

Problem sets are due at 5PM in my mailbox. You may work in groups (indeed I encourage you to all work together), but each student should turn in their own write-up.

1 Mixed Proportional Hazards (MPH)

Helpful reading: Kiefer (1988), Fitzenberger and Wilke (2006), Ridder and Woutersen (2003)

Let $Y \in \mathbb{Y} = [0, \infty)$ denote a random draw from the target population of durations, $X \in \mathbb{X} \subset \mathbb{R}^K$ a corresponding $K \times 1$ vector of observed covariates and A latent heterogeneity (assumed independent of X). Available to the econometrician is a simple random sample with N copies of $Z_i = (X_i', Y_i)'$. We posit a conditional hazard function of

$$\lambda(y|x, a; \theta) = \lambda_0(y; \alpha) e^{x' \beta + a}. \quad (1)$$

Here $\lambda_0(y; \alpha)$ is a known parametric baseline hazard function indexed by the unknown parameter α . The $e^{x' \beta + a}$ term parameterizes the effect of changes in X on the hazard rate. Our goal is to recover consistent and efficient estimates of $\theta = (\alpha, \beta)'$. You may assume that θ equals its population value (i.e., $\theta = \theta_0$) in what follows unless noted otherwise.

[a] Let $\Lambda_0(y; \alpha) = \int_0^y \lambda_0(t; \alpha) dt$ denote the integrated baseline hazard. Show that the conditional survival function equals

$$\Pr(Y > y | X = x, A = a) = S(y|x, a; \theta) = \exp\left(-\Lambda_0(y; \alpha) e^{x' \beta + a}\right). \quad (2)$$

[b] Let $y_\tau(x, a) = Q_{Y|X}(\tau | X = x, A = a)$ be the τ^{th} conditional quantile of Y given $X = x$ and $A = a$. Use the Implicit Function Theorem (as applied to $S(y_\tau(x, a) | x, a; \theta) = (1 - \tau)$) to show that

$$\begin{aligned} \frac{\partial y_\tau(x, a)}{\partial x} &= - \left\{ \frac{\partial S(y|x, a)}{\partial y} \Big|_{y=y_\tau(x, a)} \right\}^{-1} \frac{\partial S(y|x, a)}{\partial x} \Big|_{y=y_\tau(x, a)} \\ &= \left\{ \frac{\Lambda_0(y_\tau(x, a); \alpha_0)}{\lambda_0(y_\tau(x, a); \alpha_0)} \right\} \beta_0. \end{aligned}$$

Use your result to comment on any testable restrictions the MPH places on the conditional distribution of Y given X and A (and/or X alone).

[c] Let $\pi(a)$ denote the density function of A at $A = a$. The survival function conditional on $X = x$ alone is

$$S(y|x) = \int S(y|x, a) \pi_0(a) da. \quad (3)$$

We will call (3) the observed survival function.

[i] Consider the distribution of latent heterogeneity A in a subpopulation that has survived to y (i.e.,

$Y > y$) and is homogenous in $X = x$. Show that the density of A at $A = a$ in this subpopulation is

$$h(a; x, y) = \frac{S(y|x, a) \pi_0(a)}{\int S(y|x, a) \pi_0(a) da}.$$

[ii] Use your answer in part [i] above to show that the observe conditional hazard function is

$$\lambda(y|x; \theta) = \lambda_0(y; \alpha) e^{x'\beta} \mathbb{E}[e^A | Y \geq y, x]. \quad (4)$$

(Hint: use (3) to derive $\lambda(y|x; \theta)$).

Now consider the hazard function relevant for a random draw from the population of units with $X = x$. This *average structural hazard* function is

$$\bar{\lambda}(y|x; \theta) = \lambda_0(y; \alpha) e^{x'\beta} \mathbb{E}[e^A]. \quad (5)$$

Argue that (a) $\mathbb{E}[e^A | Y \geq y, x]$ is decreasing in y , and hence that (b) the observed hazard function is “rotated to the right” relative to the average structural one (5). Assuming that the MPH specification is correct, argue that a researcher who ignores unobserved heterogeneity might conclude that the baseline hazard implies (more) negative duration dependence than the actual population one.

