
Feasible Generalized Stein-Rule Restricted Ridge Regression Estimators

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Abstract

Several versions of the Stein-rule estimators of the coefficient vector in a linear regression model are proposed in the literature. In the present paper, we propose new feasible generalized Stein-rule restricted ridge regression estimators to examine multicollinearity and autocorrelation problems simultaneously for the general linear regression model, when certain additional exact restrictions are placed on these coefficients. Moreover, a Monte Carlo simulation experiment is performed to investigate the performance of the proposed estimator over the others.

Keywords: Feasible Estimator; Stein-rule Estimator; Restricted Ridge Estimator; Multicollinearity; Autocorrelation

1. INTRODUCTION

Stein estimator is proposed by Stein (1956). The family of Stein-rule (SR) estimators proposed by James and Stein (1960) has smaller variability than the ordinary least squares (OLS) estimator under quadratic risk with a simple condition that the number of explanatory variables are more than two. For the coefficient vector in a linear regression model with spherical disturbances, SR estimators have been extensively used. The comparisons under different loss functions and several versions of the SR estimators have also received considerable attention in the literature. Chaturvedi and Shukla (1990) consider a SR estimator for estimating the regression model with autocorrelated errors and derive its asymptotic properties. Wan and Chaturvedi (2000) extend the analysis of Chaturvedi and Shukla (1990) to a class of operational variants of the minimum mean squared error estimators. Srivastava and Srivastava (1983, 1984) and Srivastava and Chandra (1991) consider families of improved restricted estimators obtained by mixing SR with restricted least squares. Chaturvedi et al. (1996) extends the analysis of Srivastava and Srivastava (1984) to models with nonspherical disturbances. Chaturvedi et al. (2001)

propose a SR estimator for the general linear regression model with nonspherical disturbances and a set of linear restrictions binding the regression coefficients.

Many authors have studied the predicted performance of predictors obtained by using different estimators for either the actual values or the average values of the study variable at a time. Toutenburg and Shalabh (1996) analyzed the performance properties of predictors arising from the methods of restricted regression and mixed regression besides least squares according to the target function. Then, Toutenburg and Shalabh (2000) considered the family of SR estimators proposed by Srivastava and Srivastava (1983) and analyzed performance properties of this family when the objective is to predict values outside the sample and within the sample. Kumar et al. (2008) considered two families of SR estimators proposed by Srivastava and Srivastava (1984) and analyzed performance properties of these families under the target function. Shalabh, Toutenburg and Heumann (2009) introduced the extended balanced loss function (EBLF) under the target function and discussed the SR estimation. Moreover, Chaturvedi and Shalabh (2014) discussed the bayesian estimation of regression coefficients under the EBLF.

In the present paper, we extend the idea of Chaturvedi et al. (2001) to models under multicollinearity and propose new families of feasible generalized SR restricted ridge regression (FGSRR) estimator for the general linear regression model with autocorrelation, multicollinearity and a set of linear restrictions binding the regression coefficients, in Section 2. In Section 3, we indicate the prediction mean square error (PMSE) under the target function criterion. Moreover, we perform a Monte Carlo simulation experiment to compare the performance of the new estimators to the others in terms of the PMSE criterion under the target function in Section 4.

2. THE MODEL AND ESTIMATORS

Consider the following linear regression model

$$Y = X\beta + \varepsilon, \quad \varepsilon \sim (0, \sigma^2 I_n) \quad (1)$$

where Y is an $n \times 1$ vector of observations on the dependent variable, X is an $n \times p$ known design matrix of rank p , β is an $p \times 1$ vector of unknown parameters, and ε is an $n \times 1$ vector of random errors with zero mean and variance $\sigma^2 I_n$, where I_n is an identity matrix of order n .

The OLS estimator of β is defined as:

$$\hat{\beta} = (X'X)^{-1} X'Y. \quad (2)$$

Both the OLS estimator and its covariance matrix heavily depend on the characteristics of the $X'X$ matrix. If $X'X$ is ill-conditioned, i.e. the column vectors of X are linearly dependent, the OLS estimator is sensitive to a number of errors. One of the most popular estimator dealing with multicollinearity is the ordinary ridge regression (ORR) estimator proposed by Hoerl and Kennard (1970a) and is defined as

$$\hat{\beta}_k = (X'X + k I_p)^{-1} X'Y = (I_p + k (X'X)^{-1})^{-1} \hat{\beta}, \quad (3)$$

where the constant $k > 0$ is known as the biasing parameter.

One may often have some exact linear restrictions binding the regression coefficients. Hence, we assume the exact linear restrictions binding the regression coefficients vector β of m linearly independent rows as follows:

$$r = R\beta \quad (4)$$

where r is an $m \times 1$ vector and R is an $m \times p$ matrix of rank $m (< p)$. The well-known restricted least squares (RLS) estimator is given by

$$\hat{\beta}_R = \hat{\beta} - (X'X)^{-1} R' \left[R(X'X)^{-1} R' \right]^{-1} (r - R\hat{\beta}). \quad (5)$$

Let us consider the general linear regression model

$$Y = X\beta + \varepsilon, \quad \varepsilon \sim (0, \sigma^2 V^{-1}). \quad (6)$$

When V is a known positive definite (p.d.) matrix, the following estimators are proposed:

Aitken (1935) derived the generalized least squares (GLS) estimator as:

$$\hat{\beta}_{GLS} = (X'VX)^{-1} X'VY. \quad (7)$$

However, in this case the problem of multicollinearity may also arise. So, Trenkler (1984) extended the idea of ridge regression to reduce the effects of autocorrelation and multicollinearity problems and he proposed the generalized ridge (GR) estimator of β in the general linear regression model as:

$$\hat{\beta}_{GR}(k) = (X'VX + kI_p)^{-1} X'VY, \quad k > 0. \quad (8)$$

He concluded that the ridge regression estimator which takes the autocorrelation into account can perform better than some other methods.

