Jana Jurečková Trimmed polynomial regression

Commentationes Mathematicae Universitatis Carolinae, Vol. 24 (1983), No. 4, 597--607

Persistent URL: http://dml.cz/dmlcz/106259

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COMMENTATIONES MATHEMATICAE UNIVERSITATIS CAROLINAE 24,4 (1983)

TRIMMED POLYNOMIAL REGRESSION Jana JUREČKOVÁ

<u>Abstract</u>: Robust test about the degree of the polynomial regression is suggested. The test is based on the trimmed least-squares estimator due to Koenker and Bassett [4] and has an asymptotically distribution-free critical region for a general class of distributions. The Pitman efficiency of the test coincides with the relative asymptotic efficiency of the trimmed least-squares estimator to the ordinary leastsquares estimator.

<u>Key words</u> : Polynomial regression, regression quantile, trimmed least-squares estimator.

Classification: 62G10, 62J05, 62G20

1. <u>Introduction</u>. Let us consider the polynomial regression model

(1.1) $Y_{ni} = \beta_0 + \beta_1 x_{ni} + \ldots + \beta_p x_{ni}^p + E_{ni}$, $i=1,\ldots,n$ where $Y_n = (Y_{n1},\ldots,Y_{nn})'$ is the vector of independent observations, $x_n = (x_{n1},\ldots,x_{nn})'$ is a given vector, $\beta = (\beta_0, \beta_1,\ldots,\beta_p)'$ is a $(p+1)x_1$ vector of unknown parameters and $E_n = (E_{n1},\ldots,E_{nn})'$ is the vector of errors which are independent and identically distributed (i.i.d.) random variables with a continuous distribution function (d.f.) F. In the subsequent text, we shall omit the subscript n in Y_{ni}, x_{ni}, E_{ni} , etc., unless it causes a confusion. Our main

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interest is in robust testing the hypothesis about the degree of the polynomial regression, i.e.,

(1.2) $H_0: \beta_j = 0$, $j = p+1-m, \dots, p$, $1 \le m \le p$. Koenker and Bassett [4] introduced the concept of regression quantile, which seems to provide a basis for L-estimation and L-testing in the general linear model. The same authors proposed the trimmed least-squares estimator (trimmed LSE) as an extension of the trimmed mean to the linear model. This estimator was later on studied by Ruppert and Carroll [8]; they considered a special design with an intercept and such that the slope-columns of the design matrix sum-up to zero.

The idea to use the regression quantiles for testing the linear hypothesis was mentioned in Ruppert and Carroll [8] who proposed a test based on the trimmed LSE under the special design mentioned above. Koenker and Bassett [5] studied several robust tests of linear exclusion hypothesis based on 1, -estimation, i.e. on minimizing the sum of absolute residuals. However, neither of the mentioned procedures covers the general polynomial regression. Jurečková [3] derived the Bahadur-type representation and the asymptotic distribution of the regression quantiles and of the trimmed LSE under a more general design. The model considered in [3] covers the polynomial regression and thus enables to construct a robust test of H_. The test statistic is asymptotically distributed according to χ^2 distribution with m degrees of freedom under H_a and according to noncentral χ^2 distribution under the contiguous alternatives. The Pitman efficiency of the test with respect to the classical one based on the or-

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dinary LSE coincides with the relative asymptotic efficiency of the trimmed LSE to the ordinary LSE.

2. Notation and preliminary results. Let us fix $\alpha_1, \alpha_2, 0 < \alpha_1 < \alpha_2 < 1$. We shall start from the polynomial regression model (1.1); we shall assume that E_1, \ldots, E_n are i.i.d. with the d.f. F(x) which satisfies the following set of conditions (A):

(A.1) F is absolutely continuous with the density f.

(A.2)
$$0 < f(\mathbf{x}) < \infty$$
 for $\xi_1 - \varepsilon < \mathbf{x} < \xi_2 + \varepsilon$, $\varepsilon > 0$
where $\xi_i = \mathbf{F}^{-1}(\alpha_i)$, $i=1,2$.

(A.3) The derivative f of f exists and is bounded in neighborhoods of ξ_1 and ξ_2 .

