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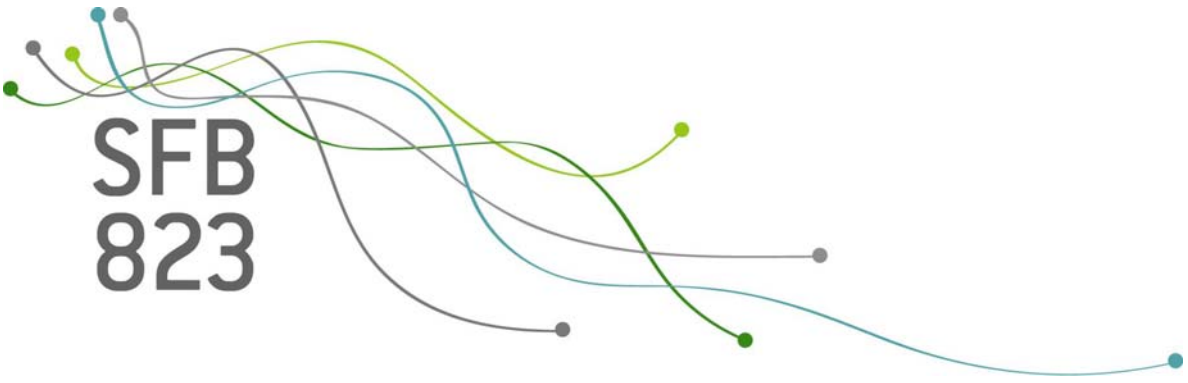

Simar and Wilson two-stage efficiency analysis for Stata

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Abstract. When analyzing what determines the efficiency of production, regressing efficiency scores estimated by DEA on explanatory variables has much intuitive appeal. Simar and Wilson (2007) show that this naïve two-stage estimation procedure suffers from severe flaws, that render its results, and in particular statistical inference based on them, questionable. At the same time they propose a statistically grounded bootstrap based two-stage estimator that eliminates the above mentioned weaknesses of its naïve predecessors and comes in two variants. This article introduces the new Stata command `simarwilson` that implements either variant of the suggested estimator in Stata. The command allows for various options, and extends the original procedure in some respects. For instance, it allows for analyzing both, output- and input-oriented efficiency. To demonstrate the capabilities of the new command `simarwilson` we use data from the Penn World Tables and the Global Competitiveness Report by the World Economic Forum to perform a cross-country empirical study about the importance of quality of governance of a country for its efficiency of output production.

Keywords: DEA, two-stage estimation, truncated regression, bootstrap, efficiency, bias correction, environmental variables.

1 Introduction

Analyzing the technical efficiency of production/decision making units (DMUs) has developed into a major field in empirical economics and management science.[1] From a methodological perspective, two major strands of the literature can be distinguished: (i) analyses that rest on parametric, regression based methods, namely stochastic frontier analysis (SFA, Aigner et al. 1977), and (ii) analyses that use non-parametric methods, namely data envelopment analysis (DEA, Charnes et al. 1978). The pros and cons of either approach have been discussed extensively (e.g. Hjalmarsson et al. 1996; Murillo-Zamorano 2004).

One of the advantages of the parametric approaches, namely the truncated-normal stochastic frontier model, is that it does not only allow for measuring inefficiency but also incorporates a model of the determinants of inefficiency.[2] In contrast, non-parametric approaches are primarily concerned with estimating a production-possibility frontier (or an input requirement frontier) and with measuring the distance of observed input-output combinations to this frontier. Yet, shedding light on what determines the magnitude of this distance is out of the narrow[3] scope of non-parametric approaches such as DEA.

For many research questions, however, identifying determinants of inefficiency is of much greater relevance than determining its magnitude for specific DMUs. For this reason, in the domain of non-parametric efficiency analysis, semi-parametric two-stage approaches that combine efficiency measurement by DEA with a regression analysis that uses DEA estimated efficiency as dependent variables have become popular. Simar and Wilson (2007) list almost fifty published articles and mention hundreds of unpublished papers that employ such two-stage procedures. In these (early) applications the second stage is typically a censored (tobit like) regression to account for the bounded nature of DEA efficiency scores, or just simply OLS (Simar and Wilson 2007).

Despite their popularity and their intuitive appeal, such naïve two-stage estimators are criticized by Simar and Wilson (2007) mainly for two reasons. Firstly, they stress the absence of a clear theory of the underlying data generating process, that would justify the naïve two-stage approach.[4] Secondly, they criticize the conventional inference

1. In a supplement to their recent survey article Emrouznejad and Yang (2018) list more than 10 000 publications, only considering the non-parametric strand of this literature.
2. The Stata command `frontier` includes the option `cm()` that allows for specifying the conditional mean of the truncated normal distribution, from which the distance to the frontier is assumed to be drawn, as linear function of exogenous variables.
3. Some DEA models were proposed that directly include environmental variables in the DEA linear programming problem (cf. Coelli et al. 2005). Yet, these models suffer from several shortcomings. For instance, they allow only for continuous environmental variables. More recently, smoothing based, fully non-parametric methods for estimating conditional frontiers, which substantially extend the familiar DEA framework, have been suggested (Daraio and Simar 2005, 2007). Unlike two-stage approaches, these model allow for environmental variables affecting the shape of the frontier. Yet, they are not considered as determinants of the distance from the frontier.
4. In a closely related article (Simar and Wilson 2011), Simar and Wilson discuss further contributions (Hoff 2007; McDonald 2009; Ramalho et al. 2010; Banker and Natarajan 2008) to the literature on two-stage estimators. These are not 'naïve' in the sense that they did not make an attempt of justifying the proposed procedures. They rather provide some kind of rationale and/or statistical justification. Simar and Wilson (2011, p. 206), however, deny the former three a decent basis

that is pursued in most of the two-stage applications, for ignoring that estimated DEA efficiency scores are calculated from a common sample of data. Treating them as if they were independent observations is not appropriate since the problems related to invalid inference due to serial correlation arise. Simar and Wilson (2007) develop a two-stage procedure that takes the above mentioned issues into account. They construct an underlying data generating process that is consistent with a two-stage estimation procedure, which – as the most obvious difference to the earlier naïve approach – implies a truncated rather than censored regression model. This reflects that the substantial share of fully efficient DMUs typically found in DEA is an artifact of the finite sample bias inherent in DEA, but does not represent a feature of the true underlying data generating process. Moreover, they develop a parametric bootstrap procedure that is consistent with the assumed data generating process and addresses the second issue. It yields estimated standard errors and confidence intervals that do not suffer from bias due to estimated efficiency scores being correlated.

The Simar and Wilson (2007) procedure has become a workhorse of empirical efficiency analysis with hundreds of applications from various fields of economics.[5] This popular, yet technically involved estimator has not yet been available to Stata users, unless they developed their own code. The present paper introduces the new Stata command `simarwilson` that allows for applying this estimator in Stata.[6] In doing this, it greatly benefits from the recently published user written Stata command `teradial` (Badunenko and Mozharovskyi 2016), which is required for running `simarwilson`. For the first time, `teradial` enables fast estimation of DEA in Stata even for large samples. This is essential for practical applications of the Simar and Wilson (2007) estimator, because it involves bootstrapping the DEA estimator.[7]

The remainder of this paper is organized as follows. The following section gives a brief summary of the Simar and Wilson (2007) two-stage estimator. The syntax of `simarwilson` is described in section 3. Section 4 presents an application to cross country data. Section 5 concludes.

2 The Simar and Wilson (2007) estimator in brief

2.1 Some essential ideas

Simar and Wilson (2007) consider a setting in which a researcher observes three types of variables $\mathbf{x}_i$, $\mathbf{y}_i$, and $\mathbf{z}_i$, for a sample of $i = 1, \ldots, N$ DMUs. $\mathbf{x}_i$ denotes a vector of P

in statistical theory. With respect to the latter they argue that the claimed desirable statistical properties rely on very restrictive assumptions.

5. Google Scholar (2018, March 27) lists more than 2200 citations (for instance Fragkiadakis et al. 2016; Pérez Urdiales et al. 2016; Glass et al. 2015; Chortareas et al. 2013, just to mention few recent applications). Interestingly, the inventors of this popular method dissociate themselves from advocating two-stage approaches (Simar and Wilson 2011, p. 216).
6. An earlier, less powerful version of the ado-file that accompanies this article has been made available through `ssc` in 2016.
7. This applies to algorithm #2 but not to algorithm #1; see section 2. Prior to `teradial` being available, algorithm #2 was hence effectively out of reach for Stata users.

inputs to production. $\mathbf{y}_i$ is a vector of Q outputs from production. $\mathbf{z}_i$ denotes a row vector of K environmental variables that may affect the ability of DMU i to efficiently combine the consumed inputs to the produced outputs. The effect of $\mathbf{z}_i$ on efficiency is in the focus of the empirical analysis. The production technology is assumed to be homogeneous across DMUs. That is, a common production-possibility frontier – the boundary of the convex production-possibility set – represents all combinations $(\mathbf{y}_j^*, \mathbf{x}_j^*)$ that are fully efficient in the sense that no output can be increased without decreasing at least one other output or increasing at least one input. A crucial assumption is that the shape of the production-possibility frontier does not depend on $\mathbf{z}_i$, which is referred to as separability in Simar and Wilson (2007).

