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Regression, Model Misspecification and Causation, with Pedagogical Demonstration

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Abstract

This paper shows, by a proposition and a numerical example, how a classic simple or multiple normal regression can achieve with 0.99 probability a near perfect fit to a random sample of any size but due to the omission of an independent variable the signs of the estimated coefficients are all wrong, thus distinguishing prediction from causation.

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1 Introduction

Model misspecification in regression has long been a well-recognized research problem (for standard textbook expositions on this topic, see, e.g., [4]); the estimation biases resulting from a misspecified model can be very serious (cf., e.g., [5]). Depending on the applications, a misidentification of a variable X as a (or even *the*) *cause* of Y may result in severe consequences. For example, careless correlation reports in health-related matters mislead the public at the minimum, and yet all too often one is provided with such information (which is not to say that there lacks rigorous research methodology; see, e.g., [9]). We are thus motivated to show in this paper how X can be a highly reliable positive predictor of Y due to a population coefficient of correlation close to 1 and yet as a deterministic *cause* $\frac{\partial Y}{\partial X} < 0$.

Section 2 below will highlight the issue on hand by the model

$$\begin{aligned} Y &= \beta_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon,\ \beta_2 < 0,\ \beta_3 > 0, && (1) \\ X_3 &= \gamma_1 + \gamma_2 X_2 + u,\ \gamma_2 > 0, && (2) \end{aligned}$$

with the random terms ϵ and u satisfying all the standard assumptions, and will also provide a detailed numerical example by a simulation of ϵ and u, resulting in two sample regression equations:

$$\begin{aligned} \hat{Y}_i &= 776.4 - 554.8 X_{i2} + 71.4 X_{i3}, \text{ with } R^2 = 0.99996; && (3) \\ \hat{Y}_i &= 1476.5 + 885.4 X_{i2}, \text{ with } R^2 = 0.97823. && (4) \end{aligned}$$

In either equation all the coefficients are significant at the two-tailed $p < 0.01$.

Finally Section 3 will conclude with a summary.

2 Analysis

Proposition 1 *Let the population regression equation be*

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon, \tag{5}$$

where:

(1) $X_1 \equiv 1$ and X_2 is nonstochastic,

(2)

$$X_3 = \gamma_1 + \gamma_2 X_2 + u, \tag{6}$$

(3)

$$\begin{aligned} \epsilon &\sim N\left(0, \sigma_\epsilon^2\right),\ E\left(\epsilon_i \epsilon_j\right) = 0,\ \forall i \neq j, && (7) \\ u &\sim N\left(0, \sigma_u^2\right),\ E\left(u_k u_l\right) = 0,\ \forall k \neq l, && (8) \\ &\text{with } \epsilon \text{ and } u \text{ being independent}, && (9) \end{aligned}$$

and

(4) $\beta_2 < 0$, $\{\beta_3, \gamma_2, \beta_2 + \beta_3 \gamma_2\} \subset (0, \infty)$, with σ_ϵ and σ_u sufficiently small relative to the absolute values of β_1, β_2, β_3, and γ_2, then a regression on a

random sample of size n as based on the ordinary least squares estimation of the form

$$\hat{Y}_i = A_1 + A_2 X_{i2},\ i = 1, \cdots, n, \tag{10}$$

is such that

$$\lim_{\sigma_\epsilon,\ \sigma_u \to 0} R^2 = 1, \tag{11}$$

$$\lim_{\sigma_\epsilon,\ \sigma_u \to 0} p_{A_j} = 0,\ j = 1, 2, \text{ with} \tag{12}$$

$$A_2 > 0. \tag{13}$$

Proof. By assumptions (1), (2) and (3), we have

$$\begin{aligned} Y &= \beta_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon \\ &= (\beta_1 + \beta_3 \gamma_1) + (\beta_2 + \beta_3 \gamma_2)\, X_2 + (\beta_3 u + \epsilon) \\ &\equiv \alpha_1 + \alpha_2 X_2 + \eta \end{aligned} \tag{14}$$

satisfying all the classical normal linear regression hypotheses. Assumption (4) implies that as $\sigma_\epsilon,\ \sigma_u \to 0$, one has $Y_i - \hat{Y}_i \to 0\ \forall i \in \{1, \cdots, n\}$, i.e., approaching a perfect fit through the sample $\{(X_i, Y_i) \mid 1 \le i \le n\}$, so that $R^2 \to 1$ and $p_{A_j} \to 0\ \forall j = 1, 2$; further, since $E(A_2) = \alpha_2 \equiv \beta_2 + \beta_3 \gamma_2 > 0$, we have $A_2 > 0$. ■

