \left[\tilde{W}(\zeta, \eta, A_n^{(\Gamma)}) - \tilde{W}(\zeta_0, \eta_0, A_n^{(\Gamma_0)}) - \tilde{W}(\zeta, \eta, A_0^{(\Gamma)}) + \tilde{W}(\zeta_0, \eta_0, A_0) \right] = -\sqrt{n} \int_0^\tau \left\{ P[W(t; \theta_0(\zeta, \lambda))] e^{-\Gamma(t)} - P[W(t; \theta_0)] e^{-\Gamma_0(t)} \right\} \times [d\tilde{G}_n(t) - d\tilde{G}_0(t)] + \epsilon_n(\zeta, \lambda) \equiv -\int_0^\tau \tilde{C}(t; \zeta, \lambda) d\mathcal{Z}_n(t) + \epsilon_n(\zeta, \lambda)$, where $\|\epsilon_n\|_\infty = o_P(1)$. The fact that the class of functions $\{\tilde{C}(\cdot; \zeta, \lambda) : (\zeta, \lambda) \in B_{\epsilon_2}^{*k_0}\}$ has uniformly bounded total variation yields asymptotic linearity and normality of $\left\{ \int_0^\tau \tilde{C}(t; \zeta, \lambda) d\mathcal{Z}_n(t) : (\zeta, \lambda) \in B_{\epsilon_2}^{*k_0} \right\}$, and the desired result follows. $\square$

Proof of theorem 2. By lemma 9, $-\tilde{X}(\hat{\zeta}_n, \hat{\gamma}_n, \hat{\Gamma}_n) = (\tilde{X}_n - \tilde{X})(\hat{\zeta}_n, \hat{\gamma}_n, \hat{\Gamma}_n) - \tilde{X}_n(\hat{\zeta}_n, \hat{\gamma}_n, \hat{\Gamma}_n) \leq O_P(n^{-1/2})$. Combining this with lemma 8, we obtain $\sqrt{n}|\hat{\zeta}_n - \zeta_0| = \sqrt{n}|\hat{\zeta}_n - \zeta_0| \mathbf{1}\{(\hat{\zeta}_n, \hat{\gamma}_n, \hat{\Gamma}_n) \in B_{\epsilon_1}^{*k_0}\} + \sqrt{n}|\hat{\zeta}_n - \zeta_0| \mathbf{1}\{(\hat{\zeta}_n, \hat{\gamma}_n, \hat{\Gamma}_n) \notin B_{\epsilon_1}^{*k_0}\} \leq -\sqrt{n}k_1^{-1} \tilde{X}(\hat{\zeta}_n, \hat{\gamma}_n, \hat{\Gamma}_n) + o_P(1) \leq O_P(1)$. The first part is proved.

For the second part, denote $U_{0\zeta}^\tau(\psi) \equiv PU_\zeta^\tau(\psi)$. By arguments similar to those used in the proof of lemma 14, we can verify that for some $e_1 > 0$, $\mathcal{F} \equiv \{U_\zeta^\tau(\psi)(h) : \|\theta - \theta_0\|_\infty \leq e_1, h \in \mathcal{H}_1\}$ is Donsker. Moreover, the continuity of the functions involved also yields that, as $\|\theta - \theta_0\|_\infty \rightarrow 0$, $\sup_{h \in \mathcal{H}_1} P \left(U_\zeta^\tau(\psi)(h) - U_{\zeta_0}^\tau(\psi_0)(h) \right)^2 \rightarrow 0$. Thus

$$(20) \quad \sqrt{n} \left(U_{n\hat{\zeta}_n}^\tau(\hat{\psi}_n) - U_{0\hat{\zeta}_n}^\tau(\hat{\psi}_n) - U_{n\zeta_0}^\tau(\psi_0) + U_{0\zeta_0}^\tau(\psi_0) \right) = o_P^{\mathcal{H}_1}(1).$$