The output-input set $(\mathbf{y}_i, \mathbf{x}_i)$ observed for DMU i, will regularly fail in realizing a point at the frontier. This deviation is necessarily directional, i.e. i produces less output than technically feasible or it consumes more input than technically feasible. The widely used output oriented Farrell (1957) distance measure quantifies the deviation from the frontier as the relative radial distance in output direction θ_i. That is θ_i denotes the factor by with output generation $\mathbf{y}_i$ of DMU i has to be proportionally increased in order to project $(\mathbf{y}_i, \mathbf{x}_i)$ onto the frontier. θ_i is hence a measure of inefficiency that is bounded to the $[1, \infty)$ interval. Alternatively, one may measure the Farrell distance in input direction as ϑ_i, that is the factor by which input consumption $\mathbf{x}_i$ of DMU i has to be proportionally reduced in order to project $(\mathbf{y}_i, \mathbf{x}_i)$ onto the frontier. ϑ_i is hence a measure of efficiency that is bounded to the $(0, 1]$ interval.[8] Yet, in Simar and Wilson (2007) the focus is on θ_i.[9]

The key idea in Simar and Wilson (2007) about the data generating process is that efficiency θ_i linearly depends on $\mathbf{z}_i$

$$\theta_i = \mathbf{z}_i\beta + \varepsilon_i \tag{1}$$

where β denotes a column vector of coefficients, estimating which is the ultimate objective of the empirical analysis. The disturbances ε_i are assumed to be – conditionally on $\mathbf{z}_i$ – indpendently[10], truncated normally distributed, with parameters $\mu = 0$ and σ, and left-truncation at $1 - \mathbf{z}_i\beta$.[11] This assumption guarantees that θ_i cannot be smaller than unity, irrespective of the values the variables in $\mathbf{z}_i$ may take. Though full efficiency $(\theta_i = 1)$ is in principle possible, it occurs with zero probability. Conditional on θ_i, DMU i chooses a set of outputs and inputs $(\mathbf{y}_i, \mathbf{x}_i)$ as $({}^1/_{\theta_i}\mathbf{y}_i^*, \mathbf{x}_i^*)$, with $(\mathbf{y}_i^*, \mathbf{x}_i^*)$ denoting some point at the production-possibility frontier.[12]

8. An alternative to the Farrell (1957) distance measure is one introduced by Shephard (1970), which is just the reciprocal of θ_i and ϑ_i, respectively. `simarwilson` accommodates the Shephard measure by the option `invert`; see sections 2.3 and 3.
9. Simar and Wilson (2007) do not explicitly consider input oriented efficiency, i.e. ϑ_i. `simarwilson` straightforwardly extends the original Simar and Wilson (2007) to accommodating input oriented efficiency too; see sections 2.3 and 3.
10. This implies that `simarwilson` is meant for being used with standard cross-sectional data but not with panel- or other types of clustered data.
11. The first and the second moment of the conditional error distribution are $E(\varepsilon_i|\mathbf{z}_i) = \sigma\lambda_i$ and $Var(\varepsilon_i|\mathbf{z}_i) = \sigma^2\left(1 + ({}^{(1-\mathbf{z}_i\beta)}/_{\sigma})(\lambda_i - \lambda_i^2)\right)$, with λ_i denoting the inverse Mills ratio $\frac{\phi({}^{(1-\mathbf{z}_i\beta)}/_{\sigma})}{1-\Phi({}^{(1-\mathbf{z}_i\beta)}/_{\sigma})}$.
12. The data generating process can hence be described as sampling from the joint distribution $f(\mathbf{x}, \mathbf{y}, \mathbf{z})$,

It is key for understanding the shortcomings of naïve two-stage approaches that θ_i is genuinely unobservable. In consequence the estimated efficiency score $\widehat{\theta}_i$ one obtains from running a DEA[13] is not θ_i. In other words, $\widehat{\theta}_i$ is not the distance of $(\mathbf{y}_i, \mathbf{x}_i)$ to the true production-possibility frontier but the distances to an estimate of the latter. Due to the boundary estimation framework of DEA, this estimate suffers from finite sample bias and in turn $\widehat{\theta}_i$ is biased towards the value of one. That means that (1) cannot be estimated straightforwardly and θ_i has to be replaced in (1) by the biased estimate $\widehat{\theta}_i$ in order to formulate an operational regression equation. As pointed out in Simar and Wilson (2007), this generates two major problems for naïve two step approaches. Firstly, although the errors ε_i are assumed to be statistically independent across DMUs, the operational errors in a regression of $\widehat{\theta}_i$ on $\mathbf{z}_i$ are not, since the $\widehat{\theta}_i$ are estimated from a common sample of data. Secondly, in any application of DEA some – usually numerous – $\widehat{\theta}_i$ take the value of one, though according to (1) θ_i takes this value with zero probability.

In the procedure[14] suggested in Simar and Wilson (2007), the former issue is addressed by estimating standard errors and confidence intervals for $\widehat{\beta}$ by the means of a parametric bootstrap procedure, in which artificial pseudo errors are independently drawn from the truncated normal distribution with left-truncation at $1 - \mathbf{z}_i\widehat{\beta}$. The latter issue is addressed in Simar and Wilson (2007) in two different ways, which leads to two different suggested estimation procedures (algorithm #1 and algorithm #2). Algorithm #1 simply excludes those DMUs from the regression analysis, for which DEA yields scores $\widehat{\theta}_i$ that equal one. These are obviously artifacts of finite sample bias. The remaining M (with $M < N$) DEA scores enter a truncated regression model (left-truncation at 1) as left-hand-side variable. Estimating this model yields $\widehat{\beta}$, which, together with the estimate for the variance parameter $\widehat{\sigma}$, enters the bootstrap procedure mentioned above. The second suggested approach (algorithm #2) is more involved and rests on bias corrected DEA scores $\widehat{\theta_i^{\text{bc}}}$ as left-hand-side variable. Since $\widehat{\theta_i^{\text{bc}}} > 1$ holds for $i = 1 \dots N$, unlike algorithm #1, all DMUs are considered in the truncated regression analysis and the subsequent bootstrap procedure. The bias correction itself rests on a bootstrap procedure that incorporates the assumptions regarding the process that generates θ_i, i.e. equation (1). For this reason, it is computationally simpler and more parametric than alternative bias correction procedures that have been suggested in the literature (Simar and Wilson 2000; Kneip et al. 2008) and have recently been made available to Stata users by the user written command `teradialbc` (Badunenko and Mozharovskyi 2016).

Figure 1 graphically illustrates the concepts of true, DEA estimated, and bias

which can be written as $f(\mathbf{x}, \mathbf{y}|\theta, \mathbf{z}) \cdot f(\theta|\mathbf{z}) \cdot f(\mathbf{z})$, (Simar and Wilson 2007, p. 35). The focus of the empirical analysis is on $f(\theta|\mathbf{z})$.

13. Discussing the linear programming problem that has to be solved to obtain $\widehat{\theta}_i$ is out of the scope of this article. Readers not familiar with DEA are referred to the seminal article Charnes et al. (1978) and standard textbooks such as Coelli et al. (2005) and Cooper et al. (2007). A Stata oriented, brief, and intuitive introduction is also provided in Badunenko and Mozharovskyi (2016).

14. The present article focuses on the intuition behind the Simar and Wilson (2007) estimator, and its practical implementation in Stata. For this reason, its statistical properties are not discussed in depth. Readers, who are interested in more theory oriented discussion of the estimator, are referred to the original article (Simar and Wilson 2007).

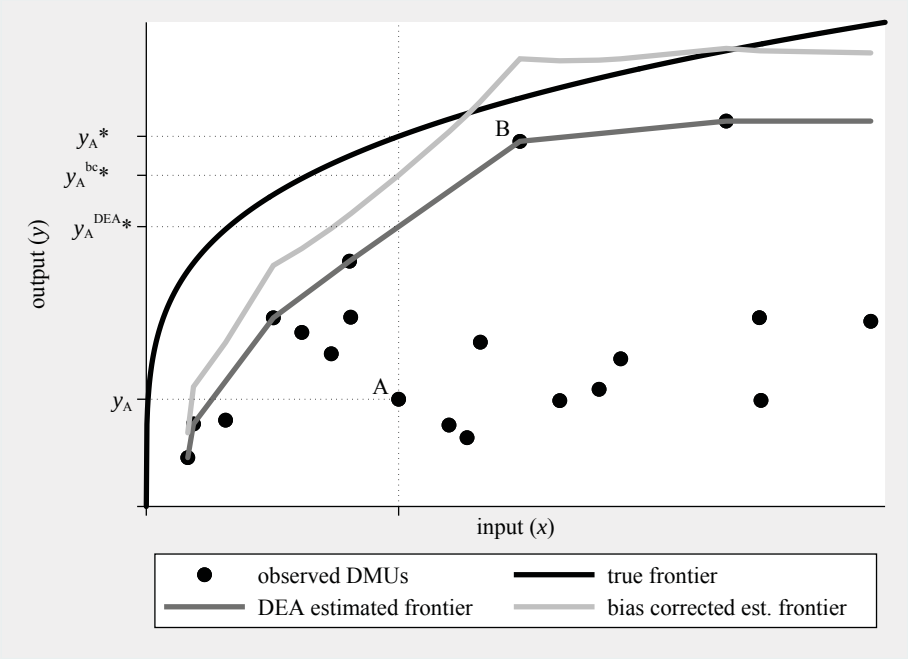

Figure 1: **Graphical illustration of true and estimated inefficiency**. Considering DMU A, true inefficiency θ_{A} is ${}^{y^*_{\mathrm{A}}}/_{y_{\mathrm{A}}}$, (uncorrected) DEA estimated inefficiency $\widehat{\theta_{\mathrm{A}}}$ is ${}^{y_{\mathrm{A}}^{\mathrm{DEA}*}}/_{y_{\mathrm{A}}}$, and bias corrected estimated inefficiency $\widehat{\theta_{\mathrm{A}}^{\mathrm{bc}}}$ is ${}^{y_{\mathrm{A}}^{\mathrm{bc}*}}/_{y_{\mathrm{A}}}$. In this finite and small ($N = 20$) artificial sample, DEA systematically underestimates true inefficiency. Bias correction adjusts estimated inefficiency upwards. DMU B for instance, which is seemingly fully efficient according to conventional DEA, is inefficient according to the bias corrected estimated frontier. Indeed, the inefficiency of B is even overestimated by $\widehat{\theta_{\mathrm{B}}^{\mathrm{bc}}}$. Unlike for conventional DEA, with bias correction the estimated production-possibility set is not convex, the estimated frontier is not even monotone. *Notes*: Input quantities x randomly drawn from continuous uniform $U(0, 2)$ distribution; true frontier (production function) $y = x^{\frac{1}{4}}$; inefficiency generated according to (1), with $\beta = \mathbf{0}$ and $\sigma = 3$; variable returns to scale assumed in the DEA; bias correction follows steps 1–4, algorithm #2 (Simar and Wilson 2007, see below). *Source*: Own calculations.

corrected estimated inefficiency, using randomly generated data and considering a simple single-input–single-output production technology.