Denote

(2.1)
$$\mathbf{x}_{n} = \mathbf{x} = \begin{pmatrix} 1 & \mathbf{x}_{1} & \dots & \mathbf{x}_{1}^{p} \\ \dots & \dots & \dots \\ 1 & \mathbf{x}_{n} & \dots & \mathbf{x}_{n}^{p} \end{pmatrix}$$

the nx(p+1) matrix. The i-th row of X_n will be denoted by x_i . We shall assume that the sequence $\{x_n\}_{n=1}^{\infty}$ satisfies the following set of conditions (B):

- (B.1) $\lim_{n \to \infty} \frac{1}{n} \sum_{n=1}^{\infty} x_n = Q, \quad Q = (q_{jk})_{j,k=0,\ldots,p}$ where Q is a positively definite (p+1)x(p+1) matrix,.
- (B.2) $\max_{\substack{j \leq i \leq n \\ 1 \leq j \leq p \\ (D.2)}} |\mathbf{x}_{i}|^{j} = O(n^{1/4}), \text{ as } n \rightarrow \infty .$
- (B.3) $\max_{\substack{1 \leq i \leq n}} |\mathbf{x}_i| \stackrel{j}{\longrightarrow} (\sum_{k=1}^n |\mathbf{x}_k| \stackrel{j}{\longrightarrow})^{-1} \longrightarrow 0, \text{ as } n \longrightarrow \infty; j=1,\ldots,p.$

The condition (B.1) means that (2.2) $\frac{1}{n} \sum_{i=1}^{n} x_{i}^{j} \rightarrow q_{j}$, $j=0,1,\ldots,2p$

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where q₀,...,q_{2D} satisfy (2.3) $q_{k,j} = q_{k+j}$, k, j=0,...,p. As an example of X satisfying (B) may serve the following sequence (2.4) $x_{ni} = J(\frac{1}{n+1})$, i=1,...,n where $J(t) : [0,1] \rightarrow \mathbb{R}^1$ is a bounded function; then $\frac{1}{n} \xrightarrow{n}_{i=1}^{n} \mathbb{X}_{ni}^k \longrightarrow \int_{0}^{1} (J(t))^k dt$, as $n \rightarrow \infty$. For $\alpha = \alpha_1, \alpha_2$, denote (2.5) $\psi_{x}(x) = \alpha - I[x < 0], x \in \mathbb{R}^{1}$ and $Q_{\mathbf{x}}(\mathbf{x}) = \mathbf{x} \cdot \boldsymbol{\psi}_{\mathbf{x}}(\mathbf{x}) , \mathbf{x} \in \mathbb{R}^{1}$ (2.6) The \checkmark -regression quantile $\hat{\beta}(\preccurlyeq)$ is then defined as the (p+1)x1 vector $t = (t_0, \dots, t_p)'$ which solves (2.7) $\sum_{i=1}^{n} Q_{i} (\mathbf{I}_{i} - \mathbf{x}_{i}' \mathbf{t}): = \min.$ The solution of (2.7) is generally not uniquely determined; suppose that a rule is given which selects a unique element of the set of solutions for $\alpha = \alpha_1, \alpha_2$. It then follows from Theorem 2.1 of Jurečková [3] that $n^{1/2}(\hat{\beta}(\alpha) - \beta - e_1 F^{-1}(\alpha))$ (2.8) $= n^{-1/2} \left[f(F^{-1}(\alpha)) \right]^{-1} \bigcup_{i=1}^{n} \sum_{i=1}^{n} \psi_{\alpha}(E_i - F^{-1}(\alpha)) + 0_p(n^{-1/4})$ for $\alpha = \alpha'_1, \alpha'_2$, where $e_1 = (1, 0, \dots, 0)'$ is a (p+1)x1 vector, Let A be the diagonal nxn matrix with the diagonal (2.9) $a_{ii} = a_i = \begin{cases} 0 & \text{if } Y_i < x_i \hat{\beta}(\alpha_1) & \text{or } Y_i > x_i \hat{\beta}(\alpha_2) \\ 1 & \text{otherwise, } i=1,...,n. \end{cases}$

The trimmed LSE is then defined as the ordinary LSE calcula-

ted after trimming-off Y_i with $a_i = 0$, i=1,...,n, i.e., (2.10) $L = L_n(\alpha_1, \alpha_2) = (X AX)^- (X AY).$