Remark 1 *It is true that one may estimate $\alpha_2 \equiv \beta_2 + \beta_3 \gamma_2$ from the above reduced equation* (14) *for predicting Y by X_2, with the regression satisfying all the standard assumptions thus to defy even the most sophisticated residual analyses (see, e.g.,* [6, 10]*) in detecting the specification error. However, prediction based on correlation is not causation; in fact, from the original full equation* (5) *one can argue that X_2 by itself is a negative factor of Y; consider for example: $X_2 = 1$ represents the male gender, which performs a certain task as measured by Y less well than the female gender $X_2 = 0$, but $X_3 \equiv$ heights is a strong positive factor of Y so that males perform the task better not because of the gender but because of the taller heights. As such, a correct regression model is to come from a theoretical mathematical deduction (for an emphasis on this point and how best to estimate regression parameters under model uncertainty, cf., e.g.,* [2, 8]*); if not, a regression equation in itself is only an extension of correlation, and correlation is not causation - - a common textbook caution, which incidentally, however, may lend itself to the erroneous notion that regression, being more sophisticated, must be about causal-effect; in this regard, even in the research literature one can find the identification of predictor with cause (see, e.g.,* [1]*).*

Remark 2 *We also note that in the above Proposition 1 the fact that X_3 is stochastic does not affect any of the desirable properties of the least squares estimation, since by assumption ϵ and u are independent. Nor is the apparent multicollinearity of X_2 and X_3 a problem, since*

$$\begin{aligned} Var(b_j) &= \frac{\sigma_\epsilon^2}{\sum_{i=1}^n \left(X_{ij}-\bar{X}_j\right)^2 (1-r_{23}^2)}, \forall j = 2,3, & (15) \\ \text{in } \hat{Y}_i &= b_1 + b_2 X_{i2} + b_3 X_{i3}, & (16) \end{aligned}$$

so that $\forall r_{23}^2 < 1$ one has

$$\lim_{\sigma_\epsilon^2 \to 0} Var(b_j) = 0; \tag{17}$$

this can be seen from the following example.

Example 1 *Given $n = 20$, $(X_{1,2},\cdots,X_{10,2},X_{11,2},\cdots,X_{20,2}) = (0,\cdots,0,1,\cdots,1)$,*

$$\begin{aligned} X_3 &= 10 + 20X_2 + u, \quad u \sim N\left(0, \sigma_u^2 = 1\right), & (18) \\ \text{and } Y &= \beta_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon, \quad \epsilon \sim N\left(0, \sigma_\epsilon^2 = 4\right), & (19) \\ & \text{with } \epsilon \text{ independent of } u, \end{aligned}$$

find $\beta_1 \in \mathbb{R}$, $\beta_2 < 0$, and $\beta_3 > 0$ such that with 0.99 probability:

(1) a regression of Y_i against (X_{i2}, X_{i3}) on a random sample of size n will yield $R^2 \geq 0.99$, with the two-tailed $p_{b_j} \leq 0.01$ $\forall j = 1,2,3$, and

(2) a simple regression of Y_i against X_{i2} will yield $R^2 \geq 0.95$, $p_{A_j} \leq 0.01$ $\forall j = 1,2$, and $A_2 > 0$.

Solution 1 *Since*

$$\sigma_\epsilon^{-2} \sum_{i=1}^{20} \left(Y_i - b_1 - b_2 X_{i2} - b_3 X_{i3}\right)^2 \sim \chi_{17}^2, \tag{20}$$

we determine the maximum error sum of squares with 0.99 probability to be

$$SSE_{\max,0.99} \equiv \chi_{0.01,17}^2 \sigma_\epsilon^2 = 33.409 \times 4 = 133.636; \tag{21}$$

then

$$s_{b_2,\max,0.99}^2 = \frac{133.636}{\sum_{i=1}^{20}\left(X_{i2}-\bar{X}_2\right)^2 \cdot \left(1 - r_{23,\max,0.99}^2\right)}, \tag{22}$$