2.2 The procedures suggested in Simar and Wilson (2007)

This subsection in detail describes the suggested procedures algorithm #1 and algorithm #2, mentioned above. In doing this, it almost one-to-one reproduces what is found at pages 41-43 in Simar and Wilson (2007). This, in particular, applies to the subsequent

paragraphs that describe the steps of the estimation procedure(s) in almost exactly the same way as they are described in the key reference.

Algorithm #1 consists of the following steps:

1. Compute $\widehat{\theta}_i$ for all DMUs $i = 1, \ldots, N$ using DEA.
2. Use those M (with $M < N$) DMUs, for which $\widehat{\theta}_i > 1$ holds, in a truncated regression (left-truncation at 1) of $\widehat{\theta}_i$ on $\mathbf{z}_i$ to obtain coefficient estimates $\widehat{\beta}$ and an estimate for variance parameter $\widehat{\sigma}$ by maximum likelihood.
3. Loop over the following steps 3.1–3.3 B times, in order to obtain a set of B bootstrap estimates $(\widehat{\beta}^b, \widehat{\sigma}^b)$, with $b = 1, \ldots, B$.
   - 3.1 For each DMU $i = 1, \ldots, M$, draw an artificial error $\widetilde{\varepsilon}_i$ from the truncated $N(0, \widehat{\sigma})$ distribution with left-truncation at $1 - \mathbf{z}_i\widehat{\beta}$.
   - 3.2 Calculate artificial efficiency scores $\widetilde{\theta}_i$ as $\mathbf{z}_i\widehat{\beta} + \widetilde{\varepsilon}_i$ for each DMU $i = 1, \ldots, M$.
   - 3.3 Run a truncated regression (left-truncation at 1) of $\widetilde{\theta}_i$ on $\mathbf{z}_i$ to obtain maximum likelihood, bootstrap estimates $\widehat{\beta}^b$ and $\widehat{\sigma}^b$.
4. Calculate confidence intervals and standard errors for $\widehat{\beta}$ and $\widehat{\sigma}$ from the bootstrap distribution of $\widehat{\beta}^b$ and $\widehat{\sigma}^b$.

The more involved **algorithm #2** consists of the following steps:

1. Compute $\widehat{\theta}_i$ for all DMUs $i = 1, \ldots, N$ using DEA.
2. Use those M ($M < N$) DMUs, for which $\widehat{\theta}_i > 1$ holds, in a truncated regression (left-truncation at 1) of $\widehat{\theta}_i$ on $\mathbf{z}_i$ to obtain coefficient estimates $\widehat{\beta}$ and an estimate for variance parameter $\widehat{\sigma}$ by maximum likelihood.
3. Loop over the following steps 3.1–3.4 B_1 times, in order to obtain a set ob B_1 bootstrap estimates $\widehat{\theta}_i^b$ for each DMU $i = 1, \ldots, N$, with $b = 1, \ldots, B_1$.
   - 3.1 For each DMU $i = 1, \ldots, N$, draw an artificial error $\widetilde{\varepsilon}_i$ from the truncated $N(0, \widehat{\sigma})$ distribution with left-truncation at $1 - \mathbf{z}_i\widehat{\beta}$.
   - 3.2 Calculate artificial efficiency scores $\widetilde{\theta}_i$ as $\mathbf{z}_i\widehat{\beta} + \widetilde{\varepsilon}_i$ for each DMU $i = 1, \ldots, N$.
   - 3.3 Generate $i = 1, \ldots, N$ artificial DMUs with input quantities $\widetilde{\mathbf{x}}_i = \mathbf{x}_i$ and output quantities $\widetilde{\mathbf{y}}_i = (\widehat{\theta}_i/\widetilde{\theta}_i)\mathbf{y}_i$.
   - 3.4 Use the N artificial DMUs, generated in step 3.3, as reference set in a DEA that yields $\widehat{\theta}_i^b$ for each original DMU $i = 1, \ldots, N$.
4. For each DMU $i = 1, \ldots, N$, calculate a bias corrected efficiency score $\widehat{\theta}_i^{\mathrm{bc}}$ as $\widehat{\theta}_i - \left(\frac{1}{B_1}\sum_{b=1}^{B_1}\widehat{\theta}_i^b - \widehat{\theta}_i\right)$.

5. Run a truncated regression (left-truncation at 1) of $\widehat{\theta}_i^{\text{bc}}$ on $\mathbf{z}_i$ to obtain coefficient estimates $\widehat{\widehat{\beta}}$ and an estimate for variance parameter $\widehat{\widehat{\sigma}}$ by maximum likelihood.

6. Loop over the following steps 6.1–6.3 B_2 times, in order to obtain a set ob B_2 bootstrap estimates $(\widehat{\widehat{\beta}}^b, \widehat{\widehat{\sigma}}^b)$, with $b = 1, \ldots, B_2$.

   6.1 For each DMU $i = 1, \ldots, N$, draw an artificial error $\widetilde{\widetilde{\varepsilon}}_i$ from the truncated $N(0, \widehat{\widehat{\sigma}})$ distribution with left-truncation at $1 - \mathbf{z}_i\widehat{\widehat{\beta}}$.

   6.2 Calculate artificial efficiency scores $\widetilde{\widetilde{\theta}}_i$ as $\mathbf{z}_i\widehat{\widehat{\beta}} + \widetilde{\widetilde{\varepsilon}}_i$ for each DMU $i = 1, \ldots, N$.

   6.3 Run a truncated regression (left-truncation at 1) of $\widetilde{\widetilde{\theta}}_i$ on $\mathbf{z}_i$ to obtain bootstrap estimates $\widehat{\widehat{\beta}}^b$ and $\widehat{\widehat{\sigma}}^b$ by maximum likelihood.

7. Calculate confidence intervals and standard errors for $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\sigma}}$ from the bootstrap distribution of $\widehat{\widehat{\beta}}^b$ and $\widehat{\widehat{\sigma}}^b$.

`simarwilson` uses the inverse transform method for generating pseudo truncated normal random variates.[15] Choosing sufficiently large values for B_1 and B_2 – the latter corresponds to B in algorithm #1 – is crucial for the bias correction and the estimation of percentile based confidence intervals yielding meaningful results. For B_1 and B_2 `simarwilson` uses the default of 100 and 1000 bootstrap repetitions, respectively. The former default value is suggested in Simar and Wilson (2007), yet depending on the data used, choosing a substantially larger number for B_1 may be advisable. If normal-approximated confidence intervals (option `cinormal`) are preferred, one may choose a much smaller number than the default for B_1, and B_2 respectively. Running `simarwilson`, in particular algorithm #2, requires a substantial amount of computing time, which rapidly increases in the number of observations. For small samples, looping over truncated regression takes the lion's share in computing time. If the sample is large, looping over DEA consumes relatively more time.[16]

15. In rare cases, for which the linear prediction $\mathbf{z}_i\widehat{\beta}$ takes extreme values, generating pseudo truncated normal random variates may fail (Chopin 2011). Therefore `simarwilson` stops and issues an error message, if the initial truncated regression (step 2 or step 5) yields $\text{abs}((1-\mathbf{z}_i\widehat{\beta})/\widehat{\sigma}) > 37.5$ for at least one observation. This provides strong indication for the model being ill-specified or the data suffering from a sever outlier problem.
16. In the application ($N = 131$, $M = 113$, $Q = 1$, $P = 3$, $K = 7$), presented in section 4, with $B = 2000$, run time for algorithm #1 is 162 seconds, while it is 170 seconds for algorithm #2, with $B_1 = 1000$ and $B_2 = 2000$ (Stata/SE 15.1, Windows 10 Enterprise, Intel® Core™ i7-3520M 2.90 GHz, 8 GB RAM). Using the default values for B, B_1, and B_2 reduces run time to 79 and 81 seconds, respectively. If the the sample is expanded by the factors 2, 5, 10, and 25, run time for algorithm #1 is increased by the factors 1.1, 1.3, 1.6, and 2.7, respectively. The corresponding factors for algorithm #2 are 1.2, 1.7, 2.4, and 5.0.

2.3 Some minor extensions

The new Stata command `simarwilson` is meant to implement the above procedures one-to-one in Stata. It only deviates from what is suggested in Simar and Wilson (2007) by allowing for some settings and features that are not explicitly considered there.