Many authors consider some estimation methods for the general linear model in case of V is unknown. So, the feasible generalized restricted least squares (FGRLS) estimator under the prior restrictions in Equation (4) is given by Chaturvedi et al. (2001)

$$\check{\beta}_R = \check{\beta} + (X'\hat{V}X)^{-1} R' [R(X'\hat{V}X)^{-1} R']^{-1} (r - R\check{\beta}), \quad (9)$$

where $\hat{V} = V(\hat{\theta})$, $\hat{\theta}$ is a consistent estimator of θ , and

$$\check{\beta} = (X'\hat{V}X)^{-1} X'\hat{V}Y \quad (10)$$

is the feasible generalized least squares (FGLS) estimator of β . Then, the feasible generalized ridge regression (FGR) estimator is given by Eledum and Zahri (2013)

$$\check{\beta}_{GR}(k) = (X' \hat{V} X + k I_p)^{-1} X' \hat{V} Y, \quad k > 0. \quad (11)$$

Chaturvedi and Shukla (1990) consider the following SR estimator of β :

$$\check{\beta}_S = \left[1 - \frac{a}{n} \frac{(Y - X \check{\beta})' \hat{V} (Y - X \check{\beta})}{\check{\beta}' X' \hat{V} X \check{\beta}} \right] \check{\beta}, \quad (12)$$

where $a \geq 0$ is the shrinkage factor. Replacing $\check{\beta}$ by $\check{\beta}_R$ in Equation (12), Chaturvedi et al. (2001) considered the following estimator as a restricted SR estimator of β ,

$$\check{\beta}_{RS} = \left[1 - \frac{a}{n} \frac{(Y - X \check{\beta}_R)' \hat{V} (Y - X \check{\beta}_R)}{\check{\beta}_R' M^* (X' \hat{V} X) M^* \check{\beta}_R} \right] \check{\beta}_R \quad (13)$$

where $M^* = I - (X' \hat{V} X)^{-1} R' [R(X' \hat{V} X)^{-1} R']^{-1} R$. Moreover, if $\check{\beta}_S$ is

replaced for $\check{\beta}$ in Equation (9), they obtain the restricted estimator,

$$\bar{\beta}_{RS} = \check{\beta}_S + (X' \hat{V} X)^{-1} R' [R(X' \hat{V} X)^{-1} R']^{-1} (r - R \check{\beta}_S) \quad (14)$$

which can be expressed equivalently as,

$$\bar{\beta}_{RS} = \check{\beta}_R - \frac{a}{n} \frac{(Y - X \check{\beta})' \hat{V} (Y - X \check{\beta})}{\check{\beta}' X' \hat{V} X \check{\beta}} \hat{S} \check{\beta} \quad (15)$$

where $\hat{S} = I_p - (X' \hat{V} X)^{-1} R' [R(X' \hat{V} X)^{-1} R']^{-1} R$.

More recently, Özbay et al. (2016) have considered replacing $\check{\beta}$ by $\check{\beta}_{GR}(k)$ in Equation (9) and extending the idea of restricted ridge estimation method (see,

Gross, 2003; Kaçırınlar et al. 2011) for the case of V is unknown, they have defined the feasible generalized restricted ridge regression (FGRR) estimator as follows:

$$\check{\beta}_{GRR}(k) = \check{\beta}_{GR}(k) + (X'\hat{V}X + kI_p)^{-1} R' [R(X'\hat{V}X + kI_p)^{-1} R']^{-1} (r - R\check{\beta}_{GR}(k)) \quad (16)$$

However, since $\check{\beta}_s$ in Equation (12) depends on the $X'\hat{V}X$ matrix, the multicollinearity problem also arises in connection with the FGLS estimator in Equation (10). To reduce the effects of the multicollinearity for the estimators $\check{\beta}_s$, $\check{\beta}_{RS}$ and $\bar{\beta}_{RS}$, we now propose the following estimators:

Combining the philosophy behind the FGR and SR estimation, if $\check{\beta}_{GR}(k)$ is replaced for $\check{\beta}$ in Equation (12), we obtain the following feasible generalized SR ridge (FGSRR) regression estimator:

$$\check{\beta}_{GSR}(k) = \left[1 - \frac{a}{n} \frac{(Y - X\check{\beta}_{GR}(k))'\hat{V}(Y - X\check{\beta}_{GR}(k))}{\check{\beta}'_{GR}(k)(X'\hat{V}X + kI_p)\check{\beta}_{GR}(k)} \right] \check{\beta}_{GR}(k). \quad (17)$$

Following Srivastava and Srivastava (1983, 1984) and Chaturvedi et al. (2001), if we replace $\check{\beta}_{GR}(k)$ by $\check{\beta}_{GRR}(k)$ in Equation (17), we obtain the following FGSR estimator:

$$\check{\beta}_{GSRR}(k) = \left[1 - \frac{a}{n} \frac{(Y - X\check{\beta}_{GRR}(k))'\hat{V}(Y - X\check{\beta}_{GRR}(k))}{\check{\beta}'_{GRR}(k)M^{**'}(X'\hat{V}X + kI_p)M^{**}\check{\beta}_{GRR}(k)} \right] \check{\beta}_{GRR}(k), \quad (18)$$

where $M^{**} = I - (X'\hat{V}X + kI_p)^{-1} R' \left[R(X'\hat{V}X + kI_p)^{-1} R' \right]^{-1} R$.

If we replace $\check{\beta}_{GR}(k)$ by $\check{\beta}_{GSR}(k)$ in Equation (16), we obtain the following FGSR estimator:

$$\bar{\beta}_{GSRR}(k) = \bar{\beta}_{GSR}(k) + (X'VX + kI_p)^{-1} R' [R(X'VX + kI_p)^{-1} R']^{-1} (r - R\bar{\beta}_{GSR}(k)) \quad (19)$$

Furthermore, our new estimators have some tempting properties. Initially, it is easy to see that the new estimator $\bar{\beta}_{GSRR}(k)$ satisfy the prior restrictions in Equation (4). In fact, from the definitions of the $\bar{\beta}_{GSR}(k)$ and $\bar{\beta}_{GSRR}(k)$, we can see that these estimators are general estimators that include the $\bar{\beta}_S$ and $\bar{\beta}_{RS}$ as special cases:

- (i) Since $\bar{\beta}_{GR}(0) = \bar{\beta}$, then $\bar{\beta}_{GSR}(0) = \bar{\beta}_S$
- (ii) Since $\bar{\beta}_{GSR}(0) = \bar{\beta}_S$, then $\bar{\beta}_{GSRR}(0) = \bar{\beta}_{RS}$.

3. THE PMSE UNDER THE TARGET FUNCTION

In this section, we will represent the prediction performance of our new estimators under the target function. Generally predictions from a linear regression model are made either for the actual values of the study variable or for the average values at a time. However, situations may occur in which one may be required to consider the predictions of both the actual and the average values simultaneously.

If $\tilde{\beta}$ denotes an estimator of β , then the predictor for the values of study variable within the sample is generally formulated as $\hat{T} = X\tilde{\beta}$ which is used for predicting either the actual values y or the average values $E(y) = X\beta$ at a time. When the situation demands prediction of both the actual and the average values together, the target function is defined as follows,

$$T(y) = ty + (1-t)E(y) \quad (20)$$

and use $\hat{T} = X\tilde{\beta}$ for predicting it where $0 \leq t \leq 1$ is a nonstochastic scalar specifying the weightage to be assigned to the prediction of actual and average values of the study variable, see Shalabh (1995), Toutenburg and Shalabh (1996), Toutenburg and Shalabh (2000), Kumar et al. (2008). The PMSE matrix under the target function of the predictor \hat{T} is given by

$$PMSE(\hat{T}) = E(\hat{T} - T)(\hat{T} - T)'. \quad (21)$$

Then, the scalar PMSE under the target function of the predictor \hat{T} is given by

$$pmse(\hat{T}) = E(\hat{T} - T)'(\hat{T} - T). \quad (22)$$

This strong criterion is used by many authors who are working on the predictive performance of the estimators. Shalabh (1995), Toutenburg and Shalabh (1996, 2000) and Kumar et al. (2008) have theoretically studied the predictive performance of some predictors obtained by using different estimators under the PMSE criterion. They derived some conditions for the superiority of the proposed estimator over the other known estimators.