where

$$\sum_{i=1}^{20}\left(X_{i2}-\bar{X}_2\right)^2 = 5 \tag{23}$$

and

$$\begin{aligned}
\left(1-r^2_{23,\max,0.99}\right) &= \frac{\left(\sum_{i=1}^{20}\left(X_{i3}-\widehat{10}-\widehat{20}X_{i2}\right)^2\right)_{\min,0.99}}{\left(\sum_{i=1}^{20}\left(X_{i3}-\bar{X}_3\right)^2\right)_{\max,0.99}} && (24)\\
&= \frac{\chi^2_{0.99,18}\sigma^2_u}{20Var\left(X_{i3}\right)_{\max,0.99}} && (25)\\
&= \frac{7.015}{20\times\left[400Var\left(X_{i2}\right)+\widehat{Var}\left(u\right)_{\max,0.99}\right]} && (26)\\
&= \frac{7.015}{2038.67} = 0.003, && (27)
\end{aligned}$$

with

$$\begin{aligned}
Var\left(X_{i2}\right) &= \frac{5}{20} \quad \textit{and} && (28)\\
\widehat{Var}\left(u\right)_{\max,0.99} &= \frac{\chi^2_{0.01,18}}{18} = \frac{34.805}{18}, && (29)
\end{aligned}$$

so that

$$\begin{aligned}
s^2_{b_2,\max,0.99} &= \frac{133.636}{5\times 0.003} = 8909 && (30)\\
\textit{and } s_{b_2,\max,0.99} &= 94.4. && (31)
\end{aligned}$$

Similarly we calculate $s^2_{b_3,\max,0.99}$ *by replacing* $\sum_{i=1}^{20}\left(X_{i2}-\bar{X}_2\right)^2$ *in Equation* (22) *with*

$$\begin{aligned}
&\left(\sum_{i=1}^{20}\left(X_{i3}-\bar{X}_3\right)^2\right)_{\min} && (32)\\
&= 20Var\left(X_{i3}\right)_{\min} && (33)\\
&= 20\times 20^2 Var\left(X_{i2}\right)\ \textit{(by dropping } Var\left(u_i\right)\textit{)} && (34)\\
&= 2000, && (35)
\end{aligned}$$

to arrive at

$$\begin{aligned}
s^2_{b_3,\max,0.99} &= \frac{133.636}{2000\times 0.003} = 22.3 && (36)\\
\textit{and } s_{b_3,\max,0.99} &= 4.7. && (37)
\end{aligned}$$

Now since

$$Cov\left(b_2, b_3\right) = \frac{-\sigma_\epsilon^2 r_{23}}{\sqrt{\sum_{i=1}^{20}\left(X_{i2}-\bar{X}_2\right)^2 \cdot \sum_{i=1}^{20}\left(X_{i3}-\bar{X}_3\right)^2} \cdot \left(1-r_{23}^2\right)} < 0, \quad (38)$$

we have

$$\begin{aligned} Var\left(b_1\right) &= \bar{X}_2^2 Var\left(b_2\right) + \bar{X}_3^2 Var\left(b_3\right) + 2\bar{X}_2\bar{X}_3 Cov\left(b_2, b_3\right) + \frac{\sigma_\epsilon^2}{n} && (39) \\ &< \bar{X}_2^2 Var\left(b_2\right) + \bar{X}_3^2 Var\left(b_3\right) + \frac{\sigma_\epsilon^2}{n}; && (40) \end{aligned}$$

thus, we set

$$\begin{aligned} s_{b_1,\max,0.99}^2 &= 0.25 \cdot s_{b_2,\max,0.99}^2 + \bar{X}_{3,\max,0.99}^2 \cdot s_{b_3,\max,0.99}^2 \\ &\quad + \frac{s_{\max,0.99}^2}{20} && (41) \\ \text{(by Eq. (21))} &= 0.25 \times 8909 + \bar{X}_{3,\max,0.99}^2 \times 22.3 + \frac{133.636/17}{20}. && (42) \end{aligned}$$

Since

$$Var\left(X_{i3}\right) = 400 Var\left(X_{i2}\right) + Var\left(u_i\right) = 400 \times 0.25 + 1 = 101, \quad (43)$$

we have

$$Var\left(\bar{X}_3\right) = \frac{1}{20^2} \cdot (20 \times 101) \approx 5 \quad (44)$$

so that

$$\begin{aligned} \bar{X}_{3,\max,0.99} &= \left(10 + 20\bar{X}_2\right) + 3\sqrt{5}, && (45) \\ & \quad \textit{three standard deviations above the mean;} && (46) \end{aligned}$$

hence,

$$\bar{X}_{3,\max,0.99}^2 = 26.7^2 \quad (47)$$

and substituting it into Equation (42), *we have*

$$\begin{aligned} s_{b_1,\max,0.99}^2 &= 18127.5 && (48) \\ \text{and } s_{b_1,\max,0.99} &= 134.6. && (49) \end{aligned}$$