- `simarwilson` allows for analyzing input oriented efficiency, while Simar and Wilson (2007) only consider the output oriented counterpart. This requires estimating an input oriented efficiency measure $\widehat{\vartheta}_i$ in step 1 (algorithm #1) and steps 1 and 3.4 (algorithm #2) and interchanging the roles of inputs and outputs in the step 3.3 (algorithm #2). Beyond this only two minor changes are required: (i) all truncated regressions, by default, consider two-sided truncation (at 0 from the left and at 1 from the right) rather than one-sided truncation. (ii) rather than sampling from a one-sided truncated normal distribution the artificial errors are drawn from a two-sided truncated normal distribution with left-truncation at $-\mathbf{z}_i\widehat{\beta}$ and right-truncation at $1-\mathbf{z}_i\widehat{\beta}$ (algorithm #2, step 6.1 $-\mathbf{z}_i\widehat{\widehat{\beta}}$ and $1-\mathbf{z}_i\widehat{\widehat{\beta}}$, respectively).[17] By this, it is taken into account that the Farrell input oriented efficiency measure is bounded to the unit interval. Specifying the option `base(input)` invokes these deviations from the default procedure. One may optionally (option `notwosided`) stick to one-sided truncation and only consider truncation from the right when analyzing input oriented efficiency. Using option `notwosided` seems questionable insofar as it rests on simulating a data generating process that is inconsistent with the non-negative nature of θ_i. In particular, `notwosided` is not recommendable with algorithm #2.[18]

- One may opt for the Shephard rather than the Farrell distance measure (option `invert`). This simply means that all (internally; see below) estimated scores are inverted through all steps of the estimation procedure. If constant returns to scale are assumed for the production technology, this is equivalent to switching from output to input oriented efficiency. For variable and non-increasing returns, this one-to-one correspondence does not hold. For option `invert` being specified with output oriented efficiency, the same changes to the estimation procedure apply as described above with respect to option `base(input)` (without option `invert`). Considering the input oriented Farrell or the output oriented Shephard efficiency measure, which are both bounded to the unit interval, may lead to counterintuitive results when performing the bias correction in algorithm #2. More precisely, it may happen that the bias corrected scores are negative for some DMUs. Negative scores do not enter the truncated regression analysis, unless option `notwosided` is specified. If negative efficiency measures occur, `simarwilson` issues a warning and recommends switching to Farrell output oriented or Shephard input oriented

17. We would like to thank Ramon Christen for suggesting implementing two-sided truncation in `simarwilson`.

18. Sampling from the right-truncated normal distribution may result in $\widetilde{\vartheta}_i < 0$ (step 3.2) and, in consequence, may make the bias correction fail ($\widetilde{\mathbf{x}}_i = (\widehat{\vartheta}_i/\widetilde{\vartheta}_i)\mathbf{x}_i < 0$; step 3.3, alg. #2). For this reason, `notwosided` is ignored in step 3.1 of algorithm #2.

efficiency, for which bias correction cannot result in negative scores. Yet, ultimately, the decision how to respond to this problem is up to the user.

- One may assume a data generating process that deviates from (1) by considering log-(in)efficiency as left-hand-side variable (option `logscore`), that is

$$\ln(\theta_i) = \mathbf{z}_i\beta + \epsilon_i \tag{2}$$

  Here ϵ_i is assumed to be truncated normally distributed, with left-truncation at $-\mathbf{z}_i\beta$.[19] If $\ln(\vartheta_i)$ is considered as left-hand-side variable, truncation at $-\mathbf{z}_i\beta$ is from the right. If all $\widehat{\theta}_i$ are close to unity, specifying the option `logscore` will make little difference. Yet, if the data include DMUs that according to the DEA are very inefficient, specifying `logscore` may result in a model specification that is more easily estimated in the truncated regressions.

- `simarwilson` allows for restricting the reference set for the DEA to a subset of the considered DMUs (option `reference()`); cf. Figure 4. Unlike `teradial`, it does not allow for considering DMUs as elements of the reference set for which no efficiency scores are estimated.[20] Restricting the reference set to a sub-sample of the considered DUMs will regularly result in some irregular (super-efficient) estimated scores. Such DMUs are ignored in the truncated regressions. In general, restricting the reference set makes the DEA model substantially deviate from what is considered in Simar and Wilson (2007). Users should, hence, carefully think about whether using the option `reference()` really makes sense.

- `simarwilson` allows for using efficiency scores which were beforehand estimated by some estimation procedure, using Stata[21] or any other software. This effectively means that step one in algorithm #1 is skipped. If externally estimated, bias corrected scores are available, one may in principle also skip steps 1–4 in algorithm #2. However, the bias correction procedure suggested above is specific and incorporates the assumptions on which the subsequent steps are based. Appropriate bias corrected scores will, hence, rarely be available. The scores calculated by `teradialbc`, though similar in some respect (cf. Simar and Wilson 2007), deviate from what is computed in steps 1–4 of algorithm #2. Since using any kind of numeric, non-negative variable as externally estimated score is technically feasible, it is the user's responsibility to make sure that this variable is a radial measure of technical efficiency.

- `simarwilson` allows for weighted estimation (only `pweight`s and `iweight`s are allowed). It is important to note that weights are immaterial for the DEA steps

19. Note that (2) is not equivalent to $\ln(\theta_i - 1) = \mathbf{z}_i\beta + \zeta_i$, with $\zeta_i \sim N\left(0, \sigma^2\right)$, which might – erroneously – be regarded as an obvious choice. Unlike (2), this process not only assumes $\theta_i = 1$ to occur with zero probability, but regards full efficiency as genuinely impossible. This conflicts with the production-possibility set including its boundary. Moreover, unlike (2), the above process assumes that for any DMU reaching some neighbourhood of $\theta_i = 1$ is relatively unlikely, i.e. $\Pr\left(1 \leq \theta_i < 1 + \tau\right) < \Pr\left(1 + \tau \leq \theta_i < 1 + 2\tau\right) \forall i$ if $\tau \to 0$.
20. This is technically infeasible since in steps 3.2 and 3.3 (algorithm #2) an estimated score is required for any DMU that contributes to the artificial reference set.
21. Besides `teradial` the user written command `dea` (Ji and Lee 2010) allows for this.

within `simarwilson`, but only affect truncated regression estimation. Zero weights can hence be used for excluding some DMUs from the truncated regression analysis that are considered in the DEA.

3 The simarwilson command

`simarwilson` requires Stata 12 or higher. Unless externally estimated efficiency scores are used, `simarwilson` requires the user written ado `teradial` including the associated plugin (`st0444`). With internal DEA the number of observations is limited by the value of [R] **matsize** that is 11 000 at the maximum. The prefix commands `by` and `svy` are not allowed. The prefix command `bootstrap` is technically allowed with externally estimated scores, however using it is entirely counterproductive. `pweight`s (default) and `iweight`s are allowed, `aweight`s and `fweight`s are not allowed; see [U] **11.1.6 weight**. Weights only affect the truncated regression steps within `simarwilson` but not the DEA steps. If `iweight`s are used, (regression) numbers of observations are expressed in terms of rounded sums of weights.

3.1 Syntax for simarwilson

The syntax for `simarwilson` reads as follows:

```
simarwilson [ (outputs = inputs) ] [ depvar ] indepvars [ if ] [ in ] [ ,
    algorithm(1|2) notwosided logscore nounit rts(crs|nirs|vrs)
    base(output|input) reference(varname) invert tename(newvar)
    tebc(newvar) biaste(newvar) reps(#) bcreps(#) saveall(name)
    bcsaveall(name) dots cinormal bbootstrap level(#) noomitted
    baselevels noprint nodeaprint trnoisily ]
```

outputs is the list of outputs from the production process, while *inputs* is the corresponding list of inputs. Either *varlist* may only include numeric, non-negative variables. Factor variables and times-series operators are not allowed. The number of output and input variables must not exceed the number of considered DMUs.

depvar specifies an existing variable that contains an externally estimated efficiency measure (score), meant to enter the regression model as dependent variable. Specifying *depvar* is only possible, if `(`*outputs* `=` *inputs*`)` is not specified. That means, with `(`*outputs* `=` *inputs*`)` specified, any variable in the following *varlist* is interpreted as element of *indepvars*. `simarwilson` expects *depvar* to be a radial efficiency measure that is either bounded to the $(0, 1]$ interval or to the $[1, \infty)$ interval. This implies that *depvar* must not be measured in percent. If some values of *depvar* are smaller than one while others exceed one, `simarwilson` issues a warning and ignores observations, depending on how the option `nounit` is specified. This may happen if the preceding efficiency analysis was carried out using a reference set that does not include all observations for which

efficiency scores are estimated. Note that Simar and Wilson (2007) do not consider this case. Only numeric and strictly positive values are allowed for *depvar*.

indepvars denotes the list of explanatory variables. Unlike *outputs* and *inputs*, factor variables are allowed in *indepvars*; see [U] **1.4.3 Factor variables**. Time-series operators such as `L.` and `F.` are not allowed.

3.2 Options for simarwilson

`algorithm(1|2)` specifies whether algorithm #1 or #2 is applied. `algorithm(2)` requires (*outputs* = *inputs*). `algorithm(1)` is the default. If external DEA scores are used as *depvar*, one has to opt for `algorithm(1)` even if the externally estimated scores are bias corrected.[22]

`notwosided` makes `simarwilson` apply a one-sided truncated regression model, irrespective of whether (regular) efficiency scores are bounded to the $(0, 1]$ interval or to the $[1, \infty)$ interval. For (regular) scores within $(0, 1]$ the default (`twosided`) is to use a two-sided truncated regression model and to sample from the two-sided truncated normal distribution. With `twosided`, the procedure hence takes into account that input oriented (Farrell) efficiency scores are not only less than or equal to 1 but are also strictly positive. The latter is ignored with `notwosided`. Hence, with `notwosided`, `simarwilson` mirror-inverted applies the procedure suggested in Simar and Wilson (2007) – that only consider scores within $[1, \infty)$ – to efficiency scores within $(0, 1]$. For (regular) efficiency scores ≥ 1, specifying `notwosided` has no effect. `notwosided` is not recommended in conjunction with `algorithm(2)`.

