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The remarks that follow are mainly critical, but that is not unusual when statisticians discuss difficult new areas of research. My criticism is not meant to obscure the paper's many positive achievements: the neat development of resampling methods for the linear regression problem, in particular Theorem 2; the extended class of weighted jackknives introduced in Section 4, and their justification in Theorem 3; and the intriguing suggestion in Section 8 for a more general weighted jackknife based on the Fisher information. The paper's main fault, in my opinion, is not the absence of interesting new ideas but rather an overinterpretation of results, which leads to bold distinctions not based on genuine differences.

(A) I reran part of the simulation experiment of Section 10, exactly as described except for the following change: Instead of taking the $e_i \sim N(0, x_i/2)$, I took them $N(0, |x_i - 5.5|)$. This gives nearly the same set of variances for the errors e_i, but with the large variances occurring at both ends of the x range, rather than just at the right end. Only the estimation of $\mathrm{Var}(\beta_0)$ (actually equal 3.64 in this situation) was considered, and only by the two estimators $v_{J(1)}$, definition (5.1), and $\hat{v}$, definition (2.9).

Here are summary statistics for 400 Monte Carlo trials:

	mean	st. dev.	rms
$v_{J(1)}$	3.47	3.14	3.14
$\hat{v}$	2.40	1.20	1.73

(rms indicates root mean square error). Now $\hat{v}$, the ordinary estimator (and also the "residual bootstrap" estimator v_b (2.9)), is biased sharply downward instead of upward as in Table 1; $v_{J(1)}$ is nearly unbiased, as it was designed to be.

However $v_{J(1)}$ *is much more variable than* $\hat{v}$, having nearly three times the standard deviation and twice the rms error for estimating $\mathrm{Var}(\beta_0)$. The percentiles of the two Monte Carlo distributions

	5%	10%	16%	50%	(true)	84%	90%	95%
$v_{J(1)}$	0.57	0.83	1.02	2.47	(3.64)	6.15	7.80	9.63
$\hat{v}$	0.88	1.12	1.27	2.14	(3.64)	3.65	4.06	4.56