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Constructing computational
algorithm with the double-
bootstrap method for the
estimation of technical efficiency
scores in two-stage semi-
parametric DEA models and
economic application

ΝΑΤΣΙΟΠΟΥΛΟΣ ΚΛΕΑΝΘΗΣ

ΕΠΙΒΛΕΠΩΝ ΚΑΘΗΓΗΤΗΣ: ΤΖΕΡΕΜΕΣ ΝΙΚΟΛΑΟΣ





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Περίληψη

Η παρούσα εργασία χωρίζεται σε δύο μέρη. Πρώτα, εφαρμόζει τους αλγόριθμους που πρότειναν αρχικά οι Simar και Wilson (2007) και κατασκευάζει μία πλήρη συναρτήσεως για κάθε έναν από αυτούς στη γλώσσα προγραμματισμού R. Το μοντέλο που χρησιμοποιούν αυτοί οι αλγόριθμοι είναι ένα μοντέλο DEA δύο σταδίων διπλής Bootstrap. Αρχικά αποτελείται από δύο στάδια. Το πρώτο είναι αυτό στο οποίο πραγματοποιείται η DEA και το δεύτερο είναι η ανάλυση παλινδρόμησης. Το πρώτο στάδιο είναι αρκετά απλό αφού η μόνη εκτίμηση που κάνει είναι για την αποτελεσματικότητα ενώ το δεύτερο αποτελείται είτε από μία είτε από δύο στάδια bootstrap. Στην περίπτωση του Algorithm #2 που χρησιμοποιεί διπλή bootstrap, στον πρώτο βρόχο υπολογίζει τη μεροληψία και της αποτελεσματικότητας και υπολογίζει ξανά τις διορθωμένες για μεροληψία αποτελεσματικότητες. Μετά συνεχίζει με τη δεύτερη bootstrap όπου κάποιες συνδιακυμάνσεις παλινδρομούνται πάνω στις εκτιμημένες διορθωμένες για μεροληψία αποτελεσματικότητες για να εξετάσουμε την επίδρασή τους πάνω σ' αυτές. Το δεύτερο μέρος είναι η οικονομική εφαρμογή που βασίζεται σ' αυτά τα μοντέλα. Η επίδραση που έχουν τα έξοδα διαφήμισης και επικοινωνίας στην αποτελεσματικότητα των τραπεζών στις Η.Π.Α. εξετάζεται και αποκαλύπτει κάποια ενδιαφέροντα αποτελέσματα. Τα τελικά αποτελέσματα υποδεικνύουν ότι μια τράπεζα θα πρέπει να συνεχίζει να ξοδεύει χρήματα στη διαφήμιση και τις επικοινωνίες μέχρι να φτάσει στο επίπεδο που η αναποτελεσματικότητά της θα αρχίσει να χρησιμοποιείται για να ελαττώνεται.

Abstract

The present thesis has two parts. Firstly, it implements the algorithms originally suggested by Simar and Wilson (2007) and constructs a full functions for each one of them in the programming language R. The model that these algorithms use is a two-stage double bootstrap DEA. It consists primarily of two stages. The first one is where the DEA procedure takes place and the second one is the regression analysis. The first stage is quite simple as the only estimation is for the efficiency scores, while the second one consists of either one or two bootstrap stages. In the case of Algorithm #2 that makes use of a double-bootstrap, in the first loop it estimates the bias of the efficiency scores and computes again the bias-corrected efficiencies. Then it continues with the second bootstrap where some covariates are regressed on the estimated bias-corrected efficiencies in order to examine the effect they have on them. The second part is the economic application based on these models. The effect that the advertising and communications expense have upon the efficiency of the banks operating in U.S. is tested, yielding some interesting results. The final results indicate that a bank should keep spending money for advertising and communications until they reach the turning point where the bank's inefficiency will start to decline.

Key words: algorithms, efficiency, two-stage DEA, double-bootstrap, R, banks

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1. Introduction

1.1. Summary of Proposal

The present thesis has two primary goals. The first goal is to construct the two algorithms described by Simar and Wilson (2007) and the second one is the economic application using these algorithms.

The first algorithm uses a two-stage semi-parametric bootstrap model that firstly computes the efficiency scores using Data Envelopment Analysis (DEA) making use of some input and output variables and the second stage uses truncated regression to estimate the impact of some external variables upon these efficiencies.

The second algorithm uses a two-stage semi-parametric double bootstrap model that is exactly like the first algorithm; however, after the calculation of the efficiency scores, a bootstrap loop is used to re-estimate the efficiencies but this time removing the bias. The second stage, as in the first algorithm, regress some external variables upon the bias corrected efficiencies.

After the construction of the two algorithms, a data sample with various variables for Banks operating in U.S. is used for the economic application. The main subject here is to determine how the Advertising and Communications expense of the banks affect their efficiency.

1.2. Research Questions/ Goals

There are two main reasons why this specific research topic was chosen. The algorithms described by Simar and Wilson (2007) are quite popular around the literature and they have been used in many applications on the field of production economics (Halkos and Tzeremes, 2013), (Alexander et al., 2010), (Keramidou and Mimis, 2011), (Latruffe et al., 2008), (Wijesiri et al., 2015), (Lee and Worthington, 2014). There are many programming languages and a great variety of packages that one can use to build these algorithms step by step but this can take time, depending on the complexity of the procedure. However, there is not yet an integrated package or a single function to do this, in spite of the great interest around the topic.

So, the first goal is the construction of a full integrated function for each algorithm provided by Simar and Wilson (2007), so everyone can make use of it and take advantage of the direct use instead of trying to build each step on his/her own. The algorithms are written in the programming language R, as it is an open source language and can be used from everyone without restrictions.

About the second part, the economic application, many studies have been done by researcher about the banks' performance (Jackson and Fethi, 2000), (Aly et al., 1990), (Hughes and Mester, 2008), (Weill, 2004). However, no one has study the impact of advertising and communications expense of the banks on their technical efficiency yet.

Thus, these two research questions are about to be answered here. How the advertising as well as the communication expenses of the American banks affects their technical efficiency.

2. Literature Review

2.1. Literature on Methods

2.1.1. DEA

The method we usually use to measure the performance and estimate the efficiency of different entities is called Data Envelopment Analysis (DEA). This is a mathematical programming technique that has been explicitly used for about 30 years now. Gattoufi et al. (2004) provide a very comprehensive list with the literature of DEA since these years.

In a production process, a firm tries to transform its inputs into outputs. Due to the increasingly competitive environment that the companies and the organizations in general operate, everyone has to be competitive enough to cope with their competitors. From economic perspective, there are two ways for an organization to be more efficient and thus more competitive. The first one is trying to minimize their cost (inputs) given a certain expected level of output. These cost minimization strategies are mostly followed by organizations in sectors that uncertainty plays a crucial role. A representative example is the agricultural sector where exogenous, like environmental factors, can definitely affect the production and at the same time these factors cannot be fully (or in some situations not at all) controlled by the organizations but they surely affect their inputs and outputs. The other strategy that can be followed is the one that the goal is to maximize the outcome (outputs) or more generally the effectiveness of the organization, given a certain level of inputs.

Each organization has to take a critical decision about the level of inputs they will use to reach a certain level of output or the way that they will handle their given inputs to reach the maximum level of outputs. In both strategies, the final goal is to maximize the efficiency. In a decision making problem like this, each organization is called a Decision Making Unit (DMU).

It's clear that the inputs are mostly under the control of the DMUs but there are some other environmental variables that also affect the production process. The difference here is that these variables usually affect the inputs and the outputs too, so the DMU has less control over the production process.

The most common way to measure efficiency is constructing a cost function made from the cost/effectiveness ratio resulted from the combination of many different input and output variables. As in most of the times is not easy to have the same measure for cost at every input variable or the same measure for effectiveness at every output variable, it is preferred to define the efficiency scores as the output/input ratio. This is what Charnes, Cooper and Rhodes used to measure the relative efficiency of a DMU. Two definitions of efficiency provided by Charnes, Cooper and Rhodes are given below:

Extended Pareto-Koopmans Efficiency: A fully efficient DMU is a DMU that cannot improve any of its inputs or outputs without worsening any of the other inputs or outputs.

Relative Efficiency: A DMU is fully efficient if and only if, based on the available information; there are no other DMUs that perform better showing that the focused one can improve its inputs or outputs without worsening any of its inputs or outputs.

The first DEA model was presented by Charnes, Cooper and Rhodes (CCR) in the 1970s following the work of Farrell (1957) who made the inception of DEA.

Except of the introduction of the DEA idea, Farrell also distinguished the different kinds of efficiencies. He separated "technical efficiency" from other kinds of efficiencies like "allocative", "scale" or "scope" efficiency.

There are many different models, many different definitions of what we mean by "efficiency", various assumptions and for each of those variants it takes lines of mathematical and graphical explanations for the reader to understand this huge topic. As the subject of this thesis is not the DEA models in particular and also for space saving reasons, the different models are not explained further here. The reader who is interested in more details can take a look at Cooper, Seiford and Zhu (2011).

The two basic DEA models are the so called CCR (Charnes et al. 1978) and BCC (Banker et al. 1984). For each of those models there are both input and output oriented versions. The difference between CCR and BCC model is that the first one allows Returns To Scale (RTS) to be only Constant Returns to Scale (CRS). The BCC model has one extra constraint that allows it to evaluate for Variable Returns to Scale (VRS) including increasing, constant and decreasing returns.

The boundary of the production possibility set P is called the technology or the production frontier. The firms that lie on this boundary are the technical efficient firms while those that operate in the interior of P , are the technical inefficient firms.

2.1.2. Two Stage DEA

The two-stage approach is widely popular in the literature of DEA as it has been used in many published studies and working papers. In a typical two-stage DEA model the efficiency scores are calculated in the first stage and then the estimated efficiencies are regressed on some covariates. Different variations of the two-stage DEA model also exist as in some studies, functions of the estimated efficiencies like ratios, Malmquist indices or other transformations (e.g. logarithmic) are regressed upon the covariates instead of the efficiency scores itself in the second stage.

Other variations suggest different regression methods like OLS, censored (Tobit) or truncated models.

The application of a censored model seems logical because of the nature of the DEA estimations of the efficiencies in the first stage. The argument behind this is that it tends to have many efficiency scores equal to one by construction. For many researchers this is a fact that makes these estimates to be censored whereas for some others this issue is not taken

into account and a simple OLS model is used. The problem that arises here is that if one assumes that the estimated efficiencies indeed tend to have many values equal to one, the results from the OLS are biased but in most of the studies, researchers take this property into account and instead use a censored (usually tobit) model (Aly et al., 1990), (Jackson and Fethi, 2000).

As Simar and Wilson (2007) report, another serious problem in the two-stage DEA models that in most of the cases arises is that the efficiency estimates are serially correlated. The reason why this happens comes from the fact that the existence of a DMU lying on the estimated frontier, affects the efficiency score of the other DMUs. This problem of serial correlation of estimated efficiencies from the DEA approach is logical as these estimates are based on the estimated frontier that is not the true unobserved one, as the maximum efficiency score is attached to the relatively most efficient DMU given a particular sample. This can also cause serial correlation in the estimated residuals from the OLS method in the second stage.

These are some of the most serious and usual problems in the context of the two-stage DEA models but they can be treated in one way or another. Another very important issue is the Data Generating Process (DGP) of the efficiencies estimated from the DEA. Because of the non-parametric maximum likelihood nature of the estimated frontier, it is necessary to describe how the unobserved true frontier, and therefore the estimated one, is derived. Without specifying this DGP, any results coming from a two-stage DEA is meaningless. For this reason, Simar and Wilson (2007) described the first consistent DGP ever done for such models in order to make inference about the results. This DGP is given also here (1).

2.1.3. Bootstrap

The bootstrap is a nonparametric simulation method relevant to the parametric Monte Carlo. Therefore, one doesn't have to know the distribution of the population as in the parametric methods. The bootstrap is a very useful simulation tool based on the resampling method that is widely used to construct confidence intervals and calculate standard errors for the statistics of interest.

Usually, one uses an estimation of a statistic $\hat{\theta}$ to estimate the population parameter θ but in most of the cases the sampling distribution is unknown. In cases like this we can use the bootstrap distribution to approximate the actual sampling distribution.

The bootstrap procedure is very simple. We randomly draw n observations with replacement from the observed data set, where n is the number of observations that the initial observed data set includes. We keep doing many times (L times) this until we create L data set simulations and then for each one of them we calculate a statistic named bootstrap estimation $\hat{\theta}_i^*$ so that the distribution of the bootstrapped estimations simulated the sampling distribution. Next we can use these simulated estimates to define confidence intervals or calculate statistics like the mean and the standard deviation. More details about bootstrap and DEA are given in the next sections while the process of the analysis will go on.

2.2. Literature on Topic

2.2.1. Banks' Performance and Technical Efficiency

The crucial role that the banks play in the economy, especially when a crisis or difficult situations are faced, makes it a hot topic for research and further investigation. As banks are the greatest financial intermediations they differ from different types of firms. So, is not only about the impact that the banks' choices have upon the whole word, but the internal performance of the bank itself as an organization is very important. A potential bankruptcy of a bank due to bad performance is a fact that would have horrible consequences on the whole economy, as happened many times before in the history.

The usage of DEA to measure the efficiency of the banks is very common among the literature. One of the advantages is that it doesn't require the use of prices as other methods and only makes use of various inputs and outputs. This is indeed very useful as it is very hard to find prices for the inputs and outputs that a bank uses. There is a great debate about whether the choices of a bank affect its risk or not. In other words, are the banks operates under the manager's decisions or the owner's? The managers' decisions and their effect on the efficiency of the banks is something that is under focused investigation the recent years.

Many researchers have investigate the banking efficiency, some of these studies are (Jackson and Fethi, 2000), (Weill,), (Berger and Mester, 2003). To mention some of them, Tahir et al. (2009), studied the Malaysian banks' efficiency for the years 2000-2006 and found that for the years 2005-2006 banks have easier access to better technologies and different environmental and this fact makes them perform more efficient than the previous years. Hughes and Mester (2008) provide some simple explanations about the efficiency in banking, explaining the theory behind the bank's performance, the models that are used to measure their efficiency and some interesting results from empirical studies.

Although various kinds of efficiencies like allocative or scale efficiency are usually studied, our focus here is strictly on the technical efficiency of a bank and especially on the effect that some environmental variables that banks faces (advertising and communications expense) have on them.

3. Methodology

3.1. Theoretical and Statistical Approach

In this section are demonstrated the statistical model and the necessary assumptions for the models and the algorithms that follow.

Firstly, let's describe the variables that are used here. The input variables can be represented as a p -dimensional matrix ($n \times p$) that takes non-negative real values as $x = (x_1, x_2, \dots, x_p) \in \mathbf{R}_+^p$ where each x_j ($j = 1, \dots, p$) is a vector with n observations. The output variables can be represented as a q -dimensional matrix ($n \times q$) that takes also non-negative real values as $y = (y_1, y_2, \dots, y_q) \in \mathbf{R}_+^q$ where each y_j ($j = 1, \dots, q$) is a vector

with n observations. The environmental variables can be described as an r -dimensional matrix ($n \times r$) that takes real values $z = (z_1, z_2, \dots, z_r) \in R^r$ where each z_j ($j = 1, \dots, r$) is a vector with n observations and has no further restrictions as the two previous vectors had. In addition, p , q and r denote the number of input, output and environmental variables respectively.

3.1.1. Theoretical Approach

In order to continue, it is necessary to set some basic but essential assumptions of the statistical model. The first assumption is about to define the semi-parametric DGP. The rest of the assumptions are about to describe in details the DGP.

This process is the one that generates the data in φ_n . The equation below is the one that describes the Data Generating Process (DGP) from which the observation set $\varphi_n = \{(x_i, y_i, z_i)\}_{i=1}^n$ is defined.

$$f(x_i, y_i, z_i) = f(x_i, \eta_i, \delta_i, z_i) = f(x_i, \eta_i | \delta_i, z_i) f(\delta_i | z_i) f(z_i) \quad (1)$$

In order to make this sequence understandable, (1) is interpreted here from right to left:

Consider the firm i facing the environmental variables z_i . These variables are drawn from $f(z_i)$.

Given these environmental variables, the firm faces an efficiency level δ_i . Thus, the efficiency of a firm is somehow based on some variables z_i . In other words, these environmental variables have an effect on the efficiency of the firm¹. This efficiency δ_i is drawn from $f(\delta_i | z_i)$.

The input x_i as well as a part of the output variables, the angle η_i ² that the firm faces is based on the environmental variables z_i and the efficiency level δ_i . Notice that while the firm has the control of its inputs, they are also restricted by some environmental variable and the efficiency level. On the other hand, the outputs are party under the control of the firm (let's say only the η_i part) and under some constrains (δ_i and z_i), as a part of y_i (the efficiency level δ_i) is anyway produced as the outcome of the environmental variables' impact. The x_i and η_i are drawn from $f(x_i, \eta_i | \delta_i, z_i)$.

This procedure results in $f(x_i, \eta_i, \delta_i, z_i)$ which is equivalent to $f(x_i, y_i, z_i)$ after the transformation of the polar coordinates (η_i, δ_i) to Cartesian coordinates (y_i) .

The two-stage model presented here has to be statistically consistent in both the first and the second stage and also be consistent with the economic theory.

We can categorize the rest 8 assumptions in 3 main categories. The assumptions A1-A3 are used to ensure the properties of the environmental variables in the model (consistency of

¹ In our case this is the effect of advertising and communications expense on the efficiency of the banks.

² For an explicit explanation about the nature of η_i and δ_i , see the Appendix.

the second stage estimators). The assumptions A4-A6 cover the classical microeconomic theory assumptions while the assumptions A7-A8 are used to assure the consistency of the DEA estimators that appear in the first stage. These 8 assumptions are presented below in more details:

A1. The input x , output y , and environmental z variables are identically, independently distributed (iid) random variables with probability density function (pdf) $f(x, y, z)$.

$P = \{(x, y) | x \text{ can produce } y\}$ is the production set where $P \subset R_+^{p+q}$.

Moreover, we can say that $f(x, y, z)$ has support over $P \times R^r$.

The overall meaning of this assumption is that the production set P , and therefore its boundary, is defined only by the inputs and outputs ($P \subset R_+^{p+q}$). though the last line explains that the environmental variables have an impact on P too ($P \times R^r$), but in a different way that is explained in the next assumption.

A2. The way that the efficiency level δ_i is created given the environmental variables z_i , meaning the generation of $f(\delta_i | z_i)$ in (1) is given by the following mechanism.

$$\delta_i = \psi(z_i, \beta) + \varepsilon_i \geq 1 \quad (2)$$

In this formation, ψ is a smooth, continuous function, β is the vector of parameters and ε_i is the error term which is an identically, independently distributed (iid) random variable independent of z_i .

The assumption simply explains the way that z_i interacts with δ_i , and given the function ψ it is practically implemented with the regression in the second-stage. It also makes clear that the way that z_i affects P has nothing to do with the Production Possibility Function (PPF) that is represented by the frontier of P as **A1** indicates, but the only effect it has is upon the efficiency score δ_i of each DMU.

Together, assumptions **A1** and **A2** imply to a separability condition about the production set P and the effect of z on δ^3 and so the dependence between y and z that arises by the DGP in (1).

³ Alternative formulations about the production possibility set can be made including an extra constraint about z and take it into account in the first-stage of linear programming (DEA). In this case, z influences the boundary surface in contrast with our assumption where it affects only the mean and variance of the efficiencies. In addition, in the case that z influences the boundary surface there is no reason to proceed in the second-stage. Model like this are discussed by Coelli et al. (1998).

A3. The error term ε_i in (2) is distributed $N(\mathbf{0}, \sigma_\varepsilon^2)$ with each i element of ε_i to be selected with left truncation at $\mathbf{1} - \psi(\mathbf{z}_i, \beta)$.

In this assumption two choices are made. The first one is about the distribution of ε_i and the second one is about the form of $\psi(\cdot)$. A full parametric method for truncated regression is assumed here as both of the two elements mentioned before are specified but other forms are possible too⁴.

A4. $\mathbf{x}(\mathbf{y}) = \{\mathbf{x} | (\mathbf{x}, \mathbf{y}) \in \mathbf{P}\}$ and $\mathbf{y}(\mathbf{x}) = \{\mathbf{y} | (\mathbf{x}, \mathbf{y}) \in \mathbf{P}\}$ are closed and convex for every $\mathbf{y} \in \mathbf{R}_+^q$, and bounded for every $\mathbf{x} \in \mathbf{R}_+^p$ respectively. Thus, \mathbf{P} is also closed and convex as the consideration for both $\mathbf{x}(\mathbf{y})$ and $\mathbf{y}(\mathbf{x})$ implies the knowledge of \mathbf{P} and vice versa.

This assumptions simply explains that \mathbf{P} is defined by the combinations of both \mathbf{x} and \mathbf{y} , (\mathbf{x}, \mathbf{y}) while at the same time the inputs of a firm are restricted by its outputs and vice versa. This is the assumptions about \mathbf{P} as described by Shephard (1970) and Fare (1988).

A5. $(\mathbf{x}, \mathbf{y}) \notin \mathbf{P}$ if $\mathbf{x} = \mathbf{0}, \mathbf{y} \geq \mathbf{0}$

This assumption means that there are no "free lunches", so there cannot be any level of production without the use of some inputs.

A6. If $(\mathbf{x}, \mathbf{y}) \in \mathbf{P}$, then $(\bar{\mathbf{x}}, \mathbf{y}) \in \mathbf{P}$ and $(\mathbf{x}, \bar{\mathbf{y}}) \in \mathbf{P}$, where $\bar{\mathbf{x}} \geq \mathbf{x}$ and $\bar{\mathbf{y}} \leq \mathbf{y}$.

This is the "free disposability" assumption and means that the inputs and outputs are strongly disposable. So that a firm may not fully utilizes its inputs. Equivalently in technical terms it is an assumption of monotonicity of the technology.

A7. $f(\mathbf{x}, \mathbf{y} | \mathbf{z})$ is strictly positive and continuous in the interior of \mathbf{P} for all \mathbf{z} , for all $(\mathbf{x}, \mathbf{y}) \in \mathbf{P}$ such that $(\theta^{-1}\mathbf{x}, \mathbf{y}) \notin \mathbf{P}$ and $(\mathbf{x}, \theta\mathbf{y}) \notin \mathbf{P}$ for $\theta > 1$.

This assumption implies the consistency of the estimator of \mathbf{P} . One could give a free description of the meaning of this assumption, as any point (\mathbf{x}, \mathbf{y}) that is weighted as described above and so lies outside the frontier, does not belong to \mathbf{P} . This, as well as the following assumption are based on Kneip et al. (1998) but adjusted to cover the environmental variables \mathbf{z} .

A8. $\delta(\mathbf{x}, \mathbf{y} | \mathbf{P})$ is differentiable in both \mathbf{x} and \mathbf{y} for all (\mathbf{x}, \mathbf{y}) .

⁴ Leave the distribution of ε_i unspecified and employ the semi-parametric form of truncated regression (Honoré and Powell, 1994) or leave the function $\psi(\cdot)$ unspecified too and employ the non-parametric method for truncated regression (Lewbel and Linton, 2002).

This is an assumption about the smoothness of the frontier and it indicates that the estimator of δ_i is consistent if the probability to observe a firm in the neighborhood of any point on the frontier is equal to 1 as the sample increases in size. So the boundary line to be smooth, continuous and thus differentiable in any point⁵.

3.1.2. Statistical Approach

Using the observation set φ_n , one can estimate the production set P with the following estimator \hat{P} :

$$\hat{P} = \{(x, y) | y \leq Yq, x \geq Xq, x'q = 1, q \in R_+^n\} \quad (3)$$

Where q denotes an $(n \times 1)$ vector of intensity variables, i is the unit vector $(n \times 1)$ and the capital letters X and Y denote the observation sets of x and y equivalently. It has been proved by Korostelev et al. (1995) that \hat{P} is a consistent estimator of P under assumptions A1 – A8.

We define the measure of output technical efficiency δ_i for a particular point (DMU) $(x_i, y_i) \in R_+^{p+q}$ as following (Farrell, 1957):

$$\delta_i = \delta(x_i, y_i | P) \equiv \sup\{\delta | (x_i, \delta y_i) \in P, \delta > 0\} \quad (4)$$

Where for every $(x_i, y_i) \in P$, there is a function $\delta(x_i, y_i | P) > 1$ that measures the Euclidean distance from this point to the boundary of P . Referring to the output oriented DEA, the direction of measurement (technical efficiency) is parallel to the output axes and orthogonal to the input axes, while referring to the input oriented model the direction of measurement is reversed.

Replacing the equation (3) in (a1) one can construct the Farrell efficiency measure estimator $\hat{\delta}$ in terms of linear programming as:

$$\hat{\delta}_i = \delta(x_i, y_i | \hat{P}) = \max\{\theta > 0 | \theta y_i \leq Yq, x_i \geq Xq, i'q = 1, q \in R_+^n\} \quad (5)$$

which is the empirical expression of (4).

A problem that appears with the non-parametric methods is the low rate of convergence that causes problems as is explained later. In this case, $\hat{\delta}_i$ has a very low rate of convergence as typically the non-parametric estimators have.

$$\hat{\delta}_i = \delta_i + O_p(n^{-2/(p+q+1)}) \quad (6)$$

⁵ This is a stronger assumption than is typically required as Kneip et al. (1998) require only Lipschitz continuity for the distance function.

This rate of convergence decreases as n increases ($O_p(0)$ as $n \rightarrow \infty$) and slows as $p + q$ increases ($O_p(1)$ as $p + q \rightarrow \infty$). The second one is known as the "curse of dimensionality" that makes the convergence very slow when many input or output variables are used.

The previous explanation is the statistical context behind the estimation of the efficiency estimators $\hat{\delta}_i$ using DEA in the step [1] in both Algorithm #1 and Algorithm #2.

One can estimate β in (2) with maximum likelihood specifying the function $\psi(\cdot)$. A typical form for this function is simply $\psi(z_i, \beta) = z_i\beta$. This makes (2) to take the following specific form:

$$\delta_i = z_i\beta + \varepsilon_i \geq 1 \quad (7)$$

As the theoretical efficiency δ_i is unknown, one computes an estimation of this using DEA. This can be simply done using the observed inputs and outputs (x_i, y_i) in φ_n in (3) and (5) yielding $\hat{\delta}_i$. Then, in the second-stage one can regress the observed z_i on the estimated $\hat{\delta}_i$ as shown in (8).

$$\hat{\delta}_i = z_i\beta + \xi_i \geq 1 \quad (8)$$

This regression will lead to the estimation of $\hat{\beta}$ and the residuals ξ_i . This is the statistical context behind the estimation of the coefficient estimators β using truncated regression in the step [2] in both Algorithm #1 and Algorithm #2.

The kind of regression that is used here for the estimation of (7) is the truncated regression for reasons that are described in (Simar and Wilson, 2007). In most of the cases before Simar and Wilson present this model, the regression method that were used was a censored (Tobit) model or sometimes a simple OLS. In the paper mentioned above, Simar and Wilson showed how faulty was the use of a Tobit model and compares it with the results from a truncated regression model. The (Figure 1) below shows clearly the superiority of the truncated regression over the Tobit models. One can see that the confidence intervals from the Tobit model are far beyond the vertical dashed line (the true parameter), while the confidence intervals from the truncated regression almost perfectly cover the true parameter, especially in the case of $p = q = 1$. Adding more dimensions arises the problem in the first-stage mentioned before in (6) because of the "course of dimensionality".

Figure 1
Source: Simar and Wilson (2007)

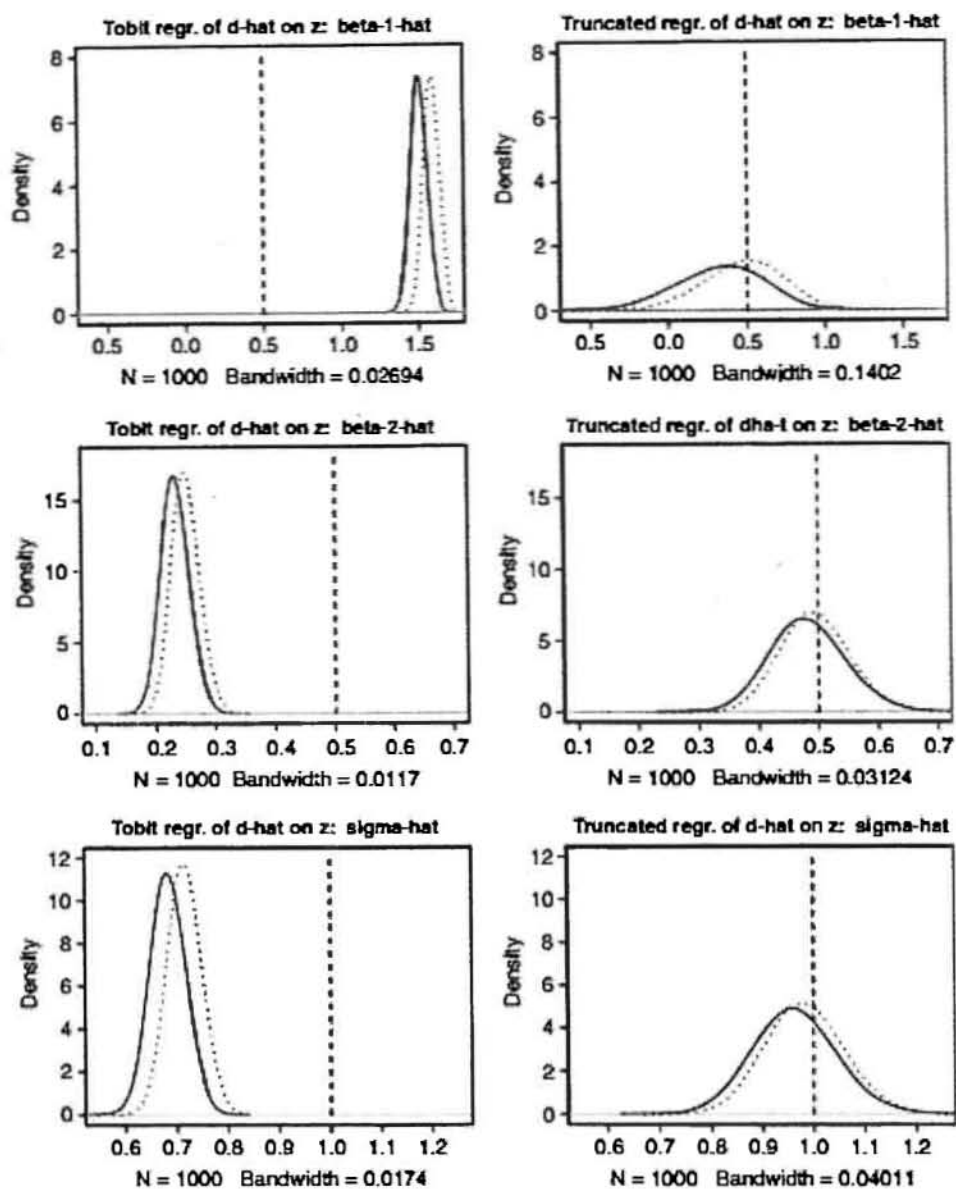


Fig. 1. Estimates of sampling densities, Algorithm #1 ($n = 400$; dotted curve for $p = q = 1$, solid curve for $p = q = 2$).

The problem that arises here is that the estimated efficiency scores δ_i are serially correlated by construction as DEA evaluates each DMU depending on the values that have been given to the other DMUs, in particular to the most efficient ones. As we can see in (5), δ_i depends on \bar{P} and \bar{P} depends on (x_i, y_i) as it's clear from (3), so consequently δ_i depends on (x_i, y_i) . This serial correlation of δ_i passes on the estimated residuals ξ_i . Now recall that due to assumption A2, x and y are correlated with z . In most of the cases it's true that $f(x, y|z) \neq f(x, y)$. This means that the z variables are not independent with respect to

(x, y) and this is the reason why we apply the second stage regression. Interpreting this sequence one can see that z is correlated with the residuals ξ_i .

Two problems arise here, the first one is the serial correlation in $\bar{\xi}_i$ and the second one is the correlation between ξ_i and z . The maximum likelihood estimators of β are still consistent but the problem disappears asymptotically with the rate of convergence of $\bar{\delta}_i$ in (6) which is very slow, rather than the usual parametric convergence rate of $n^{-1/2}$. The serial correlation problem disappears also asymptotically with the same convergence rate, but for models where $p + q > 3$ in the first-stage, this rate is very slow for standard approaches as Simar and Wilson (2007) report (based on the inversion of log-likelihood negative Hessian).

Another problem is that $\bar{\delta}_i$ is also biased downward by construction. After the estimations of (8), the Algorithm #1 proceeds to the steps [3] and [4]. Except the usefulness of the bootstrap in the second stage, the bootstrap procedure is also used in the first stage as this is the only way to approximately reach the asymptotic distribution of $\bar{\delta}_i$ in multivariate settings with $p + q > 2$ because of the complexity of these cases. Nevertheless, Gijbels et al. (1999) proved the asymptotic distribution of the output-oriented distance function (it can be also extended to the input distance function case) of Shephard (1970) for the case of $p = q = 1$ but this is not enough for the most applications. In contrast with Algorithm #1, Algorithm #2 takes care of this problem following the next procedure.

We can express $\bar{\delta}_i$ as:

$$\bar{\delta}_i = E(\bar{\delta}_i) + u_i \quad (9)$$

Where $E(\bar{\delta}_i) = 0$ and u_i is iid with zero mean. In turn, because $\bar{\delta}_i$ is biased downward as mentioned before we have:

$$E(\bar{\delta}_i) = \delta_i + BIAS(\bar{\delta}_i) \quad (10)$$

Solving (10) for $BIAS(\bar{\delta}_i)$ we have:

$$BIAS(\bar{\delta}_i) = E(\bar{\delta}_i) - \delta_i \quad (11)$$

So the true bias of $\bar{\delta}_i$ is the expected value of $\bar{\delta}_i$ (the estimated mean) minus the true population mean.

Substituting for $E(\bar{\delta}_i)$ from (9) in (11) and solving for δ_i :

$$\delta_i = \bar{\delta}_i - u_i - BIAS(\bar{\delta}_i) \quad (12)$$

The equation in (12) is the analytical expression of (7). Substituting the right-hand side of (7) in (12) we have:

$$z_i\beta + \varepsilon_i = \bar{\delta}_i - u_i - BIAS(\bar{\delta}_i) \quad (13)$$

Solving (13) for $\bar{\delta}_i$ we have another expression of (8) as:

$$\bar{\delta}_i = z_i\beta + \varepsilon_i + u_i + BIAS(\bar{\delta}_i) \quad (14)$$

Linking (14) with (8), one can see that the error term in (8) that causes the problems mentioned previously is:

$$\xi_i = \varepsilon_i + u_i + BIAS(\delta_i) \quad (15)$$

where ε_i is the theoretical error that follows all the assumption about the error terms and u_i has a zero mean and diminish asymptotically. So the problems contained in ξ_i are mostly inside the $BIAS(\delta_i)$. Thus, the problem can be easily solved just subtracting the bias from the estimated efficiencies $\hat{\delta}_i$.

The calculation of the bias is very easy using bootstrap methods. The first step to do this is to compute the bootstrap bias estimate of $BIAS(\delta_i)$:

$$B\bar{I}AS(\hat{\delta}_i) = BIAS(\delta_i) + v_i \quad (16)$$

Where, as the sample size increases, the residual v_i has smaller magnitude than $BIAS(\delta_i)$ and its variance becomes asymptotically negligible.

Expanding (11) we have:

$$BIAS(\hat{\delta}_i) = E(\hat{\delta}_i - \delta_i) \quad (17)$$

Following this, the bootstrap bias estimate $B\bar{I}AS(\hat{\delta}_i)$ is:

$$B\bar{I}AS(\hat{\delta}_i) = E(\delta_i^* - \hat{\delta}_i) = E(\delta_i^*) - \hat{\delta}_i \quad (18)$$

Where $E(\delta_i^*)$ is the mean of the all the bootstrap values and $\hat{\delta}_i$ represents the initial uncorrected estimation of the efficiency.

Taking advantage of the bootstrap technique where the initial estimator $\hat{\delta}_i$ plays the role of the population statistic and $E(\delta_i^*)$ represents the sample mean executed from the bootstrap sample distribution, one can go from (17) to (18).

Now the bias-corrected estimator of δ_i is:

$$\hat{\delta}_i = \hat{\delta}_i - B\bar{I}AS(\hat{\delta}_i) \quad (19)$$

So we finally have:

$$\hat{\delta}_i + v_i - u_i = z_i\beta + \varepsilon_i > 1 \quad (20)$$

$$\hat{\delta}_i \approx z_i\beta + \varepsilon_i > 1 \quad (21)$$

Where $\hat{\delta}_i$ is a consistent estimate.

The steps [3] and [4] in Algorithm #2 follow this method, and regress the covariates on the bias-corrected estimate $\hat{\delta}_i$.

The last part refers to the confidence intervals estimation. Two methods for confidence interval are described here, although other more sophisticated methods could be used for better results. The first method is the basic confidence interval. The estimated interval for this method is:

$$[2\hat{\beta} - q_{1-\alpha/2}^{(\beta)}, 2\hat{\beta} - q_{\alpha/2}^{(\beta)}] \quad (22)$$

Where $\hat{\beta}$ is the initial estimate, $q_{1-\alpha/2}^{(\beta)}$ is the upper quantile from the sorted bootstrap distribution and $q_{\alpha/2}^{(\beta)}$ the lower quantile from the sorted bootstrap distribution.

The other method is the percentile method. The percentile confidence intervals are constructed as:

$$[q_{\alpha/2}^{(\beta)}, q_{1-\alpha/2}^{(\beta)}] \quad (23)$$

3.2. Data

The data that were used for the empirical economic application part were received from the database of CompuStat. The data that finally used include 148 banks operating in U.S. covering the years 2006-2013 reaching the total number of observations ($n = 1184$). The variables that were used in the first stage to estimate technical efficiency include three input variables (Total Assets, Total Deposits and Employees) ($p = 3$) and two output variables (Total Securities and Gross Loans) ($q = 2$). For the second stage, two covariates were used to explain the estimated inefficiencies from the first-stage (Advertising Expense and Communications Expense) ($r = 2$) but various combinations of the logs of these two variables were also used to account for non-linearities. All variables except the number of Employees are measured in U.S. dollars. The choice of these variables as inputs and outputs was made based on the economic theory and also on other empirical studies that use the same variables (Berger and Mester, 2003).

The descriptive statistics of the final balanced panel sample are presented below:

Table 1

Statistic	Inputs		
	Total Assets	Total Deposits	Employees
Min.	122.5	108.8	0.039
Q1	772.6	591.5	0.1827
Median	1966.8	1484.6	0.429
Mean	57777.7	33926.6	8.2975
Q3	6639.5	5128.4	1.4318
Max.	2415689	1287765	288
St. Dev.	265137.5	141433.5	35.6809

Table 2

Outputs		
Statistic	Total Securities	Gross Loans
Min.	3.9	93.4
Q1	132.8	501.1
Median	346.5	1294.8
Mean	9386.6	26903.9
Q3	1295.4	4308.5
Max.	507255	918498
St. Dev.	44899.97	112640.2

Table 3

Environmental		
Statistic	Advertising Expense	Communications Expense
Min.	0.017	0
Q1	0.523	0
Median	1.587	0.645
Mean	52.254	66.343
Q3	4.859	3.491
Max.	3143	5425
St. Dev.	269.774	414.696

The full data before the sampling was an unbalanced panel with a total of 7950 observations, containing 1117 different banks covering various years from 1999 to 2014. This full data unbalanced panel had too many missing values between the variables, so a careful cleaning in order to choose the best sample was necessary.

Note that in order to take the log of the variable Communications Expense, the value of 1 was arbitrary added to every observation of the variables as it would be impossible to take the log of 0. This is very common technique for situations like this (Puig-Junoy, 1998).

3.3. Cleaning and Selection Procedures

In the research process, in order to do any kind of analysis one usually needs data. In the real world, except the fact that good data is hard to be found even if they already exist in most of the times they are difficult to be read, we call this kind of data "raw data". In order to have easy access to the data first it needs to clean the raw data and prepare them for the analysis. The new easy manageable format of the data is called "tidy data".

The procedure of converting the raw data into tidy data is very often a time consuming and rigorous part of the research. For this reason here it is also provided, for educational reasons, the R code with which the raw data used in this thesis were cleaned.

The initial data file is a Microsoft Excel (.xls) file named "banks". Converting this file into a .Comma Separated Value (.csv) file, it is much easier to enter the data in R and work with them. So, the file "banks_csv" contains exactly the same information, the only difference is that this is a .csv file.

In this section are described the two R codes that are necessary before the rest of the analysis. The first code has the name "max_info_clean_data" and is used to clean the data and find the best balanced sample to use. The second one has the name "create_balanced_panel_data" and is used to create the balanced panel data after the choice of the sample.

It is essential to set the working directory of R in the folder where the data and the R files are, before running any of the following codes. One can do this simply writing the path of the folder in the command `setwd(" ")`.

For example: `setwd("C:/User/Desktop")`

max_info_clean_data

This code firstly reads the data (`max_info_clean_data, 1-2`) and then keeps only the banks that operate in U.S. (`max_info_clean_data, 3-7`). Then, it saves in the object *all_firms* the name of each bank (in fact, the ticker that represents each bank), the first and the last year where this bank has recorded data (`max_info_clean_data, 10-18`).

In (`max_info_clean_data, 23-87`), all the possible combinations of year between 1999 and 2014 are tested to find which the best years to include in the sample are. In this procedure, the object *bounds* that is defined in (`max_info_clean_data, 29`) ensures that each bank has data for, at least, the years that are tested each time. In (`max_info_clean_data, 34-51`) two more filters are used to ensure that the banks that have at least the required years, they also don't overcome these years, so the panel will be balanced. Then, the data are stored in the object *full_data* (`max_info_clean_data, 52-71`) and the final information for each combination is saved in the object *Total* (`max_info_clean_data, 78-83`). In the first column of *Total* is written the first year of this particular year range that is tested each time, in the second column the last year, in the third column the number of banks that these years include and in the fourth column the total number of observations for these years (years times number of banks, as the panel is balanced). Finally, the object *Total* with all the possible combinations is sorted, with respect to the total number of observations, and the results are printed on the screen as well as presented in a table (`max_info_clean_data, 88-92`).

create_balanced_panel_data

This code simply creates the balance panel of our choice. The first few steps (`create_balanced_panel_data, 1-20`) are the same as in the previous code.

Here the user has to choose the preferable years and set the starting year in the object *lower* and the ending year in the object *upper* (`create_balanced_panel_data`, 24-25). In our case, the chosen years are 2006-2013. The steps (`create_balanced_panel_data`, 26-70) are the same steps that `max_info_clean_data` uses to construct the object *full_data* that contains the final balanced data set for the requested years.

In (`create_balanced_panel_data`, 72-76) the final data are saved in a txt file named "balanced_panel_data" and is automatically placed in the current working directory.

3.4. Algorithms

The first part of this thesis is the construction of the two algorithms initially described by Simar and Wilson (2007). Although the two algorithms presented here implement those that was previously mentioned, as this is one of the actual goals of this thesis, these algorithms can also be generally used to estimate various two-stage semi-parametric DEA models with a single or double bootstrap.