[c] Define

$$\rho(z; \theta) = \Lambda_0(y; \alpha) \exp(x'\beta). \quad (6)$$

Use (2) and monotonicity of the integrated baseline hazard function to show that

$$\Pr(\rho(Z; \theta) > r | X, A) = \exp(-re^A).$$

Show that this implies that conditional on A , $\rho(Z; \theta)$ is an exponential random variable with rate parameter e^A and independent of X . Show that conditional on X alone $\rho(Z; \theta)$ is a random draw from a mixture of exponentials and remains independent of X .

[d] Recall that for W a exponential random variable with rate λ we have $\mathbb{E}[W^l] = \frac{l!}{\lambda^l}$ for $l = 1, 2, 3, \dots$. Use this result, your analysis in part [c] above, and the law of iterated expectations to show that

$$\mathbb{E}[\psi(Z; \theta)] = 0$$

where

$$\psi(Z; \theta) = (X - \mathbb{E}[X]) \otimes \rho(Z; \theta)$$

with $\mathbb{E}[X]$ assumed known.

[e] Assume that $\dim(X) = K = 1$ and further that $\alpha = \alpha_0$ is known to the econometrician. Show that the method-of-moments estimate for β , based on your answer in part [d] above has an asymptotic variance of

$$\frac{2}{\mathbb{V}(X)} \frac{\mathbb{E}[e^{-2a}]}{(\mathbb{E}[e^{-a}])^2}.$$

[f] Assume that Y is conditionally Weibull such that $\Lambda_0(y; \alpha) = y^\alpha$ and that the econometrician

knowns $\beta = \beta_0$ but seeks to learn α . Show that the method-of-moments estimate for α based upon the moment function in part [d] above has an asymptotic variance of

$$\frac{\alpha^2}{\beta^2} \frac{2}{\mathbb{V}(X)} \frac{\mathbb{E}[e^{-2a}]}{(\mathbb{E}[e^{-a}])^2}.$$

What happens if $\beta \approx 0$? Comment with reference to Hahn (1994).

2 Semiparametric efficiency bound (SEB)

Helpful reading: Newey (1990), Hahn (1994) and Ridder and Woutersen (2003).

This problem maintains the basic setup and notation established in Problem 1 above.

[a] Observe that $y = \Lambda_0^{-1}(\rho(z; \theta) \exp(-x'\beta), \alpha)$. Using the change-of-variables formula to show that

$$\begin{aligned} f_{\rho|X}(\rho(z; \theta)|x) &= f(y|x; \theta, \pi) \frac{1}{\lambda(y; \alpha) \exp(x'\beta)} \\ &= f_{\rho}(\rho(z; \theta)) \end{aligned}$$

where $f(y|x; \theta, \pi) = \int f(y|x, a; \theta) \pi(a) da$ and the second equality follows from the independence of $\rho(Z; \theta)$ and X established earlier.

[b] Let $\pi(a; \eta)$ denote a parametric submodel for the nuisance heterogeneity distribution. Using the result in part [a] we have a sub-model log-likelihood function of

$$l(\theta, \eta; Z) = \ln \lambda(Y; \alpha) + X'\beta + \ln f_{\rho}(\rho(Z; \theta); \eta).$$

Can you relate your sub-model log-likelihood to the formulation used by Hahn (1994)?

[b] Differentiate with respect to $\theta = (\alpha, \beta)'$ and η to derive the sub-model scores. Conjecture the form of the nuisance tangent set based on your calculations.