However, since these conditions depend on the unknown parameters, it is difficult to know how to make use of the theoretical results in practice. Thus, we consider the prediction performance of the estimators $\check{\beta}_R$, $\check{\beta}_{GRR}(k)$, $\check{\beta}_S$, $\check{\beta}_{GSR}(k)$, $\check{\beta}_{RS}$, $\check{\beta}_{GSRR}(k)$ and $\bar{\beta}_{GSRR}(k)$ according to the PMSE criterion under the target function using a Monte Carlo simulation study.

4. A MONTE CARLO SIMULATION STUDY

In this section, we will discuss the simulation study to compare the performances of the $\check{\beta}_R$, $\check{\beta}_{GRR}(k)$, $\check{\beta}_S$, $\check{\beta}_{GSR}(k)$, $\check{\beta}_{RS}$, $\check{\beta}_{GSRR}(k)$ and $\bar{\beta}_{GSRR}(k)$ estimators. MATLAB is used for the simulation experiment. Following

McDonald and Galarneau (1975) and Kibria (2003), the explanatory variables are generated by

$$x_{ij} = (1 - \gamma^2)^{1/2} z_{ij} + \gamma z_{i,p+1}, \quad i = 1, 2, \dots, n, \quad j = 1, 2, \dots, p \quad (23)$$

where z_{ij} are independent standard normal pseudo-random numbers, γ is specified so that the correlation between any two explanatory variables is given by γ^2 . Following Kibria (2003), three different sets of correlation are considered, corresponding to $\gamma = 0.7, 0.8, 0.9$. Following Chaturvedi et al. (2001), data are generated using the following orthonormal model with $p = 4$ and $n = 20$:

$$y_i = \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + u_i; \quad i = 1, \dots, 20 \quad (24)$$

where the u_i 's are assumed to be generated by either an AR(1) process ($u_i = \rho u_{i-1} + \varepsilon_i$) or a MA(1) process ($u_i = \varepsilon_i - \rho \varepsilon_{i-1}$); where ρ is taken as -0.8, -0.4, 0.0, 0.4, 0.8, and $\varepsilon_i \sim IN(0,1)$. Also, $a = p - 3$ and $\alpha = 2$ are taken like this.

The estimators are compared according to scalar PMSE under target function defined as

$$pmse(\hat{T}) = \frac{1}{MCN} \sum_{mci=1}^{MCN} (\hat{T}_{mci} - T)' (\hat{T}_{mci} - T), \quad (25)$$

where MCN represents the number of Monte Carlo replications which is taken as 5000.

Following Kaçırınlar et al. (2011), two different types of restrictions are used to see how the number of restrictions affects the pmse values. The first type of restriction about the parameters is taken as $\beta_1 + \beta_2 + \dots + \beta_p = \frac{p(p+1)}{2} \times \tau$. For this

restriction, one may write $R = (1 \ 1 \ \dots \ 1)$, and $r = \frac{p(p+1)}{2} \times \tau$. Since the true

parameter vector is $\beta = (1 \ 2 \ \dots \ p)'$, the sum given in the restriction is equal to $\frac{p(p+1)}{2} \times \tau$. The usage of τ allows one to control whether the restriction is true or

not, and if it not true, to control the difference between the right and left hand sides of the restriction, τ is selected as 1, 1.05, or 1.10, and it is fixed constant throughout the replications. Since the left hand side of the restriction is equal to $\frac{p(p+1)}{2}$, it is obvious that the restriction $\beta_1 + \beta_2 + \dots + \beta_p = \frac{p(p+1)}{2} \times \tau$ is true

when $\tau = 1$. However, when τ is chosen as 1.05 (or 1.10), the right hand side of the restriction is equal to $\frac{p(p+1)}{2} \times 1.05$ (or $\frac{p(p+1)}{2} \times 1.10$), while the left side

remains $\frac{p(p+1)}{2}$, which leads to a 5% (or 10%) deviation on the right hand side of

the restriction. Since R , r , β , and τ are all defined at the beginning of the simulations and fixed through the replications, the restrictions are still nonstochastic. For the second type of restriction R and r are chosen as

$$R_{\frac{p}{2} \times p} = \begin{pmatrix} 1 & 1 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & \dots & 0 & 0 \\ \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 1 & 1 \end{pmatrix} \text{ and } r_{\frac{p}{2} \times 1} = \begin{pmatrix} 3 \\ 7 \\ \vdots \\ 2p-1 \end{pmatrix} \times \tau$$

where the number of restrictions is $m = p/2$. The function and values of τ are still the same as given in the first restriction.

The approaches of Hoerl et al. (1975) are used to specify the values of k .

The estimates are denoted as $\hat{k}_{HK} = \frac{\hat{\sigma}_{GLS}^2}{\sum_{i=1}^p \check{\beta}_i^2}$, $\hat{k}_{HKB} = \frac{p\hat{\sigma}_{GLS}^2}{\sum_{i=1}^p \check{\beta}_i^2}$ and

$$\hat{k}_{LW} = \frac{p\hat{\sigma}_{GLS}^2}{\sum_{i=1}^p \lambda_i \check{\beta}_i^2} \text{ respectively, where } \hat{\sigma}_{GLS}^2 = \frac{(Y - X\check{\beta})'\hat{V}(Y - X\check{\beta})}{n-p} \text{ is the FGLS}$$

estimate of error variance and λ_i 's are the eigenvalues of the matrix $X'\hat{V}X$.

The results of the simulation study are summarized in Tables 1–6.

COMMENTS:

For Tables 1 and 2, we found the pmse values of the mentioned estimators under Restriction Type 1 when it is true and AR(1) or MA(1) to study the performance of the mentioned estimators according to $t=0.1, 0.5, 0.9$ values.

We found the pmse values of the mentioned estimators under Restriction Type 1 and 2 when it is true or not and AR(1) or MA(1) according to $t=0.1, 0.5, 0.9$ values but since there are a lot of tables, we just added the results for $t=0.1$ in Tables 3-6 and for $t=0.5$ and $t=0.9$ are not added.