Note also that $\sqrt{n}|\hat{\zeta}_n - \zeta_0| = O_P(1)$ implies that $\sqrt{n} \left(U_{0\hat{\zeta}_n}^\tau(\hat{\psi}_n) - U_{0\zeta_0}^\tau(\hat{\psi}_n) \right) = o_P^{\mathcal{H}_1}(1)$. Thus, since $U_{n\hat{\zeta}_n}^\tau(\hat{\psi}_n) = 0$, (20) implies $\sqrt{n}U_{0\zeta_0}^\tau(\hat{\psi}_n) = \sqrt{n}U_{0\hat{\zeta}_n}^\tau(\hat{\psi}_n) + o_P^{\mathcal{H}_1}(1) = -\sqrt{n} \left(U_{n\zeta_0}^\tau(\psi_0) - U_{0\zeta_0}^\tau(\psi_0) \right) + o_P^{\mathcal{H}_1}(1) = O_P^B(1)$, where $O_P^B(1)$ denotes a term bounded in probability uniformly over the set B . By lemma 5, there exists a constant $e_2 > 0$ such that $\|U_{0\zeta_0}^\tau(\psi) - U_{0\zeta_0}^\tau(\psi_0)\|_{\mathcal{H}_1} \geq e_2\|\psi - \psi_0\|_\infty + o(\|\psi - \psi_0\|_\infty)$, as $\|\psi - \psi_0\|_\infty \rightarrow 0$. Hence $\sqrt{n}\|\hat{\psi}_n - \psi_0\|_\infty(e_2 - o_P(1)) \leq O_P(1)$, and we obtain the second conclusion.

For the third part, we have $\sqrt{n} \sup_{t \in [0, \tau]} |\mathbb{P}_n W(t; \hat{\theta}_n) - PW(t; \hat{\theta}_n)| = \sqrt{n} \times \sup_{t \in [0, \tau]} |(\mathbb{P}_n - P)W(t; \theta_0)| + o_P(1) = O_P(1)$ and $\sqrt{n} \sup_{t \in [0, \tau]} |PW(t; \hat{\theta}_n) - PW(t; \theta_0)| = O_P(1)$ by the first two parts of this lemma. Hence $\sqrt{n} \sup_{t \in [0, \tau]} |\mathbb{P}_n W(t; \hat{\theta}_n) - PW(t; \theta_0)| = O_P(1)$. The result now follows by the Lipschitz continuity of $\log(u)$ over strictly positive compact intervals. $\square$

Proof of lemma 10. The first inequality follows from the definitions. For the second inequality, we use a Taylor's expansion around $(\hat{\zeta}_n, \hat{\gamma}_n, \hat{\Gamma}_n)$ to obtain $\tilde{X}_n(\hat{\zeta}_n, \hat{\lambda}_n) - \tilde{X}_n(\hat{\zeta}_n, \lambda_0) =$

$$-\mathbb{P}_n U_{\hat{\zeta}_n}^\tau(\hat{\gamma}_n, A_n^{(\hat{\Gamma}_n)})(\lambda_0 - \hat{\lambda}_n) - \psi_{n,t}^{(\lambda_0 - \hat{\lambda}_n)} \left(\mathbb{P}_n \hat{\sigma}_{(\hat{\zeta}_n, \hat{\gamma}_n, t, A_n^{(\hat{\Gamma}_n, t)})} \right) (\lambda_0 - \hat{\lambda}_n),$$

for some $t \in [0, 1]$, where $\hat{\lambda}_{n,t} \equiv (\hat{\gamma}_{n,t}, \hat{\Gamma}_{n,t})$; $\hat{\gamma}_{n,t} \equiv t\hat{\gamma}_n + (1-t)\gamma_0$; $\hat{\Gamma}_{n,t} \equiv t\hat{\Gamma}_n + (1-t)\Gamma_0$; and, for any $h \in \mathcal{H}_\infty$, $\psi_{n,t}^{(h)} \equiv \left(h_1, h_2, h_3, \int_0^{(\cdot)} h_4(s) dA_n^{(\hat{\Gamma}_{n,t})}(s) \right)$. The score term is zero by definition of the NPMLE, and the second term has absolute value bounded by $\hat{K}_n \|\hat{\lambda}_n - \lambda_0\|_\infty^2$, where $\hat{K}_n$ is bounded in probability by the consistency of $\hat{\lambda}_n$ and the form of the terms in section 5.2.

Now, letting $\psi_n(\gamma, \Gamma) \equiv (\gamma, A_n^{(\Gamma)})$, we have $\tilde{X}_n(\hat{\zeta}_n, \lambda_0) - \tilde{X}_n^*(\hat{\zeta}_n)$

$$(21) \quad = \mathbb{P}_n \left\{ \left(\mathbf{1}\{Y \leq \hat{\zeta}_n\} - \mathbf{1}\{Y \leq \zeta_0\} \right) \times \left[l_1^{\psi_n(\gamma_0, \Gamma_0)}(V, \delta, Z) - l_2^{\psi_n(\gamma_0, \Gamma_0)}(V, \delta, Z) - l_1^{\psi_0}(V, \delta, Z) + l_2^{\psi_0}(V, \delta, Z) \right] \right\}$$