`logscore` makes `simarwilson` use the natural logarithm of the efficiency score as left-hand-side variable in the truncated regressions. With `logscore` specified, truncation is at 0 rather than at 1 and is always one-sided. If externally estimated scores are used, one must not take the logarithm beforehand. One rather has to specify the original untransformed score as *depvar*.

`nounit` specifies whether inefficiency is indicated by efficiency score < 1 (`unit`) or by efficiency score > 1 (`nounit`). Specifying this option will rarely be necessary. If the DEA is carried out internally, `simarwilson` internally sets `nounit` depending on how the options `base()` and `invert` are specified. If externally estimated scores are used and all observations of *depvar* are either in the $(0, 1]$ or in the $[1, \infty)$ interval, specifying the `nounit` option is also not required, since `simarwilson` recognizes which DMUs are inefficient and which are efficient. Only if external scores are used that are neither bounded to the $(0, 1]$ interval nor to the $[1, \infty)$ interval, `nounit` is required to specify which observation of *depvar* are regular (inefficient) ones and which are irregular (super-efficient) ones. Note that Simar and Wilson (2007) do not consider irregular (super-efficient) DMUs.

`rts(crs|nirs|vrs)` specifies under which assumption regarding the returns to scale of

22. With bias corrected (externally estimated) scores in hand, steps 2–4 of algorithm #1 are fully equivalent to steps 5–7 of algorithm #2; cf. section 2.2.

the considered production process, the measure of technical efficiency is estimated. `crs` requests constant returns to scale, `nirs` requests non-increasing returns to scale, and `vrs` requests variable returns to scale. `rts(crs)` is the default. `rts()` is passed through to `teradial`. If externally estimated scores are used, specifying `rts()` has no effect.

`base(output|input)` specifies orientation/base of the radial measure of technical efficiency. `output` requests output orientation while `input` requests input orientation. `base(output)` is the default. `base()` is passed through to `teradial` and has no effect if externally estimated scores are used.

`reference(`*varname*`)` specifies the indicator variable that defines which data points of `outputs` and `inputs` (DMUs) form the technology reference set. *varname* needs to be binary (numeric or string), with the (alphanumerically) larger value indicating being part of the reference set. Since for each reference DMU an efficiency score is required when running `simarwilson`, the full set of DMUs or a subset of DMUs may serve as reference set. Yet, the reference set may not include any observations for which technical efficiency is not estimated. This precludes the specification `(`*ref_outputs* `=` *ref_inputs*`)`, which is allowed in `teradial`. Specifying a subset of observation as reference set will frequently result in irregular efficiency estimates (super-efficient DMUs). Note that Simar and Wilson (2007) consider the full set of observations as reference set. Specifying a subset as reference, hence, results in a DEA model that substantially deviates from what is assumed in Simar and Wilson (2007).

`invert` makes `simarwilson` calculate and use the Shephard instead of the Farrell (default) efficiency measure. That is all estimated efficiency scores are inverted, unless they where externally estimated. `invert` is redundant for `base(crs)` since for constant returns to scale input oriented efficiency is just the reciprocal of output oriented efficiency. Hence rather than specifying `invert` one can just switch the base. Yet, this does not hold for `base(nirs)` and `base(vrs)`. With externally estimated scores, specifying `invert` has no effect. One rather has to manually invert the externally estimated scores prior to running `simarwilson`, if one wants to switch between the Farrell and the Shephard measure.

`tename(`*newvar*`)` creates the new variable *newvar* that contains estimates of radial technical efficiency (DEA scores).

`tebc(`*newvar*`)` creates the new variable *newvar* that contains bias corrected estimates of radial technical efficiency (bias corrected DEA scores). `tebc(`*newvar*`)` requires `algorithm(2)`.

`biaste(`*newvar*`)` creates the new variable *newvar* that contains bootstrap bias estimate for original radial measures of technical efficiency. `biaste(`*newvar*`)` requires `algorithm(2)`.

`reps(#)` specifies the number of bootstrap replications for estimating confidence intervals and standard errors for the regression coefficients. The default is 1000 replications.

`bcreps(#)` specifies the number of bootstrap replications for the bias correction of DEA

scores. The default is 100 replications as suggested in Simar and Wilson (2007).

`saveall(`*name*`)` makes `simarwilson` save all bootstrap estimates of the regression coefficients to the ($reps \times K + 1$) mata matrix *name*. Any existing mata matrix *name* is replaced.

`bcsaveall(`*name*`)` makes `simarwilson` save all bootstrap efficiency scores that are estimated in the bias correction procedure to the ($bcreps \times N\_dea$) mata matrix *name*. Any existing mata matrix *name* is replaced. Depending on `bcreps(#)` and the number of considered DMUs, the saved mata matrix may be huge.

`dots` makes `simarwilson` display one dot character for each bootstrap replication.

`cinormal` makes `simarwilson` display normal-approximated confidence intervals rather than percentile based bootstrap confidence intervals for the regression coefficients. One may change the reported type of confidence intervals by retyping `simarwilson` without arguments and only specifying the option `cinormal`.

`bbootstrap` makes `simarwilson` display mean bootstrap coefficients rather than the original coefficients from estimating the truncated regression model. One may change the type of the reported coefficient vector by retyping `simarwilson` without arguments and only specifying the option `bbootstrap`.

`level(#)`; see [R] **level** estimation options. One may change the reported confidence level by retyping `simarwilson` without arguments and only specifying the option `level(#)`. For percentile based confidence intervals this requires the option `saveall(`*name*`)`.

`noomitted` specifies that variables that were omitted because of collinearity not to be displayed. The default is to include in the results table any variables omitted because of collinearity and to label them as omitted by the `o.` prefix.

`baselevels` makes `simarwilson` display base categories of factor variables in the table of results and label them as base by the `#b.` prefix.

`noprint` prevents `simarwilson` from displaying warnings. Error messages are displayed irrespective of whether or not `noprint` is specified.

`nodeaprint` prevents `simarwilson` from displaying DEA output.

`trnoisily` makes `simarwilson` display genuine output of `truncreg` for the initial truncated regression(s) (not for truncated regressions within bootstrap procedures). Specifying this option might be useful if `simarwilson` issues the error message 'truncated regression failed' or 'convergence not achieved in truncated regression' and the accompanying return code is inconclusive about what makes `truncreg` fail.

In addition, `simarwilson` allows for all maximization options that are allowed with `truncreg`, which are simply passed through; see [R] maximize. Moreover, one may specify the `truncreg` options `noconstant`, `offset(`*varname*`)`, and `constraints(`*constraints*`)`, which are also passed through; see [R] **truncreg**.

3.3 Saved results for simarwilson

`simarwilson` saves the following results to `e()`:

Scalars

`e(N)`	# of observations (inefficient DMUs)	`e(chi2)`	model chi-squared
`e(N_lim)`	# of limit observations (efficient DMUs)	`e(p)`	model significance, p-value
`e(N_irreg)`	# of irregular observations (super-efficient DMUs)	`e(N_reps)`	# of completed bootstrap reps
`e(N_all)`	overall # of observations (all DMUs with eff. score)	`e(N_misreps)`	# of failed bootstrap reps
`e(wgtsum)`	sum of weights (if weights are specified)	`e(level)`	confidence level
`e(sigma)`	estimate of sigma	`e(algorithm)`	algorithm used (1 or 2)
`e(ll)`	pseudo log-likelihood (initial truncated reg.)	`e(noutps)`	# of output variables
`e(ic)`	# of iterations (initial truncated reg.)	`e(ninps)`	# of input variables
`e(converged)`	1 converged, 0 otherwise (initial truncated reg.)	`e(N_dea)`	# of DMUs for which efficiency scores are estimated
`e(rc)`	return code	`e(N_dearef)`	# of DMUs in reference set
`e(k_eq)`	# of equations in e(b)	`e(N_deaneg)`	# of negative bias corrected scores
`e(df_m)`	model degrees of freedom	`e(N_bc)`	# of completed bootstrap reps (bias correction)

Macros

`e(title)`	Simar & Wilson (2007) two-stage efficiency analysis	`e(marginsdefault)`	default `predict()` specification for `margins`
`e(shorttitle)`	Simar & Wilson (2007) eff. analysis	`e(predict)`	program used to implement `predict`
`e(cmdline)`	command as typed	`e(cinormal)`	`cinormal` (if option `cinormal` is specified)
`e(cmd)`	simarwilson	`e(bbootstrap)`	`bbootstrap` (if option `bbootstrap` is specified)
`e(unit)`	either `unit` or `nounit`	`e(scoretype)`	either `score` or `bcscore`
`e(truncation)`	either `twosided` or `onesided`	`e(invert)`	either `Farrell` or `Shephard`
`e(logscore)`	`logscore` if option `logscore` is specified	`e(biaste)`	*varname* of estimated bias (if option `biaste` is specified)
`e(wtype)`	either `pweight` or `iweight` (if weights are specified)	`e(tebc)`	*varname* of estimated bias corrected efficiency (if option `tebc` is specified)
`e(wexp)`	*exp* (if weights are specified)	`e(tename)`	*varname* of estimated uncorrected efficiency (if option `tename` is specified)
`e(depvarname)`	name of lhs variable	`e(rts)`	returns to scale (`CRS` or `NIRS` or `VRS`) (if DEA is internal)
`e(depvar)`	either *efficiency* or *inefficiency*	`e(base)`	base/orientation (`output` or `input`) (if DEA is internal)
`e(saveall)`	*name* if option `saveall(`*name*`)` is specified	`e(outputs)`	*varlist* of outputs (if DEA is internal)
`e(bcsaveall)`	*name* if option `bcsaveall(`*name*`)` is specified	`e(inputs)`	*varlist* of inputs (if DEA is internal)
`e(marginsok)`	predictions allowed by `margins`	`e(properties)`	`b V`

Matrices

`e(b)`	vector of estimated coefficients	`e(b_bstr)`	bootstrap estimates of coefficients
`e(V)`	estimated coefficient variance-covariance matrix	`e(bias_bstr)`	bootstrap estimated biases
`e(Cns)`	constraints matrix (if constraints are specified)	`e(ci_percentile)`	bootstrap percentile confidence intervals

Functions

`e(sample)`	marks estimation sample

Note that `e(sample)` and `e(N)` refer to those observations that enter the truncated regression analysis.