- When ρ value is increasing, pmse values for all mentioned estimators are decreasing for $t = 0.1$. Also, pmse values for all mentioned estimators are decreasing till ρ value equals 0 and then pmse values are increasing till ρ value equals 0.8 for $t = 0.5, 0.9$.
- When γ value is increasing, pmse values for $\check{\beta}_S$, $\check{\beta}_{RS}$ and $\check{\beta}_R$ are increasing and decreasing for $\check{\beta}_{GSR}(k)$, $\check{\beta}_{GSR}(k)$, $\check{\beta}_{GR}(k)$ and $\bar{\beta}_{GSR}(k)$ of most of k 's in general.
- For the following pair-wise comparisons among the estimators, in each row the best estimator is highlighted in bold font under each restriction, AR(1) and MA(1) error term model and $t = 0.1, 0.5, 0.9$.

- 1- When we make a comparison between $\check{\beta}_S$ and $\check{\beta}_{GSR}(k)$ estimators, we have that $\check{\beta}_{GSR}(k)$ estimator gives better results in pmse values than $\check{\beta}_S$ estimator especially for the estimated value \hat{k}_{HKB} in most cases.
- 2- When we make a comparison between $\check{\beta}_{RS}$ and $\check{\beta}_{GSRR}(k)$ estimators, we have that $\check{\beta}_{GSRR}(k)$ estimator gives better results in pmse values than $\check{\beta}_{RS}$ estimator especially for the estimated value \hat{k}_{HKB} .
- 3- When we make a comparison between $\check{\beta}_R$ and $\check{\beta}_{GRR}(k)$ estimators, we have that $\check{\beta}_{GRR}(k)$ estimator gives better results in pmse values than $\check{\beta}_R$ estimator especially for the estimated value \hat{k}_{HKB} .
- 4- When we make a comparison between $\check{\beta}_R$ and $\bar{\beta}_{GSRR}(k)$ estimators, we have that $\bar{\beta}_{GSRR}(k)$ estimator gives better results in pmse values than $\check{\beta}_R$ estimator especially for the estimated value \hat{k}_{HKB} .
- 5- When we make a comparison between $\check{\beta}_{GRR}(k)$ and $\bar{\beta}_{GSRR}(k)$ estimators, we have that $\bar{\beta}_{GSRR}(k)$ estimator gives better results in pmse values than $\check{\beta}_{GRR}(k)$ estimator especially for the estimated value \hat{k}_{HKB} .
- Under the same restriction type, when t value is increasing, pmse values for all mentioned estimators are increasing for the AR(1) error term model rapidly than for the MA(1) error term model.
- For AR(1) and MA(1), the pmse values are so close to each other for all mentioned estimators with the same restriction type and the same value of t .

5. CONCLUSION

In this study, we introduce some feasible generalized SR restricted ridge regression estimators to examine multicollinearity and autocorrelation problems simultaneously for the general linear regression model. Then we investigate the performance of the defined estimators using a Monte Carlo simulation study in which the results show that the proposed estimators have smaller pmse values relative to the other mentioned estimators especially for the estimated value \hat{k}_{HKB} in most cases under the first and the second restrictions when they are true or not and when the error term follows AR(1) or MA(1) model.

Table 1. pmse values of the mentioned estimators under Restriction Type 1 when it is true and $AR(1)$

ι	ρ	γ	$\bar{\beta}_S$	$\bar{\beta}_{GSR}(k)$	$\bar{\beta}_{RS}$	$\bar{\beta}_{CSRR}(k)$	$\bar{\beta}_R$	$\bar{\beta}_{GRR}(k)$	$\bar{\beta}_{CSRR}(k)$
0.1	-0.8	0.7	18.0752	17.5445	16.5308	18.0229	17.5803	17.1089	17.5610
0.8	0.8	18.1756	17.4352	15.9321	18.1415	18.0454	17.4712	16.3882	18.0190
0.9	0.9	18.2132	17.0279	14.7033	18.1520	19.3181	18.5618	17.4360	19.2773
-0.4	0.7	5.9627	5.9104	5.8522	5.9595	5.3915	5.3399	5.2273	5.3885
0.8	0.8	5.9161	5.8298	5.6792	5.9105	5.6359	5.5717	5.4433	5.6318
0.9	0.9	5.9253	5.7557	5.4185	5.9135	6.8395	6.7917	6.7973	6.8355
0.0	0.7	3.0574	3.0820	3.0546	3.0570	2.3542	2.3492	2.3409	2.3539
0.8	0.8	3.0462	3.0358	3.0234	3.0454	2.4226	2.4159	2.4205	2.4221
0.9	0.9	3.0330	3.0098	2.9657	3.0311	2.6078	2.5966	2.5816	2.6069
0.4	0.7	1.6191	1.6161	1.6188	1.4263	1.4227	1.4169	1.4261	1.3738
0.8	0.8	1.6580	1.6488	1.6379	1.6574	1.4323	1.4257	1.4132	1.4319
0.9	0.9	1.7016	1.6803	1.6396	1.7004	1.4234	1.4074	1.3746	1.4223
0.8	0.7	0.6778	0.6780	0.6809	0.6778	0.6731	0.6734	0.6747	0.6731
0.8	0.8	0.6789	0.6822	0.6805	0.6789	0.6716	0.6716	0.6728	0.6716
0.5	-0.8	0.7	63.4563	63.0433	62.4445	63.4386	63.6144	63.2576	62.5097
0.7	0.8	63.4838	62.9030	61.8160	63.4566	64.1478	63.7262	62.9431	64.1280
0.9	0.9	63.3291	62.3990	62.6992	62.2804	65.2011	65.0104	64.4877	65.4924
-0.4	0.7	11.9848	11.9542	11.9587	11.9828	12.1014	12.0720	12.0236	12.0997
0.8	0.8	11.9819	11.9266	11.8648	11.9782	12.3192	12.2791	12.3525	11.9807
0.9	0.9	11.9661	11.8533	11.6726	11.9780	13.5710	13.5783	13.5755	13.5707
0.0	0.7	4.7491	4.7478	4.7626	4.7494	4.8226	4.8217	4.8267	4.8222
0.8	0.8	4.7492	4.7449	4.7507	4.7488	4.8921	4.8998	4.8926	4.8925
0.9	0.9	4.7493	4.7380	4.7285	4.7484	5.0797	5.0802	5.0993	5.0797
0.4	0.7	7.3552	7.3570	7.3581	7.3571	7.5884	7.5906	7.5822	7.5796
0.8	0.8	7.3563	7.3570	7.3753	7.3562	7.5976	7.6006	7.6164	7.5976
0.9	0.9	7.3478	7.3462	7.3622	7.3476	7.5918	7.6128	7.5918	7.5810
0.8	0.7	15.0135	15.0151	15.0220	15.0135	15.1445	15.1509	15.1445	15.1344
0.9	0.9	14.9723	14.9744	14.9830	14.9223	15.1435	15.1459	15.1459	15.1345
0.9	0.9	14.9232	14.9408	14.9232	15.1404	15.1433	15.1536	15.1404	15.1343
0.9	-0.8	0.7	180.4704	180.175	179.7911	180.4573	181.2816	181.0393	180.5016
0.8	0.8	180.4249	180.0039	179.3329	180.4048	181.1882	181.6142	181.2311	181.2701
0.9	0.9	180.0779	179.4032	178.3238	180.0418	183.3571	183.092	183.1724	183.3404
-0.4	0.7	31.7677	31.7581	31.8253	31.7661	32.5715	32.5642	32.5758	32.5709
0.8	0.8	31.8078	31.8104	31.8059	32.8267	32.8751	32.8287	32.8287	32.8751
0.9	0.9	31.7677	31.7711	31.6869	31.7026	34.0626	34.4339	34.0626	34.4339
0.0	0.7	12.5208	12.5236	12.5306	12.5206	13.3742	13.3925	13.3703	13.2917
0.8	0.8	12.5322	12.5341	12.558	12.5322	13.4426	13.4476	13.4426	13.2917
0.9	0.9	12.5457	12.5471	12.5462	12.5457	13.6438	13.6438	13.6317	13.6317
0.4	0.7	23.8835	23.9324	23.8835	24.5304	24.5746	24.5304	24.5627	24.5627
0.8	0.8	23.8468	23.8575	23.9049	23.8468	24.5551	24.5677	24.5551	24.5668
0.9	0.9	23.7862	23.8044	23.7862	24.5524	24.5725	24.5524	24.5725	24.5725
0.8	0.7	49.5926	49.6074	49.5926	49.8592	49.8618	49.8704	49.8592	49.8617
0.8	0.8	49.5092	49.5132	49.5278	49.5092	49.8562	49.8735	49.8562	49.8562
0.9	0.9	49.4092	49.4169	49.4427	49.4092	49.8549	49.8807	49.8549	49.8549