$$= \int_0^\tau \mathbb{P}_n \left\{ \left(\mathbf{1}\{Y \leq \hat{\zeta}_n\} - \mathbf{1}\{Y \leq \zeta_0\} \right) \tilde{Y}(s) \tilde{K}_n(s) \right\} e^{-\Gamma_0(s)} \left[d\tilde{G}_n(s) - d\tilde{G}_0(s) \right],$$

where $\tilde{K}_n(s) = \left[\dot{G}(H_1^{\psi_{n,t}}(V)) - \delta \ddot{G}(H_1^{\psi_{n,t}}(V)) / \dot{G}(H_1^{\psi_{n,t}}(V)) \right] e^{\beta'_0 Z(s)}$

$$- \left[\dot{G}(H_2^{\psi_{n,t}}(V)) - \delta \ddot{G}(H_2^{\psi_{n,t}}(V)) / \dot{G}(H_2^{\psi_{n,t}}(V)) \right] e^{\beta'_0 Z(s) + \alpha_0 + \eta'_0 Z_2(s)}$$

and $\psi_{n,t} \equiv \left(\gamma, \int_0^{(\cdot)} \Gamma_0(u) \left[t d\tilde{G}_n(u) + (1-t) d\tilde{G}_0(u) \right] \right)$, for some $t \in [0, 1]$, by the mean value theorem. By the conditions given in section 2, we have that there is a constant $k^* < \infty$ such that $\|\tilde{K}_n(s) \Gamma_0(s)\|_v \leq k^*$ with probability 1 for all $n \geq 1$. Thus the absolute value of (21) is bounded above by $k^* \|\tilde{G}_n - \tilde{G}_0\|_\infty \times \mathbb{P}_n \left| \mathbf{1}\{Y \leq \hat{\zeta}_n\} - \mathbf{1}\{Y \leq \zeta_0\} \right| = O_P(n^{-1})$. This last statement follows because $\|\tilde{G}_n - \tilde{G}_0\|_\infty = O_P(n^{-1/2})$, $(\mathbb{P}_n - P) \left| \mathbf{1}\{Y \leq \hat{\zeta}_n\} - \mathbf{1}\{Y \leq \zeta_0\} \right| = o_P(n^{-1/2})$, and $P \left| \mathbf{1}\{Y \leq \hat{\zeta}_n\} - \mathbf{1}\{Y \leq \zeta_0\} \right| = O_P(n^{-1/2})$ by theorem 2. Now the desired result follows. $\square$

Proof of lemma 11. Note first that

$$\tilde{D}_n(\zeta) = \sqrt{n}(\mathbb{P}_n - P) \left\{ \left[\mathbf{1}\{Y \leq \zeta\} - \mathbf{1}\{Y \leq \zeta_0\} \right] \times \left[l_1^{\psi_0} - l_2^{\psi_0} \right] (V, \delta, Z) \right\}.$$

Denote $\tilde{H} \equiv [l_1^{\psi_0} - l_2^{\psi_0}](V, \delta, Z)$, and note that $|\tilde{H}| \leq c_*$ almost surely for a fixed constant $c_* < \infty$. Thus $F_\epsilon \equiv \mathbf{1}\{\zeta_0 - \epsilon \leq Y \leq \zeta_0 + \epsilon\} c_*$ serves as an envelope for the class of functions $\mathcal{F}_\epsilon \equiv \{[\mathbf{1}\{Y \leq \zeta\} - \mathbf{1}\{Y \leq \zeta_0\}] \tilde{H} : |\zeta - \zeta_0| \leq \epsilon\}$, for each $\epsilon > 0$. Note that by the assumptions on the density $\tilde{h}$ in a neighborhood of ζ_0 , we have for some $\epsilon_3 > 0$ that there exists $0 < k_*, k_{**} < \infty$ such that $k_* \epsilon \leq \tilde{p}(\epsilon) \equiv P[\zeta_0 - \epsilon \leq Y \leq \zeta_0 + \epsilon] \leq k_{**} \epsilon$ for all $0 \leq \epsilon \leq \epsilon_3$. Thus the bracketing entropy $N_{[]} (u \| F_\epsilon \|_{P,2}, \mathcal{F}_\epsilon, L_2(P)) \leq O(\epsilon / (u^2 \tilde{p}(\epsilon))) \leq O(1/(c_* u^2))$, for all $u > 0$ and $0 \leq \epsilon \leq \epsilon_3$; and thus, by theorem 2.14.2 of [33], there exists a $c_{**} < \infty$ such that $E \left[\sup_{|\zeta - \zeta_0| \leq \epsilon} |\tilde{D}(\zeta)| \right] \leq c_{**} \|F_\epsilon\|_{P,2} \leq c_{**} c_* \sqrt{k_{**} \epsilon}$, for all $0 \leq \epsilon \leq \epsilon_3$. The result now follows for $k_2 = c_{**} c_* \sqrt{k_{**}}$. $\square$