3.4 simarwilson postestimation

The postestimation commands that are available after `simarwilson` are almost the same as for `truncreg`; see [R] **truncreg postestimation**. Among others, these are `test`, `testnl`, `lincom`, `nlcom`, `predict`, `predictnl`, and [R] **margins**. `margins, dydx(`*indepvars*`)` appears to be particularly valuable. After `simarwilson`, `margins` behaves slightly differently than it behaves after `truncreg`. The default is to estimate marginal effects on expected (in)efficiency that is on $E(\theta_i|\theta_i > 1, \mathbf{z}_i)$ (Farrell output oriented) and $E(\vartheta_i|0 < \vartheta_i < 1, \mathbf{z}_i)$ (Farrell input oriented), respectively.[23] That is `margins`, by default, internally sets the options `predict(e(1,.))` and `predict(e(0,1))`, respectively.[24] If one wants to estimate marginal effects on the linear index, specifying the option `predict(xb)` is required. The options `predict(ystar(`a`,`b`))` and `predict(pr(`a`,`b`))` are not allowed with `margins` after `simarwilson`. They make `margins` consider a censored outcome, which makes little sense with `simarwilson`.

Users should, in general, be careful in interpreting the results one obtains from postestimation commands, such as `predict`, used after `simarwilson`. The postestimation commands treat the results of `simarwilson` as if they where generated by `truncreg`. One should, however, be aware that in terms of the underlying model both are not the same. Besides the estimated variance-covariance matrix, the key difference is that `truncreg` usually assumes that the left-hand-side variable of the data generating process is observed for not-truncated observation and may in principle also be observable for truncated observations. In contrast `simarwilson` rests on the assumption that the true outcome variable is genuinely unobservable. Moreover, while in many applications of `truncreg` truncation originates from missing information, for `simarwilson` truncation is a genuine feature of the data generating process; see section 2.

23. Since the data generating process (1) assumes a truncated distribution for ε_i, $E(\theta_i|\theta_i > 1, \mathbf{z}_i)$ coincides with $E(\theta_i|\mathbf{z}_i)$. I.e. $\theta_i < 1$ is not only not observed, it is rather impossible according to (1). The same line of argument applies to $E(\vartheta_i|0 < \vartheta_i < 1, \mathbf{z}_i)$ as well as to the Shephard measures. This argument would not hold for standard applications of `truncreg`, which illustrates that the `truncreg` postestimation commands should be used with some caution after `simarwilson`. With the options `nounit` and `notwosided` simultaneously specified, `margins` by default considers $E(\vartheta_i|\vartheta_i < 1, \mathbf{z}_i)$ that is the option `predict(e(.,1))` is internally set.
24. With option `logscore` the default is `predict(e(0,.))` and `predict(e(.,0))`, respectively. That is `margins`, by default, yields semi-elasticities.

4 An application of simarwilson

4.1 Comparison of estimation methods

In order to illustrate how `simarwilson` can be used in applied work, in this section we use the command for empirically addressing the question of whether the quality of governance, including quality of the judicial system, at the national level matters for the efficiency of gross domestic product (GDP) generation. The analysis is based on cross country data that is provided through the Penn World Table data base, version 9 (Feenstra et al. 2015) and the World Economic Forum, Global Competitiveness Report, version 2018-02-26 (World Economic Forum 2018; Schwab 2017). Though both data bases are publicly available on the internet, only the Penn World Table allows for being straightforwardly used with Stata. For this reason, this article is accompanied by the user written ado-file `gciget.ado` that facilitates the retrieval of the Global Competitiveness Index data using Stata. See subsection 4.3 for a more detailed description of `gciget`. The Stata log below is from using `gciget` to load three selected variables (`EOSQ048`, `EOSQ051`, `EOSQ144`) of the Global Competitiveness Index into Stata and merging them to the Penn World Table data.

```
. gciget EOSQ048 EOSQ051 EOSQ144
DISCLAIMER: The World Economic Forum is the provider of the Global
  Competitiveness Index 2017-2018, a framework and a corresponding set of
  indicators for 137 economies. The software gciget.ado provides a practical
  way to read the indicators into Stata (R). The responsibility of complying
  with the terms and conditions of use under which the owner of the data
  grants access to the indicators is entirely with the user but not with the
  authors of the software gciget.ado. Any user of gciget.ado is responsible
  for making him or herself familiar with the terms of use under which she or
  he is allowed to work with the data of the Global Competitiveness Index. For
  more information and methodology, please see http://wef.ch/gcr17. In no
  event will the authors, owners, and creators of gciget.ado, or their
  employers or any other party who may modify and/or redistribute this
  software, accept liability for any loss or damage suffered as a result of
  using the gciget.ado software.
Downloading the GCI_Dataset_2007-2017.xlsx file
Importing the GCI_Dataset_2007-2017.xlsx file
Processing EOSQ048:  1.09 Burden of government regulation, 1-7 (best)
Processing EOSQ051:  1.01 Property rights, 1-7 (best)
Processing EOSQ144:  1.06 Judicial independence, 1-7 (best)
. tempfile data_gci_selected
. quietly save `data_gci_selected´
. use "https://www.rug.nl/ggdc/docs/pwt90.dta", clear
. quietly merge 1:1 countrycode year using "`data_gci_selected´"
```

We consider a national-level production process that generates the single output real GDP (`rgdpo`) by using three inputs: capital stock (`ck`), number of persons engaged (`emp`), and human capital (`hc`). We assume variable returns to scale and consider the output oriented Farrell efficiency measure. As key explanatory variables we consider the 'burden of government regulation' (`EOSQ048`), 'property rights protection' (`EOSQ051`), and 'judicial independence' (`EOSQ144`). While all the rest of the data used are from the Penn World

Table, the latter three variables are provided through the Global Competitiveness Report. These indices are measured on a continuous scale ranging from 1 to 7 and originate from answers to the following questions in the World Economic Forum, Executive Opinion Survey (see Schwab 2017, Appendix C for details): "In your country, how burdensome is it for companies to comply with public administrations requirements (e.g., permits, regulations, reporting)? [1 = extremely burdensome; 7 = not burdensome at all]"; "In your country, to what extent are property rights, including financial assets, protected? [1 = not at all; 7 = to a great extent]"; "In your country, how independent is the judicial system from influences of the government, individuals, or companies? [1 = not independent at all; 7 = entirely independent]" (World Economic Forum 2018). In order to address possible endogeneity concerns regarding these regressors, we let them enter the model as lagged values. In addition to the three explanatory variables of primary interest, we include lagged log-population (`lpop`) as control. To allow for country-size related heterogeneity in the link between governance quality and national efficiency, we interact the governance quality indices with `lpop` in the regression models.

After loading the working data into Stata's memory, we generate the explanatory variables that we actually need in the empirical analysis and give them more telling names. Since `simarwilson` does not allow for times-series operators, we generate lagged values 'by hand'. To make the code easier to read, we place the governance quality variables in the global macro `g_list` and define the global macro `z_list` that contains the comprehensive list of explanatory variables. Since the sample size is relatively small, we opt for a rather generous level of significance by setting the confidence level to 90%. Moreover, we set a new seed for Stata's random number generator.[25] To facilitate the replication of results, the random number generator is reset to this state every time `simarwilson` runs in the application. To preserve the spirit of a randomness, this should be avoided in own applications.

```
. qui gen regu = EOSQ048[_n-1] if countrycode == countrycode[_n-1]
. qui gen prop = EOSQ051[_n-1] if countrycode == countrycode[_n-1]
. qui gen judi = EOSQ144[_n-1] if countrycode == countrycode[_n-1]
. qui gen lpop = ln(pop[_n-1]) if countrycode == countrycode[_n-1]
. global g_list "regu prop judi"
. global z_list "regu prop judi lpop c.regu#c.lpop c.prop#c.lpop c.judi#c.lpop"
. set level 90
. set seed 341566575
```

Second, we use `teradial` to generate externally estimated DEA efficiency scores (`te_vrs_o`) using the most recent year that is available in the data, that is 2014. We restrict the DEA to countries for which information on all right-hand-side variables is available.[26] Since we do not define a reference set that deviates from the sample for which efficiency measures are estimated, the option `base(o)` makes `te_vrs_o` taking

25. The default random number generator (`mt64`) of Stata 15 is used.
26. This is makes the DEA steps in algorithms #1 and #2 using the same sample. Only for the latter, the right-hand-side variables are required for estimating (bias corrected) efficiency scores; cf. step 3, alg. #2, p. 7.

vales equal or larger than one.[27] Then we let Stata report descriptive statistics for the variables used in the subsequent regressions. Due to missing information in some variables only 131 countries out of 182 covered by the Penn World Table can be used for estimation.

```
. teradial rgdpo = ck emp hc if year == 2014 & regu <. & prop <. & judi <. & lp
> op <., te(te_vrs_o) rts(v) base(o) noprint
. sum te_vrs_o regu prop judi lpop if e(sample)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
te_vrs_o	131	1.699949	.6236905	1	5.513838
regu	131	3.435143	.6711715	1.846199	5.42263
prop	131	4.304648	1.030568	1.610298	6.378975
judi	131	3.897085	1.315987	1.113236	6.678279
lpop	131	2.566502	1.586448	-1.264066	7.217087

As the next step of the analysis, we use four empirical models to explain (in)efficiency in GDP generation. Besides `simarwilson, algorithm(1)` and `algorithm(2)` we also consider `tobit` and `truncreg` as references. Since the model coefficients themselves do not allow for being straightforwardly interpreted in quantitative terms, we use `margins, dydx()` to estimate average marginal effects of the governance quality indices on national GDP efficiency.

We start with tobit estimation which – according to Simar and Wilson (2007) – erroneously regards full efficiency (`te_vrs_o = 1`) as outcome of the underlying data generating process rather than an artifact of finite sample bias.[28] Consistent with this misinterpretation we use the option `predict(ystar(1,.))` with `margins`. Estimated marginal effects are not displayed but stored with `estimates store` for later comparison. The output from `tobit` reveals that, according to DEA, 18 countries are fully efficient while 113 are found to be inefficient. With judical independence being the only exception, the governance variables are individually significant at the 10% level and bear the expected negative signs. However, because of the model including several interactions with log-population, making any statement about the link between governance quality and GDP efficiency is hardly possible without examining marginal effects. At least, the sings of coefficients attached to the interaction variables seem to indicate that possible efficiency gains trough less business regulation and better protection of property rights are first of all a matter of small countries.

27. Unless option `invert` is used, positive coefficient of a variable in `simarwilson` would imply it has a negative effect on efficiency. Conversely, negative coefficient would mean that the variable has positive effect on efficiency.
28. The options `nolstretch` and `vsquish` are just for making the displayed output fit on a printed page.