Table 2. pmse values of the mentioned estimators under Restriction Type 1 when it is true and $MA(1)$

ι	ρ	γ	$\bar{\rho}_S$	$\bar{\rho}_{GSR}(k)$	$\bar{\rho}_{GSR}(k)$	$\bar{\rho}_{KS}$	$\bar{\rho}_{GSR}(k)$	$\bar{\rho}_R$	$\bar{\rho}_{GSR}(k)$	$\bar{\rho}_{GSR}(k)$		
			\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{LW}	\hat{k}_{HK}	\hat{k}_{LW}	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{LW}		
0.1	-0.8	0.7	26.2753	25.8226	24.9881	23.96832	23.4693	22.1583	23.05688	24.2769		
	0.8	0.8	26.4985	25.8557	24.4757	26.3808	23.3478	21.9921	24.2769	23.7634		
	0.9	0.9	26.6261	25.5830	25.2555	24.0553	23.0027	20.4215	24.0226	23.6097		
	-0.4	0.7	6.7027	6.6598	6.6262	6.6999	5.3200	5.2736	5.1725	5.3173		
	0.8	0.8	6.6740	6.6029	6.4909	6.6700	5.3793	5.3174	5.1714	5.3043		
	0.9	0.9	6.6803	6.5369	6.2582	6.6700	5.3371	5.4168	5.1681	5.2585		
0.0	0.7	3.0574	3.0820	3.0546	3.0570	2.3582	2.3492	2.3409	2.3539	2.2883		
	0.8	0.8	3.0462	3.0358	3.0324	3.0454	2.4226	2.4159	2.4050	2.4221		
	0.9	0.9	3.0330	3.0098	2.9657	3.0311	2.6078	2.5816	2.6068	2.2883		
0.4	0.7	2.1772	2.1711	2.1742	2.1768	1.9868	1.9823	1.9765	1.9865	1.8847		
	0.8	0.8	2.1997	2.1789	2.1747	2.1989	1.9778	1.9619	1.9862	1.8956		
	0.9	0.9	2.2328	2.2059	2.1554	2.2310	1.9694	1.9471	1.9021	1.9679		
0.8	0.7	2.7900	2.7834	2.7905	2.7839	2.8093	2.8043	2.7997	2.8091	2.6545		
	0.8	0.8	2.7963	2.7830	2.7720	2.7956	2.6973	2.6830	2.6657	2.6966		
	0.9	0.9	2.8183	2.7867	2.7323	2.8166	2.6613	2.6295	2.5645	2.6597		
0.5	-0.8	0.7	32.3871	31.9890	31.3114	32.3773	32.0811	31.6308	30.4597	32.0707		
	0.8	0.8	32.6195	32.0476	30.8687	32.5037	32.1192	31.5225	30.0021	32.1034		
	0.9	0.9	32.6959	31.7700	29.2775	32.5665	32.1608	32.2151	28.9265	32.1313		
-0.4	0.7	10.3900	10.3655	10.3885	10.33883	10.3193	10.3096	10.2413	10.3176	10.2346		
	0.8	10.3944	10.3489	10.3112	10.3912	10.3871	10.3462	10.2761	10.3844	10.2178		
	0.9	10.4169	10.3204	10.1736	10.4097	10.5621	10.4873	10.3668	10.5656	10.2684		
0.0	0.7	4.7491	4.7479	4.7476	4.7476	4.7469	4.7422	4.8222	4.8222	4.7450		
	0.8	4.7492	4.7449	4.7507	4.7488	4.8921	4.8998	4.8925	4.8998	4.7428		
	0.9	4.7493	4.7380	4.7285	4.7484	5.0797	5.0993	5.0797	4.7500	4.7366		
0.4	0.7	7.2223	7.2230	7.2223	7.6343	7.6379	7.6332	7.6343	7.5309	7.5275		
	0.8	7.2266	7.2250	7.2417	7.2264	7.6379	7.6394	7.6379	7.5309	7.5236		
	0.9	7.2391	7.2320	7.2385	7.2385	7.6213	7.6183	7.6292	7.6210	7.5319		
0.8	0.7	12.9733	12.9733	12.9573	13.5775	13.5811	13.6022	13.5775	13.4039	13.3999		
	0.8	0.8	12.9562	12.9579	12.9274	12.9561	13.4606	13.4667	13.4603	13.3963	13.3957	
	0.9	0.9	12.9270	12.9188	12.9316	12.9264	13.4184	13.4091	13.4081	13.4179	13.3919	
0.9	-0.8	0.7	57.2239	56.8804	56.5397	57.2153	58.9189	58.5173	57.4886	58.9097	59.1666	
	0.8	57.4656	56.9644	56.9367	57.4561	58.9938	58.4222	50.0863	58.9397	59.1666	58.6214	
	0.9	57.4908	56.6799	56.5944	57.4648	58.9913	58.2124	50.1565	58.9695	58.3138	56.2844	
-0.4	0.7	25.5071	25.5008	25.5745	25.5063	26.7483	26.7374	26.7399	26.7475	26.6542	26.6187	
	0.8	25.5445	25.5247	25.5612	25.5429	26.8246	26.8085	26.8105	26.8234	26.6447	26.5961	
	0.9	25.5832	25.5335	25.5187	25.5791	27.0168	26.9875	26.9953	27.0143	26.6782	26.6573	
0.0	0.7	12.5236	12.5306	12.5008	13.3703	13.3742	13.3925	13.3703	13.2917	13.2958	13.2912	
	0.8	12.5322	12.5341	12.558	13.4426	13.4483	13.4746	13.4426	13.2917	13.2999	13.2985	
	0.9	12.5457	12.5462	12.5714	12.5456	13.6317	13.6317	13.5775	13.3917	13.3982	13.3999	
	0.4	0.7	22.8733	22.8809	22.8733	22.9789	23.8876	23.9357	23.8876	23.7721	23.7783	23.7721
	0.8	22.8594	22.8668	22.9145	22.8594	23.9068	23.8949	23.9521	23.7721	23.7789	23.8048	
	0.9	22.8513	22.8639	22.8791	22.8791	23.8954	23.8791	23.8791	23.7721	23.8341	23.7721	
	0.8	0.7	40.4963	40.5062	40.4963	41.6976	41.7443	41.6853	41.4932	41.4996	41.5067	
	0.8	40.4558	40.5255	40.4558	41.5633	41.5734	41.6173	41.5151	41.4995	41.5326	41.4932	
	0.9	40.3753	40.3906	40.4706	40.3753	41.5151	41.5282	41.5915	41.5151	41.5044	41.4935	