[c] Using your results from part [b] show that the efficient score for θ is

$$\psi^{\text{eff}}(Z; \theta) = \left\{ \begin{aligned} &\left(\frac{\frac{\partial \lambda_0(y, \alpha)}{\partial \alpha}}{\lambda_0(y, \alpha)} - \mathbb{E} \left[\frac{\frac{\partial \lambda_0(y, \alpha)}{\partial \alpha}}{\lambda_0(y, \alpha)} \middle| \rho(Z; \theta) \right] \right) + \left(\frac{\frac{\partial \Lambda_0(y, \alpha)}{\partial \alpha}}{\Lambda_0(y, \alpha)} - \mathbb{E} \left[\frac{\frac{\partial \Lambda_0(y, \alpha)}{\partial \alpha}}{\Lambda_0(y, \alpha)} \middle| \rho(Z; \theta) \right] \right) \frac{f'_{\rho}(\rho(z; \theta))}{f_{\rho}(\rho(z; \theta))} \rho(z; \theta) \\ &(X - \mathbb{E}[X]) + (X - \mathbb{E}[X]) \frac{f'_{\rho}(\rho(Z; \theta))}{f_{\rho}(\rho(Z; \theta))} \rho(Z; \theta) \end{aligned} \right\}.$$

You will need to use independence of X and $\rho(Z; \theta)$ to derive the expression above.

[d] As in Hahn (1994) show that $\theta' \psi^{\text{eff}}(Z; \theta) = 0$ when Y is conditionally Weibull. Discuss the implications of this result for estimation.

[e] Let $h(\rho(z; \theta))$ be a possibly misspecified model for the ratio $\frac{f'_{\rho}(\rho(z; \theta))}{f_{\rho}(\rho(z; \theta))}$, show that

$$\psi^{\text{dr}}(Z; \theta) = \left\{ \begin{aligned} &\left(\frac{\frac{\partial \lambda_0(y, \alpha)}{\partial \alpha}}{\lambda_0(y, \alpha)} - \mathbb{E} \left[\frac{\frac{\partial \lambda_0(y, \alpha)}{\partial \alpha}}{\lambda_0(y, \alpha)} \middle| \rho(Z; \theta) \right] \right) + \left(\frac{\frac{\partial \Lambda_0(y, \alpha)}{\partial \alpha}}{\Lambda_0(y, \alpha)} - \mathbb{E} \left[\frac{\frac{\partial \Lambda_0(y, \alpha)}{\partial \alpha}}{\Lambda_0(y, \alpha)} \middle| \rho(Z; \theta) \right] \right) h(\rho(z; \theta)) \rho(z; \theta) \\ &(X - \mathbb{E}[X]) + (X - \mathbb{E}[X]) h(\rho(z; \theta)) \rho(Z; \theta) \end{aligned} \right\},$$

is a valid moment function for θ .

[f] Assume that $e^A \sim \text{Gamma}(\eta_1, \eta_2)$. Derive an expression for $\frac{f'_\rho(\rho(Z; \theta))}{f_\rho(\rho(Z; \theta))}$ in terms of $\rho(Z; \theta)$, η_1 and η_2 . Use your expression to construct a locally efficient estimate of θ (assume that the conditional distribution of Y is such that the SEB is non-zero).

Econometrics field exam practice question

Let $\{(W_i, X_i, Y_i)\}_{i=1}^N$ be a simple random sample drawn from a population characterized by (unknown) distribution F_0 ; Y is a scalar outcome variable of interest, X a vector of policy or treatment variables, and W a vector of additional control variables or confounders. Assume that the conditional distribution of Y_i given W_i and X_i satisfies:

$$Y = X' \beta_0 + h_0(W) + U, \quad \mathbb{E}[U | W, X] = 0. \quad (7)$$

Here $\beta_0 \in \mathbb{R}^K$ is the finite dimensional parameter of interest and $h_0(W)$ an unknown function mapping from a subset of $W \in \mathbb{W} \subset \mathbb{R}^{\dim(W)}$ into $\mathcal{H} \subset \mathbb{R}$. You may assume that all the expressions which appear below are well-defined (i.e., don't worry about regularity conditions in what follows).