The theoretical procedure and steps along with the mathematical expressions and the corresponding R code interpretation of the two algorithms (`Algorithm_1_simplified` and `Algorithm_2_simplified`) described in Simar and Wilson (2007) is given below while the exact R code is given in the Appendix.

`Algorithm_1_simplified` and `Algorithm_2_simplified` are the simplistic versions of `Algorithm_1` and `Algorithm_2` respectively. This is because the structures of the last two algorithms are too complicated as they take account of every possible combination that the user can ask from the algorithms. Thus, `Algorithm_1_simplified` and `Algorithm_2_simplified` are presented here for educational reasons. The full and the simplified algorithms work exactly the same but the simplified versions result only in the confidence intervals of β and σ_ε .

Algorithm #1

[1] Compute $\hat{\delta}_i = \hat{\delta}(x, y | \bar{P}) \forall i = 1, \dots, n$ with (5) using the data in φ_n .
(`Algorithm_1_simplified`, 25-26)

[2] Estimate the maximum likelihood estimators $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ with the truncated regression (8) of $\hat{\delta}_i$ on z using the $m < n$ observations where $\hat{\delta}_i > 1$.
(`Algorithm_1_simplified`, 33-47)

[3] Repeat the steps [3.1] – [3.3] L times to obtain the bootstrap set of estimates
 $A = \{(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*)\}_{b=1}^L$.
(`Algorithm_1_simplified`, 59-100)

[3.1] For each $i = 1, \dots, m$, draw u_i from the normal distribution $N(0, \hat{\sigma}_\varepsilon^2)$ with left truncation at $c = (1 - z_i\beta)$.

(Algorithm_1_simplified, 59-73)

[3.2] For each $i = 1, \dots, m$, compute $\delta_i^* = z_i\beta + u_i$.

(Algorithm_1_simplified, 76)

[3.3] Estimate the maximum likelihood estimates $(\beta^*, \hat{\sigma}_\varepsilon^*)$ with the truncated regression of δ_i^* on z using the observations where $\delta_i^* > 1$.

(Algorithm_1_simplified, 79-93)

[4] Construct estimated confidence intervals for β and σ_ε .

(Algorithm_1_simplified, 115-152)

Algorithm #2

[1] Compute $\bar{\delta}_i = \bar{\delta}(x, y|\bar{P}) \forall i = 1, \dots, n$ with (5) using the data in φ_n .

(Algorithm_2_simplified, 25-26)

[2] Estimate the maximum likelihood estimators $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ with the truncated regression (8) of $\bar{\delta}_i$ on z using the $m < n$ observations where $\bar{\delta}_i > 1$.

(Algorithm_2_simplified, 33-47)

[3] Repeat the steps [3.1] – [3.4] L_1 times to obtain the bootstrap set of estimates

$B = \{\hat{\delta}_{i,b}^*\}_{b=1}^{L_1}$.

(Algorithm_2_simplified, 56-86)

[3.1] For each $i = 1, \dots, n$, draw u_i from the normal distribution $N(0, \hat{\sigma}_\varepsilon^2)$ with left truncation at $c = (1 - z_i\hat{\beta})$.

(Algorithm_2_simplified, 56-70)

[3.2] For each $i = 1, \dots, n$, compute $\delta_i^* = z_{i,j}\hat{\beta}_j + u_i$.

(Algorithm_2_simplified, 73)

[3.3] For all $i = 1, \dots, n$, construct the new input and output variables $x^* = x$ and $y^* = y\bar{\delta}_i/\delta_i^*$.

(Algorithm_2_simplified, 76-77)

[3.4] Compute $\bar{\delta}_i^* = \bar{\delta}(x_{i,j}, y_{i,j}|\hat{P}^*) \forall i = 1, \dots, n$ with (5) replacing x and y with x^* and y^* respectively.

(Algorithm_2_simplified, 80-81)

[4] For each $i = 1, \dots, n$, compute the bias-corrected estimator $\hat{\delta}_i$ using the initial estimate $\bar{\delta}_i$ and the bootstrap estimates in B .

(Algorithm_2_simplified, 90-95)

[5] Estimate the maximum likelihood estimators $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ with the truncated regression (21) of $\hat{\delta}_i$ on \mathbf{z} using the $m < n$ observations where $\hat{\delta}_i > 1$.

(Algorithm_2_simplified, 100-114)

[6] Repeat the steps [6.1] – [6.3] L_2 times to obtain the bootstrap set of estimates

$C = \{(\hat{\beta}_b^*, \hat{\sigma}_\varepsilon^*)\}_{b=1}^{L_2}$ where $k = 1, \dots, r + 2$.

(Algorithm_2_simplified, 124-165)

[6.1] For each $i = 1, \dots, n$, draw \mathbf{u}_i from the normal distribution $N(0, \hat{\sigma}_\varepsilon^2)$ with left truncation at $c = (1 - \mathbf{z}_i \hat{\beta})$.

(Algorithm_2_simplified, 124-138)

[6.2] For each $i = 1, \dots, n$, compute $\hat{\delta}_i^{**} = \mathbf{z}_i \hat{\beta} + \mathbf{u}_i$.

(Algorithm_2_simplified, 141)

[6.3] Estimate the maximum likelihood estimates $(\hat{\beta}_j^*, \hat{\sigma}_\varepsilon^*)$ with the truncated regression of $\hat{\delta}_i^{**}$ on \mathbf{z} using the observations where $\hat{\delta}_i^{**} > 1$.

(Algorithm_2_simplified, 144-158)

[7] Construct estimated confidence intervals for β and σ_ε .

(Algorithm_2_simplified, 180-217)

These algorithmic steps are also presented here with the corresponding R code and their interpretation.

In Algorithm_1_simplified, one can give a set of input and another one of output variables. Each of these variable sets must be in one matrix (let's name \mathbf{x} the matrix with the inputs and \mathbf{y} the matrix with the outputs) where the columns of the matrix represent the variables and the rows represent the observations as following:

$\mathbf{x}_{[n \times p]}, \mathbf{y}_{[n \times q]}$

Where n is the number of observations, p the number of input and q the number of output variables.

The environmental variable matrix has the same form as the inputs and outputs matrixes described before:

$\mathbf{z}_{[n \times r]}$

Algorithm_1_simplified

[1] The first step is about to estimate the inefficiencies $\hat{\delta}_i$ for each firm i . In step [1], DEA is used to calculate the inefficiencies and in practice the algorithm sets x and y in the DEA function (Algorithm_1_simplified, 25) and saves the estimated inefficiencies $\hat{\delta}_i$ in d_hat (Algorithm_1_simplified, 26).

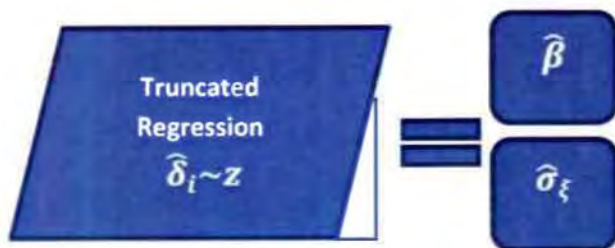
These inefficiency scores are attached to all observations (firms) with the full efficient firms taking the value of **1** and the inefficient ones values > 1 (if the DEA model is output-oriented, in the algorithm this is defined as ORIENTATION= "out"). If the DEA model is input-oriented (ORIENTATION= "in"), the full efficient firms have efficiency score equal to **1** while the inefficient ones have a score < 1 .

The other choice that the user has to make is to choose between Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) which are set in the DEA function (Algorithm_1_simplified, 25) as RTS="CRS" and RTS="VRS".



[2] The second step requires the estimation of $\hat{\beta}$ and $\hat{\sigma}_\xi$, where $\hat{\sigma}_\xi$ is the estimated standard deviation of the residuals, $\hat{\beta}$ includes the estimated constant term and the effects of the environmental variables z on the inefficiency scores $\hat{\delta}_i$ and ξ denotes the residuals.

The algorithm uses the maximum likelihood method to apply the truncated regression of z on $\hat{\delta}_i$ (the product of step [1]) resulting in the estimates $\hat{\beta}$ and the residual standard deviation estimates $\hat{\sigma}_\xi$ (Algorithm_1_simplified, 33-41). (Algorithm_1_simplified, 33-36) is used in the output-oriented case and (Algorithm_1_simplified, 38-41) in the input-oriented case. Then, it saves the constant term and slopes at $beta_hat$ and the standard deviation at sd_hat (Algorithm_1_simplified, 46-57).



[3.1] In this step the error term u_i is created using random draws from $N(0, \hat{\sigma}_\xi^2)$, where this distribution is left-truncated at $c = (1 - z_i \hat{\beta})$. This means that each u_i ($i = 1, \dots, m$) is randomly picked from the distribution mentioned before but it's not allowed to pick values that fall at the left side of c on the distribution. So, for each element of u_i the distribution is "truncated" at a different point:

$$u_1 \rightarrow c = 1 - (\hat{\beta}_1 z_{1,1} + \hat{\beta}_2 z_{1,2} + \dots + \hat{\beta}_r z_{1,r})$$

$$u_2 \rightarrow c = 1 - (\hat{\beta}_1 z_{2,1} + \hat{\beta}_2 z_{2,2} + \dots + \hat{\beta}_r z_{2,r})$$

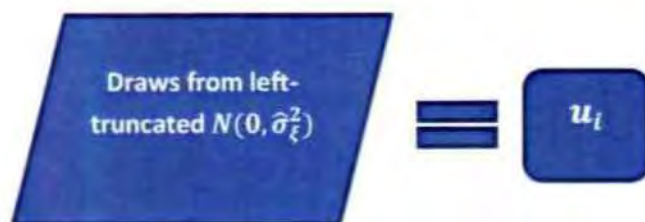
⋮

$$u_m \rightarrow c = 1 - (\hat{\beta}_1 z_{m,1} + \hat{\beta}_2 z_{m,2} + \dots + \hat{\beta}_r z_{m,r})$$

An easy way to draw each of the elements of u_i from a left-truncated normal distribution is using a modified transformation method (Simar and Wilson, 2007):

Let v denote a uniform distribution on $(0, 1)$, $c' = c/\hat{\sigma}_\xi$ and set $v' = \Phi(c') + [1 - \Phi(c')]v$. Now one can compute u_i as $u_i = \hat{\sigma}_\xi \Phi^{-1}(v')$.

The algorithm firstly computes the point of truncation for each observation c (Algorithm_1_simplified, 59-65) and then the object c' as described above (Algorithm_1_simplified, 67). The algorithmic notation of c and c' is c and cc respectively. These two objects are constructed outside the bootstrap loop [3] because their values don't change between different draws. Then, v and v' are computed (Algorithm_1_simplified, 70-72) inside the bootstrap loop [3] as the random number generator gives different values to the uniform distribution in every iteration. Their algorithmic notation is v and vv respectively. Finally, the error term u_i is constructed and saved in variable u (Algorithm_1_simplified, 73).



[3.2] The goal in this step is to compute the new inefficiencies δ_i^* . Each one of these is constructed as $\delta_i^* = \sum_{j=1}^r z_{i,j} \hat{\beta}_j + u_i$, where $i = 1, \dots, m$, $j = 1, \dots, r$ and m is the number of $\delta_i > 1$. Thus, for the construction of δ_i^* , one needs to choose from each environmental variable these observations that correspond to a $\delta_i > 1$. In particular each δ_i^* is computed as:

$$\delta_1^* = z_{1,1} \hat{\beta}_1 + z_{1,2} \hat{\beta}_2 + \dots + z_{1,r} \hat{\beta}_r + u_1$$

$$\delta_2^* = z_{2,1} \hat{\beta}_1 + z_{2,2} \hat{\beta}_2 + \dots + z_{2,r} \hat{\beta}_r + u_2$$

⋮

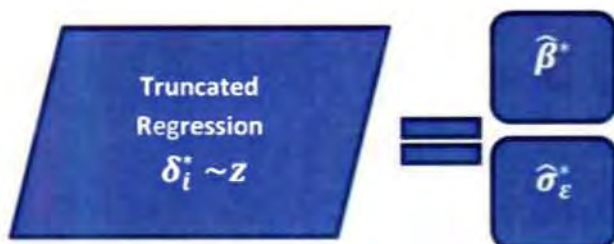
$$\delta_m^* = z_{m,1} \hat{\beta}_1 + z_{m,2} \hat{\beta}_2 + \dots + z_{m,r} \hat{\beta}_r + u_m$$

For this step, the algorithm uses the observation of z where $\delta_i > 1$ that was previously computed and saved in z_m_dt (Algorithm_1_simplified, 57) and multiplies them with the relevant $\hat{\beta}$ that are saved in zb (Algorithm_1_simplified, 64). Then, it adds these quantities plus the error term that computed before for this particular observation (Algorithm_1_simplified, 76) and saved the computed δ_i^* in d_star . Notice that for the construction of zb in (Algorithm_1_simplified, 64) the first element of $beta_hat$ (the constant term) is not used.



[3.3] Using the truncated regression of z on δ_i^* , the maximum likelihood estimates ($\hat{\beta}^*$, $\hat{\sigma}_\varepsilon^*$) are estimated.

The algorithm applies the truncated regression of z on δ_i^* : (Algorithm_1_simplified, 79-87) using (Algorithm_1_simplified, 79-82) in the output-oriented and (Algorithm_1_simplified, 84-87) in the input-oriented case and $\hat{\beta}^*$ and $\hat{\sigma}_\varepsilon^*$ are saved as $beta_hat_star$ and sd_hat_star respectively (Algorithm_1_simplified, 92-93).



The bootstrap loop [3] ends forming a matrix A containing all the bootstrapped estimates $(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*)$ found in every iteration of [3] at step [3.3].

Thus, at the end of every iteration after [3.3], the algorithm stores the estimated values of $\hat{\beta}^*$ and $\hat{\sigma}_\varepsilon^*$ at *bootstrap_beta* and *bootstrap_sd* respectively (Algorithm_1_simplified, 95-98) and when the bootstrap loop [3] ends, it binds these bootstrap groups forming a big matrix of bootstrapped sets $A = \{(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*)\}_{b=1}^b$ (Algorithm_1_simplified, 100).

[4] In the last step, confidence intervals are constructed for the constant term (β_0) , the coefficients (β_j) of all environmental variables z and the standard deviation σ_ε .

The algorithm provides two possible methods for the confidence intervals construction as well as the option to estimate both and compare the results. One has to run the algorithm choosing *ci* = "basic" for the basic method of confidence intervals, *ci* = "percentile" for the percentile method and *ci* = "all" in order to compute both and compare. In case of no choice, the percentile method is set as default. Also, the significance level *alpha* has to be chosen and again in case of no choice, *alpha* = 0.05 is set as default.

The algorithm firstly stores the appropriate lower and upper quantiles for each of the bootstrap distributions existing in A in *quantiles*(Algorithm_1_simplified, 105-109). Then, are estimated the confidence intervals (Algorithm_1_simplified, 119-160).

The basic method (Algorithm_1_simplified, 115-134) indicates the construction of the lower and the upper confidence intervals as 2 times the initial statistic of interest (for example β) minus the upper or the lower quantile, respectively:

$$\text{Lower confidence intervals for } \beta: \quad 2\hat{\beta} - q_{1-\alpha/2}^{(\beta)}$$

$$\text{Upper confidence intervals for } \beta: \quad 2\hat{\beta} - q_{\alpha/2}^{(\beta)}$$

$$\text{Lower confidence intervals for } \sigma_\varepsilon: \quad 2\hat{\sigma}_\varepsilon - q_{1-\alpha/2}^{(\sigma_\varepsilon)}$$

$$\text{Upper confidence intervals for } \sigma_\varepsilon: \quad 2\hat{\sigma}_\varepsilon - q_{\alpha/2}^{(\sigma_\varepsilon)}$$

Where $q_{\alpha/2}$ and $q_{1-\alpha/2}$ are the lower and the upper quantiles from the sorted bootstrap distribution of the statistic of interest. The algorithm calculates and stores them in the object *b_ci* (Algorithm_1_simplified, 116-121). Finally, the results are printed out on the screen (Algorithm_1_simplified, 124-133).

The same procedure is followed for the percentile confidence intervals (Algorithm_1_simplified, 137-156). The only difference here is the calculation method that indicates that the lower and upper bounds are simply the lower and upper quantiles of the sorted bootstrap distribution of the statistic of interest respectively:

Lower confidence intervals for β : $q_{\alpha/2}^{(\beta)}$

Upper confidence intervals for β : $q_{1-\alpha/2}^{(\beta)}$

Lower confidence intervals for σ_ε : $q_{\alpha/2}^{(\sigma_\varepsilon)}$

Upper confidence intervals for σ_ε : $q_{1-\alpha/2}^{(\sigma_\varepsilon)}$

The algorithm calculates and then stores them in the object *p_ci* (Algorithm_1_simplified, 142-147). Finally, the results are printed out on the screen (Algorithm_1_simplified, 146-155).

Algorithm_2_simplified

[1] The first step is about to estimate the inefficiencies δ_i for each firm *i*. In step [1], DEA is used to calculate the inefficiencies and in practice the algorithm sets *x* and *y* in the DEA function (Algorithm_2_simplified, 25) and saves the estimated inefficiencies $\hat{\delta}_i$ in *d_hat* (Algorithm_2_simplified, 26).

These inefficiency scores are attached to all observations (firms) with the full efficient firms taking the value of **1** and the inefficient ones values > 1 (if the DEA model is output-oriented, in the algorithm this is defined as ORIENTATION= "out"). If the DEA model is input-oriented (ORIENTATION= "in"), the full efficient firms have efficiency score equal to **1** while the inefficient ones have a score < 1 .

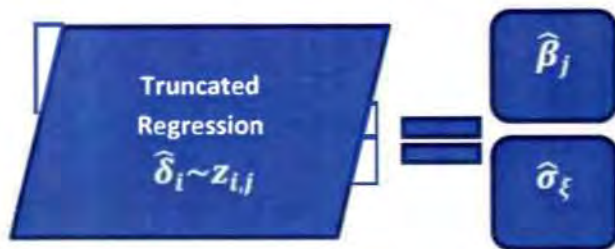
The other choice that the user has to make is to choose between Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) which are set in the DEA function (Algorithm_2_simplified, 25) as RTS="CRS" and RTS="VRS".



[2] The second step requires the estimation of $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$, where $\hat{\sigma}_\varepsilon$ is the estimated standard deviation of the residuals, $\hat{\beta}$ includes the estimated constant term and the effects of the environmental variables *z* on the inefficiency scores $\hat{\delta}_i$ and ξ denotes the residuals.

The algorithm uses the maximum likelihood method to apply the truncated regression of *z* on $\hat{\delta}_i$ (the product of step [1]) resulting in the estimates $\hat{\beta}$ and the residual standard

deviation estimates $\bar{\sigma}_\xi$ (Algorithm_2_simplified, 33-47). (Algorithm_2_simplified, 33-36) is used in the output-oriented case and (Algorithm_2_simplified, 38-41) in the input-oriented case. Then, it saves the constant term and slopes at β_hat and the standard deviation at sd_hat (Algorithm_2_simplified, 46-47).



[3.1] In this step the error term u_i is created using random draws from $N(\mathbf{0}, \bar{\sigma}_\xi^2)$, where this distribution is left-truncated at $c = (\mathbf{1} - z_{i,j}\hat{\beta}_j)$. This means that each u_i ($i = 1, \dots, n$) is randomly picked from the distribution mentioned before but it's not allowed to pick values that fall at the left side of c on the distribution. So, for each element of u_i the distribution is "truncated" at a different point:

$$u_1 \rightarrow c = \mathbf{1} - (\hat{\beta}_1 z_{1,1} + \hat{\beta}_2 z_{1,2} + \dots + \hat{\beta}_r z_{1,r})$$

$$u_2 \rightarrow c = \mathbf{1} - (\hat{\beta}_1 z_{2,1} + \hat{\beta}_2 z_{2,2} + \dots + \hat{\beta}_r z_{2,r})$$

⋮

$$u_n \rightarrow c = \mathbf{1} - (\hat{\beta}_1 z_{n,1} + \hat{\beta}_2 z_{n,2} + \dots + \hat{\beta}_r z_{n,r})$$

An easy way to draw each of the elements of u_i from a left-truncated normal distribution is using a modified transformation method (Simar and Wilson, 2007):

Let v denote a uniform distribution on $(0, 1)$, $c' = c/\bar{\sigma}_\xi$ and set $v' = \Phi(c') + [1 - \Phi(c')]v$. Now one can compute u_i as $u_i = \bar{\sigma}_\xi \Phi^{-1}(v')$.

The algorithm firstly computes the point of truncation for each observation c (Algorithm_2_simplified, 56-62) and then the object c' as described above (Algorithm_2_simplified, 64). The algorithmic notation of c and c' is c and cc respectively. These two objects are constructed outside the bootstrap loop [3] because their values don't change between different draws. Then, v and v' are computed (Algorithm_2_simplified, 68-69) inside the bootstrap loop [3] as the random number generator gives different values to the uniform distribution in every iteration. Their algorithmic notation is v and vv respectively. Finally, the error term u_i is constructed and saved in variable u (Algorithm_2_simplified, 70).



[3.2] The goal in this step is to compute the new inefficiencies δ_i^* . Each one of these is constructed as $\delta_i^* = \sum_{j=1}^r z_{i,j} \hat{\beta}_j + u_i$, where $i = 1, \dots, n, j = 1, \dots, r$. In particular each δ_i^* is computed as:

$$\delta_1^* = z_{1,1}\hat{\beta}_1 + z_{1,2}\hat{\beta}_2 + \dots + z_{1,r}\hat{\beta}_r + u_1$$

$$\delta_2^* = z_{2,1}\hat{\beta}_1 + z_{2,2}\hat{\beta}_2 + \dots + z_{2,r}\hat{\beta}_r + u_2$$

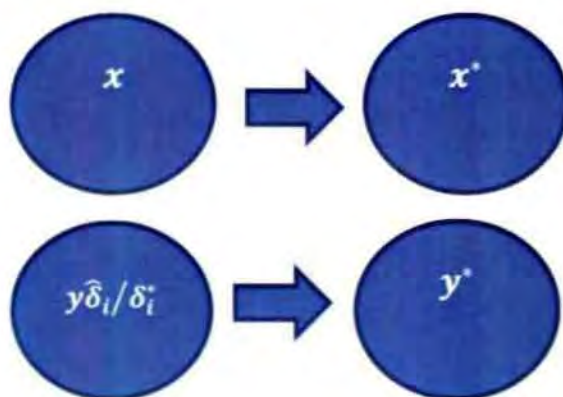
⋮

$$\delta_n^* = z_{n,1}\hat{\beta}_1 + z_{n,2}\hat{\beta}_2 + \dots + z_{n,r}\hat{\beta}_r + u_n$$

For this step, the algorithm multiplies each observation of z with the relevant $\hat{\beta}$ and saves them in zb (Algorithm_2_simplified, 56-62). Then, it adds these quantities plus the error term that computed before for this particular observation (Algorithm_2_simplified, 73) and saved the computed δ_i^* in d_star . Notice that for the construction of zb in (Algorithm_2_simplified, 56-62) the first element of $beta_hat$ (the constant term) is not used.



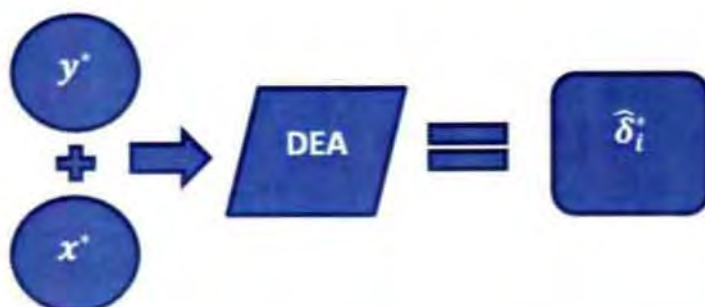
[3.3] Sets the variable x into a new object named x_star and construct the object y_star multiplying every observation of y with those of $\hat{\delta}_i$ and divide each of these quantities with the corresponding observation of δ_i^* .



[3.4] This step estimates the inefficiencies δ_i^* for each firm i . DEA is used to calculate the inefficiencies and in practice the algorithm sets x^* and y^* in the DEA function (Algorithm_2_simplified, 80) and saves the estimated inefficiencies δ_i^* in d_hat_star (Algorithm_2_simplified, 81).

These inefficiency scores are attached to all observations (firms) with the full efficient firms taking the value of 1 and the inefficient ones values > 1 (if the DEA model is output-oriented, in the algorithm this is defined as ORIENTATION= "out"). If the DEA model is input-oriented (ORIENTATION= "in"), the full efficient firms have efficiency score equal to 1 while the inefficient ones have a score < 1 .

The other choice that the user has to make is to choose between Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) which are set in the DEA function (Algorithm_2_simplified, 80) as RTS="CRS" and RTS="VRS".



[4] Here the bias-corrected estimator $\hat{\delta}_i$ is computed subtracting the bias from the initial estimator δ_i , where the bias of every observation of δ_i is estimated subtracting δ_i from the mean of the bootstrap estimators δ_i^* .

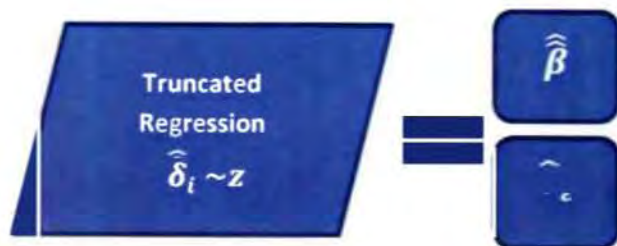
The algorithm first subtracts each observation of d_hat from those of $mean_di_hat_star$ and stores them in the object *bias* (Algorithm_2_simplified, 94-95), where in the object *mean_di_hat_star* are stored the mean values of all the bootstrap loops for every observation of δ_i (Algorithm_2_simplified, 90-92). Then it subtracts the bias stored in *bias* from d_hat and saves the resulted bias-corrected estimator $\hat{\delta}_i$ in *d_2hat*.



[5] In this step the estimators $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ are computed, where $\hat{\sigma}_\varepsilon$ is the estimated standard deviation of the residuals, $\hat{\beta}$ includes the estimated constant term and the effects of the environmental variables z on the inefficiency scores $\hat{\delta}_i$ and ε denotes the residuals.

The algorithm uses the maximum likelihood method to apply the truncated regression of z on $\hat{\delta}_i$ (the product of step [4]) resulting in the estimates $\hat{\beta}$ and the residual standard deviation estimates $\hat{\sigma}_\varepsilon$ (Algorithm_2_simplified, 100-114). (Algorithm_2_simplified, 100-

103) is used in the output-oriented case and (Algorithm_2_simplified, 105-108) in the input-oriented case. Then, it saves the constant term and slopes at β_{2hat} and the standard deviation at sd_{2hat} (Algorithm_2_simplified, 113-114).



[6.1] In this step the error term u_i is created using random draws from $N(0, \hat{\sigma}_\varepsilon^2)$, where this distribution is left-truncated at $c_i = (1 - z_{ij}\hat{\beta}_j)$. This means that each u_i ($i = 1, \dots, n$) is randomly picked from the distribution mentioned before but it's not allowed to pick values that fall at the left side of c on the distribution. So, for each element of u_i the distribution is "truncated" at a different point:

$$u_1 \rightarrow c = 1 - (\hat{\beta}_1 z_{1,1} + \hat{\beta}_2 z_{1,2} + \dots + \hat{\beta}_r z_{1,r})$$

$$u_2 \rightarrow c = 1 - (\hat{\beta}_1 z_{2,1} + \hat{\beta}_2 z_{2,2} + \dots + \hat{\beta}_r z_{2,r})$$

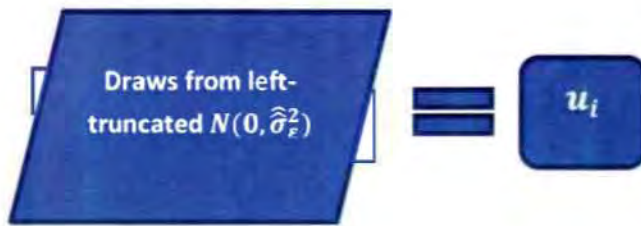
⋮

$$u_n \rightarrow c = 1 - (\hat{\beta}_1 z_{n,1} + \hat{\beta}_2 z_{n,2} + \dots + \hat{\beta}_r z_{n,r})$$

An easy way to draw each of the elements of u_i from a left-truncated normal distribution is using a modified transformation method (Simar and Wilson, 2007):

Let v denote a uniform distribution on $(0, 1)$, $c' = c/\hat{\sigma}_\varepsilon$ and set $v' = \Phi(c') + [1 - \Phi(c')]v$. Now one can compute u_i as $u_i = \hat{\sigma}_\varepsilon \Phi^{-1}(v')$.

The algorithm firstly computes the point of truncation for each observation c (Algorithm_2_simplified, 124-130) and then the object c' as described above (Algorithm_2_simplified, 132). The algorithmic notation of c and c' is c_2 and cc_2 respectively. These two objects are constructed outside the bootstrap loop [6] because their values don't change between different draws. Then, v and v' are computed (Algorithm_2_simplified, 136-137) inside the bootstrap loop [6] as the random number generator gives different values to the uniform distribution in every iteration. Their algorithmic notation is v_2 and vv_2 respectively. Finally, the error term u_i is constructed and saved in the object u_2 (Algorithm_2_simplified, 138).



[6.2] The goal in this step is to compute the new inefficiencies δ_i^{**} . Each one of these is constructed as $\delta_i^{**} = \sum_{j=1}^r z_{i,j} \hat{\beta}_j + u_i$, where $i = 1, \dots, n, j = 1, \dots, r$. In particular each δ_i^{**} is computed as:

$$\delta_1^{**} = z_{1,1} \hat{\beta}_1 + z_{1,2} \hat{\beta}_2 + \dots + z_{1,r} \hat{\beta}_r + u_1$$

$$\delta_2^{**} = z_{2,1} \hat{\beta}_1 + z_{2,2} \hat{\beta}_2 + \dots + z_{2,r} \hat{\beta}_r + u_2$$

⋮

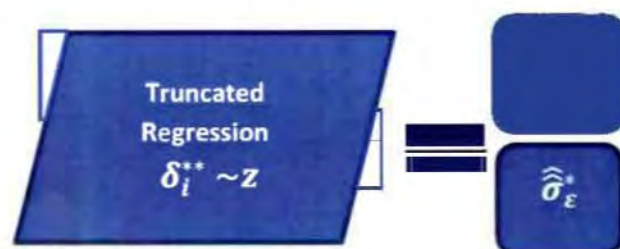
$$\delta_n^{**} = z_{n,1} \hat{\beta}_1 + z_{n,2} \hat{\beta}_2 + \dots + z_{n,r} \hat{\beta}_r + u_n$$

For this step, the algorithm constructs the object *zb_2* as the sum of the multiplication between $\hat{\beta}$ and *z* (Algorithm_2_simplified, 124-130) and adds the error term that computed before for each particular observation (Algorithm_2_simplified, 141) and saved the computed δ_i^{**} in *d_2star*. Notice that for the construction of *zb_2* in (Algorithm_2_simplified, 124-130) the first element of *beta_2hat* (the constant term) is not used.



[6.3] Using the truncated regression of *z* on δ_i^{**} , the maximum likelihood estimates $(\hat{\beta}^*, \hat{\sigma}_\epsilon^*)$ are estimated.

The algorithm applies the truncated regression of *z* on δ_i^{**} (Algorithm_2_simplified, 144-152) using (Algorithm_2_simplified, 144-147) in the output-oriented and (Algorithm_2_simplified, 149-152) in the input-oriented case and $\hat{\beta}^*$ and $\hat{\sigma}_\epsilon^*$ are saved as *beta_2hat_star* and *sd_2hat_star* respectively (Algorithm_2_simplified, 157-158).



The bootstrap loop [6] ends forming a matrix C , containing all the bootstrapped estimates $(\widehat{\beta}^*, \widehat{\sigma}_\varepsilon^*)$ found in every iteration of [6] at step [6.3].

Thus, at the end of every iteration after [6.3], the algorithm stores the estimated values of $\widehat{\beta}^*$ and $\widehat{\sigma}_\varepsilon^*$ at *bootstrap_beta* and *bootstrap_sd* respectively (Algorithm_2_simplified, 160-163) and when the bootstrap loop [6] ends, it binds these bootstrap groups forming a big matrix of bootstrapped sets $C = \{(\widehat{\beta}^*, \widehat{\sigma}_\varepsilon^*)\}_{b=1}^{b=2}$ (Algorithm_2_simplified, 165).

[7] In the last step, confidence intervals are constructed for the constant term (β_0), the coefficients (β_j) of all environmental variables z_j and the standard deviation σ_ε .

The algorithm provides two possible methods for the confidence intervals construction as well as the option to estimate both and compare the results. One has to run the algorithm choosing *ci* = "basic" for the basic method of confidence intervals, *ci* = "percentile" for the percentile method and *ci* = "all" in order to compute both and compare. In case of no choice, the percentile method is set as default. Also, the significance level *alpha* has to be chosen and again in case of no choice, *alpha* = 0.05 is set as default.

The algorithm firstly stores the appropriate lower and upper quantiles for each of the bootstrap distributions existing in C in *quantiles*(Algorithm_2_simplified, 170-174). Then, the confidence intervals are estimated (Algorithm_2_simplified, 180-217).

The basic method (Algorithm_2_simplified, 180-197) indicates the construction of the lower and the upper confidence intervals as 2 times the initial statistic of interest (for example β) minus the upper or the lower quantile, respectively:

$$\text{Lower confidence intervals for } \beta: \quad 2\widehat{\beta} - q_{1-\alpha/2}^{(\beta)}$$

$$\text{Upper confidence intervals for } \beta: \quad 2\widehat{\beta} - q_{\alpha/2}^{(\beta)}$$

$$\text{Lower confidence intervals for } \sigma_\varepsilon: \quad 2\widehat{\sigma}_\varepsilon - q_{1-\alpha/2}^{(\sigma_\varepsilon)}$$

$$\text{Upper confidence intervals for } \sigma_\varepsilon: \quad 2\widehat{\sigma}_\varepsilon - q_{\alpha/2}^{(\sigma_\varepsilon)}$$

Where $q_{\alpha/2}$ and $q_{1-\alpha/2}$ are the lower and the upper quantiles from the sorted bootstrap distribution of the statistic of interest. The algorithm calculates and stores them in the object *b_ci* (Algorithm_2_simplified, 181-186). Finally, the results are printed out on the screen (Algorithm_2_simplified, 192).

The same procedure is followed for the percentile confidence intervals (Algorithm_2_simplified, 200-217). The only difference here is the calculation method that indicates that the lower and upper bounds are simply the lower and upper quantiles of the sorted bootstrap distribution of the statistic of interest respectively:

Lower confidence intervals for β : $q_{\alpha/2}^{(\beta)}$

Upper confidence intervals for β : $q_{1-\alpha/2}^{(\beta)}$

Lower confidence intervals for σ_ε : $q_{\alpha/2}^{(\sigma_\varepsilon)}$

Upper confidence intervals for σ_ε : $q_{1-\alpha/2}^{(\sigma_\varepsilon)}$

The algorithm calculates and then stores them in the object p_ci (Algorithm_2_simplified, 201-206). Finally, the results are printed out on the screen (Algorithm_2_simplified, 216).

3.5. Application

In this empirical application, the algorithms described before are used to examine the effects of Advertising Expense and Communications Expense on the performance of banks operating in U.S. More specifically, the two-stage semi-parametric approach is used in the first-stage to estimate the inefficiency of the U.S. bank sector during the years 2006-2013, based on the sample data of 148 banks for this period. In the second stage, the effects of Advertising Expense and Communications Expense on these estimated inefficiencies are calculated constructing confidence intervals for each one of them, as well as some other interesting statistics to make the analysis more robust.

The technical efficiency that is estimated in the first-stage using DEA, uses the Total Assets, Total Deposits and the number of Employees as inputs in the production function of the banks and the Total Securities and Gross Loans as the outputs of the banks' performance. The covariates (environmental variables) that mentioned before are assumed to affect banks' performance (measured by technical efficiency) but not the Production Possibility Function (PPF) described by the frontier line. This is because of the assumptions where the algorithms are based on, about the DGP. This way, the environmental variables don't take part in the DEA stage where the frontier is estimated, but only in the second-stage of the analysis. This is supported by the assumption (A1).

At this point, a small discussion about the DGP, interpreting each one of its assumptions would be helpful for better understanding.

Reading (1) from right to left, one can see that the environmental variables \mathbf{z} are independent. So, the decision of a bank about the Advertising and Communications spending is clearly under the bank's control. On the other hand, the technical efficiency depends on \mathbf{z} , and this is the reason for the second-stage analysis. This means that a bank can change its performance (increase or decrease its efficiency) alternating the money it spends for Advertising and Communications but without overcoming its capability (PPF). For the next function, is important to remind that the outputs \mathbf{y} in terms of polar coordinates is described as (η_i, δ_i) where η_i is the angle and δ_i is the distance that determines the efficiency. Thus, this function indicates that the inputs x depend on the efficiency and so on the environmental variables \mathbf{z} and also, η_i (let's say, a part of \mathbf{y}) depends on the efficiency

and so on \mathbf{z} . Interpreting this one can say that a bank makes decisions about its inputs (Assets, Deposits, Employees) based on the money they have spent for Advertising and Communications and so based on the efficiency that these spending had. The situation about the outputs \mathbf{y} is not exactly like this, as a “part” of this (in polar coordinates, the angle η_i) depends also on the same \mathbf{z} and δ_i as the inputs but not the whole \mathbf{y} . This means that the bank can partly decide about its outputs (Securities and Loans) but a part of these is “automatically” created as the output of the spending mentioned before, this part of the output is the efficiency δ_i . The whole \mathbf{y} together with \mathbf{x} are these that determine the capability of the bank (PPF), so given certain inputs and outputs the bank sets itself a maximum of achievable efficiency.

A short interpretation of the assumptions (A1-A8) is considered also useful.

What assumptions A1 and A2 say, is that while the inputs and outputs (Assets, Deposits, Employees, Securities and Loans) are these that determine the maximum achievable efficiency, the environmental variables (Advertising and Communications expense) are those that determine its level within the boundaries that \mathbf{x} and \mathbf{y} set. The assumption A3 determines the kind of the error term in the second-stage regression.

The assumptions A4-A6 indicate that the inputs and outputs of a bank are depended to each other meaning that P also depends on the various feasible combinations of \mathbf{x} and \mathbf{y} . There are no “free lunches”, so for example a bank cannot give any Loans while its Deposits are zero. The last assumption is about the “free disposability”, that says a banks can give, for example, a Loan of 1000 \$ even if its Deposits are more (say 2000\$). The last two assumptions A7 and A8 ensure the consistency of P and δ_i .

For the empirical application, the two algorithms (Algorithm_1 and Algorithm_2) were implemented give the three inputs and the two outputs that mentioned before and various combinations of the covariates in order to examine all the possible models. In addition, both the basic and the percentile confidence intervals are constructed setting ci equal to “all”, not only for the coefficients of the covariates and the standard deviation but also for a few other statistics (sigma, P-value, R^2 , AIC, BIC and RMSE) for a more robust analysis.

All the models consider Constant Returns to Scale (CRS) as the classic microeconomic theory indicates for the second stage. The DEA model in the first-stage is output oriented in all cases as the application examines the technical efficiency. An extra parameter called seed is set equal to 1 for all the models for easy re-productivity, except some models where numerical problems occur. In these cases, the seed changed adding 1 each time until there are no numerical problems in the calculations for any loop.

The number of iterations for every bootstrap loop (L and L_2) for the construction of the confidence intervals is set equal to 2000 iterations as Simar and Wilson (2007) do. According to Hall (1986), 1000 is a sufficient number of replication for the confidence-intervals construction, but this number is doubled here for more accurate results. A sufficient number

of replications for the estimations of the bias-corrected efficiencies are 100, as Simar and Wilson (2007) suggest, but here 500 iterations (L_1) are used for better results.

All the tables with all the possible models are presented in the Appendix. For our convenience, let's name the models by the numbers in the name of the external variable in each model. For example, the model with $\ln(\text{Advertising.Expense})$, $\ln(\text{Advertising.Expense})^2$ and $\ln(\text{Communications.Expense})$ as environmental variables is the model 21. The first number represents the maximum power of the variable $\ln(\text{Advertising.Expense})$ and the second number the maximum power of the variable $\ln(\text{Communications.Expense})$.

Here is presented a Table with the summary of all the tables (except the model where the covariates are in levels rather than logarithms) with reference to the signs and the statistical significance:

Table 4

Algorithm_1	Signs (percentile)	Significance
C	Insignificant	- 13/15
$\ln(\text{Advertising.Expense})$	+ 8/8	+ 1/1
$\ln(\text{Advertising.Expense})^2$	+ 4/4	+ 1/1
$\ln(\text{Advertising.Expense})^3$	Insignificant	Insignificant
$\ln(\text{Communications.Expense})$	+ 6/6	+ 2/2
$\ln(\text{Communications.Expense})^2$	- 2/3	Insignificant
$\ln(\text{Communications.Expense})^3$	- 1/1	Insignificant

Table 5

Algorithm_2	Signs
C	+ 13/15 ⁶
$\ln(\text{Advertising.Expense})$	+ 12/12
$\ln(\text{Advertising.Expense})^2$	+ 7/7
$\ln(\text{Advertising.Expense})^3$	- 2/2
$\ln(\text{Communications.Expense})$	+ 11/11
$\ln(\text{Communications.Expense})^2$	- 5/6
$\ln(\text{Communications.Expense})^3$	- 1/1

From the original tables in the Appendix or the summary table above, one can easily see that the results from Algorithm_1 are much worse than those from Algorithm_2 as expected. Especially the confidence intervals constructed with the basic method are very far from reality as three of the six variables found to be insignificant in every model, the rest of the variables found also insignificant (with one or two exceptions) and the constant in every model falls outside of the confidence interval.

⁶ This ratio is only about the basic confidence intervals for the constant but the majority of the positive signs in this case is not very meaningful as in all of the models the mean is outside of the basic confidence interval bounds. In the case of the percentile confidence intervals, all the intervals contain zero, so they were found to be insignificant. The same happens with Algorithm_1.

The results of Algorithm_1 as computed with the percentile confidence intervals are somehow better than those from the basic method, they generally agree with the results of Algorithm_2 but with less models to confirm the positive or negative effects on the inefficiencies and the constant term along with the log of Advertising Expense in the third power was found insignificant in every model.

All these imperfections on the results of Algorithm_1 were expected as Algorithm_1 regresses the covariates on the uncorrected inefficiency scores in contrast with Algorithm_2 where the covariates are regressed on the bias-corrected inefficiencies $\hat{\delta}_i$. Also, the bad results from the basic method were probably caused because of the more complicated way of estimation rather than simply taking the quantiles of the bootstrap distribution as the percentile method does. In the basic method, extreme results may be produced in cases where the initial estimate happened to be an extreme value (whether too high or too low).

The results from Algorithm_2 clearly show that there are positive effects of the log of Advertising Expense, the log of Advertising Expense in the second power and the log of Communications Expense on the inefficiencies, negative effects of the log of Communications Expense in the second power and probably negative effect of the log of Advertising Expense and Communications Expense in the third power. The constant term is not very meaningful as it either falls outside of the confidence interval bounds or it is insignificant.

The conclusions are based on Algorithm_2 rather than Algorithm_1 as its results are much more precise. This is clear not only from this empirical study but also as the Monte Carlo simulation and the empirical example of these models shown in the original paper of Simar and Wilson (2007).