Table 3. pmse values of the mentioned estimators under Restriction Type 1, $AR(1)$ and $t = 0.1$

Table 4. pmse values of the mentioned estimators under Restriction Type 2, AR(1) and $t = 0.1$

τ	ρ	γ	$\bar{\beta}_S$	$\bar{\beta}_{GSR}(k)$	$\bar{\beta}_{GSR}(k)$	$\bar{\beta}_R$	$\bar{\beta}_R$	$\bar{\beta}_{GSR}(k)$
1	-0.8	0.7	18.0752	17.5445	16.5308	18.0529	13.0488	12.8334
	0.8	18.1756	17.4352	15.9321	18.1415	14.3349	14.2607	14.2052
	0.9	18.2132	17.0279	14.7033	18.1520	17.1246	17.2163	17.1246
-0.4	0.7	5.9627	5.9104	5.8522	5.9595	4.4686	4.4509	4.4079
	0.8	5.9161	5.8298	5.6792	5.9105	5.0654	5.0549	5.0467
	0.9	5.9253	5.7557	5.4185	5.9135	7.1330	7.1330	7.1330
0.0	0.7	3.0574	3.0520	3.0550	3.0546	2.0607	2.0595	2.0572
	0.8	3.0462	3.0358	3.0234	3.0454	2.1442	2.1426	2.1403
	0.9	3.0330	2.9698	3.0069	3.0111	2.2652	2.2652	2.2650
0.4	0.7	1.6191	1.6144	1.6161	1.6188	1.3972	1.3953	1.3908
	0.8	1.6580	1.6488	1.6379	1.6574	1.2458	1.2455	1.2455
	0.9	1.7016	1.6803	1.6396	1.7002	1.1804	1.1674	1.1334
0.8	0.7	0.6778	0.6780	0.6809	0.6778	0.6710	0.6711	0.6710
	0.8	0.6789	0.6789	0.6815	0.6789	0.6590	0.6589	0.6589
	0.9	0.6805	0.6801	0.6822	0.6804	0.6548	0.6545	0.6539
1.05	-0.8	0.7	18.0752	17.5445	16.5308	18.0529	12.5271	12.4020
	0.8	18.1756	17.4352	15.9321	18.1415	14.5257	14.5257	14.5253
	0.9	18.2132	17.0279	14.7033	18.1520	14.5954	14.5954	14.5954
-0.4	0.7	5.9627	5.9104	5.8522	5.9595	4.1739	4.1465	4.0739
	0.8	5.9161	5.8298	5.6792	5.9105	4.2731	4.2414	4.1638
	0.9	5.9253	5.7557	5.4185	5.9135	5.0281	5.0391	5.1336
0.0	0.7	3.0574	3.0620	3.0546	3.0570	2.0627	2.0557	2.0557
	0.8	3.0462	3.0358	3.0234	3.0454	1.9270	1.9176	1.8915
	0.9	3.0330	2.9657	3.0098	3.0311	2.0264	2.0057	1.9487
0.4	0.7	1.6191	1.6144	1.6161	1.6188	1.6266	1.6568	1.6623
	0.8	1.6580	1.6488	1.6379	1.6574	1.2164	1.2163	1.2163
	0.9	1.7016	1.6803	1.6396	1.7002	2.8755	2.8546	2.7969
0.8	0.7	0.6778	0.6780	0.6809	0.6778	1.9869	1.9844	1.9844
	0.8	0.6789	0.6789	0.6815	0.6789	2.5555	2.5541	2.5499
	0.9	0.6805	0.6801	0.6822	0.6804	3.2831	3.2795	3.2694
1.10	-0.8	0.7	18.0752	17.5445	16.5308	18.0529	14.5737	14.4266
	0.8	18.1756	17.4352	15.9321	18.1415	15.0164	14.8622	14.7512
	0.9	18.2132	17.0279	14.7033	18.1520	15.6912	15.6148	15.6857
-0.4	0.7	5.9627	5.9104	5.8522	5.9595	6.4567	6.4177	6.3100
	0.8	5.9161	5.8298	5.6792	5.9105	6.4757	6.4204	6.2725
	0.9	5.9253	5.7557	5.4185	5.9135	6.4581	6.4210	6.3806
0.0	0.7	3.0574	3.0620	3.0546	3.0570	3.9471	3.9356	3.9022
	0.8	3.0462	3.0358	3.0234	3.0454	4.4137	4.3942	4.3377
	0.9	3.0330	2.9657	3.0098	3.0311	4.9561	4.9553	4.7751
0.4	0.7	1.6191	1.6144	1.6161	1.6188	4.2756	4.2331	4.2175
	0.8	1.6488	1.6379	1.6396	1.7016	6.3029	6.2852	6.2339
	0.9	1.7016	1.6803	1.6396	1.7002	8.8829	8.8453	8.8005
0.8	0.7	0.6778	0.6780	0.6809	0.6778	6.0317	6.0288	6.0203
	0.8	0.6789	0.6789	0.6815	0.6789	8.2390	8.2339	8.2189
	0.9	0.6805	0.6801	0.6822	0.6804	11.0921	11.0787	11.0398

Table 5. pmse values of the mentioned estimators under Restriction Type 1, MA(1) and $t = 0.1$