Next, without loss of generality, consider the case of $\beta_1 > 0$; we wish to identify the unique value β_1^* that has a 0.01 probability to yield a $b_1 \in (0, \beta_1)$

with b_1 greater than the null-hypothesis claimed $\beta_1 = 0$ by $\left(t_{17,0.005} \cdot s_{b_1,\max,0.99}\right)$ so as to produce a two-tailed $p \leq 0.01$; i.e.,

$$\begin{aligned} b_1 &\equiv \beta_1 - t_{17,0.01} \cdot s_{b_1,\max,0.99} && (50) \\ \text{and } \frac{b_1}{s_{b_1,\max,0.99}} &= t_{17,0.005}; && (51) \\ \text{i.e., } \beta_1 &= \left(t_{17,0.005} + t_{17,0.01}\right) \cdot s_{b_1,\max,0.99} && (52) \\ &\lessapprox 2 \times t_{17,0.005} \times 134.6 && (53) \\ &\equiv \beta_1^* = 2 \times 2.898 \times 134.6. && (54) \end{aligned}$$

Thus,

$$\beta_1^* = 780.5. \tag{55}$$

Similarly,

$$\beta_2^* \equiv -2 \times 2.898 \cdot s_{b_2,\max,0.99} = -5.8 \times 94.4 = -547.1, \tag{56}$$

and

$$\beta_3^* \equiv \max\left\{2 \times 2.898 \cdot s_{b_3,\max,0.99} = 27.4, \quad \beta_3^{**}\right\}, \tag{57}$$

where β_3^{**} is determined from the requirement of $R^2 \geq 0.99$; to that end, we consider

$$\frac{SSE_{\max,0.99}}{SST_{\min}} \equiv 1 - R^2 = 0.01, \tag{58}$$

where the minimal total sum of squares as defined by $\sigma_u = \sigma_\epsilon = 0$ is

$$\begin{aligned} SST_{\min} &\equiv nVar\left(Y\right)_{\min} \quad \text{(cf. Equation (19))} && (59) \\ &= n\left[\left(\beta_2^* + 20\beta_3\right)^2 Var\left(X_2\right) + \beta_3^2\sigma_u^2 + \sigma_\epsilon^2\right]_{\sigma_u=\sigma_\epsilon=0} && (60) \\ &\equiv 20\left(\beta_2^* + 20\beta_3^{**}\right)^2 \times 0.25, && (61) \end{aligned}$$

so that (recalling Equation (21)) $100 \cdot SSE_{\max,0.99} = 13363.6 = SST_{\min} = 5\left(\beta_2^* + 20\beta_3^{**}\right)^2$, i.e., $\beta_2^* + 20\beta_3^{**} \approx \sqrt{2672}$, and since by Equation (56) $\beta_2^* = -547.1$, we have

$$\beta_3^{**} \approx \frac{\sqrt{2672} + 547.1}{20} = 29.9 \equiv \beta_3^* \text{ (cf. Equation (57))}. \tag{62}$$

To sum up, we have obtained

$$\begin{aligned} \beta_1^* &\equiv 780.5, && (63) \\ \beta_2^* &\equiv -547.1, \text{ and} && (64) \\ \beta_3^* &\equiv 29.9. && (65) \end{aligned}$$

However, the above $\beta_3^* \equiv 29.9$ is yet to be adjusted upward to provide, with 0.99 probability, that

$$\hat{Y}_i = A_1 + A_2 X_{i2}, \qquad R^2 \geq 0.95, \tag{66}$$

$$p_{A_1} \leq 0.01 \text{ and } p_{A_2} \leq 0.01. \tag{67}$$

Here in analogy with the above multiple regression, we have:

$$SSE_{\max,0.99} \equiv \chi^2_{0.01,18}\sigma^2_{(\beta_3 u+\epsilon)} = 34.805 \times (\beta_3^2 \times 1 + 4), \text{ (cf. Eq. (21))} \tag{68}$$

and (cf. Eq. (60))

$$\begin{aligned} SST_{\min,0.99} &= n\left[(\beta_2^* + 20\beta_3)^2 Var(X_2) + \chi^2_{0.99,18}\left(\beta_3^2\sigma_u^2 + \sigma_\epsilon^2\right)\right] && (69)\\ &= 20\left[(-547.1 + 20\beta_3)^2 \times 0.25 + 7.015\left(\beta_3^2 + 4\right)\right]. && (70) \end{aligned}$$