A more focused investigation of the models is essential, so the models where we have a "case" are examined explicitly. A "case" is considered a model where all the variables taking part in the model are statistically significant (only the Algorithm_2 is examined for perfect cases). A statistically significant variable is considered one that its confidence interval does not contain zero. In the tables, for every confidence interval there is the sign "!" for a significant variable and the sign "X" for an insignificant one (where the interval contains zero).

For extra support of the results, the significance is also tested looking at the P-values of the variables, where the bootstrap mean of each P-value is tested and "****" is attached when the bootstrap mean of the corresponding P-value is < 0.01 , "***" when it is between 0.01 and 0.05, "**" when it is between 0.05 and 0.1 and there is nothing when the P-value is greater than 10%. Also, the lower values of sigma, AIC, BIC and RMSE indicate a better model as well as the higher value of R^2 .

Based on the following four statistics (sigma, AIC, BIC and RMSE), the best four models are 22, 20, 31 and 30. Sigma, AIC and BIC, they all agree at this particular hierarchy of the models while RMSE indicates those four but with different order in the three last places, making the model 22 the best model in any case. The R^2 indicates a totally different order of

the best models but the R^2 values are quite close to each other (between 0.41 and 0.54), so the most preferable models are those that the first four criteria indicate.

These four models, they all agree that the signs of $\ln(\text{Advertising.Expense})$ and its second power are positive, its third power is negative, $\ln(\text{Communications.Expense})$ is positive and its second power is negative. The same signs are indicated also by the majority of the models, not only these four best. The variable $\ln(\text{Communications.Expense})^3$ is insignificant in all cases except the model where only Communications Expense raised in the second and third power. In this case, the pure log and the second power are positive while the third power is negative in their signs.

The final conclusion is made based on Algorithm_2 as its results are better than those from Algorithm_1 and the confidence intervals estimated with the basic method as this is a better approach in comparison with the simple percentile method, that is also suggested in the original paper of Simar and Wilson (2007). The models that were chosen to make inference are the model 22 as this was characterized as the best model, and the model 31, one of the four best models. The model 30 is severally and jointly interpreted with the model 03 as special cases where only one of the two environmental variables participates. Notice that model 03 is not one of those models indicated by the minimization of the statistics mentioned before, but is the best model according to the R^2 criterion.

Interpreting the model 22, one can say that:

Increasing the Advertising Expense by 1%, the inefficiency of the bank increases by 0.1005. This number varies between the 95% confidence interval [0.02582, 0.1637].

Keep increasing the Advertising Expense by 1%, the inefficiency of the bank increases by 0.04346. This number varies between the 95% confidence interval [0.03038, 0.05812]

Increasing the Communications Expense by 1%, the inefficiency of the bank increases by 0.34947. This number varies between the 95% confidence interval [0.24521, 0.4601].

Keep increasing the Communications Expense by 1%, the inefficiency of the bank decreases by 0.05396. This number varies between the 95% confidence interval [0.03795, 0.07244]⁷.

Interpreting the model 31, one can say that:

Increasing the Advertising Expense by 1%, the inefficiency of the bank increases by 0.2007. This number varies between the 95% confidence interval [0.11518, 0.26766].

Keep increasing the Advertising Expense by 1%, the inefficiency of the bank increases by 0.06711. This number varies between the 95% confidence interval [0.04419, 0.09776]

⁷ The actual coefficient in this case is -0.05396 and the confidence interval [-0.07244, -0.03795]. For better interpretation, the negative sign is omitted and is translated as a decrease. Thus, the confidence interval is inverted with positive signs.

Insisting to increase the Advertising Expense by 1%, the inefficiency of the bank decreases by 0.00674. This number varies between the 95% confidence interval [0.00404, 0.01024].

Increasing the Communications Expense by 1%, the inefficiency of the bank increases by 0.07011. This number varies between the 95% confidence interval [0.01045, 0.12406].

In the special cases where only one of the two types of expense is used as explanatory variables, the results are as follows:

Interpreting the model 30, one can say that:

Increasing the Advertising Expense by 1%, the inefficiency of the bank increases by 0.22766. This number varies between the 95% confidence interval [0.1407, 0.29301].

Keep increasing the Advertising Expense by 1%, the inefficiency of the bank increases by 0.07659. This number varies between the 95% confidence interval [0.05245, 0.10741]

Insisting to increase the Advertising Expense by 1%, the inefficiency of the bank decreases by 0.00715. This number varies between the 95% confidence interval [0.00431, 0.01075].

Interpreting the model 03, one can say that:

Increasing the Communications Expense by 1%, the inefficiency of the bank increases by 0.37014. This number varies between the 95% confidence interval [0.03767, 0.67544].

Keep increasing the Communications Expense by 1%, the inefficiency of the bank increases by 0.19014. This number varies between the 95% confidence interval [0.08583, 0.29781]

Insisting to increase the Communications Expense by 1%, the inefficiency of the bank decreases by 0.0201. This number varies between the 95% confidence interval [0.01126, 0.02963].

Comparing the model 30 with the model 31, the results are quite the same, confirming the final conclusion. In the case when the only expense is made is for Communications, the bank has to spend more money in order to reach the turning point where its inefficiency will start to decrease.

4. Results and Discussion

To sum up, in this thesis three independent R codes (`max_info_clean_data`, `create_balanced_panel_data` and `create_variables`) and four functions (`Algorithm_1_simplified`, `Algorithm_2_simplified`, `Algorithm_1` and `Algorithm_2`) were constructed and given written in the Appendix as well as in the CD rom.

Using the code named `max_info_clean_data`, one can clean the raw data and find various samples to choose between the original vast amount of data. This code finds all the possible combinations of balanced panel samples and ranks them from the one that has the greatest amount of information to the one with the less.

Using the code named `create_balanced_panel_data`, one can practically create the chosen balanced panel sample and save it in his/her own computer in txt form.

The third code named `create_variables`, is used to create all the possible combinations of variable sets that will be used later to run the algorithms. The variable sets contain the logs of the variables Advertising Expense and Communications Expense as is but also raised in the second and the third power.

The `Algorithm_1_simplified` and `Algorithm_2_simplified` are the exact realizations of the algorithms presented by Simar and Wilson (2007), as they result only in the confidence intervals for the coefficients of the covariates and the standard deviation. They were used for educational reasons as it's much easier to read and understand these short codes rather than their much longer extensions `Algorithm_1` and `Algorithm_2`. The last two algorithms work exactly the same way. The only difference is that they can also estimate confidence intervals for some extra statistics that the researcher may find useful in practice.

Results from the empirical economic application:

The empirical application showed that the money the banks operating in U.S. spend for advertising and communications have a significant effect on their performance where their performance was measured by their inefficiency scores

The results indicate that while a bank start spending money for advertising, its inefficiency grows ($\ln(\text{Advertising.Expense})$ has a positive sign) increasingly ($\ln(\text{Advertising.Expense})^2$ has a positive sign too). Only after a sufficient amount of money for advertising their inefficiency will start to decline ($\ln(\text{Advertising.Expense})^3$ has a negative sign) and so their performance will increase. As for the money the banks spend for communications, the results showed that in the beginning their inefficiency increase ($\ln(\text{Communications.Expense})$ has a positive sign) but as more money are spent for communications, they can finally start to overcome and their inefficiency decreases ($\ln(\text{Communications.Expense})^2$ has a negative sign). The special case when the only money spend are for communications, they have to spend even more money in communications to start decrease their inefficiency, so to perform better. This is probably because of the lack of the important contribution of advertising.

Thus based on this particular sample of banks operating in U.S. covering the years 2006-2013, one can conclude that the money the banks spend for advertising and communications are surely worthwhile, but only in the case when enough money are supposed to be spend. Otherwise, a small amount of money will increase the bank's inefficiency and will have a negative impact on their performance. Also, a good strategy is to spend money both for advertising and communications rather than only in one of them in order to be more effective.

5. Statement of Limitations

5.1. Alternatives

Alternatively, one could approach the analysis from another point, without changing the model's aim. For example, in the second-stage regression, different models specifying fixed or random effects rather than a simple pooled panel regression could have bring interesting results for examination.

Moreover, a full log transformation of the inefficiency scores too could be interesting as we could see the percentage change in the inefficiency as a result of the 1% change in the money spending.

5.2. Weaknesses

As it is common in the research, no model is perfect. The present study has also many weaknesses that should be taken into consideration for further research.

First of all, the run time of the algorithms, especially for Algorithm_1 and Algorithm_2 is very long. Depending on the number of the statistics one wants to estimate, the number of iterations of the loop, the length of the data and mainly the number of variables, especially the environmental. A faster computation of the same algorithms could be done in a faster programming language or even in R using some routines that could save time.

In addition, the final models could be analyzed further checking for specification errors, normality assumptions, and the general assumptions for the residuals. An econometric view on the final models could make the analysis more robust and reliable. Also, some kind of survival analysis and different model comparison could be also done. Some preliminary test for stationarity as well as test for the stability of the results would be a good support of the findings.

6. Conclusion

6.1. Contributions

The aim of this thesis is to review this specific field of production economics, and more precisely to analyze a specific tool commonly used in this area. The resulted algorithms of

this study can be freely used from anyone who is interested in, and help next researchers and students to apply models like this in a click of the mouse rather than spending hours of computing to do this.

The codes `max_info_clean_data`, `create_balanced_panel_data` and `create_variables` are not general purpose codes. They are used explicitly for the needs of this thesis, and an exact replication of these on other data rather than those used here wouldn't normally work. Of course, a careful modification of the filters, the dimensions and some other things among the codes can turn these codes into useful tools to manage faster, easier and safer the raw data.

It also provides a more clear explanation of what is going on behind the theory of the two-stage DEA model in contrast with the difficult interpretation of the original paper finally finds some interesting results about the impact of the advertising and communications expense on the inefficiency of the banks.

6.2. Importance

The importance of this thesis is not more than two things. The first one is the construction of the algorithms that for the first time (at least as the search on the internet showed) were constructed and given for free as a full function. And secondly, the results about the effect of the banks' spending on their technical efficiency that show an interesting story on the banking efficiency field.

7. Appendix

7.1. Description of the distance function

We can now express y in terms of its polar coordinates turning y_i into (η_i, δ_i) . To do that, the angle and the distance are needed. Representing the angle of the i^{th} DMU corresponding to the j^{th} output variable with $\eta_{i,j}$ and the distance with δ_i as before, we calculating the angle as

$$\eta_{ij} = \begin{cases} \arctan(y_{i,j+1}/y_{i,1}), & \text{for } y_{i,1} > 0 \\ \pi/2, & \text{if } y_{i,1} = 0 \end{cases}$$

For the calculation of distance δ_i , though it's just the vertical distance from the point to the boundary (for technical efficiency) as reported before, is hard to be found like this for more dimensions. So we set $\omega(y_i) = \sqrt{y'_i y_i}$ and we calculate the distance with the following formula that is identical to the Farrell efficient measure we demonstrated before (4).

$$\delta_i = \frac{\omega(\delta(x_i, y_i | P) y_i)}{\omega(y_i)} \quad (\text{a1})$$

Proof:

$$\delta_i = \frac{\omega(\delta(x_i, y_i | P) y_i)}{\omega(y_i)} = \delta(x_i, y_i | P)$$

$$\delta_i = \frac{\omega(\delta(x_i, y_i | P) y_i)}{\omega(y_i)} \Rightarrow \text{replacing } \omega(y_i) \text{ with } \sqrt{y'_i y_i}$$

$$\Rightarrow \frac{\sqrt{(\delta(x_i, y_i | P) y_i)' \delta(x_i, y_i | P) y_i}}{\sqrt{y'_i y_i}} \Rightarrow \text{as } \delta(x_i, y_i | P) \text{ is the Farrell formula for the distance and}$$

distance is a scalar

$$\Rightarrow \frac{\sqrt{\delta(x_i, y_i | P) y'_i \delta(x_i, y_i | P) y_i}}{\sqrt{y'_i y_i}} = \frac{\sqrt{\delta(x_i, y_i | P)^2 y'_i y_i}}{\sqrt{y'_i y_i}} = \frac{\delta(x_i, y_i | P) \sqrt{y'_i y_i}}{\sqrt{y'_i y_i}} = \delta(x_i, y_i | P)$$

For $j = 1, \dots, q - 1$ and $i = 1, \dots, n$ where n is the total number of DMUs and $y_0 = [y_{i,1} \dots y_{i,q}]$. Now we can write y_i as (η_i, δ_i) where the angle $\eta_i = [\eta_{i,1}, \dots, \eta_{i,q-1}]$.

7.2. Draws from a left-truncated normal distribution

The error term u_i with iid draws from a left-truncated $N(0, \sigma^2)$ distribution, truncated at a constant c can easily be constructed following the steps suggested by Simar and Wilson (2007):

- 1) Compute the constant c as described in the algorithm.
- 2) Compute $c' = c/\sigma$.
- 3) Generate v of length n to be uniform on $(0, 1)$.
- 4) Set $v' = \Phi(c') + [1 - \Phi(c')]v$ where Φ denotes the standard normal distribution function.
- 5) Finally, compute the error term as $u = \sigma\Phi^{-1}(v')$ where Φ^{-1} denotes the standard normal quantile function.

The estimated u is the error term drawn from the $N(0, \sigma^2)$ distribution with left-truncation at c .

7.3. Estimations in the algorithms

The Algorithm_1 and Algorithm_2 can be used for the estimation of confidence intervals for other statistics rather than the coefficients and the standard deviation. These statistics are σ , R^2 , AIC, BIC and RMSE. The σ is just one of the coefficients automatically estimated by the truncated regression. The other statistics are programmed to compute as follows:

For some reason, there is not R^2 for truncated regressions in the whole literature and its not even given by any statistical software. So, if the user ask for an estimation of R^2 , a pseudo- R^2 is constructed following the properties of a general accepted form of R^2 as the squared correlation between the fitted values of Y (\hat{Y}) and the actual Y as: $\text{cor}(Y, \hat{Y})^2$. The same way as it would be in an OLS method.

$$R^2 = \text{cor}(Y, \hat{Y})^2$$

If the user asked for the AIC (Akaike Information Criterion) it's constructed as:

$$AIC = -2 * \logLik + 2 * m$$

Where \logLik is the log Likelihood of the estimated truncated regression model and m is equal to $(k+1)$, where k is the number of parameters estimated (constant + slopes) and the +1 part is because the maximum likelihood method actually estimates the error term too (so the error term is an estimator of the model too). (In an OLS model the AIC would be the same but replacing m with k).

Almost the same happens with BIC (Bayesian Information Criterion or Schwarz Information Criterion). The formulas is:

$$BIC = -2 * \logLik + \log(n) * m$$

Where 2 is replaced by the log of the number of observations.

Functions for AIC and BIC there are already in the basic R but it doesn't take care of the special case mentioned before about the truncated regression, so it was created from the scratch inside the algorithm as described.

Finally, the RMSE (Root Mean Square Error) is computed as:

$$RMSE = \sqrt{\frac{\sum e^2}{n}}$$

7.4. Explanation of Algorithm_1_simplified

[1] Defines the algorithm "Algorithm_1_simplified"

[3-11] Checks if the needed package is already installed in the computer, if not, it installs it.

Then it loads the package.

This sequence happens for both the package "Benchmarking" and "trunreg".

[13] Sets a seed for re-productivity reasons.

[15-17] Sets the class of the variables x, y and z as matrix in case that they are not because some of the following external functions cannot cooperate with objects of different class (e.g. data.frame).

[19] Checks if the matrix z contains column names. If not, then it attaches names to every variable it contains such as (z1, z2, ... zr). This is because it causes troubles on later commands when the algorithm tries to extract the names of the variables and finds nothing.

[19-22] It keeps asking a valid value for alpha if the user has mistakenly gave a value ≥ 1 or ≤ 0 .

Finally, it saves the correct alpha (even if it was correct at the first time) as numeric because some later calculation can't be done with "character" vectors that may be mistakenly saved as by default.

[25-26] It defines the DEA model. The input data are x and y, RTS stands for Returns To Scale and it may be "CRS" (Constant Returns to Scale) or "VRS" (Variable Returns to Scale) with the "CRS" to be the default, the ORIENTATION may be "in" (input-oriented) or "out" (output-oriented) with the "out" to be the default.

Then saves the estimated efficiency scores (if ORIENTATION="in") or inefficiency scores (if ORIENTATION="out") at a variable named d_hat.

[29-47] The truncated regression part [2] in (Simar and Wilson, 2007).

[29-31] Sets the number of environmental variables at an object named r and defines two vectors that will be used later.

[33-41] Checks if the model is output or input oriented and creates the object dt which has the values of d_hat except for the observations where d_hat was ≤ 1 where it replaces these observations with NA. The same check goes for the input oriented case with the only exception of d_hat ≥ 1 instead of d_hat ≤ 1 .

This is a necessary step in order to run a truncated regression.

Then the appropriate truncated regression model is computed and saved in model_d_hat.

[43] The cells where dt has NAs are saved in the object bad.

[44] Only the values of dt that are not NAs are stores in non_na_dt.

[45] Because the truncated regression method has not an attribute for the residuals, the residuals are estimated as $Y - Y^{\wedge}$ and stored in `trunk_resid`.

[46-47] The standard deviation of the residuals are saved in `sd_hat` and the constant term and the slopes of the regression are saved in `beta_hat`.

[50-100] This is the step [3] as referred in (Simar and Wilson, 2007), although the actual loop covers rows [69-99].

[50] It creates the matrix that will contain the estimated bootstrapped values of β , this matrix is `bootstrap_beta` and its dimensions are $[L, r+1]$.

[51] It defines the vectors `bootstrap_sd` that contains the bootstrapped value of σ .

[52] It sets the number of the inefficiency scores that are >1 (or the number of the efficiency scores that are <1) in the object `m`.

[53-56] It defines the objects `c`, `zb`, `d_star` and `beta_hat_star` as vectors.

[57] It defines the matrix `z_m_dt` that contains the values of `z` which their corresponding `d_hat` value is not NA. Thus, `z_m_dt` is the `z` matrix that contains only `m` observations instead of the initial `n` observations.

[59-65] A loop that creates the point of truncation (`c`) that is needed in step [3.1] and the object `zb` that contain the values $\sum_{j=1}^m \beta_j z_{i,j}$.

[67] It creates the object `cc` that contains the element that in (Simar and Wilson, 2007) is referred as c' .

[69-99] The actual bootstrap loop.

[71-73] The remaining steps for the left-truncated draws and the creating of the error term `u`.

[71] Creates the object `v` where it represents the uniform distribution on (0,1) with `m` elements.

[72] Creates the object `vv` where it represents what in (Simar and Wilson, 2007) is referred as v' and it is also of length `m`.

[73] Creates the desired error term `u` where each of its elements was drawn from $N(0, sd_hat)$ with left-truncation at $c_i = 1 - \sum_{j=1}^{r+1} \beta_j z_{i,j}$.

[76] It computes the d^* as step [3.2] describes (`zb+u`) and stores it in the object `d_star`.

[79-93] This is the last step of the bootstrap loop [3.3] that estimates the bootstrapped statistics in every iteration.

[79-87] Checks if the model is output or input oriented and creates the object `d_star_t` which has the values of `d_star` except for the observations where `d_star` was ≤ 1 where it replaces these observations with NA. The same check goes for the input oriented case with

the only exception of $d_star \geq 1$ instead of $d_star \leq 1$.

This is a necessary step in order to run a truncated regression.

Then the appropriate truncated regression model is computed and saved in `trunk_d_star`.

[89] The cells where `d_star_t` has NAs are saved in the object `bad`.

[90] Only the values of `d_star_t` that are not NAs are stored in `non_na_d_star_t`.

[91] Because the truncated regression method has not an attribute for the residuals, the residuals are estimated as $Y - Y^{\wedge}$ and stored in `trunk_resid_2`.

[92-93] The standard deviation of the residuals are saved in `sd_hat_star` and the constant term and the slopes of the regression are saved in `beta_hat_star`.

[95-97] Stores each estimated bootstrapped value of `beta_hat_star` at the matrix `bootstrap_beta`.

[98] It stores the estimated bootstrap values of `sd_hat_star` in the vector `bootstrap_sd`.

[100] It binds the objects `bootstrap_beta` and `bootstrap_sd` into a matrix `A` of length $[L, r+2]$ where L is the number of iterations and r is the number of the external variables. The two extra columns are for the constant term and the standard deviation.

[103-152] Creates confidence intervals for the statistics.

[103] Defines the object quantiles for the storage of the bootstrap distribution quantiles. Its dimensions are $[r+2, 2]$ where $(r+2)$ is the number of columns of `A`.

[105-109] A loop that stores the lower and the upper quantiles of the bootstrap distribution of each statistic to object quantiles.

The lower quantile is the $\alpha/2$ element of the sorted bootstrap distribution of each statistic and the upper quantile is the $1 - \alpha/2$ element of the sorted bootstrap distribution of each statistic.

[110-111] Creates the objects `b_ci` and `p_ci` with dimensions $[r+2, 2]$, where $(r+2)$ is the number of columns of `A`.

[112] Defines the object statistic as a vector.

[115-132] The Basic Confidence Intervals

[116-119] Inserts the values $(2 * \text{beta_hat} - \text{Upper quantile})$ and $(2 * \text{beta_hat} - \text{Lower quantile})$ in `b_ci` that represent the lower and the upper confidence intervals respectively. Where, `beta_hat` is the initial statistic.

[120-121] Inserts the values $(2 * \text{sd_hat} - \text{Upper quantile})$ and $(2 * \text{sd_hat} - \text{Lower quantile})$ in `b_ci` that represent the lower and the upper confidence intervals respectively. Where, `sd_hat` is the initial statistic.

[123] Turns the class of `b_ci` into `data.frame`.

- [125-126] Sets the name of each β in the object statistic (for example: $\beta_0, \beta_1, \beta_2$) and then binds it to the object `b_ci`.
- [127] Prints the results (Confidence Intervals) on the screen with precision of 5 decimals.
- [129-130] Sets the name of σ "sd" in the object statistic and then binds it to the object `b_ci`.
- [131] Prints the results (Confidence Intervals) on the screen with precision of 5 decimals.
- [135-152] The Percentile Confidence Intervals
- [136-139] Inserts the Lower and the Upper quantiles of the sorted bootstrap distribution of each β in `p_ci` that represent the lower and the upper confidence intervals respectively.
- [140-141] Inserts the Lower and the Upper quantiles of the sorted bootstrap distribution of σ in `p_ci` that represent the lower and the upper confidence intervals respectively.
- [143] Turns the class of `p_ci` into `data.frame`.
- [145-146] Sets the name of each β in the object statistic (for example: $\beta_0, \beta_1, \beta_2$) and then binds it to the object `p_ci`.
- [147] Prints the results (Confidence Intervals) on the screen with precision of 5 decimals.
- [149-150] Sets the name of σ "sd" in the object statistic and then binds it to the object `p_ci`.
- [151] Prints the results (Confidence Intervals) on the screen with precision of 5 decimals.

7.5. Explanation of Algorithm_2_simplified

[1] Defines the algorithm "Algorithm_2_simplified"

[3-11] Checks if the needed package is already installed in the computer, if not, it installs it.

Then it loads the package.

This sequence happens for both the package "Benchmarking" and "trunreg".

[13] Sets a seed for re-productivity reasons.

[15-17] Sets the class of the variables x, y and z as matrix in case that they are not because some of the following external functions cannot cooperate with objects of different class (e.g. data.frame).

[19] Checks if the matrix z contains column names. If not, then it attaches names to every variable it contains such as (z1, z2, ... zr). This is because it causes troubles on later commands when the algorithm tries to extract the names of the variables and finds nothing.

[19-22] It keeps asking a valid value for alpha if the user has mistakenly gave a value ≥ 1 or ≤ 0 .

Finally, it saves the correct alpha (even if it was correct at the first time) as numeric because some later calculation can't be done with "character" vectors that may be mistakenly saved as by default.

[25-26] It defines the DEA model. The input data are x and y, RTS stands for Returns To Scale and it may be "CRS" (Constant Returns to Scale) or "VRS" (Variable Returns to Scale) with the "CRS" to be the default, the ORIENTATION may be "in" (input-oriented) or "out" (output-oriented) with the "out" to be the default.

Then saves the estimated efficiency scores (if ORIENTATION="in") or inefficiency scores (if ORIENTATION="out") at a variable named d_hat.

[29-47] The truncated regression part [2] in (Simar and Wilson, 2007).

[29-31] Sets the number of environmental variables at an object named r and defines two vectors that will be used later.

[33-41] Checks if the model is output or input oriented and creates the object d_hat_t which has the values of d_hat except for the observations where d_hat was ≤ 1 where it replaces these observations with NA. The same check goes for the input oriented case with the only exception of d_hat ≥ 1 instead of d_hat ≤ 1 .

This is a necessary step in order to run a truncated regression.

Then the appropriate truncated regression model is computed and saved in model_d_hat.

[43] The cells where d_hat_t has NAs are saved in the object bad.

[44] Only the values of d_hat_t that are not NAs are stores in non_na_d_hat_t.

[45] Because the truncated regression method has not an attribute for the residuals, the residuals are estimated as $Y - \hat{Y}$ and stored in `trunk_resid`.

[46-47] The standard deviation of the residuals are saved in `sd_hat` and the slopes of the regression are saved in `beta_hat`.

[50-86] This is the step [3] as referred in (Simar and Wilson, 2007), although the actual loop covers rows [66-86].

[50-53] It defines the objects `c`, `zb` and `d_star` as vectors and sets the object `n` equal to the number of observations in `z`.

[56-62] A loop that creates the point of truncation (`c`) that is needed in step [3.1] and the object `zb` that contain the values $\sum_{j=1}^n \beta_j z_{i,j}$.

[64] It creates the object `cc` that contains the element that in (Simar and Wilson, 2007) is referred as c' .

[65] Defines the matrix `B` with dimensions $[n, L1]$ where `L1` is the number of iteration of the first bootstrap.

[66-86] The actual bootstrap loop.

[68-70] The remaining steps for the left-truncated draws and the creating of the error term `u`.

[68] Creates the object `v` where it represents the uniform distribution on $(0,1)$ with `m` elements.

[69] Creates the object `vv` where it represents what in (Simar and Wilson, 2007) is referred as v' and it is also of length `m`.

[70] Creates the desired error term `u` where each of its elements was drawn from $N(0, sd_hat)$ with left-truncation at $c_i = 1 - \sum_{j=1}^n \beta_j z_{i,j}$.

[73] It computes the d^* as step [3.2] describes (`zb+u`) and stores it in the object `d_star`.

[76-77] Constructs the new objects `x_star` and `y_star`.

[80-81] It defines the second DEA model. The input data are `x_star` and `y_star`, `RTS` stands for Returns To Scale and it may be "CRS" (Constant Returns to Scale) or "VRS" (Variable Returns to Scale) with the "CRS" to be the default, the `ORIENTATION` may be "in" (input-oriented) or "out" (output-oriented) with the "out" to be the default.

Then saves the estimated efficiency scores (if `ORIENTATION="in"`) or inefficiency scores (if `ORIENTATION="out"`) at a variable named `d_hat_star`.

[83-85] Adds every estimated set of inefficiencies in columns of the matrix `B`.

[88] Defines the object `mean_di_hat_star` as a vector.

[90-92] Stores the mean of every set of inefficiency scores into the object `mean_di_hat_star`.

[94] Computes the bias for each observation of the inefficiency scores and stores them in the object bias.

[95] Computes the bias-corrected $\hat{\delta}$ and stores it in the object d_2hat.

[98-114] This is the last step of the bootstrap loop [5] that estimates the bootstrapped statistics in every iteration.

[98] Defines the object beta_2hat as a vector.

[100-108] Checks if the model is output or input oriented and creates the object d_2hat_t which has the values of d_2hat except for the observations where d_2hat was ≤ 1 where it replaces these observations with NA. The same check goes for the input oriented case with the only exception of d_2hat ≥ 1 instead of d_2hat ≤ 1 .

This is a necessary step in order to run a truncated regression.

Then the appropriate truncated regression model is computed and saved in model_d_2hat.

[110] The cells where d_2hat_t has NAs are saved in the object bad.

[111] Only the values of d_2hat_t that are not NAs are stores in non_na_d_2hat_t.

[112] Because the truncated regression method has not an attribute for the residuals, the residuals are estimated as $Y - Y^{\wedge}$ and stored in trunk_resid.

[113-114] The standard deviation of the residuals are saved in sd_2hat and the constant term and the slopes of the regression are saved in beta_2hat.

[117-164] This is the step [6] as referred in (Simar and Wilson, 2007), although the actual loop covers rows [134-164].

[117] It defines the matrix that will contain the estimated bootstrapped values of β , this matrix is bootstrap_beta and its dimensions are $[L2, r+1]$.

[118] It defines the vector bootstrap_sd that contains the bootstrapped value of σ .

[119-122] It defines the objects c_2, zb_2, d_2star and beta_2hat_star as vectors.

[124-130] A loop that creates the point of truncation c_2 that is needed in step [6.1] and the object zb_2 that contain the values $\sum_{j=1}^n \beta_j z_{i,j}$.

[132] It creates the object cc_2 that contains the element that in (Simar and Wilson, 2007) is referred as c' .

[134-164] The actual bootstrap loop.

[136-138] The remaining steps for the left-truncated draws and the creation of the error term u.

[136] Creates the object v_2 where it represents the uniform distribution on (0,1) with n elements.

[137] Creates the object `vv_2` where it represents what in (Simar and Wilson, 2007) is referred as v' and it is also of length n .

[138] Creates the desired error term u where each of its elements was drawn from $N(0, sd_2hat)$ with left-truncation at $c_i = 1 - \sum_{j=1}^n \beta_j z_{i,j}$ and it's stored in the object `u_2`.

[141] It computes the d^{**} as step [6.2] describes (`zb_2+u_2`) and stores it in the object `d_2star`.

[144-158] This is the last step of the bootstrap loop [6.3] that estimates the bootstrapped statistics in every iteration.

[144-152] Checks if the model is output or input oriented and creates the object `d_2star_t` which has the values of `d_2star` except for the observations where `d_2star` was ≤ 1 where it replaces these observations with NA. The same check goes for the input oriented case with the only exception of `d_2star` ≥ 1 instead of `d_2star` ≤ 1 .

This is a necessary step in order to run a truncated regression.

Then the appropriate truncated regression model is computed and saved in `model_d_2star`.

[154] The cells where `d_2star_t` has NAs are saved in the object `bad`.

[155] Only the values of `d_2star_t` that are not NAs are stores in `non_na_d_2star_t`.

[156] Because the truncated regression method has not an attribute for the residuals, the residuals are estimated as $Y - Y^{\wedge}$ and stored in `trunk_resid`.

[157-158] The standard deviation of the residuals are saved in `sd_2hat_star` and the constant term and the slopes of the regression are saved in `beta_2hat_star`.

[160-162] Stores each estimated bootstrapped value of `beta_2hat_star` at the matrix `bootstrap_beta`.

[163] it stores the estimated bootstrap values of `sd_2hat_star` in the vector `bootstrap_sd`.

[165] It binds the objects `bootstrap_beta` and `bootstrap_sd` into a matrix `C` of length $[L2, r+2]$ where $L2$ is the number of iterations and r is the number of the external variables. The two extra columns are for the constant term and the standard deviation.

[168-217] Creates confidence intervals for the statistics.

[168] Defines the object `quantiles` for the storage of the bootstrap distribution quantiles. Its dimensions are $[r+2, 2]$ where $(r+2)$ is the number of columns of `C`.

[170-174] A loop that stores the lower and the upper quantiles of the bootstrap distribution of each statistic to object `quantiles`.

The lower quantile is the $\alpha/2$ element of the sorted bootstrap distribution of each statistic and the upper quantile is the $1 - \alpha/2$ element of the sorted bootstrap distribution of each statistic.

[175-176] Creates the objects `b_ci` and `p_ci` with dimensions $[r+2, 2]$, where $(r+2)$ is the number of columns of `C`.

[177] Defines the object statistic as a vector.

[180-197] The Basic Confidence Intervals

[181-184] Inserts the values $(2*\hat{\beta}_2 - \text{Upper quantile})$ and $(2*\hat{\beta}_2 - \text{Lower quantile})$ in `b_ci` that represent the lower and the upper confidence intervals respectively. Where, $\hat{\beta}_2$ is the initial statistic.

[185-186] Inserts the values $(2*\hat{sd}_2 - \text{Upper quantile})$ and $(2*\hat{sd}_2 - \text{Lower quantile})$ in `b_ci` that represent the lower and the upper confidence intervals respectively. Where, \hat{sd}_2 is the initial statistic.

[188] Turns the class of `b_ci` into `data.frame`.

[190-191] Sets the name of each β in the object statistic (for example: $\beta_0, \beta_1, \beta_2$) and then binds it to the object `b_ci`.

[192] Prints the results (Confidence Intervals) on the screen with precision of 5 decimals.

[194-195] Sets the name of σ "sd" in the object statistic and then binds it to the object `b_ci`.

[196] Prints the results (Confidence Intervals) on the screen with precision of 5 decimals.

[200-217] The Percentile Confidence Intervals

[201-204] Inserts the Lower and the Upper quantiles of the sorted bootstrap distribution of each β in `p_ci` that represent the lower and the upper confidence intervals respectively.

[205-206] Inserts the Lower and the Upper quantiles of the sorted bootstrap distribution of σ in `p_ci` that represent the lower and the upper confidence intervals respectively.

[208] Turns the class of `p_ci` into `data.frame`.

[210-211] Sets the name of each β in the object statistic (for example: $\beta_0, \beta_1, \beta_2$) and then binds it to the object `p_ci`.

[212] Prints the results (Confidence Intervals) on the screen with precision of 5 decimals.

[214-215] Sets the name of σ "sd" in the object statistic and then binds it to the object `p_ci`.

[216] Prints the results (Confidence Intervals) on the screen with precision of 5 decimals.

Algorithm_1(x, y, z, RTS="CRS", ORIENTATION="out", l=2000, ci="all", alpha=0.05, extras=c("sigma", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	0.05662	-0.42619	0.46357	X	-0.55861	0.33114	X
2 Advertising Expense	0.00091	7e-04	0.00115	I	0.00071	0.00116	I
3 Communications Expense	-7e-05	-0.00013	-2e-05	I	-0.00013	-1e-05	I
4 sigma	0.18289	0.14144	0.22449		0.56902	0.65207	
5 P-value(b0)	0.45419	8e-05	0.97406		0.81153	1.78551	
6 P-value(b1)	0	0	0	***	0	0	***
7 P-value(b2)	0.08024	0	0.57699	*	-0.00392	0.57307	*
8 P-value(b3)	0	0	0	***	0	0	***
9 sd	0.1349	0.08808	0.19113		0.18772	0.29077	
10 R^2	0.77538	0.7275	0.81471		-0.18458	-0.09737	
11 AIC	5452.28957	-5580.71166	-5323.11863		392.07549	649.66852	
12 BIC	-5432.0511	-5560.47319	-5302.88016		412.31396	669.90699	
13 RMSE	0.95548	0.5535	1.43004		0.8774	1.75395	

Algorithm_2(x, y, z, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	0.01836	-0.67038	0.57311	X	-40.20585	-38.96236	I
2 Advertising Expense	0.01027	0.0093	0.01124	I	0.00935	0.01129	I
3 Communications Expense	-0.00124	-0.00181	-0.00066	I	-0.00184	-0.00068	I
4 sigma	1.96358	1.76488	2.19404		2.15743	2.58659	
5 P-value(b0)	0.49351	0.01287	0.97644		-0.45508	0.50849	
6 P-value(b1)	0	0	0	***	0.36086	0.36086	***
7 P-value(b2)	0.00298	0	0.02856	***	0.51056	0.53912	***
8 P-value(b3)	0	0	0	***	0.03185	0.03185	***
9 sd	1.16271	1.09146	1.24346		2.70713	2.85914	
10 R^2	0.76313	0.73531	0.78896		-0.50745	-0.4538	
11 AIC	2975.56241	2873.02592	3081.31199		-5191.96742	-4983.68135	
12 BIC	2995.86903	2893.33254	3101.61861		-5172.09109	-4963.80502	
13 RMSE	2.40475	1.92019	3.02293		38.44132	39.54406	

Algorithm_1(x, y, lnz, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	-0.05105	-1.29152	0.52601	X	0.55018	2.36772	I
2 ln(Advertising.Expenditure)	0.10781	0.04403	0.23435	I	-0.02627	0.16405	X
3 ln(Communications.Expenditure)	0.04853	0.0055	0.11333	I	-0.01886	0.08897	X
4 sigma	0.21567	0.15303	0.32018		0.16507	0.33223	
5 P-value(b0)	0.50979	0.00014	0.97319		-0.97319	-0.00014	
6 P-value(b1)	0.0249	0.00027	0.12875	**	-0.12875	-0.00027	**
7 P-value(b2)	0.13151	0.00251	0.73045		-0.72962	-0.00168	
8 P-value(b3)	0.00036	0	0.00183	***	-0.00183	0	***
9 sd	0.26472	0.13858	0.53952		-0.10943	0.29151	
10 R^2	0.20157	0.14633	0.2599		0.53593	0.6495	
11 AIC	4643.79698	-4769.89494	-4519.91188		-967.23678	-717.25371	
12 BIC	4623.55851	-4749.65647	-4499.67341		-946.99831	-697.01524	
13 RMSE	1.00051	0.47015	2.17462		-1.15802	0.54645	

Algorithm_2(x, y, lnz, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras= c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	0.00301	-0.38152	0.32428	X	-3.20841	-2.50261	I
2 ln(Advertising.Expense)	0.3992	0.31682	0.4917	I	0.31019	0.48506	I
3 ln(Communications.Expense)	0.08922	0.02086	0.16018	I	0.01648	0.1558	I
4 sigma	0.80727	0.72202	0.90237		0.42839	0.60875	
5 P-value(b0)	0.50086	0.01561	0.97073		-0.93669	0.01842	
6 P-value(b1)	0	0	0	***	1e-05	1e-05	***
7 P-value(b2)	0.07437	1e-05	0.55281	*	-0.3968	0.156	*
8 P-value(b3)	0	0	0	***	0	0	***
9 sd	0.69465	0.59847	0.81101		0.80934	1.02188	
10 R^2	0.437	0.38953	0.48179		0.16683	0.25909	
11 AIC	541.38728	432.89534	653.0114		-3443.97583	-3223.85977	
12 BIC	561.69389	453.20196	673.31802		-3424.17832	-3204.06226	
13 RMSE	1.34833	1.06441	1.69432		3.06416	3.69407	

Algorithm_1(x, y, lnz21, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=5)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.08785	-2.00941	0.5839	X	0.68439	3.2777	I
2	ln(Advertising.Expenditure)	0.07573	0.01559	0.23117	I	-0.09138	0.1242	X
3	ln(Advertising.Expenditure)^2	0.00628	-0.00162	0.01666	X	-0.00411	0.01417	X
4	ln(Communications.Expenditure)	0.03208	-0.01533	0.11192	X	-0.05349	0.07376	X
5	sigma	0.1778	0.11748	0.30064		0.14986	0.33302	
6	P-value(b0)	0.50357	1e-05	0.9773		-0.9773	-1e-05	
7	P-value(b1)	0.14457	0.01503	0.43784		-0.43776	-0.01496	
8	P-value(b2)	0.2175	0.00199	0.90898		-0.89665	0.01035	
9	P-value(b3)	0.36989	0.0361	0.95793		-0.90545	0.01638	
10	P-value(b4)	0.00251	0	0.03366	***	-0.03366	0	***
11	sd	0.23824	0.10412	0.60655		-0.25349	0.24894	
12	R^2	0.21761	0.15059	0.2904		0.60185	0.74166	
13	AIC	5540.01269	-5670.47877	-5414.80514		-81.079	174.59463	
14	BIC	-5514.7146	-5645.18068	-5389.50705		-55.78091	199.89272	
15	RMSE	1.02716	0.40763	2.80705		-1.96385	0.43557	

Algorithm_2(x, y, lnz1, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras= c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.00585	-0.43601	0.32797	X	-1.42543	-0.66146	I
2	ln(Advertising.Expense)	0.2578	0.17385	0.36443	I	0.15444	0.34503	I
3	ln(Advertising.Expense)^2	0.00692	-0.00506	0.01827	X	-0.00432	0.01901	X
4	ln(Communications.Expense)	0.07281	0.01649	0.13566	I	0.00837	0.12754	I
5	sigma	0.55633	0.48746	0.6369		0.49095	0.64039	
6	P-value(b0)	0.48996	0.01179	0.9788		-0.72657	0.24043	
7	P-value(b1)	0	0	1e-05	***	0.00026	0.00027	***
8	P-value(b2)	0.32487	0.00065	0.94742		-0.2683	0.67848	
9	P-value(b3)	0.08506	7e-05	0.56204	*	-0.39861	0.16336	*
10	P-value(b4)	0	0	0	***	0	0	***
11	sd	0.50095	0.39685	0.64453		0.47485	0.72252	
12	R^2	0.46703	0.40671	0.52782		0.20832	0.32943	
13	AIC	732.98544	-847.42021	-616.27812		-2001.64311	-1770.50101	
14	BIC	707.60217	-822.03694	-590.89485		-1976.7178	-1745.57571	
15	RMSE	1.13081	0.83755	1.52682		1.60539	2.29465	

Algorithm_1(x, y, lnz12, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras= c("sigma", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.03404	-1.14719	0.50451	X	0.40466	2.05636	I
2	ln(Advertising.Expense)	0.11611	0.05321	0.22847	I	-0.00063	0.17462	X
3	ln(Communications.Expense)	0.09737	0.01559	0.2318	I	-0.04609	0.17011	X
4	ln(Communications.Expense)^2	-0.00725	-0.02189	0.00196	X	-0.01542	0.00843	X
5	sigma	0.24063	0.17806	0.34166		0.16318	0.32679	
6	P-value(b0)	0.49703	0.00034	0.97141		-0.97133	-0.00027	
7	P-value(b1)	0.01173	6e-05	0.06608	**	-0.06608	-6e-05	**
8	P-value(b2)	0.11403	0.00424	0.56563		-0.56404	-0.00266	
9	P-value(b3)	0.28953	0.01591	0.91658		-0.82415	0.07652	
10	P-value(b4)	1e-04	0	2e-04	***	-2e-04	0	***
11	sd	0.28514	0.15809	0.54288		-0.06043	0.32435	
12	R^2	0.20508	0.15207	0.26104		0.49772	0.60669	
13	AIC	-4081.5456	-4206.40307	-3958.30014		-1534.17811	-1286.07518	
14	BIC	4056.24751	-4181.10498	-3933.00205		-1508.88002	-1260.77709	
15	RMSE	0.97214	0.49765	1.94241		-0.81264	0.63212	

Algorithm_2(x, y, lnz12, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.0117	-0.49809	0.44346	X	-7.20457	-6.26301	I
2	ln(Advertising.Expense)	0.62248	0.50509	0.74737	I	0.5046	0.74687	I
3	ln(Communications.Expense)	0.45454	0.26432	0.65873	I	0.2558	0.65022	I
4	ln(Communications.Expense)^2	-0.05016	-0.07835	-0.02222	I	-0.07935	-0.02323	I
5	sigma	1.35983	1.23543	1.49713		0.15115	0.41285	
6	P-value(b0)	0.49546	0.0138	0.97826		-0.93873	0.02573	
7	P-value(b1)	0	0	0	***	0.00147	0.00147	***
8	P-value(b2)	8e-04	0	0.00594	***	0.02793	0.03387	***
9	P-value(b3)	0.00918	0	0.09232	***	-0.0428	0.04953	***
10	P-value(b4)	0	0	0	***	0	0	***
11	sd	1.13419	1.00419	1.28762		1.44503	1.72847	
12	R^2	0.41918	0.37378	0.46457		0.09925	0.19004	
13	AIC	2273.55295	2172.70306	2377.21061		-5286.87435	-5082.3668	
14	BIC	2298.93622	2198.08633	2402.59388		-5262.36427	-5057.85672	
15	RMSE	1.78823	1.47586	2.17836		5.79084	6.49334	