τ	ρ	γ	$\bar{\beta}_S$	$\bar{\beta}_{GSR}(k)$	$\bar{\beta}_{KS}(k)$	$\bar{\beta}_R$	$\bar{\beta}_{GRR}(k)$	$\bar{\beta}_{CSRE}(k)$
1	-0.8	0.7	26.2753	25.8226	24.9881	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{LW}
	0.8	0.8	26.4985	25.8557	24.4757	26.3642	23.4693	23.59568
	0.9	26.6261	25.5850	23.2555	24.0553	26.8108	23.3478	23.9563
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	6.6029	6.6430	6.65932
	0.8	6.6740	6.6029	6.4909	6.6962	6.5371	6.5125	6.5200
	0.9	6.6803	6.5369	6.2582	6.6700	5.5371	5.4168	5.41681
0.0	0.7	3.0574	3.0520	3.0546	3.0570	2.3492	2.3409	2.3542
	0.8	3.0462	3.0358	3.0234	3.0454	2.4226	2.4159	2.4226
	0.9	3.0330	3.0098	2.9657	3.0131	2.6978	2.5816	2.5966
0.4	0.7	2.1772	2.1711	2.1742	2.1768	1.9868	1.9823	1.9765
	0.8	2.1997	2.1879	2.1747	2.1899	1.9868	1.9778	1.9619
	0.9	2.2338	2.2059	2.1554	2.2310	1.9694	1.9471	1.9021
0.8	0.7	2.7900	2.7834	2.7905	2.7896	2.8043	2.7997	2.8091
	0.8	2.7963	2.7830	2.7720	2.7956	2.6973	2.6830	2.6613
	0.9	2.8183	2.7867	2.7523	2.8166	2.6613	2.6295	2.5645
1.05	-0.8	0.7	26.2753	25.8226	24.9881	26.3642	25.1791	23.3370
	0.8	26.4985	25.8557	24.4757	26.8108	25.6992	25.0147	23.2492
	0.9	26.6261	25.5850	23.2555	26.5932	26.5195	24.4184	27.1761
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	6.0296	5.9803	5.8679
	0.8	6.6740	6.6029	6.4909	6.6692	6.1081	6.0310	5.8820
	0.9	6.6803	6.5369	6.2582	6.6700	6.0761	5.9221	5.5690
0.0	0.7	3.0574	3.0462	3.0358	3.0570	2.60546	2.51246	3.1010
	0.8	3.0462	3.0358	3.0234	3.0454	2.31920	3.1796	3.19191
	0.9	3.0330	3.0098	2.9657	3.0311	3.1360	3.1073	3.0378
0.4	0.7	2.1772	2.1711	2.1742	2.1768	2.6155	2.6071	2.6150
	0.8	2.1997	2.1879	2.1747	2.1989	2.8876	2.8730	2.8938
	0.9	2.2338	2.2059	2.1554	2.2310	3.3919	3.3593	3.2825
0.8	0.7	2.7900	2.7834	2.7720	2.7905	2.7862	3.2807	3.2741
	0.8	2.7963	2.7830	2.7723	2.7956	3.8911	3.8760	3.8456
	0.9	2.8183	2.7867	2.7523	2.8166	4.7618	4.7247	4.6444
1.10	-0.8	0.7	26.2753	25.8226	24.9881	26.3642	25.5244	29.5125
	0.8	26.4985	25.8557	24.4757	26.8108	31.5083	28.9781	30.7040
	0.9	26.6261	25.5850	23.2555	26.5932	34.6097	33.5144	30.6751
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	9.49127	9.3370	9.3077
	0.8	6.6740	6.6029	6.4909	6.6692	10.1650	4.7618	4.7247
	0.9	6.6803	6.5369	6.2582	6.6700	10.8042	10.6076	10.1248
0.0	0.7	3.0574	3.0462	3.0358	3.0454	6.3419	6.3113	6.4052
	0.8	3.0462	3.0358	3.0234	3.0454	6.9975	6.9771	6.9236
	0.9	3.0330	3.0098	2.9657	3.0311	7.0184	7.0481	6.8987
0.4	0.7	2.1772	2.1711	2.1742	2.1768	5.7086	5.6957	5.6638
	0.8	2.1997	2.1879	2.1747	2.1989	6.9086	6.8865	6.8299
	0.9	2.2338	2.2059	2.1554	2.2310	8.9248	8.8745	8.7986
0.8	0.7	2.7900	2.7834	2.7720	2.7956	6.2311	6.2247	6.2143
	0.8	2.7963	2.7830	2.7523	2.8166	11.6385	11.5910	11.4807
	0.9	2.8183	2.7867	2.7323	2.8166	11.5910	11.4807	11.3631

Table 6. pmse values of the mentioned estimators under Restriction Type 2, MA(1) and $t = 0.1$