Proof of theorem 4. From section 3 we deduce $\tilde{L}_n(\hat{\psi}_n, \zeta_{n,u}) - \tilde{L}_n(\hat{\psi}_n, \zeta_0) = \mathbb{P}_n \left\{ (\mathbf{1}\{\zeta_{n,u} < Y \leq \zeta_0\} - \mathbf{1}\{\zeta_0 < Y \leq \zeta_{n,u}\}) \left[l_2^{\hat{\psi}_n} - l_1^{\hat{\psi}_n} \right] (V, \delta, Z) \right\} = n^{-1} \times Q_n(u) + \hat{E}_n(u)$, where $\hat{E}_n(u) \equiv \mathbb{P}_n \left\{ (\mathbf{1}\{Y \leq \zeta_0\} - \mathbf{1}\{Y \leq \zeta_{n,u}\}) \left[l_2^{\hat{\psi}_n} - l_2^{\psi_0} - l_1^{\hat{\psi}_n} + l_1^{\psi_0} \right] (V, \delta, Z) \right\}$. By arguments similar to those used in the proof of

lemma 10, we can obtain constants $0 < F_1, F_2 < \infty$ such that $|l_j^{\hat{\psi}_n}(V, \delta, Z) - l_j^{\psi_0}(V, \delta, Z)| \leq F_j \|\hat{\psi}_n - \psi_0\|_\infty$ almost surely, for $j = 1, 2$. Hence $|\hat{E}_n(u)| \leq \mathbb{P}_n \left| \mathbf{1}\{Y \leq \zeta_0\} - \mathbf{1}\{Y \leq \zeta_{n,u}\} \right| O_P(n^{-1/2})$. By arguments given in the proof of lemma 11, we know $(\mathbb{P}_n - P) \left| \mathbf{1}\{Y \leq \zeta_0\} - \mathbf{1}\{Y \leq \zeta_{n,u}\} \right| = O_P^{n,M}(n^{-1})$.

Since also $\sup_{u \in [n, M]} P|\mathbf{1}\{Y \leq \zeta_0\} - \mathbf{1}\{Y \leq \zeta_{n,u}\}| = O(n^{-1})$ by condition B2(i), we now have that $\hat{E}_n = O_P(n^{-3/2})$. The desired result follows. $\square$

Proof of theorem 5. Fix $h \in \mathcal{H}_\infty$. We first establish that $(Q_n^+, \mathcal{Z}^n(h) \equiv \sqrt{n} \mathbb{P}_n U_{\zeta_0}^\tau(\psi_0)(h))$ converges weakly to $(Q^+, \mathcal{Z}(h))$, on $D_M \times \mathbb{R}$, where Q^+ and $\mathcal{Z}(h)$ are independent, for each fixed $M < \infty$, and $\mathcal{Z}(h)$ is mean zero Gaussian with variance $\tilde{\sigma}_h^2 \equiv \text{var}[U_{\zeta_0}^\tau(\psi_0)(h)]$. Accordingly, fix M , and let $0 = u_0 < u_1 < u_2 < \dots < u_J \leq M$ be a finite collection of points and $q_1, \dots, q_J, \tilde{q}$ be arbitrary real numbers. We first need to show that the characteristic function of $(Q_n^+(u_1), \dots, Q_n^+(u_J), \mathcal{Z}^n(h))$ converges to that of $(Q^+(u_1), \dots, Q^+(u_J))$ times that of $\mathcal{Z}(h)$. Since $u_1, \dots, u_J$ are arbitrary, we will have convergence of all finite-dimensional distributions. We then show that Q_n^+ is asymptotically tight to obtain the desired weak convergence.

