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# REJOINDER: CONDITIONAL GROWTH CHARTS

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First of all, we would like to thank all the discussants for their encouragement of and insightful comments on our work. We are especially appreciative of their unique perspectives brought to the topic of conditional growth charts. The discussants raised a number of interesting questions from statistical as well as clinical points of view, some of which are broader and deeper than what we will be able to address fully in this rejoinder. Our rejoinder will focus on the issues most directly related to the statistical model, called the global model, used in our paper.

**1. Conditional, marginal or joint models.** Carroll and Ruppert correctly pointed out that semiparametric efficient estimation of marginal models in the context of quantile regression calls for further research. The current literature on semiparametric efficient estimation often relies on the Gaussian likelihood, so there is no direct analogue in the quantile model without a parametric likelihood. Consider estimating the median of a univariate distribution from a correlated sample $Y_1, \dots, Y_n$. Even in this much simpler setting, it is unclear if we can find a uniformly more efficient estimator than the usual sample median. Efficiency bounds similar to those of Newey and Powell [3] are yet to be developed for longitudinal models.

We chose to use the conditional model mainly driven by the desire to take into account the subject's prior growth path. We can integrate out the prior growth path to revert to a marginal model, and if the within-subject correlation in the marginal model is indeed accounted for through the dependence on prior growth path, this might lead to efficient estimation of the marginal model, but we have not explored it in detail.

Thompson used simulation results to show that if a joint Gaussian model holds (possibly after transformations), then distribution-based estimates of quantiles are less variable than the quantile regression estimates, especially for $\tau$ near 0 or 1. This observation was also made in [2] in a simpler setting. Here we have the classical bias-variance trade-off, so our preference depends on the available sample size. Distributional assumptions might be necessary when there are no sufficient data, but our empirical work on growth data (including but not limited to the Finnish growth data presented in the paper) has shown that joint normality is often unrealistic, so not only should we worry about bias, the uncertainty estimates from such assumptions also cannot be trusted.

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