[a] Assume that the researcher knows that $h_0(W) = k(W)' \delta_0$ for some known $J \times 1$ vector of basis functions $k(W)$ (which includes a constant) and unknown parameter δ_0 . Show that the coefficient on X in the least squares fit of Y onto X and $k(W)$ has an asymptotic limiting distribution of

$$\sqrt{N} (\hat{\beta}_{\text{OLS}} - \beta_0) \xrightarrow{D} \mathcal{N} \left(0, \sigma^2 \mathbb{E} [(X - \Pi_0 k(W)) (X - \Pi_0 k(W))']^{-1} \right), \quad (8)$$

with $\Pi_0 = \mathbb{E} [X k(W)'] \mathbb{E} [k(W) k(W)']^{-1}$ the $K \times J$ matrix of projection coefficients associated with the multivariate regression of X onto $k(W)$. *Note this result maintains the additional assumption of homoscedasticity.* For your reference the partitioned matrix formula is:

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} A^{-1} + A^{-1} B (D - C A^{-1} B) C A^{-1} & -A^{-1} B (D - C A^{-1} B) \\ -(D - C A^{-1} B) C A^{-1} & (D - C A^{-1} B) \end{bmatrix}.$$

[b] Let

$$e_0(w) = \mathbb{E}[X | W = w]. \quad (9)$$

be a vector of conditional expectation functions (CEFs) of the K policy variables given the confounders. Assume that $e_0(W)$ is known. Show that following unconditional moment identifies β_0 :

$$\mathbb{E}[m(Z, \beta_0, e_0(W))] = 0. \quad (10)$$

with $m(Z, \beta_0, e_0(W)) = (Y - X' \beta_0)(X - e_0(W))$. Let $\hat{\beta}_E$ be the method-of-moments estimate associated with this restriction. Is this estimator more or less efficient than the OLS estimator described in part (a)?

[c] Augment the identifying “E-moment” (10) from part (b) with the auxiliary conditional moment

$$\mathbb{E}[(X - e_0(W)) | W] = 0. \quad (11)$$

Argue that the efficient estimator based on (10) and (11) coincides with the just-identified moment based

upon the unconditional moment restriction

$$\psi(Z, \beta_0, e_0(W), h_0(W)) = m(Z, \beta_0, e_0(W)) - \mathbb{E}^*[m(Z, \beta_0, e_0(W)) | (X - e_0(W)); W].$$

Here $\mathbb{E}^*[Y | X; W]$ denotes the linear regression of Y onto X within a subpopulation homogenous in W (i.e., a conditional linear predictor). You may assume that all “unknowns” except β_0 are known. You may not assume that “unknown unknowns are known” only that “known unknowns are known”.

Further show that

$$\psi(Z, \beta_0, e_0(W), h_0(W)) = (Y - X'\beta_0 - h_0(W))(X - e_0(W)). \quad (12)$$

[d] Replace $h_0(w)$ in (12) with some arbitrary function of w . Is (12) still mean zero? Now replace $e_0(w)$ in (12) with some arbitrary function of w . Is (12) still mean zero? Comment on the implications of your answer for estimation.

[e] Write, in the language of your choice, a short Haiku inspired by questions (a) to (d) above.

References

- Fitzenberger, B. and Wilke, R. A. (2006). *Modern Econometric Analysis*, chapter Using quantile regression for duration analysis, pages 103 – 118. Springer-Verlag, Berlin.
- Hahn, J. (1994). The efficiency bound of the mixed proportional hazards model. *Review of Economic Studies*, 61(4):607 – 629.
- Kiefer, N. M. (1988). Economic duration data and hazard functions. *Journal of Economic Literature*, 26(2):646 – 679.
- Newey, W. K. (1990). Semiparametric efficiency bounds. *Journal of Applied Econometrics*, 5(2):99 – 135.
- Ridder, G. and Woutersen, T. M. (2003). The singularity of the information matrix of the mixed proportional hazards model. *Econometrica*, 71(5):1579 – 1589.