Let $y \mapsto I_{nj}(y) \equiv \mathbf{1}\{\zeta_0 + u_{j-1}/n < y \leq \zeta_0 + u_j/n\}$, $j = 1, \dots, J$; and $F_i \equiv [l_1^{\psi_0} - l_2^{\psi_0}](V_i, \delta_i, Z_i)$ and $\mathcal{Z}_i \equiv U_{\zeta_0}^\tau(\psi_0)(h)(X_i)$, $i = 1, \dots, n$. In other words, $\mathcal{Z}_i$ is the score contribution from the i th observation. Thus

$$(22) \quad P \exp \left[i \left\{ \sum_{j=1}^J q_j [Q_n^+(u_j) - Q_n^+(u_{j-1})] + \tilde{q} \mathcal{Z}^n(h) \right\} \right] \\ = \prod_{k=1}^n P \left[\exp \left\{ \sum_{j=1}^J i q_j I_{nj}(Y_k) F_k \right\} e^{i \tilde{q} \mathcal{Z}_k / \sqrt{n}} \right].$$

However, using the facts that $e^{\sum_j w_j} - 1 = \sum_j (e^{w_j} - 1)$ when only one of the w_j 's differs from zero and $e^{uv} - 1 = u(e^v - 1)$ when u is dichotomous, we have $\exp \left\{ \sum_{j=1}^J i q_j I_{nj}(Y_k) F_k \right\} = 1 + \sum_{j=1}^J (e^{i q_j I_{nj}(Y_k) F_k} - 1) = 1 + \sum_{j=1}^J I_{nj}(Y_k) (e^{i q_j F_k} - 1)$. Combining this with condition B2 and the boundedness of F_k and $\mathcal{Z}_k$, we have $P \left[\exp \left\{ \sum_{j=1}^J i q_j I_{nj}(Y_k) F_k \right\} e^{i \tilde{q} \mathcal{Z}_k / \sqrt{n}} \right] =$

$$P e^{i \tilde{q} \mathcal{Z}_k / \sqrt{n}} + \sum_{j=1}^J \frac{(u_j - u_{j-1}) \tilde{h}(\zeta_0)}{n} P \left[(e^{i q_j F_k} - 1) e^{i \tilde{q} \mathcal{Z}_k / \sqrt{n}} \mid Y = \zeta_0 + \right] + o(n^{-1})$$

$= 1 + n^{-1} \left[-\tilde{q}^2 \tilde{\sigma}_h^2 / 2 + \tilde{h}(\zeta_0) \sum_{j=1}^J (u_j - u_{j-1}) \{\phi^+(q_j) - 1\} \right] + o(n^{-1})$, where $o(1)$ is a quantity going to zero uniformly over $k = 1, \dots, n$. Thus the right side of (22) is $\exp \left[-\tilde{q}^2 \tilde{\sigma}_h^2 / 2 + \tilde{h}(\zeta_0) \sum_{j=1}^J (u_j - u_{j-1}) \{\phi^+(q_j) - 1\} \right]$, which is precisely $P \exp \left[i \tilde{q} \mathcal{Z}(h) + i \sum_{j=1}^J q_j \{Q^+(u_j) - Q^+(u_{j-1})\} \right]$ as desired.

We next need to verify that Q_n^+ is asymptotically tight on $[0, M]$. Since there exists a constant $c_* < \infty$ such that $\max_{1 \leq i \leq n} |F_i| \leq c_* < \infty$ almost

surely, we have that $|Q_n^+(u_2) - Q_n^+(u_1)| \leq c_* n \mathbb{P}_n \mathbf{1}\{\zeta_0 + u_1/n < Y \leq \zeta_0 + u_2/n\}$, for all $0 \leq u_1 < u_2 \leq M$. Thus we are done if we can show that $u \mapsto \tilde{R}_n(u) \equiv n \mathbb{P}_n \mathbf{1}\{\zeta_0 < Y \leq \zeta_0 + u/n\}$ is tight on $[0, M]$. To this end, fix $0 \leq u_1 < u_2 \leq M$. Now, the expectation of $|\tilde{R}_n(u_2) - \tilde{R}_n(u_1)|$ is $nP\{\zeta_0 + u_1/n < Y \leq \zeta_0 + u_2/n\} \rightarrow |u_2 - u_1|\tilde{h}(\zeta_0)$, as $n \rightarrow \infty$. This implies the desired tightness since $u \mapsto \tilde{R}_n(u)$ is monotone. We have now established that $(Q_n^+, \mathcal{Z}^n(h))$ converges weakly to $(Q^+, \mathcal{Z}(h))$, on $D_M \times \mathbb{R}$, where Q^+ and $\mathcal{Z}(h)$ are independent, for each fixed $M < \infty$. Similar arguments also yield the weak convergence of $(Q_n^-, \mathcal{Z}^n(h))$ to $(Q^-, \mathcal{Z}(h))$, on $D_M \times \mathbb{R}$, where Q^- and $\mathcal{Z}(h)$ are again independent, for each fixed $M < \infty$. Thus also $(Q_n, \mathcal{Z}^n(h))$ converges weakly to $(Q, \mathcal{Z}(h))$, on $D_M \times \mathbb{R}$, where Q and $\mathcal{Z}(h)$ are independent, for each fixed $M < \infty$. Since $n(\hat{\zeta}_n - \zeta_0) = O_P(1)$, the argmax continuous mapping theorem (theorem 3.2.2 of [33]) now yields that $(n(\hat{\zeta}_n - \zeta_0), \mathcal{Z}^n(h))$ converges weakly to $(\arg\max Q, \mathcal{Z}(h))$, with the desired asymptotic independence. The remaining results follow. $\square$