Algorithm_1(x, y, lnz22, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras= c("sigma", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.02347	-1.23606	0.55952	X	0.62823	2.42381	I
2	ln(Advertising.Expense)	0.02748	-0.0208	0.10524	X	-0.0523	0.07374	X
3	ln(Advertising.Expense)^2	0.01946	0.00867	0.03898	I	4e-05	0.03034	I
4	ln(Communications.Expense)	0.13587	0.04465	0.3217	I	-0.05809	0.21896	X
5	ln(Communications.Expense)^2	-0.02136	-0.04584	-0.00793	I	-0.03393	0.00398	X
6	sigma	0.17015	0.11786	0.25507		0.1805	0.31771	
7	P-value(b0)	0.49846	2e-05	0.97791		-0.97791	-2e-05	
8	P-value(b1)	0.41401	0.05673	0.96128		-0.81994	0.08462	
9	P-value(b2)	0.02077	6e-05	0.12321	**	-0.12321	-6e-05	**
10	P-value(b3)	0.04828	0.00155	0.20344	**	-0.20344	-0.00155	**
11	P-value(b4)	0.03716	0.00058	0.17698	**	-0.17698	-0.00058	**
12	P-value(b5)	3e-04	0	0.00307	***	-0.00307	0	***
13	sd	0.2236	0.10767	0.45959		-0.11496	0.23696	
14	R^2	0.23364	0.16933	0.29671		0.6375	0.76488	
15	AIC	5490.95631	-5618.29752	-5364.90442		-192.67021	60.7229	
16	BIC	-5460.5986	-5587.93982	-5334.54671		-162.3125	91.08061	
17	RMSE	0.9066	0.39927	1.97148		-1.17057	0.40164	

Algorithm_2(x, y, Inz22, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.01239	-0.35636	0.29537	X	-1.333	-0.68127	
2	ln(Advertising.Expenditure)	0.1005	0.03707	0.17495		0.02582	0.1637	
3	ln(Advertising.Expenditure)^2	0.04346	0.03	0.05774		0.03038	0.05812	
4	ln(Communications.Expenditure)	0.34947	0.24677	0.46165		0.24521	0.4601	
5	ln(Communications.Expenditure)^2	-0.05396	-0.07162	-0.03714		-0.07244	-0.03795	
6	sigma	0.49454	0.43777	0.55956		0.49333	0.61511	
7	P-value(b0)	0.4895	0.00885	0.97386		-0.78626	0.17875	
8	P-value(b1)	0.02736	3e-05	0.22311	**	-0.1313	0.09178	**
9	P-value(b2)	1e-05	0	3e-05	***	-2e-05	1e-05	***
10	P-value(b3)	0	0	0	***	1e-05	1e-05	***
11	P-value(b4)	0	0	1e-05	***	0	1e-05	***
12	P-value(b5)	0	0	0	***	0	0	***
13	sd	0.42892	0.35324	0.52624		0.47056	0.64357	
14	R^2	0.53347	0.4834	0.58291		0.22499	0.3245	
15	AIC	-900.7409	-1015.13059	-783.98806		-1899.57627	-1668.43373	
16	BIC	870.28097	-984.67067	-753.52813		-1869.67652	-1638.53398	
17	RMSE	0.9477	0.72047	1.24231		1.50558	2.02743	

Algorithm_1(x, y, lnz32, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras= c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.01641	-1.28356	0.58655	X	0.62661	2.49672	I
2	ln(Advertising.Expense)	0.02625	-0.02109	0.10217	X	-0.05017	0.07308	X
3	ln(Advertising.Expense)^2	0.01546	-0.00188	0.04387	X	-0.01039	0.03535	X
4	ln(Advertising.Expense)^3	0.00054	-0.00186	0.00258	X	-0.00169	0.00275	X
5	ln(Communications.Expense)	0.13769	0.04793	0.32123	I	-0.04769	0.22562	X
6	ln(Communications.Expense)^2	-0.02212	-0.04702	-0.00866	I	-0.03549	0.00288	X
7	sigma	0.16421	0.11269	0.25327		0.17768	0.31826	
8	P-value(b0)	0.47292	1e-05	0.97312		-0.97312	-1e-05	
9	P-value(b1)	0.41705	0.05761	0.96404		-0.81176	0.09467	
10	P-value(b2)	0.24914	0.01279	0.90709		-0.90437	-0.01008	
11	P-value(b3)	0.44773	0.01424	0.97168		0.0532	1.01064	
12	P-value(b4)	0.04334	0.00061	0.20354	**	-0.20354	-0.00061	**
13	P-value(b5)	0.03273	0.00015	0.1745	**	-0.1745	-0.00015	**
14	P-value(b6)	0.00044	0	0.00492	***	-0.00492	0	***
15	sd	0.21404	0.09987	0.46453		-0.12503	0.23962	
16	R^2	0.23541	0.16924	0.30145		0.63675	0.76896	
17	AIC	5565.20814	-5692.89898	-5438.34048		-116.07797	138.48052	
18	BIC	5529.79082	-5657.48165	-5402.92316		-80.66065	173.89785	
19	RMSE	0.87391	0.38225	2.02193		-1.24006	0.39962	

Algorithm_2(x, y, lnz32, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	0.02096	-0.34235	0.31376	X	-1.40634	-0.75023	I
2 ln(Advertising.Expense)	0.09497	0.03549	0.16633	I	0.02321	0.15405	I
3 ln(Advertising.Expense)^2	0.05581	0.03337	0.07866	I	0.0358	0.08209	I
4 ln(Advertising.Expense)^3	-0.00181	-0.00478	0.00123	X	-0.00523	0.00079	X
5 ln(Communications.Expense)	0.32497	0.21832	0.43976	I	0.21607	0.4375	I
6 ln(Communications.Expense)^2	-0.04914	-0.06841	-0.03084	I	-0.06847	-0.03091	I
7 sigma	0.49725	0.44008	0.56277		0.49885	0.62154	
8 P-value(b0)	0.48595	0.00653	0.97722		-0.79541	0.17527	
9 P-value(b1)	0.02892	3e-05	0.24471	**	-0.13951	0.10518	**
10 P-value(b2)	8e-04	0	0.00649	***	-0.00439	0.0021	***
11 P-value(b3)	0.3149	0.00237	0.9387		-0.27712	0.65921	
12 P-value(b4)	1e-05	0	5e-05	***	3e-05	8e-05	***
13 P-value(b5)	0.00013	0	0.00102	***	-0.00086	0.00016	***
14 P-value(b6)	0	0	0	***	0	0	***
15 sd	0.42668	0.35208	0.5203		0.48529	0.6535	
16 R^2	0.54344	0.49507	0.59106		0.22098	0.31698	
17 AIC	857.22045	-970.56403	-742.16239		-1919.10663	-1690.70499	
18 BIC	821.68388	-935.02745	-706.62581		-1884.22359	-1655.82194	
19 RMSE	0.93767	0.71492	1.22777		1.55693	2.06977	

Algorithm_1(x, y, lnz23, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras=c("sigma", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.00274	-1.23329	0.56901	X	0.61918	2.42148	I
2	ln(Advertising.Expense)	0.02654	-0.02065	0.10213	X	-0.0492	0.07358	X
3	ln(Advertising.Expense)^2	0.0192	0.00834	0.03941	I	-0.00043	0.03065	X
4	ln(Communications.Expense)	0.13045	-0.01167	0.3401	X	-0.07753	0.27425	X
5	ln(Communications.Expense)^2	-0.01979	-0.07448	0.02851	X	-0.06997	0.03302	X
6	ln(Communications.Expense)^3	-0.00011	-0.00409	0.00355	X	-0.00358	0.00405	X
7	sigma	0.16853	0.11727	0.25203		0.18354	0.3183	
8	P-value(b0)	0.48566	2e-05	0.97444		-0.97444	-2e-05	
9	P-value(b1)	0.4152	0.05323	0.96427		-0.82237	0.08868	
10	P-value(b2)	0.02299	8e-05	0.14073	**	-0.14073	-8e-05	**
11	P-value(b3)	0.23203	0.011	0.88215		-0.87679	-0.00564	
12	P-value(b4)	0.42483	0.03037	0.96749		-0.65773	0.27939	
13	P-value(b5)	0.51526	0.07069	0.97394		1.00321	1.90646	
14	P-value(b6)	0.00031	0	0.00364	***	-0.00364	0	***
15	sd	0.21998	0.10637	0.46604		-0.12149	0.23818	
16	R^2	0.23473	0.17081	0.30048		0.63391	0.76357	
17	AIC	5491.53342	-5618.91093	-5364.47577		-189.09926	65.3359	
18	BIC	-5456.1161	-5583.49361	-5329.05845		-153.68194	100.75322	
19	RMSE	0.88962	0.39343	1.93926		-1.13843	0.4074	

Algorithm_2(x, y, lnz23, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	0.01711	-0.36278	0.30711	X	-1.34503	-0.67515	I
2 ln(Advertising.Expense)	0.09991	0.03634	0.17492	I	0.02578	0.16437	I
3 ln(Advertising.Expense)^2	0.04351	0.02957	0.05835	I	0.02986	0.05865	I
4 ln(Communications.Expense)	0.35144	0.17212	0.54955	I	0.16128	0.53871	I
5 ln(Communications.Expense)^2	-0.05493	-0.11996	0.00564	X	-0.11675	0.00885	X
6 ln(Communications.Expense)^3	9e-05	-0.00502	0.00523	X	-0.0051	0.00514	X
7 sigma	0.49346	0.43695	0.55889		0.49385	0.61579	
8 P-value(b0)	0.48243	0.00945	0.96653		-0.76905	0.18803	
9 P-value(b1)	0.02798	4e-05	0.22546	**	-0.13317	0.09225	**
10 P-value(b2)	1e-05	0	6e-05	***	-5e-05	2e-05	***
11 P-value(b3)	0.0071	0	0.05868	***	-0.04171	0.01696	***
12 P-value(b4)	0.19813	0.00036	0.88776		-0.49936	0.38805	
13 P-value(b5)	0.50808	0.02308	0.9793		0.99021	1.94642	
14 P-value(b6)	0	0	0	***	0	0	***
15 sd	0.42793	0.35347	0.53074		0.46613	0.6434	
16 R^2	0.53403	0.48061	0.58691		0.22083	0.32713	
17 AIC	898.42856	-1012.34957	-784.23352		-1894.90618	-1666.79013	
18 BIC	862.89198	-976.813	-748.69695		-1860.02314	-1631.90709	
19 RMSE	0.94326	0.71957	1.2445		1.50246	2.02738	

Algorithm_1(x, y, lnz33, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras= c("sigma", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.04538	-1.28323	0.61071	X	0.62942	2.52336	I
2	ln(Advertising.Expense)	0.02501	-0.02177	0.09983	X	-0.04873	0.07286	X
3	ln(Advertising.Expense)^2	0.01251	-0.00814	0.04597	X	-0.01591	0.03821	X
4	ln(Advertising.Expense)^3	0.00084	-0.00169	0.00332	X	-0.00204	0.00297	X
5	ln(Communications.Expense)	0.11117	-0.03228	0.33897	X	-0.09843	0.27282	X
6	ln(Communications.Expense)^2	-0.0117	-0.07288	0.03874	X	-0.06934	0.04228	X
7	ln(Communications.Expense)^3	-0.00088	-0.00534	0.0033	X	-0.00449	0.00415	X
8	sigma	0.15952	0.10894	0.25018		0.17844	0.31968	
9	P-value(b0)	0.46097	0	0.97648		-0.97648	0	
10	P-value(b1)	0.4244	0.05999	0.97002		-0.8083	0.10174	
11	P-value(b2)	0.37598	0.0308	0.94937		-0.90974	0.00883	
12	P-value(b3)	0.40844	0.00796	0.96656		-0.11283	0.84577	
13	P-value(b4)	0.30237	0.02269	0.92567		-0.9118	-0.00882	
14	P-value(b5)	0.49489	0.0645	0.96851		-0.30647	0.59755	
15	P-value(b6)	0.48533	0.03498	0.97278		0.33929	1.27708	
16	P-value(b7)	0.00043	0	0.00509	***	-0.00509	0	***
17	sd	0.20726	0.09409	0.47354		-0.13926	0.24019	
18	R^2	0.23607	0.16937	0.30634		0.64001	0.77699	
19	AIC	5653.65813	-5781.3503	-5525.6888		-25.12188	230.53962	
20	BIC	5613.18119	-5740.87336	-5485.21186		15.35506	271.01656	
21	RMSE	0.85814	0.36559	2.03317		-1.26251	0.40508	

Algorithm_2(x, y, Inz33, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras= c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.03062	-0.35431	0.33696	X	-1.49071	-0.79944	I
2	In(Advertising.Expense)	0.09797	0.03759	0.16838	I	0.0284	0.15919	I
3	In(Advertising.Expense)^2	0.05901	0.03172	0.0865	I	0.03699	0.09177	I
4	In(Advertising.Expense)^3	-0.00217	-0.00557	0.0015	X	-0.00642	0.00065	X
5	In(Communications.Expense)	0.37839	0.194	0.59764	I	0.1795	0.58315	I
6	In(Communications.Expense)^2	-0.07088	-0.14548	-0.00375	I	-0.14465	-0.00293	I
7	In(Communications.Expense)^3	0.00189	-0.0039	0.00812	X	-0.00385	0.00817	X
8	sigma	0.5034	0.44572	0.57081		0.49358	0.61867	
9	P-value(b0)	0.47844	0.00677	0.97309		-0.78024	0.18609	
10	P-value(b1)	0.02456	1e-05	0.20143	**	-0.1152	0.08622	**
11	P-value(b2)	0.00352	0	0.02911	***	-0.02012	0.00898	***
12	P-value(b3)	0.30256	0.00179	0.92746		-0.29049	0.63519	
13	P-value(b4)	0.00495	0	0.04032	***	-0.02426	0.01606	***
14	P-value(b5)	0.14499	0.00018	0.81389		-0.55351	0.2602	
15	P-value(b6)	0.44458	0.011	0.97712		0.21007	1.17619	
16	P-value(b7)	0	0	0	***	0	0	***
17	sd	0.43172	0.35604	0.53067		0.49033	0.66497	
18	R^2	0.53947	0.48788	0.59044		0.21337	0.31594	
19	AIC	764.02246	-876.52081	-649.74921		-1996.45138	-1769.67977	
20	BIC	723.40923	-835.90758	-609.13597		-1956.55675	-1729.78514	
21	RMSE	0.92239	0.70263	1.21951		1.57753	2.09441	

Algorithm_1(x, y, lnz31, RTS="CRS", ORIENTATION="out", l=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.04092	-1.68445	0.58446	X	0.59411	2.86301	I
2	ln(Advertising.Expense)	0.06566	0.01008	0.18853	I	-0.06574	0.11271	X
3	ln(Advertising.Expense)^2	0.01821	-0.00103	0.0527	X	-0.01535	0.03838	X
4	ln(Advertising.Expense)^3	-0.00151	-0.00509	0.00057	X	-0.00362	0.00204	X
5	ln(Communications.Expense)	0.03166	-0.01209	0.1042	X	-0.04454	0.07175	X
6	sigma	0.17945	0.12114	0.28798		0.17281	0.33965	
7	P-value(b0)	0.48366	1e-05	0.97975		-0.97975	-1e-05	
8	P-value(b1)	0.1405	0.01154	0.54161		-0.54128	-0.01121	
9	P-value(b2)	0.23661	0.01093	0.89558		-0.89233	-0.00768	
10	P-value(b3)	0.33424	0.0313	0.93327		-0.88172	0.02025	
11	P-value(b4)	0.32184	0.02202	0.92065		-0.86937	0.02926	
12	P-value(b5)	9e-04	0	0.00862	***	-0.00862	0	***
13	sd	0.23619	0.10662	0.56485		-0.20197	0.25626	
14	R^2	0.22521	0.15766	0.29394		0.60418	0.74047	
15	AIC	5363.60113	-5490.63238	-5236.82115		-265.86525	-12.05403	
16	BIC	5333.24343	-5460.27467	-5206.46345		-235.50755	18.30368	
17	RMSE	0.96712	0.40229	2.40325		-1.51382	0.48714	

Algorithm_2(x, y, lnz31, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.01615	-0.37656	0.33041	X	-1.96968	-1.26271	
2	ln(Advertising.Expense)	0.2007	0.13372	0.2862		0.11518	0.26766	
3	ln(Advertising.Expense)^2	0.06711	0.04068	0.09425		0.04419	0.09776	
4	ln(Advertising.Expense)^3	-0.00674	-0.00993	-0.00373		-0.01024	-0.00404	
5	ln(Communications.Expense)	0.07011	0.01524	0.12885		0.01045	0.12406	
6	sigma	0.58345	0.51854	0.65974		0.51536	0.65656	
7	P-value(b0)	0.48782	0.00896	0.9658		-0.85506	0.10179	
8	P-value(b1)	1e-05	0	4e-05	***	0.0027	0.00274	***
9	P-value(b2)	0.00058	0	0.00427	***	-0.00082	0.00345	***
10	P-value(b3)	0.00241	0	0.02052	***	-0.01268	0.00784	***
11	P-value(b4)	0.08689	4e-05	0.58865	*	-0.38455	0.20407	*
12	P-value(b5)	0	0	0	***	0	0	***
13	sd	0.48822	0.40772	0.59265		0.5844	0.76933	
14	R^2	0.53427	0.48252	0.58489		0.18225	0.28463	
15	AIC	446.77621	-558.24394	-331.67511		-2333.07029	-2106.50146	
16	BIC	416.31629	-527.78401	-301.21518		-2303.1918	-2076.62297	
17	RMSE	1.07399	0.81928	1.40693		2.05616	2.64381	

Algorithm_1(x, y, lnz13, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.02005	-1.26927	0.52934	X	0.4558	2.25441	I
2	ln(Advertising.Expense)	0.10566	0.04268	0.22711	I	-0.01712	0.1673	X
3	ln(Communications.Expense)	0.03728	-0.10205	0.20697	X	-0.13226	0.17676	X
4	ln(Communications.Expense)^2	0.01592	-0.02899	0.06787	X	-0.03797	0.05889	X
5	ln(Communications.Expense)^3	-0.00198	-0.00656	0.00166	X	-0.00536	0.00286	X
6	sigma	0.22663	0.16471	0.33798		0.16057	0.33384	
7	P-value(b0)	0.48826	0.00016	0.97448		-0.97447	-0.00016	
8	P-value(b1)	0.02249	0.00027	0.12161	**	-0.12161	-0.00027	**
9	P-value(b2)	0.48236	0.0542	0.96949		-0.12036	0.79494	
10	P-value(b3)	0.44834	0.02211	0.97029		-0.27992	0.66826	
11	P-value(b4)	0.39144	0.0157	0.95742		-0.62104	0.32068	
12	P-value(b5)	0.00016	0	0.00117	***	-0.00117	0	***
13	sd	0.27293	0.1461	0.56055		-0.10228	0.31216	
14	R^2	0.20499	0.14941	0.2633		0.52281	0.63669	
15	AIC	-4344.2664	-4470.24303	-4219.19144		-1273.04904	-1021.99745	
16	BIC	4313.90869	-4439.88532	-4188.83374		-1242.69133	-991.63975	
17	RMSE	0.97188	0.47429	2.09681		-1.00645	0.61607	

Algorithm_2(x, y, lnz13, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.01817	-0.49112	0.41508	X	-5.31934	-4.41315	I
2	ln(Advertising.Expense)	0.50046	0.38971	0.62672	I	0.38281	0.61981	I
3	ln(Communications.Expense)	0.23621	-0.0589	0.55702	X	-0.0811	0.53482	X
4	ln(Communications.Expense)^2	0.01482	-0.10097	0.12669	X	-0.09701	0.13065	X
5	ln(Communications.Expense)^3	-0.00462	-0.01419	0.00588	X	-0.01526	0.00482	X
6	sigma	1.10064	0.99371	1.22263		0.28098	0.5099	
7	P-value(b0)	0.48649	0.01546	0.97531		-0.93983	0.02002	
8	P-value(b1)	0	0	0	***	0.00049	0.00049	***
9	P-value(b2)	0.24646	0.00092	0.91736		-0.27313	0.64331	
10	P-value(b3)	0.49181	0.0183	0.98074		0.70058	1.66302	
11	P-value(b4)	0.38063	0.00469	0.96071		-0.09651	0.85952	
12	P-value(b5)	0	0	0	***	0	0	***
13	sd	0.92273	0.80599	1.07171		1.14529	1.41101	
14	R^2	0.43076	0.38106	0.47908		0.12623	0.22425	
15	AIC	1611.55178	1508.28781	1718.08012		-4577.59067	-4367.79835	
16	BIC	1642.0117	1538.74773	1748.54004		-4548.03564	-4338.24333	
17	RMSE	1.56253	1.25785	1.94837		4.47712	5.16764	

Algorithm_1(x, y, Inz10, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras= c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.04591	-1.11148	0.49343	X	0.43819	2.0431	I
2	ln(Advertising.Expenditure)	0.1619	0.09564	0.28824	I	0.02629	0.21888	I
3	sigma	0.25803	0.19091	0.3625		0.15902	0.33061	
4	P-value(b0)	0.51021	0.00058	0.97178		-0.97177	-0.00056	
5	P-value(b1)	0.00364	0	0.03074	***	-0.03074	0	***
6	P-value(b2)	4e-05	0	0.00012	***	-0.00012	0	***
7	sd	0.30085	0.17454	0.54794		-0.03442	0.33897	
8	R^2	0.18618	0.13746	0.23563		0.47984	0.57801	
9	AIC	3926.56988	-4051.76065	-3804.95175		-1660.58194	-1413.77304	
10	BIC	3911.39102	-4036.58179	-3789.7729		-1645.40308	-1398.59419	
11	RMSE	1.03758	0.53448	2.03233		-0.82607	0.67178	

Algorithm_2(x, y, lnz10, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras= c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.00167	-0.47778	0.39437	X	-6.24867	-5.37652	I
2	ln(Advertising.Expense)	0.66971	0.58649	0.75854	I	0.58138	0.75343	I
3	sigma	1.24493	1.12712	1.37682		0.23727	0.48698	
4	P-value(b0)	0.50222	0.01776	0.96993		-0.94176	0.01041	
5	P-value(b1)	0	0	0	***	4e-05	4e-05	***
6	P-value(b2)	0	0	0	***	0	0	***
7	sd	1.04315	0.92928	1.17718		1.3168	1.5647	
8	R^2	0.40898	0.36651	0.45038		0.12307	0.20693	
9	AIC	1850.88117	1747.43272	1957.57823		-4891.24172	-4681.09621	
10	BIC	1866.11113	1762.66269	1972.80819		-4876.5745	-4666.429	
11	RMSE	1.80258	1.46878	2.20726		5.38648	6.12497	

Algorithm_1(x, y, lnz20, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=2)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.08675	-1.80506	0.59296	X	0.6822	3.08022	I
2	ln(Advertising.Expense)	0.0892	0.02372	0.25301	I	-0.09058	0.13871	X
3	ln(Advertising.Expense)^2	0.00885	0.00174	0.01986	I	-0.00241	0.0157	X
4	sigma	0.1812	0.119	0.30135		0.15458	0.33693	
5	P-value(b0)	0.50505	1e-05	0.96882		-0.96882	-1e-05	
6	P-value(b1)	0.10294	0.01119	0.33679		-0.33679	-0.01119	
7	P-value(b2)	0.08898	0.00026	0.60409	*	-0.60405	-0.00022	*
8	P-value(b3)	0.00267	0	0.03342	***	-0.03342	0	***
9	sd	0.24117	0.10271	0.59499		-0.23583	0.25646	
10	R^2	0.21363	0.14653	0.28648		0.5943	0.73425	
11	AIC	5495.39133	-5629.19986	-5368.57457		-120.72141	139.90387	
12	BIC	5475.15286	-5608.96139	-5348.3361		-100.48294	160.14234	
13	RMSE	1.04159	0.40643	2.649		-1.78499	0.45757	

Algorithm_2(x, y, lnzc, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	0.00123	-0.457	0.33042	X	-1.45944	-0.67201	I
2 ln(Advertising.Expense)	0.29371	0.20591	0.40739	I	0.1799	0.38138	I
3 ln(Advertising.Expense)^2	0.01244	0.00113	0.02252	I	0.00253	0.02392	I
4 sigma	0.5739	0.50147	0.65933		0.48399	0.64185	
5 P-value(b0)	0.49005	0.0135	0.97325		-0.72056	0.23919	
6 P-value(b1)	0	0	0	***	9e-05	9e-05	***
7 P-value(b2)	0.11171	0	0.77771		-0.66531	0.11239	
8 P-value(b3)	0	0	0	***	0	0	***
9 sd	0.51923	0.40803	0.66933		0.4831	0.74439	
10 R^2	0.45532	0.39515	0.51532		0.20991	0.33008	
11 AIC	675.96107	-790.77201	-559.28085		-2061.95127	-1830.46011	
12 BIC	655.65445	-770.46539	-538.97423		-2042.0181	-1810.52695	
13 RMSE	1.17593	0.87051	1.59501		1.6362	2.3607	

Algorithm_1(x, y, lnz30, RTS="CRS", ORIENTATION="out", l=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	-0.04953	-1.55903	0.59058	X	0.58802	2.73763	I
2 ln(Advertising.Expense)	0.07872	0.02229	0.20285	I	-0.05698	0.12359	X
3 ln(Advertising.Expense)^2	0.02144	0.00078	0.05761	I	-0.0147	0.04213	X
4 ln(Advertising.Expense)^3	-0.00158	-0.00525	0.00056	X	-0.00366	0.00214	X
5 sigma	0.18425	0.12365	0.29287		0.1746	0.34381	
6 P-value(b0)	0.491	2e-05	0.97927		-0.97927	-2e-05	
7 P-value(b1)	0.08569	0.00676	0.29327	*	-0.29325	-0.00674	*
8 P-value(b2)	0.18435	0.00858	0.81044		-0.80965	-0.00779	
9 P-value(b3)	0.33074	0.0317	0.9303		-0.87714	0.02147	
10 P-value(b4)	0.00101	0	0.01278	***	-0.01278	0	***
11 sd	0.24138	0.10746	0.55858		-0.18781	0.2633	
12 R^2	0.22049	0.15386	0.28824		0.59759	0.73197	
13 AIC	5302.36915	-5430.27399	-5176.80701		-319.26702	-65.80004	
14 BIC	5277.07106	-5404.97591	-5151.50892		-293.96893	-40.50195	
15 RMSE	0.98994	0.40724	2.37866		-1.46219	0.50922	

Algorithm_2(x, y, lnz30, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.01188	-0.38899	0.32949	X	-2.0262	-1.30772	
2	In(Advertising.Expense)	0.22766	0.16008	0.31239		0.1407	0.29301	
3	In(Advertising.Expense)^2	0.07659	0.04974	0.1047		0.05245	0.10741	
4	In(Advertising.Expense)^3	-0.00715	-0.01045	-0.004		-0.01075	-0.00431	
5	sigma	0.6016	0.53359	0.68215		0.51043	0.65899	
6	P-value(b0)	0.49012	0.01181	0.97402		-0.86215	0.10005	
7	P-value(b1)	0	0	0	***	0.00092	0.00092	***
8	P-value(b2)	0.00012	0	0.00074	***	0.00056	0.0013	***
9	P-value(b3)	0.00179	0	0.01424	***	-0.00737	0.00687	***
10	P-value(b4)	0	0	0	***	0	0	***
11	sd	0.50342	0.42005	0.61314		0.59822	0.79131	
12	R^2	0.5269	0.47459	0.57713		0.18057	0.2831	
13	AIC	387.10457	-499.39779	-271.409		-2384.13086	-2156.14206	
14	BIC	361.72131	-474.01452	-246.02573		-2359.26763	-2131.27884	
15	RMSE	1.11324	0.84741	1.45769		2.11678	2.72706	

Algorithm_1(x, y, lnz01, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.01956	-0.88234	0.45253	X	0.39085	1.72572	I
2	ln(Communications.Expense)	0.16473	0.10383	0.26866	I	0.05735	0.22217	I
3	sigma	0.21029	0.16056	0.28495		0.23852	0.3629	
4	P-value(b0)	0.51008	0.00141	0.97565		-0.97538	-0.00115	
5	P-value(b1)	0.00067	0	0.00551	***	-0.00551	0	***
6	P-value(b2)	0	0	0	***	0	0	***
7	sd	0.24216	0.14731	0.40894		0.01261	0.27425	
8	R^2	0.28033	0.21929	0.33958		0.43654	0.55683	
9	AIC	4609.02438	-4733.38219	-4484.30256		-891.29788	-642.21825	
10	BIC	4593.84553	-4718.20334	-4469.12371		-876.11903	-627.0394	
11	RMSE	0.91838	0.50547	1.67958		-0.54882	0.62529	

Algorithm_2(x, y, lnz01, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.00024	-0.34267	0.31159	X	-5.96221	-5.30795	I
2	ln(Communications.Expense)	0.63259	0.56872	0.6998	I	0.56589	0.69697	I
3	sigma	0.9352	0.85031	1.0282		0.60369	0.78158	
4	P-value(b0)	0.50044	0.01452	0.97516		-0.94428	0.01636	
5	P-value(b1)	0	0	0	***	3e-05	3e-05	***
6	P-value(b2)	0	0	0	***	0	0	***
7	sd	0.70999	0.64208	0.78629		1.08755	1.23176	
8	R^2	0.53661	0.49295	0.57683		0.00612	0.08999	
9	AIC	1214.70628	1112.22465	1320.74542		-4007.51287	-3798.9921	
10	BIC	1229.93624	1127.45461	1335.97538		-3992.65934	-3784.13857	
11	RMSE	1.27107	1.03591	1.5362		5.31644	5.81672	

Algorithm_1(x, y, lnz02, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras= c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	-0.01638	-0.84821	0.45039	X	0.15348	1.45208	I
2	ln(Communications.Expense)	0.23206	0.12328	0.41077	I	0.04649	0.33397	I
3	ln(Communications.Expense)^2	-0.00777	-0.02046	0.00111	X	-0.01608	0.00549	X
4	sigma	0.24461	0.18913	0.32521		0.22637	0.36244	
5	P-value(b0)	0.49985	0.00127	0.97538		-0.88378	0.09034	
6	P-value(b1)	0.00212	2e-05	0.01236	***	-0.01236	-2e-05	***
7	P-value(b2)	0.23818	0.01009	0.89677		-0.7662	0.12048	
8	P-value(b3)	0	0	0	***	0	0	***
9	sd	0.27176	0.1666	0.45924		0.03191	0.32454	
10	R^2	0.27871	0.21869	0.34045		0.38428	0.50604	
11	AIC	3863.20992	-3986.48637	-3740.5456		-1639.43977	-1393.499	
12	BIC	3842.97145	-3966.2479	-3720.30713		-1619.2013	-1373.26052	
13	RMSE	0.90013	0.51466	1.6017		-0.30739	0.77965	

Algorithm_2(x, y, lnz02, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras= c("sigma", "P-value", "R^2", "AIC", "BIC", "RMSE"), seed=1)

	Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1	C	0.01009	-0.91675	0.80745	X	-29.49577	-27.77157	I
2	ln(Communications.Expense)	3.28902	2.78946	3.80313	I	2.79343	3.8071	I
3	ln(Communications.Expense)^2	-0.18251	-0.2492	-0.11539	I	-0.25196	-0.11814	I
4	sigma	3.66	3.39243	3.94919		-0.97199	-0.41523	
5	P-value(b0)	0.49352	0.02201	0.97915		-0.50231	0.45482	
6	P-value(b1)	0	0	0	***	0.38449	0.38449	***
7	P-value(b2)	6e-05	0	0.00047	***	0.47705	0.47752	***
8	P-value(b3)	0	0	0	***	0.02053	0.02053	***
9	sd	2.8849	2.69265	3.09403		4.24471	4.64609	
10	R^2	0.47659	0.43326	0.51951		-0.08477	0.00148	
11	AIC	5179.43051	5085.73874	5272.38909		-8127.85467	-7941.20432	
12	BIC	5199.73712	5106.04535	5292.6957		-8108.32813	-7921.67777	
13	RMSE	3.64212	3.22174	4.1514		21.61786	22.54752	

Algorithm_1(x, y, lnz03, RTS="CRS", ORIENTATION="out", L=2000, ci="all", alpha=0.05, extras= c("sigma", "R^2", "P-value", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	-0.02427	-1.17167	0.50861	X	0.36724	2.04752	I
2 ln(Communications.Expense)	0.04987	-0.08831	0.23305	X	-0.13251	0.18885	X
3 ln(Communications.Expense)^2	0.0524	0.01111	0.11293	I	-0.01135	0.09047	X
4 ln(Communications.Expense)^3	-0.00512	-0.01077	-0.00155	I	-0.00833	0.00889	X
5 sigma	0.21007	0.15344	0.30292		0.22282	0.3723	
6 P-value(b0)	0.49135	0.00023	0.97077		-0.96995	0.00059	
7 P-value(b1)	0.46052	0.05282	0.96547		-0.27664	0.63601	
8 P-value(b2)	0.09694	0.00107	0.58119	*	-0.57661	0.00351	*
9 P-value(b3)	0.05705	0.00069	0.309	*	-0.30778	0.00052	*
10 P-value(b4)	7e-05	0	0.00015	***	-0.00015	0	***
11 sd	0.25047	0.13544	0.48719		-0.06436	0.28739	
12 R^2	0.27104	0.2058	0.34111		0.46864	0.60394	
13 AIC	4652.65792	-4780.80843	-4526.95294		-874.00724	-620.15174	
14 BIC	4627.35983	-4755.51035	-4501.65485		-848.70915	-594.85365	
15 RMSE	0.94994	0.47618	1.93626		-0.78415	0.67593	

Algorithm_2(x, y, lnz03, RTS="CRS", ORIENTATION="out", L1=500, L2=2000, ci="all", alpha=0.05, extras=c("sigma", "R^2", "AIC", "BIC", "RMSE"), seed=1)

Variable	Coefficient	Lower Percentile CI	Upper Percentile CI	Statistical Significance	Lower Basic CI	Upper Basic CI	Statistical Significance
1 C	0.01505	-0.44469	0.40585	X	-7.01038	-6.15983	I
2 ln(Communications.Expense)	0.37014	0.0716	0.70936	I	0.03767	0.67544	I
3 ln(Communications.Expense)^2	0.19014	0.08395	0.29593	I	0.08583	0.29781	I
4 ln(Communications.Expense)^3	-0.0201	-0.02919	-0.01082	I	-0.02963	-0.01126	I
5 sigma	1.10622	1.00251	1.2251		0.48787	0.71045	
6 P-value(b0)	0.49154	0.01762	0.97154		-0.90687	0.04706	
7 P-value(b1)	0.09503	1e-04	0.61615	*	-0.10098	0.51508	*
8 P-value(b2)	0.01262	0	0.12648	**	-0.03895	0.08753	**
9 P-value(b3)	0.0029	0	0.02284	***	0.01065	0.03349	***
10 P-value(b4)	0	0	0	***	0	0	***
11 sd	0.82855	0.73881	0.94077		1.28519	1.48715	
12 R^2	0.54305	0.49477	0.58952		0.01349	0.10825	
13 AIC	1697.7132	1594.90135	1802.63765		-4521.3535	-4313.6172	
14 BIC	1723.09647	1620.28462	1828.02092		-4496.57964	-4288.84335	
15 RMSE	1.43719	1.16222	1.76708		5.99469	6.59955	

```

1 data <- read.csv("banks_csv.csv", header=TRUE, sep=";")
2 data <- data[,1:18]
3 for (i in 1:nrow(data)) {
4   if (data[i,ncol(data)]=="") data[i, ncol(data)] <- NA
5 }
6 data1 <- complete.cases(data[,7], data[,8], data[,9], data[,10], data[,11], data[,12], data[,13], data[,18])
7 data <- data[data1, ]
8 years <- data[,4]
9 firms <- data[,5]
10 unique_firms <- unique(firms)
11 all_firms <- data.frame()
12 for (i in 1:length(unique_firms)){
13   a <- which(firms==unique_firms[i])
14   b <- years[a]
15   all_firms[i,1] <- unique_firms[i]
16   all_firms[i,2] <- b[1]
17   all_firms[i,3] <- b[length(b)]
18 }
19
20 Total <- data.frame()
21 w <- 1
22
23 for(lower in 1999:2013){
24   for(upper in 2000:2014){
25     if(lower<upper){
26
27       full_data <- data.frame()

```

```

28 range <- upper-lower +1
29 bounds <- all_firms[which(all_firms[,2]<=lower & all_firms[,3]>=upper), ]
30
31 for(j in 1:nrow(bounds)){
32   from <- range*(j-1)+1
33   to <- range*j
34   a1 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),1]
35   a2 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),2]
36   a3 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),3]
37   a4 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),4]
38   a5 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),5]
39   a6 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),6]
40   a7 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),7]
41   a8 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),8]
42   a9 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),9]
43   a10 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),10]
44   a11 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),11]
45   a12 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),12]
46   a13 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),13]
47   a14 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),14]
48   a15 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),15]
49   a16 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),16]
50   a17 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),17]
51   a18 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),18]
52   if(length(a1)==range){
53     full_data[from:to,1] <- a1
54     full_data[from:to,2] <- a2

```

```

55 full_data[from:to,3] <- a3
56 full_data[from:to,4] <- a4
57 full_data[from:to,5] <- a5
58 full_data[from:to,6] <- a6
59 full_data[from:to,7] <- a7
60 full_data[from:to,8] <- a8
61 full_data[from:to,9] <- a9
62 full_data[from:to,10] <- a10
63 full_data[from:to,11] <- a11
64 full_data[from:to,12] <- a12
65 full_data[from:to,13] <- a13
66 full_data[from:to,14] <- a14
67 full_data[from:to,15] <- a15
68 full_data[from:to,16] <- a16
69 full_data[from:to,17] <- a17
70 full_data[from:to,18] <- a18
71 }
72 }
73
74 ok <- complete.cases(full_data)
75 full_data <- full_data[ok, ]
76 colnames(full_data) <- names(data)
77
78 total_banks <- length(unique(full_data[,5]))
79 total_info <- total_banks*range
80 Total[w,1] <- lower
81 Total[w,2] <- upper

```



```
82 Total[w,3] <- total_banks
83 Total[w,4] <- total_info
84 w <- w+1
85     }
86   }
87 }
88 Total <- Total[order(decreasing=TRUE, Total[,4]), ]
89 colnames(Total) <- c("From", "To", "Firms", "Observations")
90 row.names(Total) <- NULL
91 print(Total)
92 View(Total)
```

```

1 data <- read.csv("banks_csv.csv", header=TRUE, sep=";")
2 data <- data[,1:18]
3 for (i in 1:nrow(data)) {
4   if (data[i,ncol(data)]=="") data[i, ncol(data)] <- NA
5 }
6 data1 <- complete.cases(data[,7], data[,8], data[,9], data[,10], data[,11], data[,12], data[,13], data[,18])
7 data <- data[data1,]
8 years <- data[,4]
9 firms <- data[,5]
10 unique_firms <- unique(firms)
11 all_firms <- data.frame()
12 for (i in 1:length(unique_firms)){
13   a <- which(firms==unique_firms[i])
14   b <- years[a]
15   all_firms[i,1] <- unique_firms[i]
16   all_firms[i,2] <- b[1]
17   all_firms[i,3] <- b[length(b)]
18 }
19
20 Total <- data.frame()
21 full_data <- data.frame()
22
23 ## Specify date range
24 lower <- 2006
25 upper <- 2013
26 bounds <- all_firms[which(all_firms[,2]<=lower & all_firms[,3]>=upper), ]
27 range <- upper-lower +1

```

```

28
29 for(j in 1:nrow(bounds)){
30   from <- range*(j-1)+1
31   to <- range*j
32   a1 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),1]
33   a2 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),2]
34   a3 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),3]
35   a4 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),4]
36   a5 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),5]
37   a6 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),6]
38   a7 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),7]
39   a8 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),8]
40   a9 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),9]
41   a10 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),10]
42   a11 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),11]
43   a12 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),12]
44   a13 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),13]
45   a14 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),14]
46   a15 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),15]
47   a16 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),16]
48   a17 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),17]
49   a18 <- data[which(firms==bounds[j,1] & years>=lower & years<=upper),18]
50   if(length(a1)==range){
51     full_data[from:to,1] <- a1
52     full_data[from:to,2] <- a2
53     full_data[from:to,3] <- a3
54     full_data[from:to,4] <- a4

```

```
55 full_data[from:to,5] <- a5
56 full_data[from:to,6] <- a6
57 full_data[from:to,7] <- a7
58 full_data[from:to,8] <- a8
59 full_data[from:to,9] <- a9
60 full_data[from:to,10] <- a10
61 full_data[from:to,11] <- a11
62 full_data[from:to,12] <- a12
63 full_data[from:to,13] <- a13
64 full_data[from:to,14] <- a14
65 full_data[from:to,15] <- a15
66 full_data[from:to,16] <- a16
67 full_data[from:to,17] <- a17
68 full_data[from:to,18] <- a18
69 }
70 }
71
72 ok <- complete.cases(full_data)
73 full_data <- full_data[ok, ]
74 colnames(full_data) <- names(data)
75 path <- getwd()
76 write.table(full_data, file=paste0(path, "/balanced_panel_data.txt"), sep=" ", row.names=TRUE)
```



```

28
29 lnz31 <- cbind(lnz[,1], lnz[,1]^2, lnz[,1]^3, lnz[,2])
30 colnames(lnz31) <- paste0("ln(",c(rep(colnames(z)[1],3), colnames(z)[2]),c("","^2","^3",""))")
31
32 lnz13 <- cbind(lnz[,1], lnz[,2], lnz[,2]^2, lnz[,2]^3)
33 colnames(lnz13) <- paste0("ln(",c(colnames(z)[1], rep(colnames(z)[2],3)),c("","^2","^3"))")
34
35 lnz30 <- cbind(lnz[,1], lnz[,1]^2, lnz[,1]^3)
36 colnames(lnz30) <- paste0("ln(",rep(colnames(z)[1],3),c("","^2","^3"))")
37
38 lnz20 <- cbind(lnz[,1], lnz[,1]^2)
39 colnames(lnz20) <- paste0("ln(",rep(colnames(z)[1],2),c("","^2"))")
40
41 lnz10 <- cbind(lnz[,1])
42 colnames(lnz10) <- paste0("ln(",colnames(z)[1],")")
43
44 lnz03 <- cbind(lnz[,2], lnz[,2]^2, lnz[,2]^3)
45 colnames(lnz03) <- paste0("ln(",rep(colnames(z)[2],3),c("","^2","^3"))")
46
47 lnz02 <- cbind(lnz[,2], lnz[,2]^2)
48 colnames(lnz02) <- paste0("ln(",rep(colnames(z)[2],2),c("","^2"))")
49
50 lnz01 <- cbind(lnz[,2])
51 colnames(lnz01) <- paste0("ln(",colnames(z)[2],")")