It then follows from Theorem 3.1 of Jurečková [3] that

$$\begin{array}{c} n^{1/2} \left[\frac{L_n}{m} (\alpha_1, \alpha_2) - \beta_{2} - e_1 \delta \right] \\ = n^{-1/2} (\alpha_2 - \alpha_1)^{-1} \frac{p}{2}^{-1} \frac{n}{\sum_{i=1}^{n} x_i} (\psi(E_i) - E\psi(E_i)) + O_p(n^{-1/4}) \end{array}$$

where

(2.12)
$$\psi(\mathbf{x}) = \begin{cases} \xi_1 & \text{if } \mathbf{x} < \xi_1 \\ \mathbf{x} & \text{if } \xi_1 \leq \mathbf{x} \leq \xi_2 \\ \xi_2 & \text{if } \xi_2 < \mathbf{x} \end{cases}$$

and $\delta = (\alpha_2 - \alpha_1)^{-1} \int_{\alpha_1}^{\alpha_2} \mathbf{F}^{-1}(\mathbf{u}) \, d\mathbf{u}$.

where

$$\begin{aligned} & \left\{ \begin{array}{l} & \left\{ \int_{-\infty}^{2} (x_{1}, x_{2}, F) \right\} = (x_{2} - x_{1})^{-2} \left\{ \int_{-\infty}^{2} (F^{-1}(u) - \delta)^{2} du \right. \\ & \left. \left(2 \cdot 14 \right) \right. \\ & \left. + x_{1} (\xi_{1} - \delta)^{2} + (1 - x_{2}) (\xi_{2} - \delta)^{2} - \left[x_{1} (\xi_{1} - \delta) + (1 - x_{2}) (\xi_{2} - \delta) \right]^{2} \right\} \end{aligned}$$

We may see from (2.11) that only the first component L_0 of L is generally asymptotically biased. The asymptotic variance (2.14) coincides with that of the trimmed mean in the location model.

3. Test of H_0 . Let us turn back to the polynomial regression model (1.1). The distribution function F of the

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errors $\mathbf{E}_1, \ldots, \mathbf{E}_n$ is generally unspecified; we shall only assume that F satisfies the condition (A) for fixed α_1, α_2 , $0 < \alpha_1 < \alpha_2 < 1$. We wish to construct a test of the hypothesis (3.1) \mathbf{H}_0 : $\beta_j = 0$, $j=p+1-m, \ldots, p$ $(1 \le m \le p)$,

which is insensitive to the special shape of F.

Assume that the matrix \sum_n satisfies the condition (B) of Section 2. Denote

$$(3.2) \quad \mathbf{x}_{n}^{*} = \begin{pmatrix} 1 & \mathbf{x}_{1} & \dots & \mathbf{x}_{1}^{p-m} \\ \dots & \dots & \dots \\ 1 & \mathbf{x}_{n} & \dots & \mathbf{x}_{n}^{p-m} \end{pmatrix}$$

the nx(p+1-m) submatrix of X_n . Then, according to (B.1), (3.3) $\frac{1}{n} X_n^{**} X_n^{*} \longrightarrow Q^{*}$, as $n \rightarrow \infty$, where Q^{*} is a positively definite (p+1-m)x(p+1-m) submatrix of Q. Denote

(3.4)
$$\overline{Q}^{*} = \begin{pmatrix} Q^{\dagger} & Q \\ Q & Q \\ Q & Q \end{pmatrix}$$
 m
p+1-m m

the (p+1)x(p+1) matrix. Let $\underline{L} = \underline{L}_n(\propto_1, \propto_2)$ denote the trimmed LSE defined in Section 2; let $\underline{L}^* = \underline{L}_n^*(\ll_1, \ll_2)$ denote the trimmed LSE calculated under the assumption that H_0 is true. Then \underline{L}^* is a (p+1-m)x1 vector; denote (3.5) $\underline{L}^* = (\underline{L}_0^*, \dots, \underline{L}_{p-m}^*, 0, \dots, 0)^{\prime}$ its extension to (p+1)x1 vector. Consider the statistic (3.6) $\underline{T}_n = (\underline{L} - \underline{L}^*)^{\prime} \underline{X}^{\prime} \underline{X} (\underline{L} - \underline{L}^*) / S_n^2$

where

(3.7)
$$S_{n}^{2} = (\varkappa_{2} - \varkappa_{1})^{-2} [(n-m)^{-1} Z_{n}^{2} + \varkappa_{1} (\hat{\beta}_{0} (\varkappa_{1}) - L_{0})^{2} + (1 - \varkappa_{2}) (\hat{\beta}_{0} (\varkappa_{2}) - L_{0})^{2} - [\varkappa_{1} (\hat{\beta}_{0} (\varkappa_{1}) - L_{0}) + (1 - \varkappa_{2}) (\beta_{0} (\varkappa_{2}) - L_{0})]^{2}]$$

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and

We propose T_n as a test criterion for testing H_o . The corresponding asymptotic critical region is given in the following theorem.