Proof of theorem 6. We have $0 = \sqrt{n} \mathbb{P}_n U_{\hat{\zeta}_n}^\tau(\hat{\psi}_n) = \sqrt{n} \mathbb{P}_n U_{\zeta_0}^\tau(\hat{\psi}_n) + \sqrt{n}(\mathbb{P}_n - P)(U_{\hat{\zeta}_n}^\tau(\hat{\psi}_n) - U_{\zeta_0}^\tau(\hat{\psi}_n)) + \sqrt{n}P(U_{\hat{\zeta}_n}^\tau(\hat{\psi}_n) - U_{\zeta_0}^\tau(\hat{\psi}_n)) \equiv \sqrt{n} \mathbb{P}_n U_{\zeta_0}^\tau(\hat{\psi}_n) + B_{1,n} + B_{2,n}$, where the index set for the score terms is $\mathcal{H}_1$. By arguments similar to those used in the proof of theorem 2, combined with the fact that $n(\hat{\zeta}_n - \zeta_0) = O_P(1)$, we have that both $B_{1,n} = o_P^{\mathcal{H}_1}(1)$ and $B_{2,n} = o_P^{\mathcal{H}_1}(1)$. Thus $\sqrt{n} \mathbb{P}_n U_{\zeta_0}^\tau(\hat{\psi}_n) = o_P^{\mathcal{H}_1}(1)$. We also have that $\sqrt{n}(\mathbb{P}_n - P)U_{\zeta_0}^\tau(\hat{\psi}_n) - \sqrt{n}(\mathbb{P}_n - P)U_{\zeta_0}^\tau(\psi_0) = o_P^{\mathcal{H}_1}(1)$. Combining this with lemma 5, the Z-estimator master theorem (theorem 3.3.1 of [33]) now yields the desired results. $\square$

Proof of corollary 1. We first derive the unconditional limiting distribution of $\sqrt{n}(\hat{\psi}_n^\circ - \psi_0)$. If a class of measurable functions $\mathcal{F}$ is P -Glivenko-Cantelli with $\|P\|_{\mathcal{F}} < \infty$, then the class $\kappa \cdot \mathcal{F} = \{\kappa f : f \in \mathcal{F}\}$, where κ denotes a generic version of one of the weights κ_i , is also P -Glivenko-Cantelli, by theorem 3 of [34]. Thus we can apply the results of theorem 1, with only minor modification, combined with the simple fact that $\bar{\kappa} \rightarrow \mu_\kappa$ almost surely, to yield that $\hat{\psi}_n^\circ \rightarrow \psi_0$ outer almost surely. Note that the proof is made somewhat easier than before since we already know $\hat{\zeta}_n \rightarrow \zeta_0$ almost surely. Furthermore, if a class of measurable functions $\mathcal{F}$ is P -Donsker with $\|P\|_{\mathcal{F}} < \infty$, then the multiplier central limit theorem (theorem 2.9.2 of [33]) yields that the class $\kappa \cdot \mathcal{F}$ is also P -Donsker. Hence we can apply the results of theorem 5, with only minor modification, to yield that $\sqrt{n}(\hat{\psi}_n^\circ - \psi_0)$ is

asymptotically linear with influence function $\tilde{l}^\circ(h) = (\kappa/\mu_\kappa)U_{\zeta_0}^\tau(\sigma_{\theta_0}^{-1}(h))$, $h \in \mathcal{H}_1$. The factor μ_κ^{-1} occurs because the information operator for the weighted version of the likelihood is $\mu_\kappa\sigma_{\theta_0}$. We now have that $\sqrt{n}(\hat{\psi}_n^\circ - \hat{\psi}_n) = \sqrt{n}\mathbb{P}_n(\kappa/\mu_\kappa - 1)U_{\zeta_0}^\tau(\sigma_{\theta_0}^{-1}(\cdot)) + o_P^{\mathcal{H}_1}(1)$, unconditionally. Finally, the conditional multiplier central limit theorem (theorem 2.9.6 of [33]) yields part (ii) of the theorem. The factor $(\mu_\kappa/\sigma_\kappa)$ arises since $\text{var}(\kappa/\mu_\kappa) = \sigma_\kappa^2/\mu_\kappa^2$. Similar arguments establish part (i) (see [18]). $\square$