```
. tobit te_vrs_o $z_list, ll(1) nolstretch vsquish
Refining starting values:
Grid node 0:   log likelihood = -130.85914
Fitting full model:
Iteration 0:   log likelihood = -130.85914
Iteration 1:   log likelihood = -128.73992
Iteration 2:   log likelihood = -128.71027
Iteration 3:   log likelihood =  -128.7102
Iteration 4:   log likelihood =  -128.7102
Tobit regression                                  Number of obs     =        131
                                                    Uncensored      =        113
Limits: lower = 1                                   Left-censored   =         18
        upper = +inf                                Right-censored  =          0
                                                  LR chi2(7)        =      20.43
                                                  Prob > chi2       =     0.0047
Log likelihood =  -128.7102                       Pseudo R2         =     0.0735
```

te_vrs_o	Coef.	Std. Err.	t	P>|t|	[90% Conf.	Interval]
regu	-.3925008	.2014823	-1.95	0.054	-.7264042	-.0585973
prop	-.5199721	.2574393	-2.02	0.046	-.9466096	-.0933347
judi	.2488415	.1888903	1.32	0.190	-.064194	.5618771
lpop	-.8211409	.2667289	-3.08	0.003	-1.263173	-.3791084
c.regu# c.lpop	.1484147	.0687327	2.16	0.033	.0345084	.2623209
c.prop# c.lpop	.1251518	.0871451	1.44	0.153	-.0192682	.2695717
c.judi# c.lpop	-.0858924	.0693701	-1.24	0.218	-.2008549	.0290701
_cons	4.589835	.7747277	5.92	0.000	3.305929	5.873741
var(e.te_v~o)	.4098449	.0562185			.3265083	.514452

```
. qui margins, dydx($g_list) predict(ystar(1,.)) post
. estimates store tobit
```

Then we turn to the truncated regression by using `truncreg`. Unlike `tobit`, this approach does not consider observations for which `te_vrs_o = 1` holds. For this reason, we use the option `predict(e(1,.))` when estimating marginal effects. The estimated coefficients look quite different compared to their counterparts from `tobit`. Yet in terms of the signs, the results are similar to their counterparts from `tobit`. According to the results from `truncreg` judical independence seem to matter for efficiency, since both `judi` and its interaction with `lpop` are statistically significant at the 10% level. This points to judical independence being negatively associated with efficiency, at least in small countries. However, following the argument of Simar and Wilson (2007), this result might be an artifact of incorrectly estimated standard errors.

```
. truncreg te_vrs_o $z_list, ll(1) nolstretch vsquish
(note: 18 obs. truncated)

Fitting full model:

Iteration 0:   log likelihood = -76.432745
Iteration 1:   log likelihood = -68.518139
Iteration 2:   log likelihood = -67.617016
Iteration 3:   log likelihood = -67.606346
Iteration 4:   log likelihood = -67.606307
Iteration 5:   log likelihood = -67.606307

Truncated regression
Limit:   lower =          1                     Number of obs     =        113
         upper =       +inf                     Wald chi2(7)      =      18.90
Log likelihood = -67.606307                     Prob > chi2       =     0.0085
```

te_vrs_o	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
regu	-.9258069	.4299484	-2.15	0.031	-1.633009	-.2186048
prop	-1.243902	.4991533	-2.49	0.013	-2.064936	-.4228676
judi	.7784162	.3780368	2.06	0.039	.156601	1.400231
lpop	-1.739993	.5952224	-2.92	0.003	-2.719046	-.7609389
c.regu#						
c.lpop	.4253728	.1720618	2.47	0.013	.1423563	.7083894
c.prop#						
c.lpop	.2581352	.1794841	1.44	0.150	-.0370899	.5533604
c.judi#						
c.lpop	-.2592945	.1497392	-1.73	0.083	-.5055935	-.0129955
_cons	7.447817	1.629842	4.57	0.000	4.766965	10.12867
/sigma	.7222912	.0925133	7.81	0.000	.5701204	.8744621

```
. qui margins, dydx($g_list) predict(e(1,.)) post
. estimates store truncreg
```

Hence, in the next step, we turn to `simarwilson, algorithm(1)`. Since externally estimated efficiency scores are already available, we do not rerun the DEA within `simarwilson` but use `te_vrs_o` as dependent variable. Using the `(rgdpo = ck emp hc)` syntax instead, and specifying the options `rts(v)` and `base(o)` would have generated identical results. Since we report percentile confidence intervals for the coefficients, we request a large number (2000) for the bootstrap replications. This choice results in a substantial computing time of 162 seconds (Stata/SE 15.1).[29] Specifying the option `predict()` is not required for `margins`, since the appropriate specification is set internally. As a practical matter we advise to use 1 processor in the MP version of Stata by typing `set processors 1` before executing `simarwilson`. The estimated coefficient necessarily coincide with what we got from `truncreg`, since `simarwilson, algorithm(1)` only affects the estimated standard errors and confidence intervals. Yet, even with respect to the latter two, the deviation from their naïve counterparts from `truncreg` is rather moderate. This is in line with what is frequently found in applications of algorithm #1.

29. Carrying out the DEA internally affects computing time just marginally.

```
. simarwilson te_vrs_o $z_list, reps(2000)
Simar & Wilson (2007) eff. analysis      Number of obs             =       113
(algorithm #1)                           Number of efficient DMUs  =        18
                                         Number of bootstr. reps   =      2000
                                         Wald chi2(7)              =     21.63
inefficient if te_vrs_o > 1              Prob > chi2(7)            =    0.0029
```

Data Envelopment Analysis: externally estimated scores

inefficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [90% Conf.	Interval]
te_vrs_o						
regu	-.9258069	.4021808	-2.30	0.021	-1.61701	-.2838173
prop	-1.243902	.4715584	-2.64	0.008	-2.042034	-.5066595
judi	.7784162	.356048	2.19	0.029	.1985666	1.371619
lpop	-1.739993	.5688841	-3.06	0.002	-2.670876	-.8296476
c.regu#c.l~p	.4253728	.1611459	2.64	0.008	.1649802	.6971241
c.prop#c.l~p	.2581352	.1692766	1.52	0.127	-.013744	.5414581
c.judi#c.l~p	-.2592945	.1400455	-1.85	0.064	-.4829779	-.0310317
_cons	7.447817	1.557957	4.78	0.000	4.988534	9.974977
/sigma	.7222912	.0877174	8.23	0.000	.5537709	.8368937

```
. qui margins, dydx($g_list) post
. estimates store alg_1
```

Then we turn to `algorithm(2)`. In this procedure tailored, bias corrected efficiency scores enter the regression model at the left-hand-side. Hence, we cannot use externally estimated scores but let `simarwilson` carry out the bias correction internally. This requires the `(rgdpo = ck emp hc)` syntax along with the options `rts(v)` and `base(o)`. The latter two determine the DEA model used. By specifying the option `tebc(tebc_vrs_o)` we save the estimated, bias corrected efficiency scores for possible later use. We opt for 1000 replications in the bias correction bootstrap, which is well above the default suggested in Simar and Wilson (2007). Estimating this model takes 170 seconds. Due to the relatively small sample size, using `algorithm(2)` increases computing time by only 5%; cf. footnote 16. Since we de not use externally estimated scores as left-hand-side variable, but let `simarwilson` run the DEA internally, the reported output also involves comprehensive information about the DEA model used.[30] In the present application, using bias corrected instead of uncorrected scores has just a moderate impact on the estimated coefficients and the associated estimated confidence intervals, see the output below.

30. The option `nodeaprint` suppresses displaying the DEA related information.