```

```

1 Algorithm_1_simplified <- function(x, y, z, RTS="CRS", ORIENTATION="out", L=500, ci="percentile", alpha=0.05, seed=1){
2
3   if ("Benchmarking" %in% rownames(installed.packages()) == FALSE){
4     install.packages("Benchmarking")
5   }
6   library(Benchmarking)
7
8   if ("truncreg" %in% rownames(installed.packages()) == FALSE){
9     install.packages("truncreg")
10  }
11  library(truncreg)
12
13  set.seed(seed)
14
15  if (class(x)!="matrix") x <- as.matrix(x)
16  if (class(y)!="matrix") y <- as.matrix(y)
17  if (class(z)!="matrix") z <- as.matrix(z)
18
19  while (alpha<=0 || alpha>=1) {
20    alpha <- readline("Choose a relatively small significance level between 0 and 1. e.g.(0.05) ")
21  }
22  alpha <- as.numeric(alpha)
23
24  ## [1] DEA
25  dea <- dea(x, y, RTS = RTS, ORIENTATION = ORIENTATION)
26  d_hat <- eff(dea)
27

```

```

28 ## [2] Truncated Regression
29 r <- ncol(z)
30 auxiliary <- c()
31 beta_hat <- c()
32
33 if (ORIENTATION=="out") {
34     dt <- ifelse(d_hat > 1, d_hat, NA)
35     model_d_hat <- truncreg(dt ~ z, point = 1, direction = "left")
36 }
37
38 if (ORIENTATION=="in") {
39     dt <- ifelse(d_hat < 1, d_hat, NA)
40     model_d_hat <- truncreg(dt ~ z, point = 1, direction = "right")
41 }
42
43 bad <- is.na(dt)
44 non_na_dt <- dt[!bad]
45 trunc_resid <- non_na_dt - model_d_hat[fitted.values]
46 sd_hat <- sd(trunc_resid)
47 beta_hat <- summary(model_d_hat)$coefficients[1:(r+1),1]
48
49 ## [3] Bootstrap Loop
50 bootstrap_beta = matrix(nrow=L, ncol=r+1)
51 bootstrap_sd = c()
52 m <- length(non_na_dt)
53 c <- c()
54 zb <- c()

```

```

55 d_star <- c()
56 beta_hat_star <- c()
57 z_m_dt <- matrix(z[complete.cases(dt,z)], ,r)
58
59 for ( i in 1:m) {
60   for (j in 1:r) {
61     auxiliary[j] <- z_m_dt[i,j]*beta_hat[j+1]
62   }
63   c[i] <- 1 - sum(auxiliary)
64   zb[i] <- sum(auxiliary)
65 }
66
67 cc <- c/sd_hat
68
69 for (j in 1:L) {
70   ## [3.1] Draws from left-truncated normal distribution
71   v <- runif(m, min=0, max=1)
72   vv <- pnorm(cc) + (1 - pnorm(cc))*v
73   u <- sd_hat*qnorm(vv)
74
75   ## [3.2] computation of d*
76   d_star <- zb + u
77
78   ## [3.3] estimation of b^* and sigma^*
79   if (ORIENTATION=="out") {
80     d_star_t <- ifelse(d_star > 1, d_star, NA)
81     trunc_d_star <- truncreg(d_star_t ~ z_m_dt, point = 1, direction = "left")

```

```

82 }
83
84 if (ORIENTATION=="in") {
85   d_star_t <- ifelse(d_star < 1, d_star, NA)
86   trunc_d_star <- truncreg(d_star_t ~ z_m_dt, point = 1, direction = "right")
87 }
88
89 bad <- is.na(d_star_t)
90 non_na_d_star_t <- d_star_t[!bad]
91 trunc_resid_2 <- non_na_d_star_t - trunc_d_star$fitted.values
92 sd_hat_star <- sd(trunc_resid_2)
93 beta_hat_star <- summary(trunc_d_star)$coefficients[1:(r+1),1]
94
95 for (i in 1:(r+1)) {
96   bootstrap_beta[j,i] <- beta_hat_star[i]
97 }
98 bootstrap_sd[j] <- sd_hat_star
99 }
100 A <- cbind(bootstrap_beta, bootstrap_sd)
101
102 ## [4] Confidence intervals
103 quantiles <- matrix(nrow=ncol(A), ncol=2)
104
105 for (i in 1:ncol(A)) {
106   for (j in 1:2) {
107     quantiles[j,i] <- quantile(A[,i],c(alpha/2,1-(alpha/2)))[j]
108   }

```



```

109 }
110 b_ci <- matrix(nrow=ncol(A), ncol=2)
111 p_ci <- matrix(nrow=ncol(A), ncol=2)
112 statistic <- c()
113
114 ## Basic Confidence Intervals
115 if (ci=="basic") {
116   for (i in 1:(r+1)) {
117     b_ci[i,1] <- 2*beta_hat[i] - quantiles[i,2]
118     b_ci[i,2] <- 2*beta_hat[i] - quantiles[i,1]
119   }
120   b_ci[r+2,1] <- 2*sd_hat - quantiles[r+2,2]
121   b_ci[r+2,2] <- 2*sd_hat - quantiles[r+2,1]
122
123   b_ci <- as.data.frame(b_ci)
124   for (i in 1:(r+1)) {
125     statistic <- paste0("b",i-1)
126     b_ci <- cbind(b_ci[,1:2],statistic)
127     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%f, %f]", b_ci[i,1], b_ci[i,2]), sep="", "\n")
128   }
129   statistic <- c("sd")
130   b_ci <- cbind(b_ci[,1:2],statistic)
131   cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%f, %f]", b_ci[r+2,1], b_ci[r+2,2]), sep="", "\n")
132 }
133
134 ## Percentile Confidence Intervals
135 if (ci=="percentile") {

```

```

136   for (i in 1:(r+1)) {
137     p_ci[i,1] <- quantiles[i,1]
138     p_ci[i,2] <- quantiles[i,2]
139   }
140   p_ci[r+2,1] <- quantiles[r+2,1]
141   p_ci[r+2,2] <- quantiles[r+2,2]
142
143   p_ci <- as.data.frame(p_ci)
144   for (i in 1:(r+1)) {
145     statistic <- paste0("b", i-1)
146     p_ci <- cbind(p_ci[,1:2], statistic)
147     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]", p_ci[i,1], p_ci[i,2]), sep="", "\n")
148   }
149   statistic <- c("sd")
150   p_ci <- cbind(p_ci[,1:2], statistic)
151   cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]", p_ci[nrow(p_ci),1], p_ci[nrow(p_ci),2]), sep="", "\n")
152 }
153 }

```

```

1 Algorithm_2_simplified <- function(x, y, z, RTS="CRS", ORIENTATION="out", L1=100, L2=500, ci="percentile", alpha=0.05, seed=1) {
2
3   if ("Benchmarking" %in% rownames(installed.packages()) == FALSE){
4     install.packages("Benchmarking")
5   }
6   library(Benchmarking)
7
8   if ("truncreg" %in% rownames(installed.packages()) == FALSE){
9     install.packages("truncreg")
10  }
11  library(truncreg)
12
13  set.seed(seed)
14
15  if (class(x)!="matrix") x <- as.matrix(x)
16  if (class(y)!="matrix") y <- as.matrix(y)
17  if (class(z)!="matrix") z <- as.matrix(z)
18
19  while (alpha<=0 || alpha>=1) {
20    alpha <- readline("Choose a relatively small significance level between 0 and 1. e.g.(0.05) ")
21  }
22  alpha <- as.numeric(alpha)
23
24  ## [1] DEA, computation of d^
25  dea <- dea(x, y, RTS = RTS, ORIENTATION = ORIENTATION)
26  d_hat <- eff(dea)
27

```

```

28 ## [2] Truncated Regression
29 r <- ncol(z)
30 auxiliary <- c()
31 beta_hat <- c()
32
33 if (ORIENTATION=="out") {
34   d_hat_t <- ifelse(d_hat > 1, d_hat, NA)
35   model_d_hat <- truncreg(d_hat_t ~ z, point = 1, direction = "left")
36 }
37
38 if (ORIENTATION=="in") {
39   d_hat_t <- ifelse(d_hat < 1, d_hat, NA)
40   model_d_hat <- truncreg(d_hat_t ~ z, point = 1, direction = "right")
41 }
42
43 bad <- is.na(d_hat_t)
44 non_na_d_hat_t <- d_hat_t[!bad]
45 trunc_resid <- non_na_d_hat_t - model_d_hat$fit$predicted.values
46 sd_hat <- sd(trunc_resid)
47 beta_hat <- summary(model_d_hat)$coefficients[2:(r+1),1]
48
49 ## [3] Bootstrap Loop 1
50 c <- c()
51 zb <- c()
52 n <- nrow(z)
53 d_star <- c()
54

```

```

55 ## [3.1] Draws from left-truncated normal distribution
56 for ( i in 1:n) {
57   for (j in 1:r) {
58     auxiliary[j] <- z[i,j]*beta_hat[j]
59   }
60   c[i] <- 1 - sum(auxiliary)
61   zb[i] <- sum(auxiliary)
62 }
63
64 cc <- c/sd_hat
65 B <- matrix(nrow=n, ncol=L1)
66 for (j in 1:L1) {
67
68   v <- runif(n, min=0, max=1)
69   vv <- pnorm(cc) + (1 - pnorm(cc))*v
70   u <- sd_hat*qnorm(vv)
71
72   ## [3.2] computation of d*
73   d_star <- zb + u
74
75   ## [3.3] setting x* and y*
76   x_star <- x
77   y_star <- y*d_hat/d_star
78
79   ## [3.4] DEA, computation of d^*
80   dea_2 <- dea(x_star, y_star, RTS = RTS, ORIENTATION = ORIENTATION)
81   d_hat_star <- eff(dea_2)

```

```

82     for (i in 1:n) {
83         B[i,] <- d_hat_star[i]
84     }
85 }
86
87 ## [4] computation of bias-corrected d^^
88 mean_di_hat_star <- c()
89
90 for (i in 1:nrow(B)) {
91     mean_di_hat_star[i] <- mean(B[i, ])
92 }
93
94 bias <- mean_di_hat_star - d_hat
95 d_2hat <- d_hat - bias
96
97 ## [5] estimation of b^^ and sigma^^
98 beta_2hat <- c()
99
100 if (ORIENTATION=="out") {
101     d_2hat_t <- ifelse(d_2hat > 1, d_2hat, NA)
102     model_d_2hat <- truncreg(d_2hat_t ~ z, point = 1, direction = "left")
103 }
104
105 if (ORIENTATION=="in") {
106     d_2hat_t <- ifelse(d_2hat < 1, d_2hat, NA)
107     model_d_2hat <- truncreg(d_2hat_t ~ z, point = 1, direction = "right")
108 }

```



```

109 bad <- is.na(d_2hat_t)
110 non_na_d_2hat_t <- d_2hat_t[!bad]
111 trunc_resid <- non_na_d_2hat_t - model_d_2hat$fitted.values
112 sd_2hat <- sd(trunc_resid)
113 beta_2hat <- summary(model_d_2hat)$coefficients[1:(r+1),1]
114
115
116 ## [6] Bootstrap loop 2
117 bootstrap_beta = matrix(nrow=L2, ncol=r+1)
118 bootstrap_sd = c()
119 c_2 <- c()
120 zb_2 <- c()
121 d_2star <- c()
122 beta_2hat_star <- c()
123
124 for ( i in 1:n) {
125   for ( j in 1:r) {
126     auxiliary[j] <- z[i,j]*beta_2hat[j+1]
127   }
128   c_2[i] <- 1 - sum(auxiliary)
129   zb_2[i] <- sum(auxiliary)
130 }
131
132 cc_2 <- c_2/sd_2hat
133
134 for ( j in 1:L2) {
135   ## [6.1] Draws from left-truncated normal distribution

```

```

136 v_2 <- runif(n, min=0, max=1)
137 vv_2 <- pnorm(cc_2) + (1 - pnorm(cc_2))*v_2
138 u_2 <- sd_2hat*qnorm(vv_2)
139
140 ## [6.2] computation of d**
141 d_2star <- zb_2 + u_2
142
143 ## [6.3] estimation of  $b^{\wedge\wedge}$  and  $\sigma^{\wedge\wedge}$ 
144 if (ORIENTATION=="out") {
145   d_2star_t <- ifelse(d_2star > 1, d_2star, NA)
146   model_d_2star <- truncreg(d_2star_t ~ z, point = 1, direction = "left")
147 }
148
149 if (ORIENTATION=="in") {
150   d_2star_t <- ifelse(d_2star < 1, d_2star, NA)
151   model_d_2star <- truncreg(d_2star_t ~ z, point = 1, direction = "right")
152 }
153
154 bad <- is.na(d_2star_t)
155 non_na_d_2star_t <- d_2star_t[!bad]
156 trunc_resid <- non_na_d_2star_t - model_d_2star$fit.fitted.values
157 sd_2hat_star <- sd(trunc_resid)
158 beta_2hat_star <- summary(model_d_2star)$coefficients[1:(r+1),1]
159
160 for (i in 1:(r+1)) {
161   bootstrap_beta[j,i] <- beta_2hat_star[i]
162 }

```

```

163 bootstrap_sd[j] <- sd_2hat_star
164 }
165 C <- cbind(bootstrap_beta, bootstrap_sd)
166
167 ## [7] Confidence intervals
168 quantiles <- matrix(nrow=ncol(C), ncol=2)
169
170 for (i in 1:ncol(C)) {
171   for (j in 1:2) {
172     quantiles[i,j] <- quantile(C[,j],c(alpha/2,1-(alpha/2)))[j]
173   }
174 }
175 b_ci <- matrix(nrow=ncol(C), ncol=2)
176 p_ci <- matrix(nrow=ncol(C), ncol=2)
177 statistic <- c()
178
179 ## Basic Confidence Intervals
180 if (ci=="basic") {
181   for (i in 1:(r+1)) {
182     b_ci[i,1] <- 2*beta_2hat[i] - quantiles[i,2]
183     b_ci[i,2] <- 2*beta_2hat[i] - quantiles[i,1]
184   }
185   b_ci[r+2,1] <- 2*sd_2hat - quantiles[r+2,2]
186   b_ci[r+2,2] <- 2*sd_2hat - quantiles[r+2,1]
187
188   b_ci <- as.data.frame(b_ci)
189   for (i in 1:(r+1)) {

```

```

190     statistic <- paste0("b",i-1)
191     b_ci <- cbind(b_ci[,1:2],statistic)
192     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%0.5f, %0.5f]", b_ci[i,1], b_ci[i,2]), sep="", "\n")
193 }
194 statistic <- c("sd")
195 b_ci <- cbind(b_ci[,1:2],statistic)
196 cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%0.5f, %0.5f]", b_ci[r+2,1], b_ci[r+2,2]), sep="", "\n")
197 }
198
199 ## Percentile Confidence Intervals
200 if (ci=="percentile") {
201   for (i in 1:(r+1)) {
202     p_ci[i,1] <- quantiles[i,1]
203     p_ci[i,2] <- quantiles[i,2]
204   }
205   p_ci[r+2,1] <- quantiles[r+2,1]
206   p_ci[r+2,2] <- quantiles[r+2,2]
207
208   p_ci <- as.data.frame(p_ci)
209   for (i in 1:(r+1)) {
210     statistic <- paste0("b",i-1)
211     p_ci <- cbind(p_ci[,1:2],statistic)
212     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%0.5f, %0.5f]", p_ci[i,1], p_ci[i,2]), sep="", "\n")
213   }
214   statistic <- c("sd")
215   p_ci <- cbind(p_ci[,1:2],statistic)
216   cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%0.5f, %0.5f]", p_ci[r+2,1], p_ci[r+2,2]), sep="", "\n")

```

217)

218 }

```

1 Algorithm_1<- function(x, y, z, RTS="CRS", ORIENTATION="out", L=500, ci="percentile", alpha=0.05, extras=c(), seed=1, histogram=FALSE, bar=FALSE) {
2
3   if ("Benchmarking" %in% rownames(installed.packages()) == FALSE){
4     install.packages("Benchmarking")
5   }
6   library(Benchmarking)
7
8   if ("truncreg" %in% rownames(installed.packages()) == FALSE){
9     install.packages("truncreg")
10  }
11  library(truncreg)
12
13  if ("ggplot2" %in% rownames(installed.packages()) == FALSE){
14    install.packages("ggplot2")
15  }
16  library(ggplot2)
17
18  set.seed(seed)
19
20  if (class(x)!="matrix") x <- as.matrix(x)
21  if (class(y)!="matrix") y <- as.matrix(y)
22  if (class(z)!="matrix") z <- as.matrix(z)
23
24  if (length(colnames(z))== 0) colnames(z) <- paste0("z",1:ncol(z))
25
26  while (alpha<=0 || alpha>=1) {
27    alpha <- readline("Choose a relatively small significance level between 0 and 1. e.g.(0.05) ")

```



```

28 }
29 alpha <- as.numeric(alpha)
30
31 ## [1] DEA
32 dea <- dea(x, y, RTS = RTS, ORIENTATION = ORIENTATION)
33 d_hat <- eff(dea)
34
35 ## [2] Truncated Regression
36 r <- ncol(z)
37 auxiliary <- c()
38 beta_hat <- c()
39
40 if (ORIENTATION=="out") {
41   dt <- ifelse(d_hat > 1, d_hat, NA)
42   model_d_hat <- truncreg(dt ~ z, point = 1, direction = "left")
43 }
44
45 if (ORIENTATION=="in") {
46   dt <- ifelse(d_hat < 1, d_hat, NA)
47   model_d_hat <- truncreg(dt ~ z, point = 1, direction = "right")
48 }
49
50 bad <- is.na(dt)
51 non_na_dt <- dt[!bad]
52 trunc_resid <- non_na_dt - model_d_hat$fitted.values
53 sd_hat <- sd(trunc_resid)
54 beta_hat <- summary(model_d_hat)$coefficients[1:(r+1),1]

```

```

55 if ("sigma" %in% extras) sigma <- summary(model_d_hat)$coefficients[r+2,1]
56 if ("P-value" %in% extras & "sigma" %in% extras) Pr_z <- summary(model_d_hat)$coefficients[1:(r+2),4]
57 if ("P-value" %in% extras & !("sigma" %in% extras)) Pr_z <- summary(model_d_hat)$coefficients[1:(r+1),4]
58 if ("R^2" %in% extras) R_2 <- cor(model_d_hat$fitted.values, non_na_dt)^2
59 if ("AIC" %in% extras) AIC <- -2 * model_d_hat$logLik + 2 * length(model_d_hat$coefficients)
60 if ("BIC" %in% extras) BIC <- -2 * model_d_hat$logLik + log(length(model_d_hat$fitted.values)) * length(model_d_hat$coefficients)
61 if ("RMSE" %in% extras) RMSE <- sqrt(sum(trunc_resid^2)/length(trunc_resid))
62
63 ## [3] Bootstrap Loop
64 bootstrap_beta = matrix(nrow=L, ncol=r+1)
65 bootstrap_sd = c()
66 bootstrap_sigma = c()
67 bootstrap_R_2 = c()
68 if ("P-value" %in% extras & "sigma" %in% extras) bootstrap_pr_z = matrix(nrow=L, ncol=r+2)
69 if ("P-value" %in% extras & !("sigma" %in% extras)) bootstrap_pr_z = matrix(nrow=L, ncol=r+1)
70 if (!("P-value" %in% extras)) bootstrap_pr_z = c()
71 bootstrap_AIC = c()
72 bootstrap_BIC = c()
73 bootstrap_RMSE = c()
74 m <- length(non_na_dt)
75 c <- c()
76 zb <- c()
77 d_star <- c()
78 beta_hat_star <- c()
79 z_m_dt <- matrix(z[complete.cases(dt,z)], ,r)
80
81 for ( i in 1:m) {

```

```

82   for (j in 1:r) {
83     auxiliary[j] <- z_m_dt[i,j]*beta_hat[j+1]
84   }
85   c[j] <- 1 - sum(auxiliary)
86   zb[j] <- sum(auxiliary)
87 }
88
89   cc <- c/sd_hat
90
91   for (j in 1:l) {
92     ## [3.1] Draws from left-truncated normal distribution
93     v <- runif(m, min=0, max=1)
94     vv <- pnorm(cc) + (1 - pnorm(cc))*v
95     u <- sd_hat*qnorm(vv) #change
96
97     ## [3.2] computation of d*
98     d_star <- zb + u
99
100    ## [3.3] estimation of b^* and sigma^*
101
102    if (ORIENTATION=="out") {
103      d_star_t <- ifelse(d_star > 1, d_star, NA)
104      trunc_d_star <- truncreg(d_star_t ~ z_m_dt, point = 1, direction = "left")
105    }
106
107    if (ORIENTATION=="in") {
108      d_star_t <- ifelse(d_star < 1, d_star, NA)

```

```

109   trunc_d_star <- truncreg(d_star_t ~ z_m_dt, point = 1, direction = "right")
110 }
111
112 bad <- is.na(d_star_t)
113 non_na_d_star_t <- d_star_t[!bad]
114 trunc_resid_2 <- non_na_d_star_t - trunc_d_star$fitted.values
115 sd_hat_star <- sd(trunc_resid_2)
116 beta_hat_star <- summary(trunc_d_star)$coefficients[1:(r+1),1]
117 if ("sigma" %in% extras) sigma_star <- summary(trunc_d_star)$coefficients[r+2,1]
118 if ("P-value" %in% extras & "sigma" %in% extras) Pr_z_star <- summary(trunc_d_star)$coefficients[1:(r+2),4]
119 if ("P-value" %in% extras & !("sigma" %in% extras)) Pr_z_star <- summary(trunc_d_star)$coefficients[1:(r+1),4]
120 if ("R^2" %in% extras) R_2_star <- cor(trunc_d_star$fitted.values, non_na_d_star_t)^2
121 if ("AIC" %in% extras) AIC_star <- -2*trunc_d_star$logLik + 2*length(trunc_d_star$coefficients)
122 if ("BIC" %in% extras) BIC_star <- -2*trunc_d_star$logLik + log(length(trunc_d_star$fitted.values))*length(trunc_d_star$coefficients)
123 if ("RMSE" %in% extras) RMSE_star <- sqrt(sum(trunc_resid_2^2)/length(trunc_resid_2))
124
125 for (i in 1:(r+1)) {
126   bootstrap_beta[j,i] <- beta_hat_star[i]
127   if ("P-value" %in% extras & !("sigma" %in% extras)) bootstrap_pr_z[j,i] <- Pr_z_star[i]
128 }
129 if ("P-value" %in% extras & "sigma" %in% extras) {
130   for (j in 1:(r+2)) {
131     if ("P-value" %in% extras) bootstrap_pr_z[j,i] <- Pr_z_star[i]
132   }
133 }
134 bootstrap_sd[j] <- sd_hat_star
135 if ("sigma" %in% extras) bootstrap_sigma[j] <- sigma_star

```

```

136   if ("R^2" %in% extras) bootstrap_R_2[j] <- R_2_star
137   if ("AIC" %in% extras) bootstrap_AIC[j] <- AIC_star
138   if ("BIC" %in% extras) bootstrap_BIC[j] <- BIC_star
139   if ("RMSE" %in% extras) bootstrap_RMSE[j] <- RMSE_star
140 }
141 A <- cbind(bootstrap_beta)
142 if ("sigma" %in% extras) A <- cbind(A, bootstrap_sigma)
143 if ("P-value" %in% extras) A <- cbind(A, bootstrap_pr_z)
144 A <- cbind(A, bootstrap_sd)
145 if ("R^2" %in% extras) A <- cbind(A, bootstrap_R_2)
146 if ("AIC" %in% extras) A <- cbind(A, bootstrap_AIC)
147 if ("BIC" %in% extras) A <- cbind(A, bootstrap_BIC)
148 if ("RMSE" %in% extras) A <- cbind(A, bootstrap_RMSE)
149
150 if (histogram==TRUE) {
151   for (i in 1:ncol(A)) {
152     hist(A[,i])
153   }
154 }
155
156 ## [4] Confidence intervals
157 quantiles <- matrix(nrow=ncol(A), ncol=2)
158
159 for (i in 1:ncol(A)) {
160   for (j in 1:2) {
161     quantiles[i,j] <- quantile(A[,i],c(alpha/2,1-(alpha/2)))[j]
162   }

```

```

163 }
164
165 bootstrap_beta <- as.data.frame(bootstrap_beta)
166 bootstrap_pr_z <- as.data.frame(bootstrap_pr_z)
167 coeff_beta <- round(sapply(bootstrap_beta, sum)/L,5)
168 names(coeff_beta) <- NULL
169 if ("P-value" %in% extras) {
170   coeff_Pvalue <- round(sapply(bootstrap_pr_z, sum)/L,5)
171   names(coeff_Pvalue) <- NULL
172 }
173
174 statistic <- c()
175 ## Percentile Confidence Intervals
176 if (ci=="percentile" || ci=="all") {
177   p_ci <- matrix(nrow=ncol(A), ncol=2)
178   p_ci <- as.data.frame(p_ci)
179   for (i in 1:(r+1)) {
180     p_ci[i,1] <- quantiles[i,1]
181     p_ci[i,2] <- quantiles[i,2]
182     statistic <- paste0("b",i-1)
183     p_ci <- cbind(p_ci[,1:2],statistic)
184     cat("Percentile Confidence Interval for", " ", statistic, " ", sprintf("[%%.5f, %.5f]", p_ci[i,1], p_ci[i,2]), sep="", "\n")
185     if (bar==TRUE) print(ggplot(p_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
186       +ggtitle(paste("Percentile Confidence Interval for", statistic))+geom_hline(yintercept=0, color="red",linetype = "longdash"))
187   )
188   if ("sigma" %in% extras) {
189     p_ci[r+2,1] <- quantiles[r+2,1]

```



```

190 p_ci[r+2,2] <- quantiles[r+2,2]
191 statistic <- c("sigma")
192 p_ci <- cbind(p_ci[,1:2], statistic)
193 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]", p_ci[r+2,1], p_ci[r+2,2]), sep="", "\n")
194 if (bar==TRUE) print(ggplot(p_ci[r+2, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
195 +ggtitle(paste("Percentile Confidence Interval for", statistic))+geom_hline(yintercept=0, color="red", linetype = "longdash"))
196   if ("P-value" %in% extras) {
197     Pval_b <- c()
198     sign_Pvalue <- c()
199     for (i in (r+3):(2*r+4)) {
200       p_ci[i,1] <- quantiles[i,1]
201       p_ci[i,2] <- quantiles[i,2]
202       statistic <- paste0("P-value(b", i-r-3, ")")
203       Pval_b[i-r-2] <- statistic
204       p_ci <- cbind(p_ci[,1:2], statistic)
205       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]", p_ci[i,1], p_ci[i,2]), sep="", "\n")
206       if (bar==TRUE) print(ggplot(p_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
207       +ggtitle(paste("Percentile Confidence Interval for", statistic))
208       +geom_hline(yintercept=0, color="red", linetype = "longdash"))
209       if (coeff_Pvalue[i-r-2] > 0.1) sign_Pvalue[i-r-2] <- " "
210       if (coeff_Pvalue[i-r-2] <= 0.1 & coeff_Pvalue[i-r-2] > 0.05) sign_Pvalue[i-r-2] <- "*"
211       if (coeff_Pvalue[i-r-2] <= 0.05 & coeff_Pvalue[i-r-2] > 0.01) sign_Pvalue[i-r-2] <- "***"
212       if (coeff_Pvalue[i-r-2] <= 0.01) sign_Pvalue[i-r-2] <- "****"
213     }
214     p_ci[2*r+5,1] <- quantiles[2*r+5,1]
215     p_ci[2*r+5,2] <- quantiles[2*r+5,2]
216     statistic <- c("sd")

```

```

217 p_ci <- cbind(p_ci[,1:2],statistic)
218 cat("Percentile Confidence Interval for", " ", statistic, " ", printf("[%5f", p_ci[2*r+5,1], p_ci[2*r+5,2]), sep="", "\n")
219 if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
220 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
221 if ("R^2" %in% extras) {
222   p_ci[2*r+6,1] <- quantiles[2*r+6,1]
223   p_ci[2*r+6,2] <- quantiles[2*r+6,2]
224   statistic <- c("R^2")
225   p_ci <- cbind(p_ci[,1:2],statistic)
226   cat("Percentile Confidence Interval for", " ", statistic, " ", printf("[%5f", %5f]",
227     p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
228   if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
229   +ggtitle(paste("Percentile Confidence Interval for", statistic)))
230   if ("AIC" %in% extras) {
231     p_ci[2*r+7,1] <- quantiles[2*r+7,1]
232     p_ci[2*r+7,2] <- quantiles[2*r+7,2]
233     statistic <- c("AIC")
234     p_ci <- cbind(p_ci[,1:2],statistic)
235     cat("Percentile Confidence Interval for", " ", statistic, " ", printf("[%5f", %5f]",
236       p_ci[2*r+7,1], p_ci[2*r+7,2]), sep="", "\n")
237     if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
238     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
239     if ("BIC" %in% extras) {
240       p_ci[2*r+8,1] <- quantiles[2*r+8,1]
241       p_ci[2*r+8,2] <- quantiles[2*r+8,2]
242       statistic <- c("BIC")
243       p_ci <- cbind(p_ci[,1:2],statistic)

```

```

244 cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
245     p_ci[2*r+8,1], p_ci[2*r+8,2]), sep="", "\n")
246 if (bar==TRUE) print(ggplot(p_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
247 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
248 if ("RMSE" %in% extras) {
249     p_ci[2*r+9,1] <- quantiles[2*r+9,1]
250     p_ci[2*r+9,2] <- quantiles[2*r+9,2]
251     statistic <- c("RMSE")
252     p_ci <- cbind(p_ci[, 1:2], statistic)
253     cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
254         p_ci[2*r+9,1], p_ci[2*r+9,2]), sep="", "\n")
255     if (bar==TRUE) print(ggplot(p_ci[2*r+9, ], aes(statistic, ymin = V1, ymax = V2))
256 +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
257 }
258 }
259 }
260 if ( !"AIC" %in% extras) {
261     if ("BIC" %in% extras) {
262         p_ci[2*r+7,1] <- quantiles[2*r+7,1]
263         p_ci[2*r+7,2] <- quantiles[2*r+7,2]
264         statistic <- c("BIC")
265         p_ci <- cbind(p_ci[, 1:2], statistic)
266         cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
267             p_ci[2*r+7,1], p_ci[2*r+7,2]), sep="", "\n")
268         if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
269 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
270         if ("RMSE" %in% extras) {

```

```

271 p_ci[2*r+8,1] <- quantiles[2*r+8,1]
272 p_ci[2*r+8,2] <- quantiles[2*r+8,2]
273 statistic <- c("RMSE")
274 p_ci <- cbind(p_ci[,1:2],statistic)
275 cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
276       p_ci[2*r+8,1], p_ci[2*r+8,2]), sep=" ", "\n")
277 if (bar==TRUE) print(ggplot(p_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))
278       +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
279   }
280 }
281 if ( !("BIC" %in% extras) ) {
282   if ("RMSE" %in% extras) {
283     p_ci[2*r+7,1] <- quantiles[2*r+7,1]
284     p_ci[2*r+7,2] <- quantiles[2*r+7,2]
285     statistic <- c("RMSE")
286     p_ci <- cbind(p_ci[,1:2],statistic)
287     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
288       p_ci[2*r+7,1], p_ci[2*r+7,2]), sep=" ", "\n")
289     if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))
290       +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
291   }
292 }
293 }
294 }
295 if ( !("R^2" %in% extras) ) {
296   if ("AIC" %in% extras) {
297     p_ci[2*r+6,1] <- quantiles[2*r+6,1]

```

```

298 p_ci[2*r+6,2] <- quantiles[2*r+6,2]
299 statistic <- c("AIC")
300 p_ci <- cbind(p_ci[,1:2],statistic)
301 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
302     p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
303 if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
304 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
305 if ("BIC" %in% extras) {
306     p_ci[2*r+7,1] <- quantiles[2*r+7,1]
307     p_ci[2*r+7,2] <- quantiles[2*r+7,2]
308     statistic <- c("BIC")
309     p_ci <- cbind(p_ci[,1:2],statistic)
310     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
311         p_ci[2*r+7,1], p_ci[2*r+7,2]), sep="", "\n")
312     if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
313 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
314     if ("RMSE" %in% extras) {
315         p_ci[2*r+8,1] <- quantiles[2*r+8,1]
316         p_ci[2*r+8,2] <- quantiles[2*r+8,2]
317         statistic <- c("RMSE")
318         p_ci <- cbind(p_ci[,1:2],statistic)
319         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
320             p_ci[2*r+8,1], p_ci[2*r+8,2]), sep="", "\n")
321         if (bar==TRUE) print(ggplot(p_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))
322 +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
323     }
324 }

```

```

325 }
326 if (!"AIC" %in% extras) {
327   if ("BIC" %in% extras) {
328     p_ci[2*r+6,1] <- quantiles[2*r+6,1]
329     p_ci[2*r+6,2] <- quantiles[2*r+6,2]
330     statistic <- c("BIC")
331     p_ci <- cbind(p_ci[,1:2],statistic)
332     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
333       p_ci[2*r+6,1], p_ci[2*r+6,2]), sep=" ", "\n")
334     if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
335       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
336     if ("RMSE" %in% extras) {
337       p_ci[2*r+7,1] <- quantiles[2*r+7,1]
338       p_ci[2*r+7,2] <- quantiles[2*r+7,2]
339       statistic <- c("RMSE")
340       p_ci <- cbind(p_ci[,1:2],statistic)
341       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
342         p_ci[2*r+7,1], p_ci[2*r+7,2]), sep=" ", "\n")
343       if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))
344         +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
345     }
346   }
347 }
348 if (!"BIC" %in% extras) {
349   if ("RMSE" %in% extras) {
350     p_ci[2*r+6,1] <- quantiles[2*r+6,1]
351     p_ci[2*r+6,2] <- quantiles[2*r+6,2]
352     statistic <- c("RMSE")

```



```

352 p_ci <- cbind(p_ci[,1:2],statistic)
353 cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%%.5f, %%.5f]",
354     p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
355 if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))
356     +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
357 }
358 }
359 }
360 }
361 }
362 }
363 if ( !("P-value" %in% extras)) {
364     p_ci[r+3,1] <- quantiles[r+3,1]
365     p_ci[r+3,2] <- quantiles[r+3,2]
366     statistic <- c("sd")
367     p_ci <- cbind(p_ci[,1:2],statistic)
368     cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%%.5f", p_ci[r+3,1], p_ci[r+3,2]), sep="", "\n")
369     if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
370         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
371     if ("R^2" %in% extras) {
372         p_ci[r+4,1] <- quantiles[r+4,1]
373         p_ci[r+4,2] <- quantiles[r+4,2]
374         statistic <- c("R^2")
375         p_ci <- cbind(p_ci[,1:2],statistic)
376         cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%%.5f, %%.5f]",
377             p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
378         if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()

```

```

379 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
380 if ("AIC" %in% extras) {
381   p_ci[r+5,1] <- quantiles[r+5,1]
382   p_ci[r+5,2] <- quantiles[r+5,2]
383   statistic <- c("AIC")
384   p_ci <- cbind(p_ci[, 1:2], statistic)
385   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
386     p_ci[r+5,1], p_ci[r+5,2]), sep="", "\n")
387   if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
388     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
389   if ("BIC" %in% extras) {
390     p_ci[r+6,1] <- quantiles[r+6,1]
391     p_ci[r+6,2] <- quantiles[r+6,2]
392     statistic <- c("BIC")
393     p_ci <- cbind(p_ci[, 1:2], statistic)
394     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
395       p_ci[r+6,1], p_ci[r+6,2]), sep="", "\n")
396     if (bar==TRUE) print(ggplot(p_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
397       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
398     if ("RMSE" %in% extras) {
399       p_ci[r+7,1] <- quantiles[r+7,1]
400       p_ci[r+7,2] <- quantiles[r+7,2]
401       statistic <- c("RMSE")
402       p_ci <- cbind(p_ci[, 1:2], statistic)
403       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
404         p_ci[r+7,1], p_ci[r+7,2]), sep="", "\n")
405       if (bar==TRUE) print(ggplot(p_ci[r+7, ], aes(statistic, ymin = V1, ymax = V2))

```

```

406 +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
407 }
408 }
409 }
410 if (!("AIC" %in% extras)) {
411   if ("BIC" %in% extras) {
412     p_ci[r+5,1] <- quantiles[r+5,1]
413     p_ci[r+5,2] <- quantiles[r+5,2]
414     statistic <- c("BIC")
415     p_ci <- cbind(p_ci[, 1:2], statistic)
416     cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("%.5f", %5f),
417         p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
418     if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
419 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
420     if ("RMSE" %in% extras) {
421       p_ci[r+6,1] <- quantiles[r+6,1]
422       p_ci[r+6,2] <- quantiles[r+6,2]
423       statistic <- c("RMSE")
424       p_ci <- cbind(p_ci[, 1:2], statistic)
425       cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("%.5f", %5f),
426         p_ci[r+6,1], p_ci[r+6,2]), sep=" ", "\n")
427       if (bar==TRUE) print(ggplot(p_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))
428 +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
429     }
430 }
431 if (!("BIC" %in% extras)) {
432   if ("RMSE" %in% extras) {

```

```

433 p_ci[r+5,1] <- quantiles[r+5,1]
434 p_ci[r+5,2] <- quantiles[r+5,2]
435 statistic <- c("RMSE")
436 p_ci <- cbind(p_ci[,1:2],statistic)
437 cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
438     p_ci[r+5,1], p_ci[r+5,2]), sep="", "\n")
439 if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
440     +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
441     }
442   }
443 }
444 }
445 if ( !("R^2" %in% extras)) {
446   if ("AIC" %in% extras) {
447     p_ci[r+4,1] <- quantiles[r+4,1]
448     p_ci[r+4,2] <- quantiles[r+4,2]
449     statistic <- c("AIC")
450     p_ci <- cbind(p_ci[,1:2],statistic)
451     cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
452         p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
453     if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
454         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
455     if ("BIC" %in% extras) {
456       p_ci[r+5,1] <- quantiles[r+5,1]
457       p_ci[r+5,2] <- quantiles[r+5,2]
458       statistic <- c("BIC")
459       p_ci <- cbind(p_ci[,1:2],statistic)

```

```

460 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
461     p_ci[r+5,1], p_ci[r+5,2]), sep="", "\n")
462 if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
463 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
464 if ("RMSE" %in% extras) {
465     p_ci[r+6,1] <- quantiles[r+6,1]
466     p_ci[r+6,2] <- quantiles[r+6,2]
467     statistic <- c("RMSE")
468     p_ci <- cbind(p_ci[,1:2],statistic)
469     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
470         p_ci[r+6,1], p_ci[r+6,2]), sep="", "\n")
471     if (bar==TRUE) print(ggplot(p_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))
472 +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
473 }
474 }
475 }
476 if ( !"AIC" %in% extras) {
477     if ("BIC" %in% extras) {
478         p_ci[r+4,1] <- quantiles[r+4,1]
479         p_ci[r+4,2] <- quantiles[r+4,2]
480         statistic <- c("BIC")
481         p_ci <- cbind(p_ci[,1:2],statistic)
482         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
483             p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
484         if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
485 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
486         if ("RMSE" %in% extras) {

```

```

487 p_ci[r+5,1] <- quantiles[r+5,1]
488 p_ci[r+5,2] <- quantiles[r+5,2]
489 statistic <- c("RMSE")
490 p_ci <- cbind(p_ci[,1:2],statistic)
491 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
492     p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
493 if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
494     +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
495 }
496 }
497 if ( !("BIC" %in% extras)) {
498     if ("RMSE" %in% extras) {
499         p_ci[r+4,1] <- quantiles[r+4,1]
500         p_ci[r+4,2] <- quantiles[r+4,2]
501         statistic <- c("RMSE")
502         p_ci <- cbind(p_ci[,1:2],statistic)
503         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
504             p_ci[r+4,1], p_ci[r+4,2]), sep=" ", "\n")
505         if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))
506             +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
507     }
508 }
509 }
510 }
511 }
512 }
513 }

```



```

514 if ("P-value" %in% extras & !("sigma" %in% extras)) {
515   Pval_b <- c()
516   sign_Pvalue <- c()
517   for (i in (r+2):(2*r+2)) {
518     p_ci[i,1] <- quantiles[i,1]
519     p_ci[i,2] <- quantiles[i,2]
520     statistic <- paste0("P-value(b", i-r-2, ")")
521     Pval_b[i-r-1] <- statistic
522     p_ci <- cbind(p_ci[,1:2], statistic)
523     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]", p_ci[i,1], p_ci[i,2]), sep="", "\n")
524     if (bar==TRUE) print(ggplot(p_ci[, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
525       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
526     if (coeff_Pvalue[i-r-1] >0.1) sign_Pvalue[i-r-1] <- " "
527     if (coeff_Pvalue[i-r-1] <=0.1 & coeff_Pvalue[i-r-1] >0.05) sign_Pvalue[i-r-1] <- "***"
528     if (coeff_Pvalue[i-r-1] <=0.05 & coeff_Pvalue[i-r-1] >0.01) sign_Pvalue[i-r-1] <- "****"
529     if (coeff_Pvalue[i-r-1] <=0.01) sign_Pvalue[i-r-1] <- "*****"
530   }
531   p_ci[2*r+3,1] <- quantiles[2*r+3,1]
532   p_ci[2*r+3,2] <- quantiles[2*r+3,2]
533   statistic <- c("sd")
534   p_ci <- cbind(p_ci[,1:2], statistic)
535   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]", p_ci[2*r+3,1], p_ci[2*r+3,2]), sep="", "\n")
536   if (bar==TRUE) print(ggplot(p_ci[2*r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
537     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
538   if ("R^2" %in% extras) {
539     p_ci[2*r+4,1] <- quantiles[2*r+4,1]
540     p_ci[2*r+4,2] <- quantiles[2*r+4,2]

```

```

541 statistic <- c("R^2")
542 p_ci <- cbind(p_ci[,1:2], statistic)
543 cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f", %5f]", p_ci[2*r+4,1], p_ci[2*r+4,2]), sep="", "\n")
544 if (bar==TRUE) print(ggplot(p_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
545 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
546 if ("AIC" %in% extras) {
547   p_ci[2*r+5,1] <- quantiles[2*r+5,1]
548   p_ci[2*r+5,2] <- quantiles[2*r+5,2]
549   statistic <- c("AIC")
550   p_ci <- cbind(p_ci[,1:2], statistic)
551   cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f", %5f]",
552     p_ci[2*r+5,1], p_ci[2*r+5,2]), sep="", "\n")
553   if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
554 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
555   if ("BIC" %in% extras) {
556     p_ci[2*r+6,1] <- quantiles[2*r+6,1]
557     p_ci[2*r+6,2] <- quantiles[2*r+6,2]
558     statistic <- c("BIC")
559     p_ci <- cbind(p_ci[,1:2], statistic)
560     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f", %5f]",
561       p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
562     if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
563 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
564     if ("RMSE" %in% extras) {
565       p_ci[2*r+7,1] <- quantiles[2*r+7,1]
566       p_ci[2*r+7,2] <- quantiles[2*r+7,2]
567       statistic <- c("RMSE")