Proof of lemma 12. Standard arguments reveal that the given score function satisfies (14) by the smoothness of the log-likelihood (see [18]). $\square$

Proof of lemma 13. Note that a consequence of the Donsker theorem for contiguous alternatives (theorem 3.10.12 of [33]) is that for any bounded P -Donsker class $\mathcal{F}$, $\|\mathbb{P}_n - P\|_{\mathcal{F}} \xrightarrow{P_n} 0$. Thus the proof of lemma 3 can be reconstituted to yield boundedness in probability of $\|\hat{A}_0\|_{[0,\tau]}$ under P_n , since all of the function classes involved are bounded P -Donsker classes. We can similarly modify the proof of theorem 1 (see [18]) to yield $\|\hat{\psi}_0 - \psi_0^*\|_\infty \xrightarrow{P_n} 0$. $\square$

Proof of theorem 7. The basic idea of the proof is to use the Donsker theorem for contiguous alternatives in combination with key arguments in the proof of theorem 6 and the form of the score and information operators under model C2'. Pursuing this course, we obtain for any $(h_1, h_2) \in \mathbb{R}^{q+1}$,

$$\begin{aligned} (h_1, h_2)' \hat{S}_1(\zeta) &= \sqrt{n}\mathbb{P}_n(1, 1) \left[\begin{pmatrix} U_{\zeta,1}^\tau \\ U_{\zeta,2}^\tau \end{pmatrix} (\psi_0^*) \begin{pmatrix} h_1 \\ h_2 \end{pmatrix} \right. \\ &\quad \left. - \begin{pmatrix} U_{\zeta_0,3}^\tau \\ U_{\zeta_0,4}^\tau \end{pmatrix} (\psi_0^*) \left([\sigma_*^{22}]^{-1} \sigma_*^{21}(\zeta) \begin{pmatrix} h_1 \\ h_2 \end{pmatrix} \right) \right] + o_{P_n}^{[a,b]}(1) \end{aligned}$$

$\equiv \sqrt{n}\mathbb{P}_n H_*(\zeta) + o_{P_n}^{[a,b]}(1)$, where $o_{P_n}^B(1)$ denotes a quantity going to zero in probability, under P_n , uniformly over the set B . Now the Donsker theorem for contiguous alternatives yields that the right-hand side converges to a tight, Gaussian process with covariance $P[H_*(\zeta_1)H_*(\zeta_2)]$, for all $\zeta_1, \zeta_2 \in [a, b]$, and mean $P\left[H_*\left\{U_{\zeta_0,1}^\tau(\psi_0^*)(\alpha_*) + U_{\zeta_0,2}^\tau(\psi_0^*)(\eta_*)\right\}\right]$. Note that we only need to compute the moments under the null distribution P . Careful calculations verify that this yields the desired results. $\square$

Proof of corollary 2. The limiting results under P_n follow from theorem 7 and the continuous mapping theorem, provided we can show that

$$(23) \quad \inf_{\zeta \in [a,b], v \in \mathbb{R}^{q+1}: \|v\|=1} v' V_*(\zeta) v > 0.$$

The limiting null distribution results will similarly follow from the fact that under the null distribution P , $\nu_*(\zeta) = 0$ for all $\zeta \in [a, b]$. Note that in both

the null and alternative settings, $V_*(\zeta)$ only depends on the null limiting distribution. It is sufficient to verify that $\sigma_{\psi_0^*, \zeta_n}$ is one-to-one for all sequences $\zeta_n \in [a, b]$ and $h_n \in \mathcal{H}_\infty$. Note that we can ignore any differences between ζ_0 and ζ in calculating $\zeta \mapsto \sigma_{\psi_0^*, \zeta}^{22}$ because of the non-identifiability of ζ under the null hypothesis, ie., $\zeta \mapsto \sigma_{\psi_0^*, \zeta}^{22}$ is constant. Assume now that there exists sequences $\zeta_n \in [a, b]$ and $h_n \in \mathcal{H}_\infty$ such that $\sigma_{\psi_0^*, \zeta_n} h_n \rightarrow 0$. We will now show that this forces $h_n \rightarrow 0$. Without loss of generality, we can assume $\zeta_n \rightarrow \zeta_*$ and $h_n \rightarrow h$. Since the map $h \mapsto \sigma_{\psi_0^*, \zeta} h$ is continuous and since $\zeta \mapsto \sigma_{\psi_0^*, \zeta} h$ is cadlag, we can further assume without loss of generality that either $\sigma_{\psi_0^*, \zeta_*} h = 0$ or that $\sigma_{\psi_0^*, \zeta_*^-} h = 0$ (the ζ_*^- denotes that we are converging to ζ_* from below). The arguments for either case are the same, so we will for brevity only give the proof for the first case.