τ	ρ	γ	$\bar{\beta}_S$	$\bar{\beta}_{GSR}(k)$	$\bar{\beta}_{GSR}(k)$	$\bar{\beta}_R$	$\bar{\beta}_{GR}(k)$	$\bar{\beta}_{GSR}(k)$
1	-0.8	0.7	26.2753	25.8226	24.9881	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{LW}
	0.8	0.8	26.4985	25.8557	24.4757	\hat{k}_{LW}	\hat{k}_{HKB}	\hat{k}_{LW}
	0.9	26.6261	25.5850	23.2555	26.5932	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{HKB}
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{LW}
	0.8	6.6740	6.6029	6.4989	6.6692	\hat{k}_{LW}	\hat{k}_{HKB}	\hat{k}_{LW}
	0.9	6.6803	6.5369	6.2582	6.6700	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{HKB}
0.0	0.7	3.0574	3.0520	3.0546	3.0550	\hat{k}_{LW}	\hat{k}_{HKB}	\hat{k}_{LW}
	0.8	3.0462	3.0358	3.0234	3.0454	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{HKB}
	0.9	3.0330	3.0098	2.9657	3.0111	\hat{k}_{LW}	\hat{k}_{HKB}	\hat{k}_{HKB}
0.4	0.7	2.1772	2.1711	2.1742	2.1768	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{LW}
	0.8	2.1997	2.1879	2.1747	2.1899	\hat{k}_{LW}	\hat{k}_{HKB}	\hat{k}_{HKB}
	0.9	2.2328	2.2059	2.1554	2.2310	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{LW}
0.8	0.7	2.7900	2.7834	2.7905	2.7896	\hat{k}_{LW}	\hat{k}_{HKB}	\hat{k}_{HKB}
	0.8	2.7963	2.7830	2.7720	2.7956	\hat{k}_{HK}	\hat{k}_{HKB}	\hat{k}_{HKB}
	0.9	2.8183	2.7867	2.7523	2.8166	\hat{k}_{LW}	\hat{k}_{HKB}	\hat{k}_{HKB}
1.05	-0.8	0.7	26.2753	25.8226	24.9881	26.6642	21.0643	20.6749
	0.8	26.4985	25.8557	24.4757	21.989	1.6111	1.6048	1.5884
	0.9	26.6261	25.5850	23.2555	26.5932	1.4762	1.4597	1.4166
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	4.0522	4.0226	3.9418
	0.8	6.6740	6.6029	6.4989	6.6692	4.1305	4.0842	3.9585
	0.9	6.6803	6.5369	6.2582	6.6700	4.1583	4.0657	3.8218
0.0	0.7	3.0574	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.8	3.0462	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.9	3.0330	3.0098	2.9657	3.0311	2.0264	2.0057	1.9487
0.4	0.7	2.1772	2.1711	2.1742	2.1768	1.6027	1.6086	1.5866
	0.8	2.1997	2.1879	2.1747	2.1989	2.0692	2.0579	2.0264
	0.9	2.2328	2.2059	2.1554	2.2310	2.7661	2.7423	2.6760
0.8	0.7	2.7900	2.7834	2.7720	2.7905	2.7436	2.7836	2.7346
	0.8	2.7963	2.7830	2.7723	2.7905	2.7184	2.7218	2.7087
	0.9	2.8183	2.7867	2.7523	2.8166	4.1887	4.1709	4.1205
1.10	-0.8	0.7	26.2753	25.8226	24.9881	26.6642	25.8610	25.4744
	0.8	26.4985	25.8557	24.4757	27.5968	27.0674	29.0311	25.6344
	0.9	26.6261	25.5850	23.2555	26.5932	30.4461	29.5796	27.3452
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	4.9503	4.7272	4.7370
	0.8	6.6740	6.6029	6.4989	6.6692	5.2059	5.2750	5.2727
	0.9	6.6803	6.5369	6.2582	6.6700	8.5177	8.3880	8.0320
0.0	0.7	3.0574	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.8	3.0462	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.9	3.0330	3.0098	2.9657	3.0311	2.0264	2.0057	1.9487
0.4	0.7	2.1772	2.1711	2.1742	2.1768	1.6027	1.6086	1.5866
	0.8	2.1997	2.1879	2.1747	2.1989	2.0692	2.0579	2.0264
	0.9	2.2328	2.2059	2.1554	2.2310	2.7661	2.7423	2.6760
0.8	0.7	2.7900	2.7834	2.7720	2.7905	2.7436	2.7836	2.7346
	0.8	2.7963	2.7830	2.7723	2.7905	2.7184	2.7218	2.7087
	0.9	2.8183	2.7867	2.7523	2.8166	4.1887	4.1709	4.1205
1.10	-0.8	0.7	26.2753	25.8226	24.9881	26.6642	25.8610	25.4744
	0.8	26.4985	25.8557	24.4757	27.5968	27.0674	29.0311	25.6344
	0.9	26.6261	25.5850	23.2555	26.5932	30.4461	29.5796	27.3452
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	4.9503	4.7272	4.7370
	0.8	6.6740	6.6029	6.4989	6.6692	5.2059	5.2750	5.2727
	0.9	6.6803	6.5369	6.2582	6.6700	8.5177	8.3880	8.0320
0.0	0.7	3.0574	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.8	3.0462	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.9	3.0330	3.0098	2.9657	3.0311	2.0264	2.0057	1.9487
0.4	0.7	2.1772	2.1711	2.1742	2.1768	1.6027	1.6086	1.5866
	0.8	2.1997	2.1879	2.1747	2.1989	2.0692	2.0579	2.0264
	0.9	2.2328	2.2059	2.1554	2.2310	2.7661	2.7423	2.6760
0.8	0.7	2.7900	2.7834	2.7720	2.7905	2.7436	2.7836	2.7346
	0.8	2.7963	2.7830	2.7723	2.7905	2.7184	2.7218	2.7087
	0.9	2.8183	2.7867	2.7523	2.8166	4.1887	4.1709	4.1205
1.10	-0.8	0.7	26.2753	25.8226	24.9881	26.6642	25.8610	25.4744
	0.8	26.4985	25.8557	24.4757	27.5968	27.0674	29.0311	25.6344
	0.9	26.6261	25.5850	23.2555	26.5932	30.4461	29.5796	27.3452
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	4.9503	4.7272	4.7370
	0.8	6.6740	6.6029	6.4989	6.6692	5.2059	5.2750	5.2727
	0.9	6.6803	6.5369	6.2582	6.6700	8.5177	8.3880	8.0320
0.0	0.7	3.0574	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.8	3.0462	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.9	3.0330	3.0098	2.9657	3.0311	2.0264	2.0057	1.9487
0.4	0.7	2.1772	2.1711	2.1742	2.1768	1.6027	1.6086	1.5866
	0.8	2.1997	2.1879	2.1747	2.1989	2.0692	2.0579	2.0264
	0.9	2.2328	2.2059	2.1554	2.2310	2.7661	2.7423	2.6760
0.8	0.7	2.7900	2.7834	2.7720	2.7905	2.7436	2.7836	2.7346
	0.8	2.7963	2.7830	2.7723	2.7905	2.7184	2.7218	2.7087
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	0.9	26.6261	25.5850	23.2555	26.5932	30.4461	29.5796	27.3452
-0.4	0.7	6.7027	6.6598	6.6262	6.6999	4.9503	4.7272	4.7370
	0.8	6.6740	6.6029	6.4989	6.6692	5.2059	5.2750	5.2727
	0.9	6.6803	6.5369	6.2582	6.6700	8.5177	8.3880	8.0320
0.0	0.7	3.0574	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.8	3.0462	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.9	3.0330	3.0098	2.9657	3.0311	2.0264	2.0057	1.9487
0.4	0.7	2.1772	2.1711	2.1742	2.1768	1.6027	1.6086	1.5866
	0.8	2.1997	2.1879	2.1747	2.1989	2.0692	2.0579	2.0264
	0.9	2.2328	2.2059	2.1554	2.2310	2.7661	2.7423	2.6760
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	0.8	6.6740	6.6029	6.4989	6.6692	5.2059	5.2750	5.2727
	0.9	6.6803	6.5369	6.2582	6.6700	8.5177	8.3880	8.0320
0.0	0.7	3.0574	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.8	3.0462	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.9	3.0330	3.0098	2.9657	3.0311	2.0264	2.0057	1.9487
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	0.9	26.6261	25.5850	23.2555	26.5932	30.4461	29.5796	27.3452
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	0.8	6.6740	6.6029	6.4989	6.6692	5.2059	5.2750	5.2727
	0.9	6.6803	6.5369	6.2582	6.6700	8.5177	8.3880	8.0320
0.0	0.7	3.0574	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.8	3.0462	3.0358	3.0234	3.0454	3.0570	3.0642	3.0485
	0.9	3.0330	3.0098	2.9657	3.0311	2.0264	2.0057	1.9487
0.4	0.7	2.1772	2.1711	2.1742	2.1768	1.6027	1.6086	1.5866
	0.8	2.1997	2.1879	2.1747	2.1989	2.0692	2.0579	2.0264
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1.10	-0.8	0.7	26.2753	25.8226	24.9881	26.6642	25.8610	25.4744
	0.8	26.4985	25.8557	24.4757	27.5968	27.0674	29.0311	25.63

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