```

```

568 p_ci <- cbind(p_ci[,1:2], statistic)
569 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
570     p_ci[2*r+7,1], p_ci[2*r+7,2]), sep="", "\n")
571 if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
572     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
573 }
574 }
575 }
576 if ( !("AIC" %in% extras) ) {
577   if ("BIC" %in% extras) {
578     p_ci[2*r+5,1] <- quantiles[2*r+5,1]
579     p_ci[2*r+5,2] <- quantiles[2*r+5,2]
580     statistic <- c("BIC")
581     p_ci <- cbind(p_ci[,1:2], statistic)
582     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
583         p_ci[2*r+5,1], p_ci[2*r+5,2]), sep="", "\n")
584     if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
585         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
586     if ("RMSE" %in% extras) {
587       p_ci[2*r+6,1] <- quantiles[2*r+6,1]
588       p_ci[2*r+6,2] <- quantiles[2*r+6,2]
589       statistic <- c("RMSE")
590       p_ci <- cbind(p_ci[,1:2], statistic)
591       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
592         p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
593       if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
594         +ggtitle(paste("Percentile Confidence Interval for", statistic)))

```

```

595     }
596   }
597   if ( !("BIC" %in% extras) ) {
598     if ("RMSE" %in% extras) {
599       p_ci[2*r+5,1] <- quantiles[2*r+5,1]
600       p_ci[2*r+5,2] <- quantiles[2*r+5,2]
601       statistic <- c("RMSE")
602       p_ci <- cbind(p_ci[,1:2],statistic)
603       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
604         p_ci[2*r+5,1], p_ci[2*r+5,2]), sep=" ", "\n")
605       if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
606         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
607     }
608   }
609 }
610 }
611 if ( !("R^2" %in% extras) ) {
612   if ("AIC" %in% extras) {
613     p_ci[2*r+4,1] <- quantiles[2*r+4,1]
614     p_ci[2*r+4,2] <- quantiles[2*r+4,2]
615     statistic <- c("AIC")
616     p_ci <- cbind(p_ci[,1:2],statistic)
617     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
618       p_ci[2*r+4,1], p_ci[2*r+4,2]), sep=" ", "\n")
619     if (bar==TRUE) print(ggplot(p_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
620       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
621   }

```

```

622 p_ci[2*r+5,1] <- quantiles[2*r+5,1]
623 p_ci[2*r+5,2] <- quantiles[2*r+5,2]
624 statistic <- c("BIC")
625 p_ci <- cbind(p_ci[,1:2],statistic)
626 cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f, %.5f]",
627     p_ci[2*r+5,1], p_ci[2*r+5,2]), sep=" ", "\n")
628 if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
629 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
630 if ("RMSE" %in% extras) {
631     p_ci[2*r+6,1] <- quantiles[2*r+6,1]
632     p_ci[2*r+6,2] <- quantiles[2*r+6,2]
633     statistic <- c("RMSE")
634     p_ci <- cbind(p_ci[,1:2],statistic)
635     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f, %.5f]",
636         p_ci[2*r+6,1], p_ci[2*r+6,2]), sep=" ", "\n")
637     if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
638 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
639 }
640 }
641 }
642 if ( !("AIC" %in% extras)) {
643     if ("BIC" %in% extras) {
644         p_ci[2*r+4,1] <- quantiles[2*r+4,1]
645         p_ci[2*r+4,2] <- quantiles[2*r+4,2]
646         statistic <- c("BIC")
647         p_ci <- cbind(p_ci[,1:2],statistic)
648         cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f, %.5f]",

```

```

649   p_ci[2*r+4,1], p_ci[2*r+4,2]], sep="", "\n")
650   if (bar==TRUE) print(ggplot(p_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
651   +ggtitle(paste("Percentile Confidence Interval for", statistic)))
652   if ("RMSE" %in% extras) {
653     p_ci[2*r+5,1] <- quantiles[2*r+5,1]
654     p_ci[2*r+5,2] <- quantiles[2*r+5,2]
655     statistic <- c("RMSE")
656     p_ci <- cbind(p_ci[,1:2],statistic)
657     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
658     p_ci[2*r+5,1], p_ci[2*r+5,2]), sep="", "\n")
659     if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
660     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
661   }
662 }
663 if ( !("BIC" %in% extras) ) {
664   if ("RMSE" %in% extras) {
665     p_ci[2*r+4,1] <- quantiles[2*r+4,1]
666     p_ci[2*r+4,2] <- quantiles[2*r+4,2]
667     statistic <- c("RMSE")
668     p_ci <- cbind(p_ci[,1:2],statistic)
669     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
670     p_ci[2*r+4,1], p_ci[2*r+4,2]), sep="", "\n")
671     if (bar==TRUE) print(ggplot(p_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
672     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
673   }
674 }
675 }

```



```

676     }
677   }
678
679   if ( !("P-value" %in% extras) & !("sigma" %in% extras) ) {
680     p_ci[r+2,1] <- quantiles[r+2,1]
681     p_ci[r+2,2] <- quantiles[r+2,2]
682     statistic <- c("sd")
683     p_ci <- cbind(p_ci[,1:2],statistic)
684     cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]", p_ci[r+2,1], p_ci[r+2,2]), sep="", "\n")
685     if (bar==TRUE) print(ggplot(p_ci[r+2, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
686     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
687     if ("R^2" %in% extras) {
688       p_ci[r+3,1] <- quantiles[r+3,1]
689       p_ci[r+3,2] <- quantiles[r+3,2]
690       statistic <- c("R^2")
691       p_ci <- cbind(p_ci[,1:2],statistic)
692       cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]", p_ci[r+3,1], p_ci[r+3,2]), sep="", "\n")
693       if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
694       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
695       if ("AIC" %in% extras) {
696         p_ci[r+4,1] <- quantiles[r+4,1]
697         p_ci[r+4,2] <- quantiles[r+4,2]
698         statistic <- c("AIC")
699         p_ci <- cbind(p_ci[,1:2],statistic)
700         cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
701         p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
702         if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()

```

```

703 +ggtitle(paste("Percentile Confidence Interval for", statistic))
704 if ("BIC" %in% extras) {
705   p_ci[r+5,1] <- quantiles[r+5,1]
706   p_ci[r+5,2] <- quantiles[r+5,2]
707   statistic <- c("BIC")
708   p_ci <- cbind(p_ci[,1:2],statistic)
709   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
710     p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
711   if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
712     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
713   if ("RMSE" %in% extras) {
714     p_ci[r+6,1] <- quantiles[r+6,1]
715     p_ci[r+6,2] <- quantiles[r+6,2]
716     statistic <- c("RMSE")
717     p_ci <- cbind(p_ci[,1:2],statistic)
718     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
719       p_ci[r+6,1], p_ci[r+6,2]), sep=" ", "\n")
720     if (bar==TRUE) print(ggplot(p_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
721       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
722   }
723 }
724 }
725 if (!("AIC" %in% extras)) {
726   if ("BIC" %in% extras) {
727     p_ci[r+4,1] <- quantiles[r+4,1]
728     p_ci[r+4,2] <- quantiles[r+4,2]
729     statistic <- c("BIC")

```

```

730 p_ci <- cbind(p_ci[,1:2],statistic)
731 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
732     p_ci[r+4,1], p_ci[r+4,2]), sep=" ", "\n")
733 if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
734 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
735 if ("RMSE" %in% extras) {
736     p_ci[r+5,1] <- quantiles[r+5,1]
737     p_ci[r+5,2] <- quantiles[r+5,2]
738     statistic <- c("RMSE")
739     p_ci <- cbind(p_ci[,1:2],statistic)
740     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
741         p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
742     if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
743 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
744 }
745 }
746 if ( !("BIC" %in% extras)) {
747     if ("RMSE" %in% extras) {
748         p_ci[r+4,1] <- quantiles[r+4,1]
749         p_ci[r+4,2] <- quantiles[r+4,2]
750         statistic <- c("RMSE")
751         p_ci <- cbind(p_ci[,1:2],statistic)
752         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
753             p_ci[r+4,1], p_ci[r+4,2]), sep=" ", "\n")
754         if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
755 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
756     }

```

```

757     }
758   }
759 }
760 if ( !("R^2" %in% extras) ) {
761   if ("AIC" %in% extras) {
762     p_ci[r+3,1] <- quantiles[r+3,1]
763     p_ci[r+3,2] <- quantiles[r+3,2]
764     statistic <- c("AIC")
765     p_ci <- cbind(p_ci[,1:2],statistic)
766     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
767       p_ci[r+3,1], p_ci[r+3,2]), sep=" ", "\n")
768     if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
769       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
770     if ("BIC" %in% extras) {
771       p_ci[r+4,1] <- quantiles[r+4,1]
772       p_ci[r+4,2] <- quantiles[r+4,2]
773       statistic <- c("BIC")
774       p_ci <- cbind(p_ci[,1:2],statistic)
775       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
776         p_ci[r+4,1], p_ci[r+4,2]), sep=" ", "\n")
777       if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
778         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
779       if ("RMSE" %in% extras) {
780         p_ci[r+5,1] <- quantiles[r+5,1]
781         p_ci[r+5,2] <- quantiles[r+5,2]
782         statistic <- c("RMSE")
783         p_ci <- cbind(p_ci[,1:2],statistic)

```

```

784   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
785       p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
786   if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
787       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
788   }
789   }
790   }
791   if ( !("AIC" %in% extras) ) {
792     if ("BIC" %in% extras) {
793       p_ci[r+3,1] <- quantiles[r+3,1]
794       p_ci[r+3,2] <- quantiles[r+3,2]
795       statistic <- c("BIC")
796       p_ci <- cbind(p_ci[,1:2],statistic)
797       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
798           p_ci[r+3,1], p_ci[r+3,2]), sep=" ", "\n")
799       if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
800           +ggtitle(paste("Percentile Confidence Interval for", statistic)))
801       if ("RMSE" %in% extras) {
802         p_ci[r+4,1] <- quantiles[r+4,1]
803         p_ci[r+4,2] <- quantiles[r+4,2]
804         statistic <- c("RMSE")
805         p_ci <- cbind(p_ci[,1:2],statistic)
806         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
807             p_ci[r+4,1], p_ci[r+4,2]), sep=" ", "\n")
808         if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
809             +ggtitle(paste("Percentile Confidence Interval for", statistic)))
810     }

```

```

811 }
812 if ( !("BIC" %in% extras) ) {
813   if ("RMSE" %in% extras) {
814     p_ci[r+3,1] <- quantiles[r+3,1]
815     p_ci[r+3,2] <- quantiles[r+3,2]
816     statistic <- c("RMSE")
817     p_ci <- cbind(p_ci[,1:2],statistic)
818     cat("Percentile Confidence Interval for", " ", statistic, " ", sprintf("[%5f, %5f]",
819       p_ci[r+3,1], p_ci[r+3,2]), sep=" ", "\n")
820     if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
821       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
822   }
823 }
824 }
825 }
826 }
827 }
828 }
829 ## Basic Confidence Intervals
830 if (ci=="basic" || ci=="all") {
831   b_ci <- matrix(nrow=ncol(A), ncol=2)
832   b_ci <- as.data.frame(b_ci)
833   for (i in 1:(r+1)) {
834     b_ci[i,1] <- 2*beta_hat[i] - quantiles[i,2]
835     b_ci[i,2] <- 2*beta_hat[i] - quantiles[i,1]
836     statistic <- paste0("b",i-1)
837     b_ci <- cbind(b_ci[,1:2],statistic)

```

```

838 cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]", b_ci[i,1], b_ci[i,2]), sep="", "\n")
839 if (bar==TRUE) print(ggplot(b_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
840 +ggtitle(paste("Basic Confidence Interval for", statistic))+geom_hline(yintercept=0, color="red", linetype = "longdash"))
841 }
842 if ("sigma" %in% extras) {
843   b_ci[r+2,1] <- 2*sigma - quantiles[r+2,2]
844   b_ci[r+2,2] <- 2*sigma - quantiles[r+2,1]
845   statistic <- c("sigma")
846   b_ci <- cbind(b_ci[, 1:2], statistic)
847   cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]", b_ci[r+2,1], b_ci[r+2,2]), sep="", "\n")
848   if (bar==TRUE) print(ggplot(b_ci[r+2, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
849   +ggtitle(paste("Basic Confidence Interval for", statistic)))
850   if ("P-value" %in% extras) {
851     Pval_b <- c()
852     sign_Pvalue <- c()
853     for (i in (r+3):(2*r+4)) {
854       b_ci[i,1] <- 2*Pr_z[i-r-2] - quantiles[i,2]
855       b_ci[i,2] <- 2*Pr_z[i-r-2] - quantiles[i,1]
856       statistic <- paste0("P-value(b", i-r-3, ")")
857       Pval_b[i-r-2] <- statistic
858       b_ci <- cbind(b_ci[, 1:2], statistic)
859       cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]", b_ci[i,1], b_ci[i,2]), sep="", "\n")
860       if (bar==TRUE) print(ggplot(b_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
861       +ggtitle(paste("Basic Confidence Interval for", statistic)))
862       if (coeff_Pvalue[i-r-2] > 0.1) sign_Pvalue[i-r-2] <- " "
863       if (coeff_Pvalue[i-r-2] <= 0.1 & coeff_Pvalue[i-r-2] > 0.05) sign_Pvalue[i-r-2] <- "*"
864       if (coeff_Pvalue[i-r-2] <= 0.05 & coeff_Pvalue[i-r-2] > 0.01) sign_Pvalue[i-r-2] <- "***"

```



```

865   if (coeff_pvalue[i-r-2] <= 0.01) sign_pvalue[i-r-2] <- "****"
866 }
867 b_ci[2*r+5,1] <- 2*sd_hat - quantiles[2*r+5,2]
868 b_ci[2*r+5,2] <- 2*sd_hat + quantiles[2*r+5,1]
869 statistic <- c("sd")
870 b_ci <- cbind(b_ci[,1:2], statistic)
871 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("%.5f", b_ci[2*r+5,1]), b_ci[2*r+5,2]), sep="", "\n")
872 if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
873 +ggtitle(paste("Basic Confidence Interval for", statistic)))
874 if ("R^2" %in% extras) {
875   b_ci[2*r+6,1] <- 2*R_2 - quantiles[2*r+6,2]
876   b_ci[2*r+6,2] <- 2*R_2 + quantiles[2*r+6,1]
877   statistic <- c("R^2")
878   b_ci <- cbind(b_ci[,1:2], statistic)
879   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("%.5f",
880     b_ci[2*r+6,1]), b_ci[2*r+6,2]), sep="", "\n")
881   if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
882   +ggtitle(paste("Basic Confidence Interval for", statistic)))
883   if ("AIC" %in% extras) {
884     b_ci[2*r+7,1] <- 2*AIC - quantiles[2*r+7,2]
885     b_ci[2*r+7,2] <- 2*AIC + quantiles[2*r+7,1]
886     statistic <- c("AIC")
887     b_ci <- cbind(b_ci[,1:2], statistic)
888     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("%.5f",
889       b_ci[2*r+7,1]), b_ci[2*r+7,2]), sep="", "\n")
890     if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
891     +ggtitle(paste("Basic Confidence Interval for", statistic)))

```

```

892 if ("BIC" %in% extras) {
893   b_ci[2*r+8,1] <- 2*BIC - quantiles[2*r+8,2]
894   b_ci[2*r+8,2] <- 2*BIC - quantiles[2*r+8,1]
895   statistic <- c("BIC")
896   b_ci <- cbind(b_ci[,1:2],statistic)
897   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
898     b_ci[2*r+8,1], b_ci[2*r+8,2]), sep="", "\n")
899   if (bar==TRUE) print(ggplot(b_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
900     +ggtitle(paste("Basic Confidence Interval for", statistic)))
901   if ("RMSE" %in% extras) {
902     b_ci[2*r+9,1] <- 2*RMSE - quantiles[2*r+9,2]
903     b_ci[2*r+9,2] <- 2*RMSE - quantiles[2*r+9,1]
904     statistic <- c("RMSE")
905     b_ci <- cbind(b_ci[,1:2],statistic)
906     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
907       b_ci[2*r+9,1], b_ci[2*r+9,2]), sep="", "\n")
908     if (bar==TRUE) print(ggplot(b_ci[2*r+9, ], aes(statistic, ymin = V1, ymax = V2))
909       +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
910   }
911 }
912 }
913 if (!("AIC" %in% extras)) {
914   if ("BIC" %in% extras) {
915     b_ci[2*r+7,1] <- 2*BIC - quantiles[2*r+7,2]
916     b_ci[2*r+7,2] <- 2*BIC - quantiles[2*r+7,1]
917     statistic <- c("BIC")
918     b_ci <- cbind(b_ci[,1:2],statistic)

```

```

919 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
920     b_ci[2*r+7,1], b_ci[2*r+7,2]), sep=" ", "\n")
921 if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
922     +ggtitle(paste("Basic Confidence Interval for", statistic)))
923     if ("RMSE" %in% extras) {
924         b_ci[2*r+8,1] <- 2*RMSE - quantiles[2*r+8,2]
925         b_ci[2*r+8,2] <- 2*RMSE + quantiles[2*r+8,1]
926         statistic <- c("RMSE")
927         b_ci <- cbind(b_ci[,1:2],statistic)
928         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
929             b_ci[2*r+8,1], b_ci[2*r+8,2]), sep=" ", "\n")
930         if (bar==TRUE) print(ggplot(b_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))
931             +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
932     }
933 }
934 if ( !("BIC" %in% extras) ) {
935     if ("RMSE" %in% extras) {
936         b_ci[2*r+7,1] <- 2*RMSE - quantiles[2*r+7,2]
937         b_ci[2*r+7,2] <- 2*RMSE + quantiles[2*r+7,1]
938         statistic <- c("RMSE")
939         b_ci <- cbind(b_ci[,1:2],statistic)
940         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
941             b_ci[2*r+7,1], b_ci[2*r+7,2]), sep=" ", "\n")
942         if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))
943             +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
944     }
945 }

```

```

946     }
947 }
948 if ( !("R^2" %in% extras) ) {
949   if ("AIC" %in% extras) {
950     b_ci[2*r+6,1] <- 2*AIC - quantiles[2*r+6,2]
951     b_ci[2*r+6,2] <- 2*AIC - quantiles[2*r+6,1]
952     statistic <- c("AIC")
953     b_ci <- cbind(b_ci[,1:2],statistic)
954     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
955         b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
956     if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
957         +ggtitle(paste("Basic Confidence Interval for", statistic)))
958     if ("BIC" %in% extras) {
959       b_ci[2*r+7,1] <- 2*BIC - quantiles[2*r+7,2]
960       b_ci[2*r+7,2] <- 2*BIC - quantiles[2*r+7,1]
961       statistic <- c("BIC")
962       b_ci <- cbind(b_ci[,1:2],statistic)
963       cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
964         b_ci[2*r+7,1], b_ci[2*r+7,2]), sep="", "\n")
965       if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
966         +ggtitle(paste("Basic Confidence Interval for", statistic)))
967       if ("RMSE" %in% extras) {
968         b_ci[2*r+8,1] <- 2*RMSE - quantiles[2*r+8,2]
969         b_ci[2*r+8,2] <- 2*RMSE - quantiles[2*r+8,1]
970         statistic <- c("RMSE")
971         b_ci <- cbind(b_ci[,1:2],statistic)
972         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",

```

```

973     b_ci[2*r+8,1], b_ci[2*r+8,2]), sep="", "\n")
974   if (bar==TRUE) print(ggplot(b_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))
975     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
976 }
977 }
978 }
979 if (!("AIC" %in% extras)) {
980   if ("BIC" %in% extras) {
981     b_ci[2*r+6,1] <- 2*BIC - quantiles[2*r+6,2]
982     b_ci[2*r+6,2] <- 2*BIC - quantiles[2*r+6,1]
983     statistic <- c("BIC")
984     b_ci <- cbind(b_ci[,1:2],statistic)
985     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
986       b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
987   if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
988     +ggtitle(paste("Basic Confidence Interval for", statistic)))
989   if ("RMSE" %in% extras) {
990     b_ci[2*r+7,1] <- 2*RMSE - quantiles[2*r+7,2]
991     b_ci[2*r+7,2] <- 2*RMSE - quantiles[2*r+7,1]
992     statistic <- c("RMSE")
993     b_ci <- cbind(b_ci[,1:2],statistic)
994     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
995       b_ci[2*r+7,1], b_ci[2*r+7,2]), sep="", "\n")
996   if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))
997     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
998 }
999 }

```

```

1000 if ( !("BIC" %in% extras) ) {
1001   if ("RMSE" %in% extras) {
1002     b_ci[2*r+6,1] <- 2*RMSE - quantiles[2*r+6,2]
1003     b_ci[2*r+6,2] <- 2*RMSE - quantiles[2*r+6,1]
1004     statistic <- c("RMSE")
1005     b_ci <- cbind(b_ci[,1:2],statistic)
1006     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1007       b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1008     if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))
1009       +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1010   }
1011 }
1012 }
1013 }
1014 }
1015 }
1016 if ( !("P-value" %in% extras) ) {
1017   b_ci[r+3,1] <- 2*sd_hat - quantiles[r+3,2]
1018   b_ci[r+3,2] <- 2*sd_hat - quantiles[r+3,1]
1019   statistic <- c("sd")
1020   b_ci <- cbind(b_ci[,1:2],statistic)
1021   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f", b_ci[r+3,1], b_ci[r+3,2]), sep="", "\n")
1022   if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1023     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1024   if ("R^2" %in% extras) {
1025     b_ci[r+4,1] <- 2*R_2 - quantiles[r+4,2]
1026     b_ci[r+4,2] <- 2*R_2 - quantiles[r+4,1]

```

```

1027 statistic <- c("R^2")
1028 b_ci <- cbind(b_ci[,1:2],statistic)
1029 cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f", b_ci[r+4,1]), b_ci[r+4,2]), sep="", "\n")
1030 if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1031 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1032 if ("AIC" %in% extras) {
1033   b_ci[r+5,1] <- 2*AIC - quantiles[r+5,2]
1034   b_ci[r+5,2] <- 2*AIC - quantiles[r+5,1]
1035   statistic <- c("AIC")
1036   b_ci <- cbind(b_ci[,1:2],statistic)
1037   cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f", b_ci[r+5,1]),
1038       b_ci[r+5,2]), sep="", "\n")
1039   if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1040 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1041   if ("BIC" %in% extras) {
1042     b_ci[r+6,1] <- 2*BIC - quantiles[r+6,2]
1043     b_ci[r+6,2] <- 2*BIC - quantiles[r+6,1]
1044     statistic <- c("BIC")
1045     b_ci <- cbind(b_ci[,1:2],statistic)
1046     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f", b_ci[r+6,1]),
1047         b_ci[r+6,2]), sep="", "\n")
1048     if (bar==TRUE) print(ggplot(b_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1049 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1050     if ("RMSE" %in% extras) {
1051       b_ci[r+7,1] <- 2*RMSE - quantiles[r+7,2]
1052       b_ci[r+7,2] <- 2*RMSE - quantiles[r+7,1]
1053       statistic <- c("RMSE")

```



```

1054 b_ci <- cbind(b_ci[,1:2],statistic)
1055 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1056     b_ci[r+7,1], b_ci[r+7,2]), sep="", "\n")
1057 if (bar==TRUE) print(ggplot(b_ci[r+7, ], aes(statistic, ymin = V1, ymax = V2))
1058     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1059
1060 }
1061 }
1062 if ( !("AIC" %in% extras) ) {
1063   if ("BIC" %in% extras) {
1064     b_ci[r+5,1] <- 2*BIC - quantiles[r+5,2]
1065     b_ci[r+5,2] <- 2*BIC - quantiles[r+5,1]
1066     statistic <- c("BIC")
1067     b_ci <- cbind(b_ci[, 1:2],statistic)
1068     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1069         b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1070     if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1071         +ggtitle(paste("Basic Confidence Interval for", statistic)))
1072     if ("RMSE" %in% extras) {
1073       b_ci[r+6,1] <- 2*RMSE - quantiles[r+6,2]
1074       b_ci[r+6,2] <- 2*RMSE - quantiles[r+6,1]
1075       statistic <- c("RMSE")
1076       b_ci <- cbind(b_ci[,1:2],statistic)
1077       cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1078           b_ci[r+6,1], b_ci[r+6,2]), sep="", "\n")
1079       if (bar==TRUE) print(ggplot(b_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))
1080           +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))

```

```

1081 }
1082 }
1083 if ( !("BIC" %in% extras) ) {
1084   if ("RMSE" %in% extras) {
1085     b_ci[r+5,1] <- 2*BIC - quantiles[r+5,2]
1086     b_ci[r+5,2] <- 2*BIC - quantiles[r+5,1]
1087     statistic <- c("RMSE")
1088     b_ci <- cbind(b_ci[,1:2],statistic)
1089     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
1090       b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1091     if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
1092       +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1093   }
1094 }
1095 }
1096 }
1097 if ( !("R^2" %in% extras) ) {
1098   if ("AIC" %in% extras) {
1099     b_ci[r+4,1] <- 2*AIC - quantiles[r+4,2]
1100     b_ci[r+4,2] <- 2*AIC - quantiles[r+4,1]
1101     statistic <- c("AIC")
1102     b_ci <- cbind(b_ci[,1:2],statistic)
1103     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
1104       b_ci[r+4,1], b_ci[r+4,2]), sep="", "\n")
1105     if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1106       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1107     if ("BIC" %in% extras) {

```

```

1108 b_ci[r+5,1] <- 2*BIC - quantiles[r+5,2]
1109 b_ci[r+5,2] <- 2*BIC - quantiles[r+5,1]
1110 statistic <- c("BIC")
1111 b_ci <- cbind(b_ci[,1:2],statistic)
1112 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1113     b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1114 if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1115 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1116 if ("RMSE" %in% extras) {
1117     b_ci[r+6,1] <- 2*RMSE - quantiles[r+6,2]
1118     b_ci[r+6,2] <- 2*RMSE - quantiles[r+6,1]
1119     statistic <- c("RMSE")
1120     b_ci <- cbind(b_ci[,1:2],statistic)
1121     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1122         b_ci[r+6,1], b_ci[r+6,2]), sep="", "\n")
1123     if (bar==TRUE) print(ggplot(b_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))
1124 +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1125 }
1126 }
1127 }
1128 if ( !("AIC" %in% extras)) {
1129     if ("BIC" %in% extras) {
1130         b_ci[r+4,1] <- 2*BIC - quantiles[r+4,2]
1131         b_ci[r+4,2] <- 2*BIC - quantiles[r+4,1]
1132         statistic <- c("BIC")
1133         b_ci <- cbind(b_ci[,1:2],statistic)
1134         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",

```

```

1135     b_ci[r+4,1], b_ci[r+4,2]), sep="", "\n")
1136   if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1137   +ggtitle(paste("Basic Confidence Interval for", statistic)))
1138   if ("RMSE" %in% extras) {
1139     b_ci[r+5,1] <- 2*RMSE - quantiles[r+5,2]
1140     b_ci[r+5,2] <- 2*RMSE - quantiles[r+5,1]
1141     statistic <- c("RMSE")
1142     b_ci <- cbind(b_ci[,1:2],statistic)
1143     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%%.5f, %%.5f]",
1144     b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1145     if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
1146     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1147   }
1148 }
1149 if ( !"BIC" %in% extras) {
1150   if ("RMSE" %in% extras) {
1151     b_ci[r+4,1] <- 2*RMSE - quantiles[r+4,2]
1152     b_ci[r+4,2] <- 2*RMSE - quantiles[r+4,1]
1153     statistic <- c("RMSE")
1154     b_ci <- cbind(b_ci[,1:2],statistic)
1155     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%%.5f, %%.5f]",
1156     b_ci[r+4,1], b_ci[r+4,2]), sep="", "\n")
1157     if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))
1158     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1159   }
1160 }
1161 }

```

```

1162     }
1163   }
1164 }
1165
1166 if ("P-value" %in% extras & !("sigma" %in% extras)) {
1167   Pval_b <- c()
1168   sign_Pvalue <- c()
1169   for (i in (r+2):(2*r+2)) {
1170     b_ci[i,1] <- 2*Pr_z[i-r-1] - quantiles[i,2]
1171     b_ci[i,2] <- 2*Pr_z[i-r-1] - quantiles[i,1]
1172     statistic <- paste0("P-value(b",i-r-2,")")
1173     Pval_b[i-r-1] <- statistic
1174     b_ci <- cbind(b_ci[,1:2],statistic)
1175     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]", b_ci[i,1], b_ci[i,2]), sep="", "\n")
1176     if (bar==TRUE) print(ggplot(b_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1177       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1178     if (coeff_Pvalue[i-r-1] >0.1) sign_Pvalue[i-r-1] <- ""
1179     if (coeff_Pvalue[i-r-1] <=0.1 & coeff_Pvalue[i-r-1] >0.05) sign_Pvalue[i-r-1] <- "*"
1180     if (coeff_Pvalue[i-r-1] <=0.05 & coeff_Pvalue[i-r-1] >0.01) sign_Pvalue[i-r-1] <- "***"
1181     if (coeff_Pvalue[i-r-1] <=0.01) sign_Pvalue[i-r-1] <- "****"
1182   }
1183   b_ci[2*r+3,1] <- 2*sd_hat - quantiles[2*r+3,2]
1184   b_ci[2*r+3,2] <- 2*sd_hat - quantiles[2*r+3,1]
1185   statistic <- c("sd")
1186   b_ci <- cbind(b_ci[,1:2],statistic)
1187   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]", b_ci[2*r+3,1], b_ci[2*r+3,2]), sep="", "\n")
1188   if (bar==TRUE) print(ggplot(b_ci[2*r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()

```

```

1189 +ggtitle(paste("Basic Confidence Interval for", statistic))
1190 if ("R^2" %in% extras) {
1191   b_ci[2*r+4,1] <- 2*R_2 - quantiles[2*r+4,2]
1192   b_ci[2*r+4,2] <- 2*R_2 - quantiles[2*r+4,1]
1193   statistic <- c("R^2")
1194   b_ci <- cbind(b_ci[,1:2],statistic)
1195   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f", b_ci[2*r+4,1], b_ci[2*r+4,2]), sep="", "\n")
1196   if (bar==TRUE) print(ggplot(b_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1197     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1198   if ("AIC" %in% extras) {
1199     b_ci[2*r+5,1] <- 2*AIC - quantiles[2*r+5,2]
1200     b_ci[2*r+5,2] <- 2*AIC - quantiles[2*r+5,1]
1201     statistic <- c("AIC")
1202     b_ci <- cbind(b_ci[,1:2],statistic)
1203     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f", b_ci[2*r+5,1], b_ci[2*r+5,2]), sep="", "\n")
1204     b_ci[2*r+5,1], b_ci[2*r+5,2]), sep="", "\n")
1205   if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1206     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1207   if ("BIC" %in% extras) {
1208     b_ci[2*r+6,1] <- 2*BIC - quantiles[2*r+6,2]
1209     b_ci[2*r+6,2] <- 2*BIC - quantiles[2*r+6,1]
1210     statistic <- c("BIC")
1211     b_ci <- cbind(b_ci[,1:2],statistic)
1212     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f", b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1213     b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1214   if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1215     +ggtitle(paste("Basic Confidence Interval for", statistic)))

```

```

1216 if ("RMSE" %in% extras) {
1217   b_ci[2*r+7,1] <- 2*RMSE - quantiles[2*r+7,2]
1218   b_ci[2*r+7,2] <- 2*RMSE + quantiles[2*r+7,1]
1219   statistic <- c("RMSE")
1220   b_ci <- cbind(b_ci[,1:2],statistic)
1221   cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%f, %f]",
1222     b_ci[2*r+7,1], b_ci[2*r+7,2]), sep=" ", "\n")
1223   if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1224     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1225 }
1226 }
1227 }
1228 if (!("AIC" %in% extras)) {
1229   if ("BIC" %in% extras) {
1230     b_ci[2*r+5,1] <- 2*BIC - quantiles[2*r+5,2]
1231     b_ci[2*r+5,2] <- 2*BIC + quantiles[2*r+5,1]
1232     statistic <- c("BIC")
1233     b_ci <- cbind(b_ci[,1:2],statistic)
1234     cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%f, %f]",
1235       b_ci[2*r+5,1], b_ci[2*r+5,2]), sep=" ", "\n")
1236     if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1237       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1238     if ("RMSE" %in% extras) {
1239       b_ci[2*r+6,1] <- 2*RMSE - quantiles[2*r+6,2]
1240       b_ci[2*r+6,2] <- 2*RMSE + quantiles[2*r+6,1]
1241       statistic <- c("RMSE")
1242       b_ci <- cbind(b_ci[,1:2],statistic)

```



```

1243   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
1244       b_ci[2*r+6,1], b_ci[2*r+6,2]), sep=" ", "\n")
1245   if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1246       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1247   }
1248 }
1249 if ( !("BIC" %in% extras) ) {
1250   if ("RMSE" %in% extras) {
1251     b_ci[2*r+5,1] <- 2*RMSE - quantiles[2*r+5,2]
1252     b_ci[2*r+5,2] <- 2*RMSE - quantiles[2*r+5,1]
1253     statistic <- c("RMSE")
1254     b_ci <- cbind(b_ci[,1:2],statistic)
1255     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
1256         b_ci[2*r+5,1], b_ci[2*r+5,2]), sep=" ", "\n")
1257     if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1258         +ggtitle(paste("Basic Confidence Interval for", statistic)))
1259   }
1260 }
1261 }
1262 }
1263 if ( !("R^2" %in% extras) ) {
1264   if ("AIC" %in% extras) {
1265     b_ci[2*r+4,1] <- 2*AIC - quantiles[2*r+4,2]
1266     b_ci[2*r+4,2] <- 2*AIC - quantiles[2*r+4,1]
1267     statistic <- c("AIC")
1268     b_ci <- cbind(b_ci[,1:2],statistic)
1269     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",

```

```

1270     b_ci[2*r+4,1], b_ci[2*r+4,2]], sep="", "\n")
1271   if (bar==TRUE) print(ggplot(b_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1272   +ggtitle(paste("Basic Confidence Interval for", statistic)))
1273   if ("BIC" %in% extras) {
1274     b_ci[2*r+5,1] <- 2*BIC - quantiles[2*r+5,2]
1275     b_ci[2*r+5,2] <- 2*BIC - quantiles[2*r+5,1]
1276     statistic <- c("BIC")
1277     b_ci <- cbind(b_ci[,1:2],statistic)
1278     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1279     b_ci[2*r+5,1], b_ci[2*r+5,2]), sep="", "\n")
1280     if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1281     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1282     if ("RMSE" %in% extras) {
1283       b_ci[2*r+6,1] <- 2*RMSE - quantiles[2*r+6,2]
1284       b_ci[2*r+6,2] <- 2*RMSE - quantiles[2*r+6,1]
1285       statistic <- c("RMSE")
1286       b_ci <- cbind(b_ci[,1:2],statistic)
1287       cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1288       b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1289       if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1290       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1291     }
1292   }
1293 }
1294 if ( !("AIC" %in% extras)) {
1295   if ("BIC" %in% extras) {
1296     b_ci[2*r+4,1] <- 2*BIC - quantiles[2*r+4,2]

```

```

1297 b_ci[2*r+4,2] <- 2*BIC - quantiles[2*r+4,1]
1298 statistic <- c("BIC")
1299 b_ci <- cbind(b_ci[,1:2],statistic)
1300 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1301     b_ci[2*r+4,1], b_ci[2*r+4,2]), sep="", "\n")
1302 if (bar==TRUE) print(ggplot(b_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1303 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1304 if ("RMSE" %in% extras) {
1305     b_ci[2*r+5,1] <- 2*RMSE - quantiles[2*r+5,2]
1306     b_ci[2*r+5,2] <- 2*RMSE - quantiles[2*r+5,1]
1307     statistic <- c("RMSE")
1308     b_ci <- cbind(b_ci[,1:2],statistic)
1309     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1310         b_ci[2*r+5,1], b_ci[2*r+5,2]), sep="", "\n")
1311     if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1312 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1313 }
1314 }
1315 if ( !"BIC" %in% extras) {
1316     if ("RMSE" %in% extras) {
1317         b_ci[2*r+4,1] <- 2*RMSE - quantiles[2*r+4,2]
1318         b_ci[2*r+4,2] <- 2*RMSE - quantiles[2*r+4,1]
1319         statistic <- c("RMSE")
1320         b_ci <- cbind(b_ci[,1:2],statistic)
1321         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1322             b_ci[2*r+4,1], b_ci[2*r+4,2]), sep="", "\n")
1323         if (bar==TRUE) print(ggplot(b_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()

```

```

1324 +ggtitle(paste("Basic Confidence Interval for", statistic))
1325 }
1326 }
1327 }
1328 }
1329 }
1330 }
1331 if ( !("P-value" %in% extras) & !("sigma" %in% extras) ) {
1332   b_ci[r+2,1] <- 2*sd_hat - quantiles[r+2,2]
1333   b_ci[r+2,2] <- 2*sd_hat - quantiles[r+2,1]
1334   statistic <- c("sd")
1335   b_ci <- cbind(b_ci[,1:2], statistic)
1336   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f", b_ci[r+2,1], b_ci[r+2,2]), sep="", "\n")
1337   if (bar==TRUE) print(ggplot(b_ci[r+2, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1338     +ggtitle(paste("Basic Confidence Interval for", statistic))
1339     if ("R^2" %in% extras) {
1340       b_ci[r+3,1] <- 2*R_2 - quantiles[r+3,2]
1341       b_ci[r+3,2] <- 2*R_2 - quantiles[r+3,1]
1342       statistic <- c("R^2")
1343       b_ci <- cbind(b_ci[,1:2], statistic)
1344       cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f", b_ci[r+3,1], b_ci[r+3,2]), sep="", "\n")
1345       if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1346         +ggtitle(paste("Basic Confidence Interval for", statistic))
1347         if ("AIC" %in% extras) {
1348           b_ci[r+4,1] <- 2*AIC - quantiles[r+4,2]
1349           b_ci[r+4,2] <- 2*AIC - quantiles[r+4,1]
1350           statistic <- c("AIC")

```

```

1351 b_ci <- cbind(b_ci[,1:2],statistic)
1352 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]", b_ci[r+4,1], b_ci[r+4,2]), sep="", "\n")
1353 if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1354 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1355 if ("BIC" %in% extras) {
1356     b_ci[r+5,1] <- 2*BIC - quantiles[r+5,2]
1357     b_ci[r+5,2] <- 2*BIC - quantiles[r+5,1]
1358     statistic <- c("BIC")
1359     b_ci <- cbind(b_ci[,1:2],statistic)
1360     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1361         b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1362     if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1363 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1364     if ("RMSE" %in% extras) {
1365         b_ci[r+6,1] <- 2*RMSE - quantiles[r+6,2]
1366         b_ci[r+6,2] <- 2*RMSE - quantiles[r+6,1]
1367         statistic <- c("RMSE")
1368         b_ci <- cbind(b_ci[,1:2],statistic)
1369         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1370             b_ci[r+6,1], b_ci[r+6,2]), sep="", "\n")
1371         if (bar==TRUE) print(ggplot(b_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1372 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1373     }
1374 }
1375 }
1376 if ( !("AIC" %in% extras) ) {
1377     if ("BIC" %in% extras) {

```

```

1378 b_ci[r+4,1] <- 2*BIC - quantiles[r+4,2]
1379 b_ci[r+4,2] <- 2*BIC - quantiles[r+4,1]
1380 statistic <- c("BIC")
1381 b_ci <- cbind(b_ci[,1:2],statistic)
1382 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1383       b_ci[r+4,1], b_ci[r+4,2]), sep=" ", "\n")
1384 if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1385 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1386 if ("RMSE" %in% extras) {
1387   b_ci[r+5,1] <- 2*RMSE - quantiles[r+5,2]
1388   b_ci[r+5,2] <- 2*RMSE - quantiles[r+5,1]
1389   statistic <- c("RMSE")
1390   b_ci <- cbind(b_ci[,1:2],statistic)
1391   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1392     b_ci[r+5,1], b_ci[r+5,2]), sep=" ", "\n")
1393   if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1394 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1395 }
1396 }
1397 if ( !("BIC" %in% extras)) {
1398   if ("RMSE" %in% extras) {
1399     b_ci[r+4,1] <- 2*RMSE - quantiles[r+4,2]
1400     b_ci[r+4,2] <- 2*RMSE - quantiles[r+4,1]
1401     statistic <- c("RMSE")
1402     b_ci <- cbind(b_ci[,1:2],statistic)
1403     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1404       b_ci[r+4,1], b_ci[r+4,2]), sep=" ", "\n")

```

```

1405 if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1406 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1407 }
1408 }
1409 }
1410 }
1411 if ( !("R^2" %in% extras) ) {
1412   if ("AIC" %in% extras) {
1413     b_ci[r+3,1] <- 2 * AIC - quantiles[r+3,2]
1414     b_ci[r+3,2] <- 2 * AIC - quantiles[r+3,1]
1415     statistic <- c("AIC")
1416     b_ci <- cbind(b_ci[, 1:2], statistic)
1417     cat("Basic Confidence Interval for", " ", statistic, ". ", sprintf("[%5f, %5f]", b_ci[r+3,1], b_ci[r+3,2]), sep="", "\n")
1418   if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1419 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1420   if ("BIC" %in% extras) {
1421     b_ci[r+4,1] <- 2 * BIC - quantiles[r+4,2]
1422     b_ci[r+4,2] <- 2 * BIC - quantiles[r+4,1]
1423     statistic <- c("BIC")
1424     b_ci <- cbind(b_ci[, 1:2], statistic)
1425     cat("Basic Confidence Interval for", " ", statistic, ". ", sprintf("[%5f, %5f]",
1426         b_ci[r+4,1], b_ci[r+4,2]), sep="", "\n")
1427   if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1428 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1429   if ("RMSE" %in% extras) {
1430     b_ci[r+5,1] <- 2 * RMSE - quantiles[r+5,2]
1431     b_ci[r+5,2] <- 2 * RMSE - quantiles[r+5,1]

```



```

1432 statistic <- c("RMSE")
1433 b_ci <- cbind(b_ci[,1:2],statistic)
1434 cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f", %5f)",
1435     b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1436 if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1437     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1438 }
1439 }
1440 }
1441 if (!"AIC" %in% extras) {
1442     if ("BIC" %in% extras) {
1443         b_ci[r+3,1] <- 2*BIC - quantiles[r+3,2]
1444         b_ci[r+3,2] <- 2*BIC - quantiles[r+3,1]
1445         statistic <- c("BIC")
1446         b_ci <- cbind(b_ci[,1:2],statistic)
1447         cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f", %5f)",
1448             b_ci[r+3,1], b_ci[r+3,2]), sep="", "\n")
1449         if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1450             +ggtitle(paste("Basic Confidence Interval for", statistic)))
1451         if ("RMSE" %in% extras) {
1452             b_ci[r+4,1] <- 2*RMSE - quantiles[r+4,2]
1453             b_ci[r+4,2] <- 2*RMSE - quantiles[r+4,1]
1454             statistic <- c("RMSE")
1455             b_ci <- cbind(b_ci[,1:2],statistic)
1456             cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f", %5f)",
1457                 b_ci[r+4,1], b_ci[r+4,2]), sep="", "\n")
1458             if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()