By the arguments surrounding expressions (17), (18) and (19), combined with the non-identifiability of ζ under the null model, we obtain that expression (19) must now hold for all $t \in (0, \tau]$ but with ζ_* replacing ζ_0 . In other words, $\tilde{Y}(t)(h_1 \mathbf{1}(Y > \zeta_*) + h'_2 Z_2(t) \mathbf{1}(Y > \zeta_*) + h'_3 Z + h_4(t)) = 0$, almost surely, for all $t \in (0, \tau]$. Since $\text{var}[Z(t_4)|Y > \zeta_*] \geq \text{var}[Z(t_4)|Y > b] \times P[Y > b] / P[Y > \zeta_*]$ is positive definite by condition B4, we have $h_3 = 0$. We can similarly use B4 to verify that $\text{var}[Z(t_3)|Y \leq \zeta_*]$ is positive definite and thus $h_2 = 0$. Now $h_1 = 0$ and $h_4 = 0$ easily follow. Hence $h \mapsto \sigma_{\psi_0^*, \zeta} h$ is uniformly one-to-one in a manner which yields the conclusion (23). $\square$

Proof of theorem 8. The results follow from arguments similar to those used in the proof of theorem 7, but based on the conditional multiplier central limit theorem for contiguous alternatives, theorem 9 below. $\square$

THEOREM 9. *(Conditional multiplier central limit theorem for contiguous alternatives) Let $\mathcal{F}$ be a P -Donsker class of measurable functions, and let P_n satisfy*

$$\int \left[\sqrt{n}(dP_n^{1/2} - dP^{1/2}) - \frac{1}{2} h dP^{1/2} \right]^{1/2} \rightarrow 0,$$

as $n \rightarrow \infty$, for some real valued, measurable function h . Also assume $\lim_{M \rightarrow \infty} \limsup_{n \rightarrow \infty} P_n(f - Pf)^2 \mathbf{1}\{|f - Pf| > M\} = 0$ for all $f \in \mathcal{F}$, and that the multipliers in the weighted bootstrap, $\kappa_1, \dots, \kappa_n$, are i.i.d. and independent of the data, with mean $0 < \mu_\kappa < \infty$ and variance $0 < \sigma_\kappa^2 < \infty$, and with $\int_0^\infty \sqrt{P(\kappa_1 > u)} du < \infty$. Then $(\mu_\kappa / \sigma_\kappa)(\mathbb{P}_n^\circ - \mathbb{P}_n) \xrightarrow[\circ]{P_n} \mathbb{G}$ in $\ell^\infty(\mathcal{F})$, where $\mathbb{G}$ is a tight, mean zero Brownian bridge process.

Proof. The proof is in chapter 11 of [16] (see also [18]). $\square$

Proof of corollary 3. Assume at first that $\tilde{M}_n$ is a fixed number $\tilde{M} < \infty$. Theorem 8 now yields that the collection $\{\hat{S}_{1,1}^\circ - \hat{S}_1, \dots, \hat{S}_{1,\tilde{M}_n}^\circ - \hat{S}_1\}$ converges jointly, conditionally on the data, to $\tilde{M}$ i.i.d. copies of $\mathbb{Z}_*$. Thus $\hat{V}_n$ converges weakly to the sample covariance process (divided by $\tilde{M}_n$ instead of $\tilde{M}_n - 1$) of an i.i.d. sample of $\tilde{M}_n$ copies of $\mathbb{Z}_*$. The same result holds true if $\tilde{M}_n$ to go to ∞ slowly enough. Since the Gaussian processes involved are tight, $\hat{V}_n$ is consistent for Σ_* , uniformly over $\zeta \in [a, b]$. Similar arguments yield pointwise consistency of $\hat{\mathbb{F}}$ and $\hat{\mathbb{F}}$ at continuity points of $\hat{\mathbb{T}}_*$ and $\hat{\mathbb{T}}_*$. Since $\hat{\mathbb{T}}_*$ and $\hat{\mathbb{T}}_*$ are continuous, the consistency extends to uniform consistency. $\square$

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