We next solve for β_3 in

$$\begin{aligned} 0.05 &= \frac{34.805\,(\beta_3+2)^2}{5\,(-547.1+20\beta_3)^2} && (71)\\ &> \frac{SSE_{\max,0.99}}{SST_{\min,0.99}}, && (72) \end{aligned}$$

and we obtain

$$\check{\beta}_3 = 71, \tag{73}$$

which is sufficient (but not necessary) for $p_{A_j} \leq 0.01\ \forall j = 1, 2$ with 0.99 probability, as shown below:

For $p_{A_2} \leq 0.01$ we solve for β_3 in

$$\frac{\alpha_2\,(\equiv \beta_2^* + \beta_3\gamma_2)}{s_{A_2,\max,0.99}} = 2t_{18,0.005}, \text{ (recall Eq. (53))} \tag{74}$$

where $\beta_2^* = -547.1$, $\gamma_2 = 20$, $t_{18,0.005} = 2.878$, and

$$\begin{aligned} s_{A_2,\max,0.99} &= \sqrt{\left(\frac{SSE_{\max,0.99}}{18}\right)\left(\sum_{i=1}^{20}\left(X_{i2}-\bar{X}_2\right)^2\right)^{-1}} && (75)\\ &< \sqrt{\left(\frac{34.805\,(\beta_3+2)^2}{18}\right)\cdot\frac{1}{5}} \text{ (as in Eq. (72))} && (76)\\ &= 0.62\,(\beta_3+2), && (77) \end{aligned}$$

so that Equation (74) yields

$$\begin{aligned} 20\beta_3 - 547.1 &= 2 \times 2.878 \times 0.62\,(\beta_3+2) = 3.57\,(\beta_3+2), && (78)\\ \text{and thus, } \beta_3 &= 33.7 < \check{\beta}_3 = 71. && (79) \end{aligned}$$

For p_{A_1} we calculate

$$\frac{\alpha_1 \left(\equiv \beta_1^* + \beta_3 \gamma_1\right)}{s_{A_1,\max,0.99}} \tag{80}$$

by substituting $\beta_1^* \equiv 780.5$, $\check{\beta}_3 = 71$, $\gamma_1 = 10$, and $s_{A_1,\max,0.99}$

$$= \sqrt{\left(\frac{SSE_{\max,0.99}}{18}\right) \cdot \left(\frac{1}{n} + \frac{\bar{X}_2^2}{\sum_{i=1}^{20}\left(X_{i2} - \bar{X}_2\right)^2}\right)} \tag{81}$$

$$= \sqrt{\left(\frac{34.805\left(71^2+4\right)}{18}\right)} \times 0.1 = 31.2 \text{ (by Eq. (68), (73))}, \tag{82}$$

and we find

$$\frac{\alpha_1}{s_{A_1,\max,0.99}} = 47.8, \tag{83}$$

which clearly yields a $p_{A_1} << 0.01$.

We thus have established

$$Y_i = 780.5 - 547.1X_{i2} + 71X_{i3} + \epsilon_i, \;\; \epsilon_i \sim N\left(0, 4\right). \tag{84}$$

A simulation of Equation (18) yielded

$(X_{1,3},\cdots,X_{20,3}) = (9.2, 10.6, 10.9, 9.7, 7.5, 10.0, 10.2, 9.6, 9.5, 10.8, 31.9, 31.3, 29.9, 29.6, 28.9, 29.3, 29.0, 29.7, 29.8, 30.3)$,

substituting which into Equation (84) with a simulation of ϵ_i then yielded

$(Y_1, \cdots, Y_{20}) = (1431.8, 1536.1, 1553.5, 1466.5, 1311.9, 1491.7, 1504.2, 1463.4, 1456.0, 1549.4, 2499.7, 2456.3, 2352.0, 2339.4, 2293.7, 2312.3, 2294.8, 2334.0, 2349.7, 2386.6)$,