```

```

1459         +ggtitle(paste("Basic Confidence Interval for", statistic)))
1460     }
1461 }
1462 if (!("BIC" %in% extras)) {
1463     if ("RMSE" %in% extras) {
1464         b_ci[r+3,1] <- 2*RMSE - quantiles[r+3,2]
1465         b_ci[r+3,2] <- 2*RMSE + quantiles[r+3,1]
1466         statistic <- c("RMSE")
1467         b_ci <- cbind(b_ci[,1:2],statistic)
1468         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1469             b_ci[r+3,1], b_ci[r+3,2]), sep="", "\n")
1470         if (bar==TRUE) print(eggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1471             +ggtitle(paste("Basic Confidence Interval for", statistic)))
1472     }
1473 }
1474 }
1475 }
1476 }
1477 }
1478 }
1479 Table <- cbind( c("C", colnames(z)))
1480 if ("sigma" %in% extras) Table <- cbind(c(Table, "sigma"))
1481 if ("P-value" %in% extras) Table <- cbind(c(Table, Pval_b))
1482 Table <- cbind(c(Table, "sd"))
1483 if ("R^2" %in% extras) Table <- cbind(c(Table, "R^2"))
1484 if ("AIC" %in% extras) Table <- cbind(c(Table, "AIC"))
1485 if ("BIC" %in% extras) Table <- cbind(c(Table, "BIC"))

```

```

1486 if ("RMSE" %in% extras) Table <- cbind(c(Table, "RMSE"))
1487
1488 if (ci=="basic") {
1489   Table <- cbind(Table,
1490     c(coeff_beta, if ("sigma" %in% extras) round(sum(bootstrap_sigma)/L,5), if ("P-value" %in% extras) coeff_Pvalue,
1491     round(sum(bootstrap_sd)/L,5), if ("R^2" %in% extras) round(sum(bootstrap_R_2)/L,5),
1492     if ("AIC" %in% extras) round(sum(bootstrap_AIC)/L,5), if ("BIC" %in% extras) round(sum(bootstrap_BIC)/L,5),
1493     if ("RMSE" %in% extras) round(sum(bootstrap_RMSE)/L,5),
1494     round(b_ci[,1],5),
1495     round(b_ci[,2],5),
1496     c(ifelse(b_ci[1:(r+1),1]<0 & b_ci[1:(r+1),2]>0, "X", "I"),
1497       if ("sigma" %in% extras) c(" "),
1498       if ("P-value" %in% extras) sign_Pvalue,
1499       c(" "),
1500       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==4) c(" ", " ", " ", " "),
1501       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==3) c(" ", " ", " "),
1502       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==2) c(" ", " "),
1503       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==1) c(" ")
1504     )
1505     colnames(Table) <- c("Variable", "Coefficient", "Lower Basic CI", "Upper Basic CI", "Statistical Significance")
1506     View(Table)
1507   }
1508
1509 if (ci=="percentile") {
1510   Table <- cbind(Table,
1511     c(coeff_beta, if ("sigma" %in% extras) round(sum(bootstrap_sigma)/L,5), if ("P-value" %in% extras) coeff_Pvalue,
1512     round(sum(bootstrap_sd)/L,5), if ("R^2" %in% extras) round(sum(bootstrap_R_2)/L,5),

```



```

1540 if ("P-value" %in% extras) sign_Pvalue,
1541 c(" "),
1542 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 4) c(" ", " ", " ", " "),
1543 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 3) c(" ", " ", " "),
1544 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 2) c(" ", " "),
1545 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 1) c(" "),
1546 round(b_ci[,1],5),
1547 round(b_ci[,2],5),
1548 c(ifelse(b_ci[1:(r+1),1] < 0 & b_ci[1:(r+1),2] > 0, "X", "I")),
1549 if ("sigma" %in% extras) c(" "),
1550 if ("P-value" %in% extras) sign_Pvalue,
1551 c(" "),
1552 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 4) c(" ", " ", " ", " "),
1553 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 3) c(" ", " ", " "),
1554 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 2) c(" ", " "),
1555 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 1) c(" ")
1556 )
1557 colnames(Table) <- c("Variable", "Coefficient", "Lower Percentile CI", "Upper Percentile CI", "Statistical Significance",
1558 "Lower Basic CI", "Upper Basic CI", "Statistical Significance")
1559 View(Table)
1560 }
1561 }

```

```

1 Algorithm_2 <- function(x, y, z, RTS="CRS", ORIENTATION="out", L1=100, L2=500, ci="percentile", alpha=0.05, extras=c(), seed=1, histogram=FALSE,
2 bar=FALSE) {
3
4   if ("Benchmarking" %in% rownames(installed.packages()) == FALSE){
5     install.packages("Benchmarking")
6   }
7   library(Benchmarking)
8
9   if ("truncreg" %in% rownames(installed.packages()) == FALSE){
10    install.packages("truncreg")
11  }
12  library(truncreg)
13
14  if ("ggplot2" %in% rownames(installed.packages()) == FALSE){
15    install.packages("ggplot2")
16  }
17  library(ggplot2)
18
19  set.seed(seed)
20
21  if (class(x)!="matrix") x <- as.matrix(x)
22  if (class(y)!="matrix") y <- as.matrix(y)
23  if (class(z)!="matrix") z <- as.matrix(z)
24
25  if (length(colnames(z))!= 0) colnames(z) <- paste0("z",1:ncol(z))
26
27  while (alpha<=0 || alpha>=1) {

```

```

28 alpha <- readline("Choose a relatively small significance level between 0 and 1. e.g.(0.05) ")
29 }
30 alpha <- as.numeric(alpha)
31
32 ## [1] DEA, computation of d^
33 dea <- dea(x, y, RTS = RTS, ORIENTATION = ORIENTATION)
34 d_hat <- eff(dea)
35
36 ## [2] Truncated Regression
37 r <- ncol(z)
38 auxiliary <- c()
39 beta_hat <- c()
40
41 if (ORIENTATION=="out") {
42   d_hat_t <- ifelse(d_hat > 1, d_hat, NA)
43   model_d_hat <- truncreg(d_hat_t ~ z, point = 1, direction = "left")
44 }
45
46 if (ORIENTATION=="in") {
47   d_hat_t <- ifelse(d_hat < 1, d_hat, NA)
48   model_d_hat <- truncreg(d_hat_t ~ z, point = 1, direction = "right")
49 }
50
51 bad <- is.na(d_hat_t)
52 non_na_d_hat_t <- d_hat_t[!bad]
53 trunc_resid <- non_na_d_hat_t - model_d_hat_t$fit.fitted.values
54 sd_hat <- sd(trunc_resid)

```



```

55
56
57 for (i in 2:(r+1)) {
58   beta_hat[i-1] <- model_d_hat$coefficients[i]
59 }
60 ## [3] Bootstrap Loop 1
61 c <- c()
62 zb <- c()
63 n <- nrow(z)
64 d_star <- c()
65
66 ## [3.1] Draws from left-truncated normal distribution
67 for (i in 1:n) {
68   for (j in 1:r) {
69     auxiliary[j] <- z[i,j]*beta_hat[j]
70   }
71   c[i] <- 1 - sum(auxiliary)
72   zb[i] <- sum(auxiliary)
73 }
74
75 cc <- c/sd_hat
76 B <- matrix(nrow=n, ncol=L1)
77 for (j in 1:L1) {
78
79   v <- runif(n, min=0, max=1)
80   vv <- pnorm(cc) + (1 - pnorm(cc))*v
81   u <- sd_hat*qnorm(vv)

```

```

82
83 ## [3.2] computation of d*
84 d_star <- zb + u
85
86 ## [3.3] setting x* and y*
87 x_star <- x
88 y_star <- y * d_hat / d_star
89
90 ## [3.4] DEA, computation of d**
91 dea_2 <- dea(x_star, y_star, RTS = RTS, ORIENTATION = ORIENTATION)
92 d_hat_star <- eff(dea_2)
93
94 for (i in 1:n) {
95     B[i,j] <- d_hat_star[i]
96 }
97
98 ## [4] computation of bias-corrected d**
99 mean_di_hat_star <- c()
100
101 for (i in 1:nrow(B)) {
102     mean_di_hat_star[i] <- mean(B[i, ])
103 }
104
105 bias <- mean_di_hat_star - d_hat
106 d_2hat <- d_hat - bias
107
108 ## [5] estimation of b** and ó**

```

```

109 beta_2hat <- c()
110
111 if (ORIENTATION=="out") {
112     d_2hat_t <- ifelse(d_2hat > 1, d_2hat, NA)
113     model_d_2hat <- truncreg(d_2hat_t ~ z, point = 1, direction = "left")
114 }
115
116 if (ORIENTATION=="in") {
117     d_2hat_t <- ifelse(d_2hat < 1, d_2hat, NA)
118     model_d_2hat <- truncreg(d_2hat_t ~ z, point = 1, direction = "right")
119 }
120
121 bad <- is.na(d_2hat_t)
122 non_na_d_2hat_t <- d_2hat_t[!bad]
123 trunc_resid <- non_na_d_2hat_t - model_d_2hat$fitted.values
124 sd_2hat <- sd(trunc_resid)
125 beta_2hat <- summary(model_d_2hat)$coefficients[1:(r+1),1]
126 if ("sigma" %in% extras) sigma <- summary(model_d_2hat)$coefficients[r+2,1]
127 if ("P-value" %in% extras & "sigma" %in% extras) Pr_z <- summary(model_d_2hat)$coefficients[1:(r+1),4]
128 if ("P-value" %in% extras & !("sigma" %in% extras)) Pr_z <- summary(model_d_2hat)$coefficients[1:(r+1),4]
129 if ("R^2" %in% extras) R_2 <- cor(model_d_2hat$fitted.values, non_na_d_2hat_t)^2
130 if ("AIC" %in% extras) AIC <- -2*model_d_2hat$logLik + 2*length(model_d_2hat$coefficients)
131 if ("BIC" %in% extras) BIC <- -2*model_d_2hat$logLik + log(length(model_d_2hat$fitted.values))*length(model_d_2hat$coefficients)
132 if ("RMSE" %in% extras) RMSE <- sqrt(sum(trunc_resid^2)/length(trunc_resid))
133
134 ## [6] Bootstrap loop 2
135 bootstrap_beta = matrix(nrow=L2, ncol=r+1)

```

```

136 bootstrap_sd = c()
137 bootstrap_sigma = c()
138 bootstrap_R_2 = c()
139 if ("P-value" %in% extras & "sigma" %in% extras) bootstrap_pr_z = matrix(nrow=L2, ncol=r+2)
140 if ("P-value" %in% extras & !("sigma" %in% extras)) bootstrap_pr_z = matrix(nrow=L2, ncol=r+1)
141 if (!("P-value" %in% extras)) bootstrap_pr_z = c()
142 bootstrap_AIC = c()
143 bootstrap_BIC = c()
144 bootstrap_RMSE = c()
145 c_2 <- c()
146 zb_2 <- c()
147 d_2star <- c()
148 beta_2hat_star <- c()
149
150 for ( i in 1:n) {
151   for (j in 1:r) {
152     auxiliary[j] <- z[i,j]*beta_2hat[j+1]
153   }
154   c_2[i] <- 1 - sum(auxiliary)
155   zb_2[i] <- sum(auxiliary)
156 }
157
158 cc_2 <- c_2/sd_2hat
159
160 for (j in 1:L2) {
161   ## [6.1] Draws from left-truncated normal distribution
162   v_2 <- runif(n, min=0, max=1)

```

```

163 vv_2 <- pnorm(cc_2) + (1 - pnorm(cc_2))*v_2
164 u_2 <- sd_2hat*qnorm(vv_2)
165
166 ## [6.2] computation of d**
167 d_2star <- zb_2 + u_2
168
169 ## [6.3] estimation of b^^* and ó^^*
170 if (ORIENTATION=="out") {
171   d_2star_t <- ifelse(d_2star > 1, d_2star, NA)
172   model_d_2star <- truncreg(d_2star_t ~ z, point = 1, direction = "left")
173 }
174
175 if (ORIENTATION=="in") {
176   d_2star_t <- ifelse(d_2star < 1, d_2star, NA)
177   model_d_2star <- truncreg(d_2star_t ~ z, point = 1, direction = "right")
178 }
179
180 bad <- is.na(d_2star_t)
181 non_na_d_2star_t <- d_2star_t[!bad]
182 trunc_resid <- non_na_d_2star_t - model_d_2star$fitted.values
183 sd_2hat_star <- sd(trunc_resid)
184 beta_2hat_star <- summary(model_d_2star)$coefficients[1:(r+1),1]
185 if ("sigma" %in% extras) sigma_star <- summary(model_d_2star)$coefficients[r+2,1]
186 if ("P-value" %in% extras & "sigma" %in% extras) Pr_z_star <- summary(model_d_2star)$coefficients[1:(r+2),4]
187 if ("P-value" %in% extras & !("sigma" %in% extras)) Pr_z_star <- summary(model_d_2star)$coefficients[1:(r+1),4]
188 if ("R^2" %in% extras) R_2_star <- cor(model_d_2star$fitted.values, non_na_d_2star_t)^2
189 if ("AIC" %in% extras) AIC_star <- -2*model_d_2star$logLik + 2*length(model_d_2star$coefficients)

```

```

190 if ("BIC" %in% extras) BIC_star <- -2*model_d_2star$logLik + log(length(model_d_2star$fitted.values))*length(model_d_2star$coefficients)
191 if ("RMSE" %in% extras) RMSE_star <- sqrt(sum(trunc_resid^2)/length(trunc_resid))
192
193 for (i in 1:(r+1)) {
194   bootstrap_beta[j,i] <- beta_2hat_star[i]
195   if ("P-value" %in% extras & !("sigma" %in% extras)) bootstrap_pr_z[j,i] <- Pr_z_star[i]
196 }
197 if ("P-value" %in% extras & "sigma" %in% extras) {
198   for (i in 1:(r+2)) {
199     if ("P-value" %in% extras) bootstrap_pr_z[j,i] <- Pr_z_star[i]
200   }
201 }
202 bootstrap_sd[j] <- sd_2hat_star
203 if ("sigma" %in% extras) bootstrap_sigma[j] <- sigma_star
204 if ("R^2" %in% extras) bootstrap_R_2[j] <- R_2_star
205 if ("AIC" %in% extras) bootstrap_AIC[j] <- AIC_star
206 if ("BIC" %in% extras) bootstrap_BIC[j] <- BIC_star
207 if ("RMSE" %in% extras) bootstrap_RMSE[j] <- RMSE_star
208 }
209 C <- cbind(bootstrap_beta)
210 if ("sigma" %in% extras) C <- cbind(C, bootstrap_sigma)
211 if ("P-value" %in% extras) C <- cbind(C, bootstrap_pr_z)
212 C <- cbind(C, bootstrap_sd)
213 if ("R^2" %in% extras) C <- cbind(C, bootstrap_R_2)
214 if ("AIC" %in% extras) C <- cbind(C, bootstrap_AIC)
215 if ("BIC" %in% extras) C <- cbind(C, bootstrap_BIC)
216 if ("RMSE" %in% extras) C <- cbind(C, bootstrap_RMSE)

```

```

217
218 if (histogram==TRUE) {
219   for (i in 1:ncol(C)) {
220     hist(C[,i])
221   }
222 }
223
224 ## [7] Confidence intervals
225 quantiles <- matrix(nrow=ncol(C), ncol=2)
226
227 for (i in 1:ncol(C)) {
228   for (j in 1:2) {
229     quantiles[i,j] <- quantile(C[,i],c(alpha/2,1-(alpha/2)))[j]
230   }
231 }
232
233 bootstrap_beta <- as.data.frame(bootstrap_beta)
234 bootstrap_pr_z <- as.data.frame(bootstrap_pr_z)
235 coeff_beta <- round(sapply(bootstrap_beta, sum)/L2,5)
236 names(coeff_beta) <- NULL
237 if ("P-value" %in% extras) {
238   coeff_Pvalue <- round(sapply(bootstrap_pr_z, sum)/L2,5)
239   names(coeff_Pvalue) <- NULL
240 }
241
242 statistic <- c()
243 ## Percentile Confidence Intervals

```



```

244 if (ci=="percentile" | ci=="all") {
245   p_ci <- matrix(nrow=ncol(C), ncol=2)
246   p_ci <- as.data.frame(p_ci)
247   for (i in 1:(r+1)) {
248     p_ci[i,1] <- quantiles[i,1]
249     p_ci[i,2] <- quantiles[i,2]
250     statistic <- paste0("b", i-1)
251     p_ci <- cbind(p_ci[,1:2], statistic)
252     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]", p_ci[i,1], p_ci[i,2]), sep="", "\n")
253     if (bar==TRUE) print(ggplot(p_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
254       +ggtitle(paste("Percentile Confidence Interval for", statistic))+geom_hline(yintercept=0, color="red", linetype = "longdash"))
255   }
256   if ("sigma" %in% extras) {
257     p_ci[r+2,1] <- quantiles[r+2,1]
258     p_ci[r+2,2] <- quantiles[r+2,2]
259     statistic <- c("sigma")
260     p_ci <- cbind(p_ci[,1:2], statistic)
261     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]", p_ci[r+2,1], p_ci[r+2,2]), sep="", "\n")
262     if (bar==TRUE) print(ggplot(p_ci[r+2, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
263       +ggtitle(paste("Percentile Confidence Interval for", statistic))+geom_hline(yintercept=0, color="red", linetype = "longdash"))
264     if ("P-value" %in% extras) {
265       Pval_b <- c()
266       sign_Pvalue <- c()
267       for (i in (r+3):(2*r+4)) {
268         p_ci[i,1] <- quantiles[i,1]
269         p_ci[i,2] <- quantiles[i,2]
270         statistic <- paste0("P-value(b", i-r-3, ")")

```

```

271 Pval_b[i-r-2] <- statistic
272 p_ci <- cbind(p_ci[,1:2],statistic)
273 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]", p_ci[i,1], p_ci[i,2]), sep="", "\n")
274 if (bar==TRUE) print(ggplot(p_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
275 +ggtitle(paste("Percentile Confidence Interval for", statistic))
276 +geom_hline(yintercept=0, color="red", linetype = "longdash"))
277 if (coeff_Pvalue[i-r-2] >0.1) sign_Pvalue[i-r-2] <- " "
278 if (coeff_Pvalue[i-r-2] <=0.1 & coeff_Pvalue[i-r-2] >0.05) sign_Pvalue[i-r-2] <- "*"
279 if (coeff_Pvalue[i-r-2] <=0.05 & coeff_Pvalue[i-r-2] >0.01) sign_Pvalue[i-r-2] <- "***"
280 if (coeff_Pvalue[i-r-2] <=0.01) sign_Pvalue[i-r-2] <- "****"
281
282 }
283 p_ci[2*r+5,1] <- quantiles[2*r+5,1]
284 p_ci[2*r+5,2] <- quantiles[2*r+5,2]
285 statistic <- c("sd")
286 p_ci <- cbind(p_ci[,1:2],statistic)
287 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]", p_ci[2*r+5,1], p_ci[2*r+5,2]), sep="", "\n")
288 if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
289 +ggtitle(paste("Percentile Confidence Interval for", statistic))
290 if ("R^2" %in% extras) {
291 p_ci[2*r+6,1] <- quantiles[2*r+6,1]
292 p_ci[2*r+6,2] <- quantiles[2*r+6,2]
293 statistic <- c("R^2")
294 p_ci <- cbind(p_ci[,1:2],statistic)
295 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
296 p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
297 if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
298 +ggtitle(paste("Percentile Confidence Interval for", statistic)))

```

```

298   if ("AIC" %in% extras) {
299     p_ci[2*r+7,1] <- quantiles[2*r+7,1]
300     p_ci[2*r+7,2] <- quantiles[2*r+7,2]
301     statistic <- c("AIC")
302     p_ci <- cbind(p_ci[,1:2], statistic)
303     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f", %5f)",
304         p_ci[2*r+7,1], p_ci[2*r+7,2]), sep=" ", "\n")
305     if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
306 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
307     if ("BIC" %in% extras) {
308       p_ci[2*r+8,1] <- quantiles[2*r+8,1]
309       p_ci[2*r+8,2] <- quantiles[2*r+8,2]
310       statistic <- c("BIC")
311       p_ci <- cbind(p_ci[,1:2], statistic)
312       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f", %5f)",
313         p_ci[2*r+8,1], p_ci[2*r+8,2]), sep=" ", "\n")
314       if (bar==TRUE) print(ggplot(p_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
315 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
316       if ("RMSE" %in% extras) {
317         p_ci[2*r+9,1] <- quantiles[2*r+9,1]
318         p_ci[2*r+9,2] <- quantiles[2*r+9,2]
319         statistic <- c("RMSE")
320         p_ci <- cbind(p_ci[,1:2], statistic)
321         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f", %5f)",
322           p_ci[2*r+9,1], p_ci[2*r+9,2]), sep=" ", "\n")
323         if (bar==TRUE) print(ggplot(p_ci[2*r+9, ], aes(statistic, ymin = V1, ymax = V2))
324 +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))

```

```

325     }
326   }
327 }
328 if ( !("AIC" %in% extras) ) {
329   if ("BIC" %in% extras) {
330     p_ci[2*r+7,1] <- quantiles[2*r+7,1]
331     p_ci[2*r+7,2] <- quantiles[2*r+7,2]
332     statistic <- c("BIC")
333     p_ci <- cbind(p_ci[,1:2],statistic)
334     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
335       p_ci[2*r+7,1], p_ci[2*r+7,2]), sep=" ", "\n")
336     if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
337       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
338     if ("RMSE" %in% extras) {
339       p_ci[2*r+8,1] <- quantiles[2*r+8,1]
340       p_ci[2*r+8,2] <- quantiles[2*r+8,2]
341       statistic <- c("RMSE")
342       p_ci <- cbind(p_ci[,1:2],statistic)
343       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
344         p_ci[2*r+8,1], p_ci[2*r+8,2]), sep=" ", "\n")
345       if (bar==TRUE) print(ggplot(p_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))
346         +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
347     }
348   }
349   if ( !("BIC" %in% extras) ) {
350     if ("RMSE" %in% extras) {
351       p_ci[2*r+7,1] <- quantiles[2*r+7,1]

```

```

352 p_ci[2*r+7,2] <- quantiles[2*r+7,2]
353 statistic <- c("RMSE")
354 p_ci <- cbind(p_ci[,1:2],statistic)
355 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
356     p_ci[2*r+7,1], p_ci[2*r+7,2]), sep=" ", "\n")
357 if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))
358     +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
359 }
360 }
361 }
362 }
363 if ( !("R^2" %in% extras)) {
364   if ("AIC" %in% extras) {
365     p_ci[2*r+6,1] <- quantiles[2*r+6,1]
366     p_ci[2*r+6,2] <- quantiles[2*r+6,2]
367     statistic <- c("AIC")
368     p_ci <- cbind(p_ci[,1:2],statistic)
369     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
370         p_ci[2*r+6,1], p_ci[2*r+6,2]), sep=" ", "\n")
371     if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
372         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
373     if ("BIC" %in% extras) {
374       p_ci[2*r+7,1] <- quantiles[2*r+7,1]
375       p_ci[2*r+7,2] <- quantiles[2*r+7,2]
376       statistic <- c("BIC")
377       p_ci <- cbind(p_ci[,1:2],statistic)
378       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",

```

```

379   p_ci[2*r+7,1], p_ci[2*r+7,2]), sep="", "\n")
380   if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
381   +ggtitle(paste("Percentile Confidence Interval for", statistic)))
382   if ("RMSE" %in% extras) {
383     p_ci[2*r+8,1] <- quantiles[2*r+8,1]
384     p_ci[2*r+8,2] <- quantiles[2*r+8,2]
385     statistic <- c("RMSE")
386     p_ci <- cbind(p_ci[, 1:2], statistic)
387     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f", %5f",
388         p_ci[2*r+8,1], p_ci[2*r+8,2]), sep="", "\n")
389     if (bar==TRUE) print(ggplot(p_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))
390     +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
391   }
392 }
393 }
394 if ( !("AIC" %in% extras)) {
395   if ("BIC" %in% extras) {
396     p_ci[2*r+6,1] <- quantiles[2*r+6,1]
397     p_ci[2*r+6,2] <- quantiles[2*r+6,2]
398     statistic <- c("BIC")
399     p_ci <- cbind(p_ci[, 1:2], statistic)
400     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f", %5f",
401         p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
402     if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
403     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
404     if ("RMSE" %in% extras) {
405       p_ci[2*r+7,1] <- quantiles[2*r+7,1]

```

```

406 p_ci[2*r+7,2] <- quantiles[2*r+7,2]
407 statistic <- c("RMSE")
408 p_ci <- cbind(p_ci[,1:2],statistic)
409 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
410     p_ci[2*r+7,1], p_ci[2*r+7,2]), sep="", "\n")
411 if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))
412     +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
413     }
414   }
415   if ( !("BIC" %in% extras) ) {
416     if ("RMSE" %in% extras) {
417       p_ci[2*r+6,1] <- quantiles[2*r+6,1]
418       p_ci[2*r+6,2] <- quantiles[2*r+6,2]
419       statistic <- c("RMSE")
420       p_ci <- cbind(p_ci[,1:2],statistic)
421       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
422         p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
423       if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))
424         +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
425     }
426   }
427 }
428 }
429 }
430 }
431 if ( !("P-value" %in% extras) ) {
432   p_ci[r+3,1] <- quantiles[r+3,1]

```



```

433 p_ci[r+3,2] <- quantiles[r+3,2]
434 statistic <- c("sd")
435 p_ci <- cbind(p_ci[,1:2],statistic)
436 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f", p_ci[r+3,1]), p_ci[r+3,2]), sep=" ", "\n")
437 if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
438 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
439 if ("R^2" %in% extras) {
440   p_ci[r+4,1] <- quantiles[r+4,1]
441   p_ci[r+4,2] <- quantiles[r+4,2]
442   statistic <- c("R^2")
443   p_ci <- cbind(p_ci[,1:2],statistic)
444   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f",
445     p_ci[r+4,1]), p_ci[r+4,2]), sep=" ", "\n")
446   if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))
447   +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
448   if ("AIC" %in% extras) {
449     p_ci[r+5,1] <- quantiles[r+5,1]
450     p_ci[r+5,2] <- quantiles[r+5,2]
451     statistic <- c("AIC")
452     p_ci <- cbind(p_ci[,1:2],statistic)
453     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f",
454       p_ci[r+5,1]), p_ci[r+5,2]), sep=" ", "\n")
455     if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
456     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
457     if ("BIC" %in% extras) {
458       p_ci[r+6,1] <- quantiles[r+6,1]
459       p_ci[r+6,2] <- quantiles[r+6,2]

```

```

460 statistic <- c("BIC")
461 p_ci <- cbind(p_ci[,1:2],statistic)
462 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
463     p_ci[r+6,1], p_ci[r+6,2]), sep=" ", "\n")
464 if (bar==TRUE) print(ggplot(p_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
465     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
466     if ("RMSE" %in% extras) {
467         p_ci[r+7,1] <- quantiles[r+7,1]
468         p_ci[r+7,2] <- quantiles[r+7,2]
469         statistic <- c("RMSE")
470         p_ci <- cbind(p_ci[,1:2],statistic)
471         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
472             p_ci[r+7,1], p_ci[r+7,2]), sep=" ", "\n")
473         if (bar==TRUE) print(ggplot(p_ci[r+7, ], aes(statistic, ymin = V1, ymax = V2))
474             +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
475     }
476 }
477 }
478 if ( !"AIC" %in% extras) {
479     if ("BIC" %in% extras) {
480         p_ci[r+5,1] <- quantiles[r+5,1]
481         p_ci[r+5,2] <- quantiles[r+5,2]
482         statistic <- c("BIC")
483         p_ci <- cbind(p_ci[,1:2],statistic)
484         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
485             p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
486         if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(

```

```

487 +ggtitle(paste("Percentile Confidence Interval for", statistic))
488 if ("RMSE" %in% extras) {
489   p_ci[r+6,1] <- quantiles[r+6,1]
490   p_ci[r+6,2] <- quantiles[r+6,2]
491   statistic <- c("RMSE")
492   p_ci <- cbind(p_ci[,1:2], statistic)
493   cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f, %.5f)",
494       p_ci[r+6,1], p_ci[r+6,2]), sep=" ", "\n")
495   if (bar==TRUE) print(ggplot(p_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))
496       +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
497   }
498 }
499 if ( !("BIC" %in% extras)) {
500   if ("RMSE" %in% extras) {
501     p_ci[r+5,1] <- quantiles[r+5,1]
502     p_ci[r+5,2] <- quantiles[r+5,2]
503     statistic <- c("RMSE")
504     p_ci <- cbind(p_ci[,1:2], statistic)
505     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("%.5f, %.5f)",
506         p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
507     if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
508         +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
509   }
510 }
511 }
512 }
513 if ( !("R^2" %in% extras)) {

```

```

514 if ("AIC" %in% extras) {
515   p_ci[r+4,1] <- quantiles[r+4,1]
516   p_ci[r+4,2] <- quantiles[r+4,2]
517   statistic <- c("AIC")
518   p_ci <- cbind(p_ci[,1:2],statistic)
519   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
520     p_ci[r+4,1], p_ci[r+4,2]), sep=" ", "\n")
521   if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
522     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
523   if ("BIC" %in% extras) {
524     p_ci[r+5,1] <- quantiles[r+5,1]
525     p_ci[r+5,2] <- quantiles[r+5,2]
526     statistic <- c("BIC")
527     p_ci <- cbind(p_ci[,1:2],statistic)
528     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
529       p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
530     if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
531       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
532     if ("RMSE" %in% extras) {
533       p_ci[r+6,1] <- quantiles[r+6,1]
534       p_ci[r+6,2] <- quantiles[r+6,2]
535       statistic <- c("RMSE")
536       p_ci <- cbind(p_ci[,1:2],statistic)
537       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
538         p_ci[r+6,1], p_ci[r+6,2]), sep=" ", "\n")
539       if (bar==TRUE) print(ggplot(p_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))
540         +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))

```

```

541     }
542   }
543 }
544 if ( !("AIC" %in% extras) ) {
545   if ("BIC" %in% extras) {
546     p_ci[r+4,1] <- quantiles[r+4,1]
547     p_ci[r+4,2] <- quantiles[r+4,2]
548     statistic <- c("BIC")
549     p_ci <- cbind(p_ci[,1:2], statistic)
550     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%0.5f, %0.5f]",
551       p_ci[r+4,1], p_ci[r+4,2]), sep=" ", "\n")
552     if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
553       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
554     if ("RMSE" %in% extras) {
555       p_ci[r+5,1] <- quantiles[r+5,1]
556       p_ci[r+5,2] <- quantiles[r+5,2]
557       statistic <- c("RMSE")
558       p_ci <- cbind(p_ci[,1:2], statistic)
559       cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%0.5f, %0.5f]",
560         p_ci[r+5,1], p_ci[r+5,2]), sep=" ", "\n")
561       if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
562         +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
563     }
564   }
565   if ( !("BIC" %in% extras) ) {
566     if ("RMSE" %in% extras) {
567       p_ci[r+4,1] <- quantiles[r+4,1]

```

```

568 p_ci[r+4,2] <- quantiles[r+4,2]
569 statistic <- c("RMSE")
570 p_ci <- cbind(p_ci[,1:2],statistic)
571 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
572     p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
573 if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))
574     +geom_errorbar()+ggtitle(paste("Percentile Confidence Interval for", statistic)))
575 }
576 }
577 }
578 }
579 }
580 }
581 }
582 if ("P-value" %in% extras & !("sigma" %in% extras)) {
583   Pval_b <- c()
584   sign_Pvalue <- c()
585   for (i in (r+2):(2*r+2)) {
586     p_ci[i,1] <- quantiles[i,1]
587     p_ci[i,2] <- quantiles[i,2]
588     statistic <- paste0("P-value(b", i-r-2, ")")
589     Pval_b[i-r-1] <- statistic
590     p_ci <- cbind(p_ci[,1:2],statistic)
591     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]", p_ci[i,1], p_ci[i,2]), sep="", "\n")
592     if (bar==TRUE) print(ggplot(p_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
593         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
594     if (coeff_Pvalue[i-r-1] > 0.1) sign_Pvalue[i-r-1] <- "-"

```

```

595   if (coeff_Pvalue[i-r-1] <=0.1 & coeff_Pvalue[i-r-1] >0.05) sign_Pvalue[i-r-1] <- "*"
596   if (coeff_Pvalue[i-r-1] <=0.05 & coeff_Pvalue[i-r-1] >0.01) sign_Pvalue[i-r-1] <- "***"
597   if (coeff_Pvalue[i-r-1] <=0.01) sign_Pvalue[i-r-1] <- "****"
598
599   p_ci[2*r+3,1] <- quantiles[2*r+3,1]
600   p_ci[2*r+3,2] <- quantiles[2*r+3,2]
601   statistic <- c("sd")
602   p_ci <- cbind(p_ci[,1:2],statistic)
603   cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%.5f", p_ci[2*r+3,1], p_ci[2*r+3,2]), sep="", "\n")
604   if (bar==TRUE) print(ggplot(p_ci[2*r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
605   +ggtitle(paste("Percentile Confidence Interval for", statistic)))
606   if ("R^2" %in% extras) {
607     p_ci[2*r+4,1] <- quantiles[2*r+4,1]
608     p_ci[2*r+4,2] <- quantiles[2*r+4,2]
609     statistic <- c("R^2")
610     p_ci <- cbind(p_ci[,1:2],statistic)
611     cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%.5f", p_ci[2*r+4,1], p_ci[2*r+4,2]), sep="", "\n")
612     if (bar==TRUE) print(ggplot(p_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
613     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
614     if ("AIC" %in% extras) {
615       p_ci[2*r+5,1] <- quantiles[2*r+5,1]
616       p_ci[2*r+5,2] <- quantiles[2*r+5,2]
617       statistic <- c("AIC")
618       p_ci <- cbind(p_ci[,1:2],statistic)
619       cat("Percentile Confidence Interval for", " ", statistic, ":", " ", sprintf("[%.5f", %5f]",
620       p_ci[2*r+5,1], p_ci[2*r+5,2]), sep="", "\n")
621       if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()

```



```

622 +ggtitle(paste("Percentile Confidence Interval for", statistic))
623 if ("BIC" %in% extras) {
624   p_ci[2*r+6,1] <- quantiles[2*r+6,1]
625   p_ci[2*r+6,2] <- quantiles[2*r+6,2]
626   statistic <- c("BIC")
627   p_ci <- cbind(p_ci[,1:2], statistic)
628   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
629     p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
630   if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
631     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
632   if ("RMSE" %in% extras) {
633     p_ci[2*r+7,1] <- quantiles[2*r+7,1]
634     p_ci[2*r+7,2] <- quantiles[2*r+7,2]
635     statistic <- c("RMSE")
636     p_ci <- cbind(p_ci[,1:2], statistic)
637     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
638       p_ci[2*r+7,1], p_ci[2*r+7,2]), sep="", "\n")
639     if (bar==TRUE) print(ggplot(p_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
640       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
641   }
642 }
643 }
644 if (!("AIC" %in% extras)) {
645   if ("BIC" %in% extras) {
646     p_ci[2*r+5,1] <- quantiles[2*r+5,1]
647     p_ci[2*r+5,2] <- quantiles[2*r+5,2]
648     statistic <- c("BIC")

```

```

649 p_ci <- cbind(p_ci[,1:2],statistic)
650 cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
651     p_ci[2*r+5,1], p_ci[2*r+5,2]), sep=" ", "\n")
652 if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
653 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
654 if ("RMSE" %in% extras) {
655     p_ci[2*r+6,1] <- quantiles[2*r+6,1]
656     p_ci[2*r+6,2] <- quantiles[2*r+6,2]
657     statistic <- c("RMSE")
658     p_ci <- cbind(p_ci[,1:2],statistic)
659     cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
660         p_ci[2*r+6,1], p_ci[2*r+6,2]), sep=" ", "\n")
661     if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
662 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
663 }
664 }
665 if ( !("BIC" %in% extras)) {
666     if ("RMSE" %in% extras) {
667         p_ci[2*r+5,1] <- quantiles[2*r+5,1]
668         p_ci[2*r+5,2] <- quantiles[2*r+5,2]
669         statistic <- c("RMSE")
670         p_ci <- cbind(p_ci[,1:2],statistic)
671         cat("Percentile Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
672             p_ci[2*r+5,1], p_ci[2*r+5,2]), sep=" ", "\n")
673         if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
674 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
675     }

```

```

676     }
677   }
678 }
679 if ( !("R^2" %in% extras) ) {
680   if ("AIC" %in% extras) {
681     p_ci[2*r+4,1] <- quantiles[2*r+4,1]
682     p_ci[2*r+4,2] <- quantiles[2*r+4,2]
683     statistic <- c("AIC")
684     p_ci <- cbind(p_ci[,1:2],statistic)
685     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
686       p_ci[2*r+4,1], p_ci[2*r+4,2]), sep=" ", "\n")
687     if (bar==TRUE) print(ggplot(p_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
688       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
689     if ("BIC" %in% extras) {
690       p_ci[2*r+5,1] <- quantiles[2*r+5,1]
691       p_ci[2*r+5,2] <- quantiles[2*r+5,2]
692       statistic <- c("BIC")
693       p_ci <- cbind(p_ci[,1:2],statistic)
694       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
695         p_ci[2*r+5,1], p_ci[2*r+5,2]), sep=" ", "\n")
696       if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
697         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
698       if ("RMSE" %in% extras) {
699         p_ci[2*r+6,1] <- quantiles[2*r+6,1]
700         p_ci[2*r+6,2] <- quantiles[2*r+6,2]
701         statistic <- c("RMSE")
702         p_ci <- cbind(p_ci[,1:2],statistic)

```

```

703   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
704       p_ci[2*r+6,1], p_ci[2*r+6,2]), sep="", "\n")
705   if (bar==TRUE) print(ggplot(p_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
706       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
707   }
708   }
709   }
710   if ( !("AIC" %in% extras) ) {
711     if ("BIC" %in% extras) {
712       p_ci[2*r+4,1] <- quantiles[2*r+4,1]
713       p_ci[2*r+4,2] <- quantiles[2*r+4,2]
714       statistic <- c("BIC")
715       p_ci <- cbind(p_ci[,1:2],statistic)
716       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
717           p_ci[2*r+4,1], p_ci[2*r+4,2]), sep="", "\n")
718       if (bar==TRUE) print(ggplot(p_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
719           +ggtitle(paste("Percentile Confidence Interval for", statistic)))
720       if ("RMSE" %in% extras) {
721         p_ci[2*r+5,1] <- quantiles[2*r+5,1]
722         p_ci[2*r+5,2] <- quantiles[2*r+5,2]
723         statistic <- c("RMSE")
724         p_ci <- cbind(p_ci[,1:2],statistic)
725         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
726             p_ci[2*r+5,1], p_ci[2*r+5,2]), sep="", "\n")
727         if (bar==TRUE) print(ggplot(p_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
728             +ggtitle(paste("Percentile Confidence Interval for", statistic)))
729       }

```

```

730 }
731 if ( !("BIC" %in% extras) ) {
732   if ("RMSE" %in% extras) {
733     p_ci[2*r+4,1] <- quantiles[2*r+4,1]
734     p_ci[2*r+4,2] <- quantiles[2*r+4,2]
735     statistic <- c("RMSE")
736     p_ci <- cbind(p_ci[,1:2],statistic)
737     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
738       p_ci[2*r+4,1], p_ci[2*r+4,2]), sep=" ", "\n")
739     if (bar==TRUE) print(ggplot(p_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
740       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
741   }
742 }
743 }
744 }
745 }
746 }
747 if ( !("P-value" %in% extras) & !("sigma" %in% extras) ) {
748   p_ci[r+2,1] <- quantiles[r+2,1]
749   p_ci[r+2,2] <- quantiles[r+2,2]
750   statistic <- c("sd")
751   p_ci <- cbind(p_ci[,1:2],statistic)
752   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]", p_ci[r+2,1], p_ci[r+2,2]), sep=" ", "\n")
753   if (bar==TRUE) print(ggplot(p_ci[r+2, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
754     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
755   if ("R^2" %in% extras) {
756     p_ci[r+3,1] <- quantiles[r+3,1]

```

```

757 p_ci[r+3,2] <- quantiles[r+3,2]
758 statistic <- c("R^2")
759 p_ci <- cbind(p_ci[,1:2], statistic)
760 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f", p_ci[r+3,1], p_ci[r+3,2]), sep="", "\n")
761 if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
762 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
763 if ("AIC" %in% extras) {
764   p_ci[r+4,1] <- quantiles[r+4,1]
765   p_ci[r+4,2] <- quantiles[r+4,2]
766   statistic <- c("AIC")
767   p_ci <- cbind(p_ci[,1:2], statistic)
768   cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f",
769     p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
770   if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
771   +ggtitle(paste("Percentile Confidence Interval for", statistic)))
772   if ("BIC" %in% extras) {
773     p_ci[r+5,1] <- quantiles[r+5,1]
774     p_ci[r+5,2] <- quantiles[r+5,2]
775     statistic <- c("BIC")
776     p_ci <- cbind(p_ci[,1:2], statistic)
777     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f",
778       p_ci[r+5,1], p_ci[r+5,2]), sep="", "\n")
779     if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
780     +ggtitle(paste("Percentile Confidence Interval for", statistic)))
781     if ("RMSE" %in% extras) {
782       p_ci[r+6,1] <- quantiles[r+6,1]
783       p_ci[r+6,2] <- quantiles[r+6,2]

```

```

784     statistic <- c("RMSE")
785     p_ci <- cbind(p_ci[,1:2], statistic)
786     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
787         p_ci[r+6,1], p_ci[r+6,2]), sep="", "\n")
788     if (bar==TRUE) print(ggplot(p_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
789         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
790 }
791 }
792 }
793 if ( !("AIC" %in% extras) ) {
794     if ("BIC" %in% extras) {
795         p_ci[r+4,1] <- quantiles[r+4,1]
796         p_ci[r+4,2] <- quantiles[r+4,2]
797         statistic <- c("BIC")
798         p_ci <- cbind(p_ci[,1:2], statistic)
799         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
800             p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
801         if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
802             +ggtitle(paste("Percentile Confidence Interval for", statistic)))
803         if ("RMSE" %in% extras) {
804             p_ci[r+5,1] <- quantiles[r+5,1]
805             p_ci[r+5,2] <- quantiles[r+5,2]
806             statistic <- c("RMSE")
807             p_ci <- cbind(p_ci[,1:2], statistic)
808             cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
809                 p_ci[r+5,1], p_ci[r+5,2]), sep="", "\n")
810             if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()

```



```

811 +ggtitle(paste("Percentile Confidence Interval for", statistic))
812 }
813 }
814 if ( !("BIC" %in% extras) ) {
815   if ("RMSE" %in% extras) {
816     p_ci[r+4,1] <- quantiles[r+4,1]
817     p_ci[r+4,2] <- quantiles[r+4,2]
818     statistic <- c("RMSE")
819     p_ci <- cbind(p_ci[,1:2], statistic)
820     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f, %.5f",
821       p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
822     if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
823       +ggtitle(paste("Percentile Confidence Interval for", statistic)))
824   }
825 }
826 }
827 }
828 if ( !("R^2" %in% extras) ) {
829   if ("AIC" %in% extras) {
830     p_ci[r+3,1] <- quantiles[r+3,1]
831     p_ci[r+3,2] <- quantiles[r+3,2]
832     statistic <- c("AIC")
833     p_ci <- cbind(p_ci[,1:2], statistic)
834     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("%.5f, %.5f",
835       p_ci[r+3,1], p_ci[r+3,2]), sep="", "\n")
836     if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
837       +ggtitle(paste("Percentile Confidence Interval for", statistic)))