<u>Theorem 3.1.</u> Let Y_1, \ldots, Y_n be independent observations satisfying the model (1.1) with the i.i.d. errors distributed according to the d.f. F satisfying the condition (A). Let χ_n satisfy the condition (B). Then, under H_0 , the statistics T_n are asymptotically distributed, as $n \rightarrow \infty$, according to χ^2 distribution with m degrees of freedom.

The following theorem gives the asymptotic distribution of T_n under the local alternatives.

<u>Theorem 3.2</u>. Let Y_1, \ldots, Y_n and X_n satisfy the assumptions of Theorem 3.1. Then, under the sequences of alternatives (3.9) $K_n : \beta_{nk} = \sqrt{n} b_k$; $b_k \in \mathbb{R}^1$, $k=p+1-m, \ldots, p$, the statistics T_n are asymptotically distributed according to noncentral χ^2 distribution with m degrees of freedom and with the noncentrality parameter (3.10) $M^2 = \sum_{p=1}^{\infty} Q \sum_{p=1}^{\infty} / G^2(\alpha_1, \alpha_2, F)$ where (3.11) $\sum_{p=1}^{\infty} = (0, \ldots, 0, b_{p+1-m}, \ldots, b_p)^*$.

It follows from Theorem 3.2 that the Pitman efficiency of

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the test based on T_n with respect to the clasical F-test coincides with the relative asymptotic efficiency of the trimmed LSE to the ordinary LSE.

4. <u>Proofs of Theorems 3.1 and 3.2</u>. The theorems will be proved with the aid of three lemmas.

Lemma 4.1. Under the assumptions of Theorem 3.1, the statistics

$$(4.1) \quad (6^{2}(\alpha_{1},\alpha_{2},F))^{-1} V_{n}$$

where

(4.2) $V_n = (L - L^*) X X (L - L^*)$ are asymptotically distributed as χ^2 with m degrees of freedom under H_0 and as noncentral χ^2 with m degrees of freedom and noncentrality parameter η^2 of (3.10) under K_n , respectively.

<u>Proof</u>. Let us first consider the asymptotic distribution under H_o. Consider the partitions

(4.3)
$$Q = \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ p+1-m & m \end{pmatrix} \stackrel{p+1-m}{=} m$$

and

(4.4)
$$Q^{-1} = \begin{pmatrix} Q^{11} & Q^{12} \\ Q^{21} & Q^{22} \end{pmatrix}$$

Moreover, denote

$$(4.5) \quad \underset{\sim}{\mathbf{B}} = \begin{pmatrix} \underset{\circ}{\mathbf{Q}}^{*-1} & \underset{\circ}{\mathbf{Q}} \\ \underset{\circ}{\mathbf{Q}} & \underset{\circ}{\mathbf{Q}} \end{pmatrix}$$

the (p+1)x(p+1) matrix and (4.6) $C = Q^{-1} - B$.

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It follows from the symmetry of C that

(4.7)
$$C = Q^{-1}Q C = \begin{pmatrix} Q^{12}(Q^{22})^{-1}Q^{21} & Q^{12} \\ Q^{21} & Q^{22} \end{pmatrix}$$

and

(4.8) C'QC = C; C is of rank m. It follows from (B.1), (4.8) and (2.11) that, under Ho, $(L-\overline{L}^*)$ X X $(L-\overline{L}^*)$

$$(4.9) = (\alpha_2 - \alpha_1)^{-2} \left[n^{-1/2} \sum_{i=1}^{n} x_i (\psi(E_i) - E\psi(E_i)) \right]^* C \cdot \left[n^{-1/2} \sum_{i=1}^{n} x_i (\psi(E_i) - E\psi(E_i)) \right] + o_p(1)$$

as $n \rightarrow \infty$, and it follows from the classical central limit theorem that

$$\overset{\&}{\leftarrow} \left\{ (\alpha_2 - \alpha_1)^{-1} n^{-1/2} \sum_{i=1}^{n} x_i (\psi(E_i) - E\psi(E_i)) \right\}$$

.10)
$$\longrightarrow N_{p+1} (0, 6^2 (\alpha_1, \alpha_2, F) 0), \text{ as } n \to \infty$$

(4

(4.8), (4.9) and (4.10) together with Proposition VIII of Section 8a.2 of Rao [7] imply that (4.1) is, under H_o, asymptotically χ^2 distributed with m degrees of freedom.