and a regression of Y_i against (X_{i2}, X_{i3}) yielded

$$\hat{Y}_i = 776.4 - 554.8X_{i2} + 71.4X_{i3},\; R^2 = 0.99996,\; S.E. = 2.93, \tag{85}$$

$$p_1 = 9.3 \times 10^{-26},\; p_2 = 5.1 \times 10^{-18}, \text{ and } p_3 = 4.7 \times 10^{-25}, \tag{86}$$

but the simple regression of Y_i against X_{i2} resulted in

$$\hat{Y}_i = 1476.5 + 885.4X_{i2},\; R^2 = 0.97823,\; S.E. = 69.62, \tag{87}$$

$$p_1 = 4.7 \times 10^{-23}, \text{ and } p_2 = 2.1 \times 10^{-16}. \tag{88}$$

Remark 3 *A comparison between the above* $R^2_{simple} = 0.97823$ *and* $R^2_{multi} = 0.99996$ *attests the validity of applying* $R^2 \approx 1$ *as a criterion for correct model specification (cf., e.g.,* [3, 11], *for other methods of testing models).*

Remark 4 *The above Example 1 highlights the basic fact that with* β_1, β_2,$\cdots$, β_K, β_{K+1} *sufficiently large relative to* σ_ϵ *in*

$$Y = \beta_1 + \beta_2 X_2 + \cdots + \beta_K X_K + \beta_{K+1} X_{K+1} + \epsilon, \quad K \geq 2, \tag{89}$$

one can always achieve a sample regression with all the desirable statistics; under such conditions, if

$$X_{K+1} = \sum_{j=1}^{K} \gamma_j X_j \tag{90}$$

$$\text{with } (\beta_{K+1}\gamma_j + \beta_j)\,\beta_j < \; < 0 \text{ for some } j, \tag{91}$$

then a sample regression with X_{K+1} *excluded is to produce* b_j *carrying the opposite sign to that with* X_{K+1} *included. Here one is also reminded that the above Equation* (90) *can be nonlinear (cf., e.g.,* [7], *for estimation of multivariable polynomial regression equations).*

3 Summary Remark

The above analysis has shown that simple regression with low R^2 achieves little purpose and multiple regression with $R^2 \approx 1$ is a criterion for correct model specification, but even a multiple regression with the best inferential statistics is no guarantee for being a correct model. Thus, correct regression models must come theoretical mathematical deduction; for example, in economics the aim of regression is mostly about estimation of the parameters of a theoretically derived equation, rather than an empirical hypothesis testing; likewise, universal physical constants, such as Planck h has been estimated from known functional forms. To conclude, either for intrinsic aesthetic value or for extrinsic utilitarian consideration, prediction is better served by cause-effect than by correlation.

References

[1] E. Boros, P.L. Hammer and J.N. Hooker, Predicting cause-effect relationships from incomplete discrete observations, *SIAM J. Disc. Math.* 7(4) (1994), 531-543.

[2] P.J. Kempthorne, Admissible variable-selection procedures when fitting regression models by least squares for prediction, *Biometrika*, 71 (1984), 593–597.

[3] J.-S. Kim and E. Frees, Omitted variables in multilevel models, *Psychometrika*, 71(4) (2006), 659-690.

[4] J. Kmenta, *Elements of Econometrics*, Macmillan, New York, 1971.

[5] H.J. Larson and T.A. Bancroft, Biases in prediction by regression for certain incompletely specified models, *Biometrika*, 50 (1963), 391–402.

[6] D.Y. Lin, L.J. Wei and Z. Ying, Model-checking techniques based on cumulative residuals, *Biometrics*, 58(1) (2002), 1-12.

[7] J.G. Lin, Modeling test responses by multivariable polynomials of higher degrees, *SIAM J. Sci. Comput.*, 28(3) (2006), 832–867.

[8] J.R. Magnus, The traditional pretest estimator, *Theory Probab. Appl.*, 44(2) (2000), 293-308.

[9] M. Palta and C. Seplaki, Causes, problems and benefits of different between and within effects in the analysis of clustered data, *Health Serv. and Outcomes Res. Meth.*, 3(3-4) (2002), 177-193.

[10] Z. Pan and D.Y. Lin, Goodness-of-fit methods for generalized linear mixed models, *Biometrics*, 61(4) (2005), 1000-1009.

[11] Y. Xia, Model checking in regression via dimension reduction, *Biometrika*, 96(1) (2009), 133-148.

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