```

```

838   if ("BIC" %in% extras) {
839     p_ci[r+4,1] <- quantiles[r+4,1]
840     p_ci[r+4,2] <- quantiles[r+4,2]
841     statistic <- c("BIC")
842     p_ci <- cbind(p_ci[,1:2], statistic)
843     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
844         p_ci[r+4,1], p_ci[r+4,2]), sep="", "\n")
845     if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
846         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
847     if ("RMSE" %in% extras) {
848       p_ci[r+5,1] <- quantiles[r+5,1]
849       p_ci[r+5,2] <- quantiles[r+5,2]
850       statistic <- c("RMSE")
851       p_ci <- cbind(p_ci[,1:2], statistic)
852       cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
853         p_ci[r+5,1], p_ci[r+5,2]), sep="", "\n")
854       if (bar==TRUE) print(ggplot(p_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
855         +ggtitle(paste("Percentile Confidence Interval for", statistic)))
856     }
857   }
858 }
859 if (!("AIC" %in% extras)) {
860   if ("BIC" %in% extras) {
861     p_ci[r+3,1] <- quantiles[r+3,1]
862     p_ci[r+3,2] <- quantiles[r+3,2]
863     statistic <- c("BIC")
864     p_ci <- cbind(p_ci[,1:2], statistic)

```

```

865 cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
866     p_ci[r+3,1], p_ci[r+3,2]), sep=" ", "\n")
867 if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
868 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
869 if ("RMSE" %in% extras) {
870     p_ci[r+4,1] <- quantiles[r+4,1]
871     p_ci[r+4,2] <- quantiles[r+4,2]
872     statistic <- c("RMSE")
873     p_ci <- cbind(p_ci[,1:2],statistic)
874     cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
875         p_ci[r+4,1], p_ci[r+4,2]), sep=" ", "\n")
876     if (bar==TRUE) print(ggplot(p_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
877 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
878 }
879 }
880 if ( !("BIC" %in% extras)) {
881     if ("RMSE" %in% extras) {
882         p_ci[r+3,1] <- quantiles[r+3,1]
883         p_ci[r+3,2] <- quantiles[r+3,2]
884         statistic <- c("RMSE")
885         p_ci <- cbind(p_ci[,1:2],statistic)
886         cat("Percentile Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
887             p_ci[r+3,1], p_ci[r+3,2]), sep=" ", "\n")
888         if (bar==TRUE) print(ggplot(p_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
889 +ggtitle(paste("Percentile Confidence Interval for", statistic)))
890     }
891 }

```

```

892     }
893   }
894 }
895 }
896
897 ## Basic Confidence Intervals
898 if (ci=="basic" || ci=="all") {
899   b_ci <- matrix(nrow=ncol(C), ncol=2)
900   b_ci <- as.data.frame(b_ci)
901   for (i in 1:(r+1)) {
902     b_ci[i,1] <- 2*beta_2hat[i] - quantiles[i,2]
903     b_ci[i,2] <- 2*beta_2hat[i] - quantiles[i,1]
904     statistic <- paste0("b",i-1)
905     b_ci <- cbind(b_ci[,1:2],statistic)
906     cat("Basic Confidence Interval for", " ", statistic, ".: ", sprintf("[%5f, %5f]", b_ci[i,1], b_ci[i,2]), sep="", "\n")
907     if (bar==TRUE) print(ggplot(b_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
908       +ggtitle(paste("Basic Confidence Interval for", statistic))+geom_hline(yintercept=0, color="red", linetype = "longdash"))
909   )
910   if ("sigma" %in% extras) {
911     b_ci[r+2,1] <- 2*sigma - quantiles[r+2,2]
912     b_ci[r+2,2] <- 2*sigma - quantiles[r+2,1]
913     statistic <- c("sigma")
914     b_ci <- cbind(b_ci[,1:2],statistic)
915     cat("Basic Confidence Interval for", " ", statistic, ".: ", sprintf("[%5f, %5f]", b_ci[r+2,1], b_ci[r+2,2]), sep="", "\n")
916     if (bar==TRUE) print(ggplot(b_ci[r+2, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
917       +ggtitle(paste("Basic Confidence Interval for", statistic)))
918     if ("P-value" %in% extras) {

```

```

919 Pval_b <- c()
920 sign_Pvalue <- c()
921 for (i in (r+3):(2*r+4)) {
922   b_ci[i,1] <- 2*Pr_z[i-r-2] - quantiles[i,2]
923   b_ci[i,2] <- 2*Pr_z[i-r-2] - quantiles[i,1]
924   statistic <- paste0("P-value(b", i-r-3, ")")
925   Pval_b[i-r-2] <- statistic
926   b_ci <- cbind(b_ci[,1:2], statistic)
927   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("%.5f", b_ci[i,1]), b_ci[i,2]), sep=" ", "\n")
928   if (bar==TRUE) print(ggplot(b_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
929     +ggtitle(paste("Basic Confidence Interval for", statistic)))
930   if (coeff_Pvalue[i-r-2] >0.1) sign_Pvalue[i-r-2] <- " "
931   if (coeff_Pvalue[i-r-2] <=0.1 & coeff_Pvalue[i-r-2] >0.05) sign_Pvalue[i-r-2] <- "*"
932   if (coeff_Pvalue[i-r-2] <=0.05 & coeff_Pvalue[i-r-2] >0.01) sign_Pvalue[i-r-2] <- "***"
933   if (coeff_Pvalue[i-r-2] <=0.01) sign_Pvalue[i-r-2] <- "****"
934 }
935 b_ci[2*r+5,1] <- 2*sd_2hat - quantiles[2*r+5,2]
936 b_ci[2*r+5,2] <- 2*sd_2hat - quantiles[2*r+5,1]
937 statistic <- c("sd")
938 b_ci <- cbind(b_ci[,1:2], statistic)
939 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("%.5f", b_ci[2*r+5,1]), b_ci[2*r+5,2]), sep=" ", "\n")
940 if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
941   +ggtitle(paste("Basic Confidence Interval for", statistic)))
942 if ("R^2" %in% extras) {
943   b_ci[2*r+6,1] <- 2*R_2 - quantiles[2*r+6,2]
944   b_ci[2*r+6,2] <- 2*R_2 - quantiles[2*r+6,1]
945   statistic <- c("R^2")

```

```

946 b_ci <- cbind(b_ci[,1:2],statistic)
947 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
948     b_ci[2*r+6,1], b_ci[2*r+6,2]), sep=" ", "\n")
949 if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
950 +ggtitle(paste("Basic Confidence Interval for", statistic)))
951 if ("AIC" %in% extras) {
952     b_ci[2*r+7,1] <- 2*AIC - quantiles[2*r+7,2]
953     b_ci[2*r+7,2] <- 2*AIC - quantiles[2*r+7,1]
954     statistic <- c("AIC")
955     b_ci <- cbind(b_ci[,1:2],statistic)
956     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
957         b_ci[2*r+7,1], b_ci[2*r+7,2]), sep=" ", "\n")
958     if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
959 +ggtitle(paste("Basic Confidence Interval for", statistic)))
960     if ("BIC" %in% extras) {
961         b_ci[2*r+8,1] <- 2*BIC - quantiles[2*r+8,2]
962         b_ci[2*r+8,2] <- 2*BIC - quantiles[2*r+8,1]
963         statistic <- c("BIC")
964         b_ci <- cbind(b_ci[,1:2],statistic)
965         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
966             b_ci[2*r+8,1], b_ci[2*r+8,2]), sep=" ", "\n")
967         if (bar==TRUE) print(ggplot(b_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
968 +ggtitle(paste("Basic Confidence Interval for", statistic)))
969         if ("RMSE" %in% extras) {
970             b_ci[2*r+9,1] <- 2*RMSE - quantiles[2*r+9,2]
971             b_ci[2*r+9,2] <- 2*RMSE - quantiles[2*r+9,1]
972             statistic <- c("RMSE")

```

```

973 b_ci <- cbind(b_ci[,1:2], statistic)
974 cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
975     b_ci[2*r+9,1], b_ci[2*r+9,2]), sep=" ", "\n")
976 if (bar==TRUE) print(ggplot(b_ci[2*r+9, ], aes(statistic, ymin = V1, ymax = V2))
977     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
978 }
979 }
980 }
981 if ( !("AIC" %in% extras) ) {
982   if ("BIC" %in% extras) {
983     b_ci[2*r+7,1] <- 2*BIC - quantiles[2*r+7,2]
984     b_ci[2*r+7,2] <- 2*BIC - quantiles[2*r+7,1]
985     statistic <- c("BIC")
986     b_ci <- cbind(b_ci[,1:2], statistic)
987     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
988         b_ci[2*r+7,1], b_ci[2*r+7,2]), sep=" ", "\n")
989     if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
990         +ggtitle(paste("Basic Confidence Interval for", statistic)))
991     if ("RMSE" %in% extras) {
992       b_ci[2*r+8,1] <- 2*RMSE - quantiles[2*r+8,2]
993       b_ci[2*r+8,2] <- 2*RMSE - quantiles[2*r+8,1]
994       statistic <- c("RMSE")
995       b_ci <- cbind(b_ci[,1:2], statistic)
996       cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
997         b_ci[2*r+8,1], b_ci[2*r+8,2]), sep=" ", "\n")
998       if (bar==TRUE) print(ggplot(b_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))
999         +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))

```

```

1000 }
1001 }
1002 if ( !("BIC" %in% extras) ) {
1003   if ("RMSE" %in% extras) {
1004     b_ci[2*r+7,1] <- 2*RMSE - quantiles[2*r+7,2]
1005     b_ci[2*r+7,2] <- 2*RMSE - quantiles[2*r+7,1]
1006     statistic <- c("RMSE")
1007     b_ci <- cbind(b_ci[,1:2],statistic)
1008     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1009       b_ci[2*r+7,1], b_ci[2*r+7,2]), sep="", "\n")
1010     if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))
1011       +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1012   }
1013 }
1014 }
1015 }
1016 if ( !("R^2" %in% extras) ) {
1017   if ("AIC" %in% extras) {
1018     b_ci[2*r+6,1] <- 2*AIC - quantiles[2*r+6,2]
1019     b_ci[2*r+6,2] <- 2*AIC - quantiles[2*r+6,1]
1020     statistic <- c("AIC")
1021     b_ci <- cbind(b_ci[,1:2],statistic)
1022     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1023       b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1024     if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1025       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1026     if ("BIC" %in% extras) {

```



```

1027 b_ci[2*r+7,1] <- 2*BIC - quantiles[2*r+7,2]
1028 b_ci[2*r+7,2] <- 2*BIC - quantiles[2*r+7,1]
1029 statistic <- c("BIC")
1030 b_ci <- cbind(b_ci[,1:2],statistic)
1031 cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
1032     b_ci[2*r+7,1], b_ci[2*r+7,2]), sep="", "\n")
1033 if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1034 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1035 if ("RMSE" %in% extras) {
1036     b_ci[2*r+8,1] <- 2*RMSE - quantiles[2*r+8,2]
1037     b_ci[2*r+8,2] <- 2*RMSE - quantiles[2*r+8,1]
1038     statistic <- c("RMSE")
1039     b_ci <- cbind(b_ci[,1:2],statistic)
1040     cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
1041         b_ci[2*r+8,1], b_ci[2*r+8,2]), sep="", "\n")
1042     if (bar==TRUE) print(ggplot(b_ci[2*r+8, ], aes(statistic, ymin = V1, ymax = V2))
1043 +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1044 }
1045 }
1046 }
1047 if ( !("AIC" %in% extras)) {
1048     if ("BIC" %in% extras) {
1049         b_ci[2*r+6,1] <- 2*BIC - quantiles[2*r+6,2]
1050         b_ci[2*r+6,2] <- 2*BIC - quantiles[2*r+6,1]
1051         statistic <- c("BIC")
1052         b_ci <- cbind(b_ci[,1:2],statistic)
1053         cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",

```

```

1054     b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1055   if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1056     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1057   if ("RMSE" %in% extras) {
1058     b_ci[2*r+7,1] <- 2*RMSE - quantiles[2*r+7,2]
1059     b_ci[2*r+7,2] <- 2*RMSE + quantiles[2*r+7,1]
1060     statistic <- c("RMSE")
1061     b_ci <- cbind(b_ci[,1:2], statistic)
1062     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
1063       b_ci[2*r+7,1], b_ci[2*r+7,2]), sep="", "\n")
1064     if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))
1065       +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1066   }
1067 }
1068 if ( !"BIC" %in% extras) {
1069   if ("RMSE" %in% extras) {
1070     b_ci[2*r+6,1] <- 2*RMSE - quantiles[2*r+6,2]
1071     b_ci[2*r+6,2] <- 2*RMSE + quantiles[2*r+6,1]
1072     statistic <- c("RMSE")
1073     b_ci <- cbind(b_ci[,1:2], statistic)
1074     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
1075       b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1076     if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))
1077       +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1078   }
1079 }
1080 }

```

```

1081     }
1082   }
1083
1084   if ( !("P-value" %in% extras) ) {
1085     b_ci[r+3,1] <- 2*sd_2hat - quantiles[r+3,2]
1086     b_ci[r+3,2] <- 2*sd_2hat + quantiles[r+3,1]
1087     statistic <- c("sd")
1088     b_ci <- cbind(b_ci[,1:2],statistic)
1089     cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("%.5f", b_ci[r+3,1]), b_ci[r+3,2]), sep="", "\n")
1090     if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1091     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1092     if ("R^2" %in% extras) {
1093       b_ci[r+4,1] <- 2*R_2 - quantiles[r+4,2]
1094       b_ci[r+4,2] <- 2*R_2 + quantiles[r+4,1]
1095       statistic <- c("R^2")
1096       b_ci <- cbind(b_ci[,1:2],statistic)
1097       cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("%.5f", b_ci[r+4,1]), b_ci[r+4,2]), sep="", "\n")
1098       if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1099       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1100       if ("AIC" %in% extras) {
1101         b_ci[r+5,1] <- 2*AIC - quantiles[r+5,2]
1102         b_ci[r+5,2] <- 2*AIC + quantiles[r+5,1]
1103         statistic <- c("AIC")
1104         b_ci <- cbind(b_ci[,1:2],statistic)
1105         cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("%.5f", %5f",
1106         b_ci[r+5,1]), b_ci[r+5,2]), sep="", "\n")
1107         if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()

```

```

1108 +ggtitle(paste("Basic Confidence Interval for", statistic))
1109 if ("BIC" %in% extras) {
1110   b_ci[r+6,1] <- 2*BIC - quantiles[r+6,2]
1111   b_ci[r+6,2] <- 2*BIC - quantiles[r+6,1]
1112   statistic <- c("BIC")
1113   b_ci <- cbind(b_ci[,1:2],statistic)
1114   cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
1115     b_ci[r+6,1], b_ci[r+6,2]), sep="", "\n")
1116   if (bar==TRUE) print(ggplot(b_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar(
1117     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1118     if ("RMSE" %in% extras) {
1119       b_ci[r+7,1] <- 2*RMSE - quantiles[r+7,2]
1120       b_ci[r+7,2] <- 2*RMSE - quantiles[r+7,1]
1121       statistic <- c("RMSE")
1122       b_ci <- cbind(b_ci[,1:2],statistic)
1123       cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
1124         b_ci[r+7,1], b_ci[r+7,2]), sep="", "\n")
1125       if (bar==TRUE) print(ggplot(b_ci[r+7, ], aes(statistic, ymin = V1, ymax = V2))
1126         +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1127     }
1128   }
1129 }
1130 if ( !"AIC" %in% extras) {
1131   if ("BIC" %in% extras) {
1132     b_ci[r+5,1] <- 2*BIC - quantiles[r+5,2]
1133     b_ci[r+5,2] <- 2*BIC - quantiles[r+5,1]
1134     statistic <- c("BIC")

```

```

1135 b_ci <- cbind(b_ci[,1:2], statistic)
1136 cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
1137     b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1138 if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1139 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1140 if ("RMSE" %in% extras) {
1141     b_ci[r+6,1] <- 2*RMSE - quantiles[r+6,2]
1142     b_ci[r+6,2] <- 2*RMSE + quantiles[r+6,1]
1143     statistic <- c("RMSE")
1144     b_ci <- cbind(b_ci[,1:2], statistic)
1145     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
1146         b_ci[r+6,1], b_ci[r+6,2]), sep="", "\n")
1147     if (bar==TRUE) print(ggplot(b_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))
1148 +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1149 }
1150 }
1151 if (!"BIC" %in% extras) {
1152     if ("RMSE" %in% extras) {
1153         b_ci[r+5,1] <- 2*BIC - quantiles[r+5,2]
1154         b_ci[r+5,2] <- 2*BIC + quantiles[r+5,1]
1155         statistic <- c("RMSE")
1156         b_ci <- cbind(b_ci[,1:2], statistic)
1157         cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
1158             b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1159         if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
1160 +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1161     }

```

```

1162     }
1163   }
1164 }
1165 if ( !("R^2" %in% extras) ) {
1166   if ("AIC" %in% extras) {
1167     b_ci[r+4,1] <- 2*AIC - quantiles[r+4,2]
1168     b_ci[r+4,2] <- 2*AIC - quantiles[r+4,1]
1169     statistic <- c("AIC")
1170     b_ci <- cbind(b_ci[,1:2],statistic)
1171     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1172       b_ci[r+4,1], b_ci[r+4,2]), sep=" ", "\n")
1173   if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1174     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1175   if ("BIC" %in% extras) {
1176     b_ci[r+5,1] <- 2*BIC - quantiles[r+5,2]
1177     b_ci[r+5,2] <- 2*BIC - quantiles[r+5,1]
1178     statistic <- c("BIC")
1179     b_ci <- cbind(b_ci[,1:2],statistic)
1180     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1181       b_ci[r+5,1], b_ci[r+5,2]), sep=" ", "\n")
1182   if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1183     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1184   if ("RMSE" %in% extras) {
1185     b_ci[r+6,1] <- 2*RMSE - quantiles[r+6,2]
1186     b_ci[r+6,2] <- 2*RMSE - quantiles[r+6,1]
1187     statistic <- c("RMSE")
1188     b_ci <- cbind(b_ci[,1:2],statistic)

```

```

1189   cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
1190     b_ci[r+6,1], b_ci[r+6,2]), sep=" ", "\n")
1191   if (bar==TRUE) print(ggplot(b_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))
1192     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1193   }
1194   }
1195   }
1196   if ( !("AIC" %in% extras)) {
1197     if ("BIC" %in% extras) {
1198       b_ci[r+4,1] <- 2*BIC - quantiles[r+4,2]
1199       b_ci[r+4,2] <- 2*BIC - quantiles[r+4,1]
1200       statistic <- c("BIC")
1201       b_ci <- cbind(b_ci[,1:2], statistic)
1202       cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
1203         b_ci[r+4,1], b_ci[r+4,2]), sep=" ", "\n")
1204       if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1205         +ggtitle(paste("Basic Confidence Interval for", statistic)))
1206       if ("RMSE" %in% extras) {
1207         b_ci[r+5,1] <- 2*RMSE - quantiles[r+5,2]
1208         b_ci[r+5,2] <- 2*RMSE - quantiles[r+5,1]
1209         statistic <- c("RMSE")
1210         b_ci <- cbind(b_ci[,1:2], statistic)
1211         cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
1212           b_ci[r+5,1], b_ci[r+5,2]), sep=" ", "\n")
1213         if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
1214           +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1215       }

```

```

1216 }
1217 if (!("BIC" %in% extras)) {
1218   if ("RMSE" %in% extras) {
1219     b_ci[r+4,1] <- 2*RMSE - quantiles[r+4,2]
1220     b_ci[r+4,2] <- 2*RMSE - quantiles[r+4,1]
1221     statistic <- c("RMSE")
1222     b_ci <- cbind(b_ci[,1:2],statistic)
1223     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("%.5f, %.5f",
1224       b_ci[r+4,1], b_ci[r+4,2]), sep="", "\n")
1225     if (bar==TRUE) print(eggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))
1226       +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1227   }
1228 }
1229 }
1230 }
1231 }
1232 }
1233 }
1234 if ("P-value" %in% extras & !("sigma" %in% extras)) {
1235   Pval_b <- c()
1236   sign_Pvalue <- c()
1237   for (i in (r+2):(2*r+2)) {
1238     b_ci[i,1] <- 2*Pr_z[i-r-1] - quantiles[i,2]
1239     b_ci[i,2] <- 2*Pr_z[i-r-1] - quantiles[i,1]
1240     statistic <- paste0("P-value(b", i-r-2, ")")
1241     Pval_b[i-r-1] <- statistic
1242     b_ci <- cbind(b_ci[,1:2],statistic)

```



```

1243 cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("%.5f", b_ci[i,1]), b_ci[i,2]), sep="", "\n")
1244 if (bar==TRUE) print(ggplot(b_ci[i, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1245 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1246 if (coeff_Pvalue[i-r-1] >0.1) sign_Pvalue[i-r-1] <- " "
1247 if (coeff_Pvalue[i-r-1] <=0.1 & coeff_Pvalue[i-r-1] >0.05) sign_Pvalue[i-r-1] <- "*"
1248 if (coeff_Pvalue[i-r-1] <=0.05 & coeff_Pvalue[i-r-1] >0.01) sign_Pvalue[i-r-1] <- "***"
1249 if (coeff_Pvalue[i-r-1] <=0.01) sign_Pvalue[i-r-1] <- "****"
1250 }
1251 b_ci[2*r+3,1] <- 2*sd_2hat - quantiles[2*r+3,2]
1252 b_ci[2*r+3,2] <- 2*sd_2hat - quantiles[2*r+3,1]
1253 statistic <- c("sd")
1254 b_ci <- cbind(b_ci[, 1:2], statistic)
1255 cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("%.5f", b_ci[2*r+3,1]), b_ci[2*r+3,2]), sep="", "\n")
1256 if (bar==TRUE) print(ggplot(b_ci[2*r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1257 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1258 if ("R^2" %in% extras) {
1259   b_ci[2*r+4,1] <- 2*R_2 - quantiles[2*r+4,2]
1260   b_ci[2*r+4,2] <- 2*R_2 - quantiles[2*r+4,1]
1261   statistic <- c("R^2")
1262   b_ci <- cbind(b_ci[, 1:2], statistic)
1263   cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("%.5f", b_ci[2*r+4,1]), b_ci[2*r+4,2]), sep="", "\n")
1264   if (bar==TRUE) print(ggplot(b_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1265   +ggtitle(paste("Basic Confidence Interval for", statistic)))
1266   if ("AIC" %in% extras) {
1267     b_ci[2*r+5,1] <- 2*AIC - quantiles[2*r+5,2]
1268     b_ci[2*r+5,2] <- 2*AIC - quantiles[2*r+5,1]
1269     statistic <- c("AIC")

```

```

1270 b_ci <- cbind(b_ci[,1:2], statistic)
1271 cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%f, %f]",
1272     b_ci[2*r+5,1], b_ci[2*r+5,2]), sep=" ", "\n")
1273 if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1274 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1275 if ("BIC" %in% extras) {
1276     b_ci[2*r+6,1] <- 2*BIC - quantiles[2*r+6,2]
1277     b_ci[2*r+6,2] <- 2*BIC - quantiles[2*r+6,1]
1278     statistic <- c("BIC")
1279     b_ci <- cbind(b_ci[,1:2], statistic)
1280     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%f, %f]",
1281         b_ci[2*r+6,1], b_ci[2*r+6,2]), sep=" ", "\n")
1282     if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1283 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1284     if ("RMSE" %in% extras) {
1285         b_ci[2*r+7,1] <- 2*RMSE - quantiles[2*r+7,2]
1286         b_ci[2*r+7,2] <- 2*RMSE - quantiles[2*r+7,1]
1287         statistic <- c("RMSE")
1288         b_ci <- cbind(b_ci[,1:2], statistic)
1289         cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%f, %f]",
1290             b_ci[2*r+7,1], b_ci[2*r+7,2]), sep=" ", "\n")
1291         if (bar==TRUE) print(ggplot(b_ci[2*r+7, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1292 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1293     }
1294 }
1295 }
1296 if ( !("AIC" %in% extras)) {

```

```

1297 if ("BIC" %in% extras) {
1298   b_ci[2*r+5,1] <- 2*BIC - quantiles[2*r+5,2]
1299   b_ci[2*r+5,2] <- 2*BIC - quantiles[2*r+5,1]
1300   statistic <- c("BIC")
1301   b_ci <- cbind(b_ci[,1:2],statistic)
1302   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1303     b_ci[2*r+5,1], b_ci[2*r+5,2]), sep="", "\n")
1304   if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1305     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1306   if ("RMSE" %in% extras) {
1307     b_ci[2*r+6,1] <- 2*RMSE - quantiles[2*r+6,2]
1308     b_ci[2*r+6,2] <- 2*RMSE - quantiles[2*r+6,1]
1309     statistic <- c("RMSE")
1310     b_ci <- cbind(b_ci[,1:2],statistic)
1311     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1312       b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1313     if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1314       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1315   }
1316 }
1317 if ( !("BIC" %in% extras)) {
1318   if ("RMSE" %in% extras) {
1319     b_ci[2*r+5,1] <- 2*RMSE - quantiles[2*r+5,2]
1320     b_ci[2*r+5,2] <- 2*RMSE - quantiles[2*r+5,1]
1321     statistic <- c("RMSE")
1322     b_ci <- cbind(b_ci[,1:2],statistic)
1323     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",

```

```

1324     b_ci[2*r+5,1], b_ci[2*r+5,2]), sep="", "\n")
1325   if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1326     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1327   }
1328   }
1329   }
1330 }
1331 if ( !("R^2" %in% extras) ) {
1332   if ("AIC" %in% extras) {
1333     b_ci[2*r+4,1] <- 2*AIC - quantiles[2*r+4,2]
1334     b_ci[2*r+4,2] <- 2*AIC - quantiles[2*r+4,1]
1335     statistic <- c("AIC")
1336     b_ci <- cbind(b_ci[,1:2],statistic)
1337     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
1338       b_ci[2*r+4,1], b_ci[2*r+4,2]), sep="", "\n")
1339     if (bar==TRUE) print(ggplot(b_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1340       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1341     if ("BIC" %in% extras) {
1342       b_ci[2*r+5,1] <- 2*BIC - quantiles[2*r+5,2]
1343       b_ci[2*r+5,2] <- 2*BIC - quantiles[2*r+5,1]
1344       statistic <- c("BIC")
1345       b_ci <- cbind(b_ci[,1:2],statistic)
1346       cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%0.5f, %0.5f]",
1347         b_ci[2*r+5,1], b_ci[2*r+5,2]), sep="", "\n")
1348       if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1349         +ggtitle(paste("Basic Confidence Interval for", statistic)))
1350       if ("RMSE" %in% extras) {

```

```

1351 b_ci[2*r+6,1] <- 2*RMSE - quantiles[2*r+6,2]
1352 b_ci[2*r+6,2] <- 2*RMSE - quantiles[2*r+6,1]
1353 statistic <- c("RMSE")
1354 b_ci <- cbind(b_ci[,1:2],statistic)
1355 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1356       b_ci[2*r+6,1], b_ci[2*r+6,2]), sep="", "\n")
1357 if (bar==TRUE) print(ggplot(b_ci[2*r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1358       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1359   }
1360 }
1361 }
1362 if ( !"AIC" %in% extras) {
1363   if ("BIC" %in% extras) {
1364     b_ci[2*r+4,1] <- 2*BIC - quantiles[2*r+4,2]
1365     b_ci[2*r+4,2] <- 2*BIC - quantiles[2*r+4,1]
1366     statistic <- c("BIC")
1367     b_ci <- cbind(b_ci[,1:2],statistic)
1368     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1369           b_ci[2*r+4,1], b_ci[2*r+4,2]), sep="", "\n")
1370     if (bar==TRUE) print(ggplot(b_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1371           +ggtitle(paste("Basic Confidence Interval for", statistic)))
1372     if ("RMSE" %in% extras) {
1373       b_ci[2*r+5,1] <- 2*RMSE - quantiles[2*r+5,2]
1374       b_ci[2*r+5,2] <- 2*RMSE - quantiles[2*r+5,1]
1375       statistic <- c("RMSE")
1376       b_ci <- cbind(b_ci[,1:2],statistic)
1377       cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",

```

```

1378     b_ci[2*r+5,1], b_ci[2*r+5,2]], sep="", "\n")
1379   if (bar==TRUE) print(ggplot(b_ci[2*r+5, ], aes(statistic, ymin = V1, ymax = V2))
1380     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1381   }
1382 }
1383 if ( !("BIC" %in% extras) ) {
1384   if ("RMSE" %in% extras) {
1385     b_ci[2*r+4,1] <- 2*RMSE - quantiles[2*r+4,2]
1386     b_ci[2*r+4,2] <- 2*RMSE - quantiles[2*r+4,1]
1387     statistic <- c("RMSE")
1388     b_ci <- cbind(b_ci[,1:2],statistic)
1389     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1390       b_ci[2*r+4,1], b_ci[2*r+4,2]), sep="", "\n")
1391   if (bar==TRUE) print(ggplot(b_ci[2*r+4, ], aes(statistic, ymin = V1, ymax = V2))
1392     +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1393   }
1394 }
1395 }
1396 }
1397 }
1398 }
1399 if ( !("P-value" %in% extras) & !("sigma" %in% extras) ) {
1400   b_ci[r+2,1] <- 2*sd_2hat - quantiles[r+2,2]
1401   b_ci[r+2,2] <- 2*sd_2hat - quantiles[r+2,1]
1402   statistic <- c("sd")
1403   b_ci <- cbind(b_ci[,1:2],statistic)
1404   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]", b_ci[r+2,1], b_ci[r+2,2]), sep="", "\n")

```

```

1405 if (bar==TRUE) print(ggplot(b_ci[r+2, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1406 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1407 if ("R^2" %in% extras) {
1408   b_ci[r+3,1] <- 2*R_2 - quantiles[r+3,2]
1409   b_ci[r+3,2] <- 2*R_2 - quantiles[r+3,1]
1410   statistic <- c("R^2")
1411   b_ci <- cbind(b_ci[,1:2],statistic)
1412   cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]", b_ci[r+3,1], b_ci[r+3,2]), sep="", "\n")
1413   if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1414 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1415   if ("AIC" %in% extras) {
1416     b_ci[r+4,1] <- 2*AIC - quantiles[r+4,2]
1417     b_ci[r+4,2] <- 2*AIC - quantiles[r+4,1]
1418     statistic <- c("AIC")
1419     b_ci <- cbind(b_ci[,1:2],statistic)
1420     cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]", b_ci[r+4,1], b_ci[r+4,2]), sep="", "\n")
1421     if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1422 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1423     if ("BIC" %in% extras) {
1424       b_ci[r+5,1] <- 2*BIC - quantiles[r+5,2]
1425       b_ci[r+5,2] <- 2*BIC - quantiles[r+5,1]
1426       statistic <- c("BIC")
1427       b_ci <- cbind(b_ci[,1:2],statistic)
1428       cat("Basic Confidence Interval for", " ", statistic, ": ", sprintf("[%5f, %5f]",
1429         b_ci[r+5,1], b_ci[r+5,2]), sep="", "\n")
1430       if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1431 +ggtitle(paste("Basic Confidence Interval for", statistic)))

```

```

1432 if ("RMSE" %in% extras) {
1433   b_ci[r+6,1] <- 2 * RMSE - quantiles[r+6,2]
1434   b_ci[r+6,2] <- 2 * RMSE + quantiles[r+6,1]
1435   statistic <- c("RMSE")
1436   b_ci <- cbind(b_ci[, 1:2], statistic)
1437   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1438     b_ci[r+6,1], b_ci[r+6,2]), sep=" ", "\n")
1439   if (bar==TRUE) print(ggplot(b_ci[r+6, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1440     +ggtitle(paste("Basic Confidence Interval for", statistic)))
1441 }
1442 }
1443 }
1444 if ( !("AIC" %in% extras)) {
1445   if ("BIC" %in% extras) {
1446     b_ci[r+4,1] <- 2 * BIC - quantiles[r+4,2]
1447     b_ci[r+4,2] <- 2 * BIC + quantiles[r+4,1]
1448     statistic <- c("BIC")
1449     b_ci <- cbind(b_ci[, 1:2], statistic)
1450     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%f, %f]",
1451       b_ci[r+4,1], b_ci[r+4,2]), sep=" ", "\n")
1452     if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1453       +ggtitle(paste("Basic Confidence Interval for", statistic)))
1454     if ("RMSE" %in% extras) {
1455       b_ci[r+5,1] <- 2 * RMSE - quantiles[r+5,2]
1456       b_ci[r+5,2] <- 2 * RMSE + quantiles[r+5,1]
1457       statistic <- c("RMSE")
1458       b_ci <- cbind(b_ci[, 1:2], statistic)

```



```

1459   cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1460       b_ci[r+5,1], b_ci[r+5,2]), sep=" ", "\n")
1461   if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(statistic, ymin = V1, ymax = V2))
1462       +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1463   }
1464   }
1465   if ( !("BIC" %in% extras) ) {
1466     if ("RMSE" %in% extras) {
1467       b_ci[r+4,1] <- 2*RMSE - quantiles[r+4,2]
1468       b_ci[r+4,2] <- 2*RMSE - quantiles[r+4,1]
1469       statistic <- c("RMSE")
1470       b_ci <- cbind(b_ci[,1:2],statistic)
1471       cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]",
1472           b_ci[r+4,1], b_ci[r+4,2]), sep=" ", "\n")
1473     }
1474     if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))
1475         +geom_errorbar()+ggtitle(paste("Basic Confidence Interval for", statistic)))
1476   }
1477   }
1478   }
1479   if ( !("R^2" %in% extras) ) {
1480     if ("AIC" %in% extras) {
1481       b_ci[r+3,1] <- 2*AIC - quantiles[r+3,2]
1482       b_ci[r+3,2] <- 2*AIC - quantiles[r+3,1]
1483       statistic <- c("AIC")
1484       b_ci <- cbind(b_ci[,1:2],statistic)
1485       cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%.5f, %.5f]", b_ci[r+3,1], b_ci[r+3,2]), sep=" ", "\n")

```

```

1486 if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(Statistic, ymin = V1, ymax = V2))+geom_errorbar()
1487 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1488 if ("BIC" %in% extras) {
1489     b_ci[r+4,1] <- 2*BIC - quantiles[r+4,2]
1490     b_ci[r+4,2] <- 2*BIC - quantiles[r+4,1]
1491     statistic <- c("BIC")
1492     b_ci <- cbind(b_ci[,1:2], statistic)
1493     cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
1494         b_ci[r+4,1], b_ci[r+4,2]), sep=" ", "\n")
1495     if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(Statistic, ymin = V1, ymax = V2))+geom_errorbar()
1496 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1497     if ("RMSE" %in% extras) {
1498         b_ci[r+5,1] <- 2*RMSE - quantiles[r+5,2]
1499         b_ci[r+5,2] <- 2*RMSE - quantiles[r+5,1]
1500         statistic <- c("RMSE")
1501         b_ci <- cbind(b_ci[,1:2], statistic)
1502         cat("Basic Confidence Interval for", " ", statistic, ":", " ", sprintf("[%5f, %5f]",
1503             b_ci[r+5,1], b_ci[r+5,2]), sep=" ", "\n")
1504         if (bar==TRUE) print(ggplot(b_ci[r+5, ], aes(Statistic, ymin = V1, ymax = V2))+geom_errorbar()
1505 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1506     }
1507 }
1508 }
1509 if ( !("AIC" %in% extras)) {
1510     if ("BIC" %in% extras) {
1511         b_ci[r+3,1] <- 2*BIC - quantiles[r+3,2]
1512         b_ci[r+3,2] <- 2*BIC - quantiles[r+3,1]

```

```

1513 statistic <- c("BIC")
1514 b_ci <- cbind(b_ci[,1:2],statistic)
1515 cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1516     b_ci[r+3,1], b_ci[r+3,2]), sep=" ", "\n")
1517 if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1518 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1519 if ("RMSE" %in% extras) {
1520     b_ci[r+4,1] <- 2*RMSE - quantiles[r+4,2]
1521     b_ci[r+4,2] <- 2*RMSE - quantiles[r+4,1]
1522     statistic <- c("RMSE")
1523     b_ci <- cbind(b_ci[,1:2],statistic)
1524     cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1525         b_ci[r+4,1], b_ci[r+4,2]), sep=" ", "\n")
1526     if (bar==TRUE) print(ggplot(b_ci[r+4, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1527 +ggtitle(paste("Basic Confidence Interval for", statistic)))
1528 }
1529 }
1530 if ( !("BIC" %in% extras)) {
1531     if ("RMSE" %in% extras) {
1532         b_ci[r+3,1] <- 2*RMSE - quantiles[r+3,2]
1533         b_ci[r+3,2] <- 2*RMSE - quantiles[r+3,1]
1534         statistic <- c("RMSE")
1535         b_ci <- cbind(b_ci[,1:2],statistic)
1536         cat("Basic Confidence Interval for", " ", statistic, ":", sprintf("[%5f, %5f]",
1537             b_ci[r+3,1], b_ci[r+3,2]), sep=" ", "\n")
1538         if (bar==TRUE) print(ggplot(b_ci[r+3, ], aes(statistic, ymin = V1, ymax = V2))+geom_errorbar()
1539 +ggtitle(paste("Basic Confidence Interval for", statistic)))

```

```

1540     }
1541   }
1542 }
1543 }
1544 }
1545 }
1546 }
1547 Table <- cbind( c("C", colnames(z)))
1548 if ("sigma" %in% extras) Table <- cbind(c(Table, "sigma"))
1549 if ("P-value" %in% extras) Table <- cbind(c(Table, Pval_b))
1550 Table <- cbind(c(Table, "sd"))
1551 if ("R^2" %in% extras) Table <- cbind(c(Table, "R^2"))
1552 if ("AIC" %in% extras) Table <- cbind(c(Table, "AIC"))
1553 if ("BIC" %in% extras) Table <- cbind(c(Table, "BIC"))
1554 if ("RMSE" %in% extras) Table <- cbind(c(Table, "RMSE"))
1555
1556 if (ci=="basic") {
1557   Table <- cbind(Table,
1558     c(coeff_beta, if ("sigma" %in% extras) round(sum(bootstrap_sigma)/L2,5), if ("P-value" %in% extras) coeff_Pvalue,
1559     round(sum(bootstrap_sd)/L2,5), if ("R^2" %in% extras) round(sum(bootstrap_R_2)/L2,5),
1560     if ("AIC" %in% extras) round(sum(bootstrap_AIC)/L2,5), if ("BIC" %in% extras) round(sum(bootstrap_BIC)/L2,5),
1561     if ("RMSE" %in% extras) round(sum(bootstrap_RMSE)/L2,5)),
1562     round(b_ci[,1],5),
1563     round(b_ci[,2],5),
1564     c(ifelse(b_ci[1:(r+1),1]<0 & b_ci[1:(r+1),2]>0, "X", "I"),
1565       if ("sigma" %in% extras) c(""),
1566       if ("P-value" %in% extras) sign_Pvalue,

```

```

1567 c(" "),
1568 if (length(which(c("R^2","AIC","BIC","RMSE") %in% extras == TRUE))==4) c(" ", " ", " ", " "),
1569 if (length(which(c("R^2","AIC","BIC","RMSE") %in% extras == TRUE))==3) c(" ", " ", " "),
1570 if (length(which(c("R^2","AIC","BIC","RMSE") %in% extras == TRUE))==2) c(" ", " "),
1571 if (length(which(c("R^2","AIC","BIC","RMSE") %in% extras == TRUE))==1) c(" ")
1572 )
1573 colnames(Table) <- c("Variable", "Coefficient", "Lower Basic CI", "Upper Basic CI", "Statistical Significance")
1574 View(Table)
1575 }
1576
1577 if (ci=="percentile") {
1578   Table <- cbind(Table,
1579     c(coeff_beta, if ("sigma" %in% extras) round(sum(bootstrap_sigma)/L2,5), if ("P-value" %in% extras) coeff_Pvalue,
1580     round(sum(bootstrap_sd)/L2,5), if ("R^2" %in% extras) round(sum(bootstrap_R_2)/L2,5),
1581     if ("AIC" %in% extras) round(sum(bootstrap_AIC)/L2,5), if ("BIC" %in% extras) round(sum(bootstrap_BIC)/L2,5),
1582     if ("RMSE" %in% extras) round(sum(bootstrap_RMSE)/L2,5)),
1583     round(p_cil[,1],5),
1584     round(p_cil[,2],5),
1585     c(ifelse(p_cil[1:(r+1),1]<0 & p_cil[1:(r+1),2]>0, "X", "!")),
1586     if ("sigma" %in% extras) c(" "),
1587     if ("P-value" %in% extras) sign_Pvalue,
1588     c(" "),
1589     if (length(which(c("R^2","AIC","BIC","RMSE") %in% extras == TRUE))==4) c(" ", " ", " ", " "),
1590     if (length(which(c("R^2","AIC","BIC","RMSE") %in% extras == TRUE))==3) c(" ", " ", " "),
1591     if (length(which(c("R^2","AIC","BIC","RMSE") %in% extras == TRUE))==2) c(" ", " "),
1592     if (length(which(c("R^2","AIC","BIC","RMSE") %in% extras == TRUE))==1) c(" ")
1593   )

```

```

1594 colnames(Table) <- c("Variable", "Coefficient", "Lower Percentile CI", "Upper Percentile CI", "Statistical Significance")
1595 View(Table)
1596 }
1597
1598 if (ci=="all") {
1599   Table <- cbind(Table,
1600     c(coeff_beta, if ("sigma" %in% extras) round(sum(bootstrap_sigma)/L2,5), if ("P-value" %in% extras) coeff_Pvalue,
1601     round(sum(bootstrap_sd)/L2,5), if ("R^2" %in% extras) round(sum(bootstrap_R_2)/L2,5),
1602     if ("AIC" %in% extras) round(sum(bootstrap_AIC)/L2,5), if ("BIC" %in% extras) round(sum(bootstrap_BIC)/L2,5),
1603     if ("RMSE" %in% extras) round(sum(bootstrap_RMSE)/L2,5),
1604     round(p_ci[,1],5),
1605     round(p_ci[,2],5),
1606     c(ifelse(p_ci[1:(r+1),1]<0 & p_ci[1:(r+1),2]>0, "X", "I"),
1607       if ("sigma" %in% extras) c(" "),
1608       if ("P-value" %in% extras) sign_Pvalue,
1609       c(" "),
1610       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==4) c(" ", " ", " ", " "),
1611       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==3) c(" ", " ", " "),
1612       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==2) c(" ", " "),
1613       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==1) c(" ")),
1614     round(b_ci[,1],5),
1615     round(b_ci[,2],5),
1616     c(ifelse(b_ci[1:(r+1),1]<0 & b_ci[1:(r+1),2]>0, "X", "I"),
1617       if ("sigma" %in% extras) c(" "),
1618       if ("P-value" %in% extras) sign_Pvalue,
1619       c(" "),
1620       if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE))==4) c(" ", " ", " ", " "),

```

```

1621 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 3) c(" ", " ", " ", " "),
1622 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 2) c(" ", " ", " "),
1623 if (length(which(c("R^2", "AIC", "BIC", "RMSE") %in% extras == TRUE)) == 1) c(" ")
1624 )
1625 colnames(Table) <- c("Variable", "Coefficient", "Lower Percentile CI", "Upper Percentile CI", "Statistical Significance",
1626 "Lower Basic CI", "Upper Basic CI", "Statistical Significance")
1627 View(Table)
1628 }
1629 }

```

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ΠΑΝΕΠΙΣΤΗΜΙΟ ΘΕΣΣΑΛΙΑΣ
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