Proceeding quite analogously, we get that, under K,, $(4.11) \qquad (\mathfrak{S}^{2}(\boldsymbol{\alpha}_{1},\boldsymbol{\alpha}_{2},\mathbf{F}))^{-1}(\underline{\boldsymbol{L}}-\underline{\boldsymbol{\Sigma}}^{*}-\mathbf{n}^{-1/2}\underline{\boldsymbol{\Sigma}})'\underline{\boldsymbol{X}}'\underline{\boldsymbol{X}}(\underline{\boldsymbol{L}}-\underline{\boldsymbol{\Sigma}}^{*}-\mathbf{n}^{-1/2}\underline{\boldsymbol{\Sigma}})$ is asymptotically χ^2 -distributed with m degrees of freedom; this completes the proof of the lemma.

Lemma 4.2. Under the conditions (A) and (B), (4.12) $S_n^2 \xrightarrow{P} \mathfrak{G}^2(\alpha_1, \alpha_2, F), \xrightarrow{BB} n \longrightarrow \infty$.

<u>Proof</u>. The estimator S_n^2 of σ^2 was suggested by Ruppert

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and Carroll [8] who proved its consistency under a special design. The proof of the lemma rests on the following lemma which could be proved quite analogously as Lemma 3.1 of Jurečková [3].

Lemma 4.3. Let U_1, \ldots, U_n be i.i.d. random variables with the d.f. F satisfying the condition (A). Denote (4.13) $T_n(\underline{y}) = n^{-1/2} \frac{n}{1-1} U_1^2 I \left[U_1 \leq F^{-1}(\alpha) + n^{-1/2} \underline{x_1} \underline{v} \right] , \underline{v} \in \mathbb{R}^{p+1}$ with $\alpha = \alpha_1, \alpha_2$. Then, provided the matrix \underline{X}_n with the rows $\underline{x_1}, i=1, \ldots, n$ satisfy the condition (B), (4.14) $\sup_{\|\underline{u}\| \leq K} |T_n(\underline{v}) - T_n(\underline{0}) - n^{-1}(F^{-1}(\alpha))^2 f(F^{-1}(\alpha)) \frac{n}{1-1} \underline{x_1} \underline{v} | \xrightarrow{P} 0$ as $n \rightarrow \infty$, for any K > 0.

$$(n-m)^{-1} \stackrel{()}{=} \stackrel{(X,X)}{=} (X \stackrel{(X,\Delta,X)}{=} X \stackrel{(X,\Delta,X)}{=} X \stackrel{(X,\Delta,X)}{=} ((L-\beta)^{-1} ((L-\beta)) \stackrel{(X,\Delta,X)}{=} ((L-\beta)^{-1} ((L-\beta)) \stackrel{(X,\Delta,X)}{=} ((L-\beta)) \stackrel{(X,\Lambda,X)}{=} ((L$$

and this, by (2.11), can be rewritten as

$$(\alpha_{2}-\alpha_{1})^{-1} \left[n^{-1} \sum_{i=1}^{n} x_{i} (\psi(E_{i}) - E\psi(E_{i})) Q^{-1} + e_{1} (\alpha_{2}-\alpha_{1}) \delta \right]^{\prime} Q_{\cdot}$$
(4.18) $\cdot \left[n^{-1} \sum_{i=1}^{n} x_{i} (\psi(E_{i}) - E\psi(E_{i})) Q^{-1} + e_{1} (\alpha_{2}-\alpha_{1}) \delta \right]^{\prime} + o_{p}(1)$

$$= (\alpha_{2}-\alpha_{1}) \delta^{2} + o_{p}(1).$$

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Combining (4.15), (4.17) and (4.18), we get (4.19) $(n-m)^{-1} Z_n^2 \xrightarrow{p} \int_{z_n}^{z_n} (x-\delta)^2 dF(x).$

Moreover, it follows from (2.8) and (2.11) that

(4.20)
$$\hat{\beta}_{0}(\alpha_{i}) - L_{0} = F^{-1}(\alpha_{i}) - \delta + o_{p}(1), i=1,2.$$

(4.19) and (4.20) then complete the proof of Lemma 4.2.Theorems 3.1 and 3.2 then follow from Lemmas 4.1 and 4.2.

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