```
. simarwilson (rgdpo = ck emp hc) $z_list if year == 2014, alg(2) rts(v) base(o
> ) reps(2000) bcreps(1000) tebc(tebc_vrs_o)
```

Simar & Wilson (2007) eff. analysis	Number of obs	= 131
(algorithm #2)	Number of efficient DMUs	= 0
	Number of bootstr. reps	= 2000
	Wald chi2(7)	= 21.10
inefficient if tebc_vrs_o > 1	Prob > chi2(7)	= 0.0036

Data Envelopment Analysis:	Number of DMUs	= 131
	Number of ref. DMUs	= 131
output oriented (Farrell)	Number of outputs	= 1
variable returns to scale	Number of inputs	= 3
bias corrected efficiency measure	Number of reps (bc)	= 1000

inefficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [90% Conf.	Interval]
tebc_vrs_o						
regu	-.9161716	.3876275	-2.36	0.018	-1.547635	-.2845122
prop	-1.209787	.5058764	-2.39	0.017	-2.062226	-.4182389
judi	.6717764	.3638639	1.85	0.065	.0861624	1.271846
lpop	-1.796833	.5587313	-3.22	0.001	-2.725979	-.8933189
c.regu#c.l~p	.4237473	.1520378	2.79	0.005	.1775733	.6736762
c.prop#c.l~p	.2335061	.1755503	1.33	0.183	-.0346361	.53319
c.judi#c.l~p	-.2302095	.1372156	-1.68	0.093	-.45712	-.0115268
_cons	7.887194	1.604777	4.91	0.000	5.281076	10.45693
/sigma	.8735555	.1007678	8.67	0.000	.6807801	1.010889

```
. estimates store alg_2_raw
. qui margins, dydx($g_list) post
. estimates store alg_2
```

`sum` gives us descriptive statistics for estimated, bias corrected inefficiency. Comparing them to the descriptives for `te_vrs_o` shows that the bias correction adjusts the estimated scores away from unity, ruling out (seemingly) fully efficient countries.

```
. sum tebc_vrs_o
```

Variable	Obs	Mean	Std. Dev.	Min	Max
tebc_vrs_o	131	1.956169	.7083735	1.068883	6.482759

In order to allow for interpreting the results in qualitative terms we examine the estimated mean marginal effects. This yields a rather clear picture. While, on average, the regulatory burden and judical independence appear to be immaterial for the efficiency of GDP generation, the protection of property rights matters. Except for `tobit`, the estimated marginal effect is clearly significant and amounts to roughly 1/3 (Farrell, output-oriented) units, by which inefficiency is reduced in response to an one unit increase in property rights protection. This appears to be a strong effect that corresponds to a shift from the median to the 27th percentile of the sample distribution of `tebc_vrs_o`.

```
. estimates table tobit truncreg alg_1 alg_2, title(Estimated Mean Marginal Eff
> ects) p
Estimated Mean Marginal Effects
```

Variable	tobit	truncreg	alg_1	alg_2
regu	-.02001409	.04003719	.04003719	.04118827
	0.8110	0.6720	0.6607	0.6814
prop	-.17286701	-.33398801	-.33398801	-.33925269
	0.1211	0.0049	0.0042	0.0108
judi	.02948397	.08804266	.08804266	.06698891
	0.7278	0.3449	0.3325	0.5203

legend: b/p

Measuring effects in terms of Farrell (output oriented) efficiency units appears not to be particularly telling. One may, hence, prefer a scaled efficiency measure, that allows for interpreting marginal effects in terms of percentage points. This calls for switching from the Farrell to the Shephard efficiency measure. Switching from output to input oriented efficiency, which would also yield efficiency scores within the unit interval, does not have much appeal for the present application. It would imply the thought experiment of reducing input consumption, which appears rather odd given that the national capital stock and human capital are among the inputs variables.

While switching to the Shephard measure was straightforward for `algorithm(1)` – one just has to use the reciprocal of `te_vrs_o` as dependent variable – in the present application it causes difficulties with `algorithm(2)`. As indicated by a warning issued by `simarwilson` (see below), the bias correction yields some negative scores; cf. subsection 2.3. These are not used in the truncated regressions. Thus only 127, not 131, countries enter the regression analysis. In qualitative terms, using the Shephard measure as left-hand-side variable does not change the general pattern of results. As expected (see footnote 27), the signs of all coefficients are just reversed and all coefficients remain statistically significant.

```
. simarwilson (rgdpo = ck emp hc) $z_list if year == 2014, alg(2) rts(v) base(o
> ) reps(2000) bcreps(1000) invert
warning: bias-correction yields at least one negative score; consider
  dropping opt. invert or switching to base(input)
```

Simar & Wilson (2007) eff. analysis	Number of obs	=	127
(algorithm #2)	Number of efficient DMUs	=	0
	Number of bootstr. reps	=	2000
inefficient if bcscore < 1	Wald chi2(7)	=	93.44
twosided truncation	Prob > chi2(7)	=	0.0000

Data Envelopment Analysis:	Number of DMUs	=	131
	Number of ref. DMUs	=	131
output oriented (Shephard)	Number of outputs	=	1
variable returns to scale	Number of inputs	=	3
bias corrected efficiency measure	Number of reps (bc)	=	1000

efficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [90% Conf.	Interval]
bcscore						
regu	.0691237	.0376769	1.83	0.067	.006694	.1316281
prop	.2030272	.049161	4.13	0.000	.123413	.2827933
judi	-.1056821	.0366765	-2.88	0.004	-.1656055	-.0459
lpop	.2506157	.0484025	5.18	0.000	.1726308	.3321083
c.regu#c.l~p	-.0408009	.013037	-3.13	0.002	-.062014	-.0190109
c.prop#c.l~p	-.0632933	.0165594	-3.82	0.000	-.0897817	-.0356286
c.judi#c.l~p	.0520734	.013219	3.94	0.000	.0304517	.074041
_cons	-.3667276	.1422998	-2.58	0.010	-.605271	-.1369738
/sigma	.1190544	.0076651	15.53	0.000	.1025166	.1276049

```
. qui margins, dydx($g_list) post
. estimates store alg_2_inv
```

One may force `simarwilson` to use negative bias corrected scores in the regression analysis by combining `invert` with the option `notwosided`. By doing this one accepts, however, two inconsistencies. Besides allowing for negative efficiency scores, which arguably makes little sense, one makes `simarwilson` apply different truncation rules in different steps of the estimation procedure; see footnote 18. As can be seen from the output below, `simarwilson` points the user to this issue. Indeed, forcing `simarwilson` to consider the few observations with negative scores has noticeable impact on the estimated coefficients.

```
. simarwilson (rgdpo = ck emp hc) $z_list if year == 2014, alg(2) rts(v) base(o
> ) reps(2000) bcreps(1000) invert notwosided
warning: opt. notwosided not recommendable with alg. #2; in step 3.1
  (alg. #2) sampling is from the twosided-truncated normal distribution
warning: bias-correction yields at least one negative score; consider
  dropping opt. invert or switching to base(input)

Simar & Wilson (2007) eff. analysis      Number of obs             =       131
(algorithm #2)                           Number of efficient DMUs  =         0
                                         Number of bootstr. reps   =      2000
inefficient if bcscore < 1               Wald chi2(7)              =     98.54
onesided truncation                      Prob > chi2(7)            =    0.0000

Data Envelopment Analysis:               Number of DMUs            =       131
                                         Number of ref. DMUs       =       131
output oriented (Shephard)               Number of outputs         =         1
variable returns to scale                Number of inputs          =         3
bias corrected efficiency measure        Number of reps (bc)       =      1000

------------------------------------------------------------------------------
             |  Observed   Bootstrap                         Percentile
  efficiency |      Coef.   Std. Err.      z    P>|z|     [90% Conf. Interval]
-------------+----------------------------------------------------------------
bcscore      |
        regu |   .0400735   .0429141     0.93   0.350     -.031693    .1113316
        prop |   .2704966   .0544725     4.97   0.000      .1828421    .3623146
        judi |  -.1504577   .0401147    -3.75   0.000      -.216313   -.0863225
        lpop |   .2538996    .056574     4.49   0.000      .1615896    .3499556
c.regu#c.l~p |  -.0301825   .0149123    -2.02   0.043     -.0546047   -.0048266
c.prop#c.l~p |  -.0856331   .0186131    -4.60   0.000     -.1159246   -.0555597
c.judi#c.l~p |   .0696979   .0147094     4.74   0.000      .0452582    .0940363
       _cons |  -.4241697   .1654795    -2.56   0.010     -.7034528   -.1535988
-------------+----------------------------------------------------------------
      /sigma |   .1404817   .0088438    15.88   0.000      .1210069    .1504123
------------------------------------------------------------------------------

. qui margins, dydx($g_list) post

. estimates store alg_2_notwo
```

In order to specify a model which renders interpreting estimation results in quantitative terms more convenient, using the option `logscore` is a possible alternative to `invert`. By considering log-inefficiency as left-hand-side variable, marginal effects can be interpreted as percentage reductions in inefficiency. Hence we rerun or preferred model (algorithm #2, Farrell output-oriented efficiency) using the option `logscore`. The statistical significance and the signs of the estimated coefficients are equivalent to those from the specification of reference.

```
. simarwilson (rgdpo = ck emp hc) $z_list if year == 2014, alg(2) rts(v) base(o
> ) reps(2000) bcreps(1000) logscore
Simar & Wilson (2007) eff. analysis      Number of obs             =       131
(algorithm #2)                           Number of efficient DMUs  =         0
                                         Number of bootstr. reps   =      2000
                                         Wald chi2(7)              =     37.48
inefficient if ln(bcscore) > 0           Prob > chi2(7)            =    0.0000
------------------------------------------------------------------------------
Data Envelopment Analysis:               Number of DMUs            =       131
                                         Number of ref. DMUs       =       131
output oriented (Farrell)                Number of outputs         =         1
variable returns to scale                Number of inputs          =         3
bias corrected efficiency measure        Number of reps (bc)       =      1000
------------------------------------------------------------------------------
             |  Observed   Bootstrap                         Percentile
inefficiency |     Coef.   Std. Err.      z    P>|z|     [90% Conf. Interval]
-------------+----------------------------------------------------------------
ln(bcscore)  |
        regu |  -.2212588   .0942768    -2.35   0.019    -.3813767   -.0688785
        prop |  -.3127128   .1199882    -2.61   0.009    -.5092462   -.1177127
        judi |   .1617935   .0877577     1.84   0.065     .0224931    .3082684
        lpop |  -.4737086   .1279737    -3.70   0.000    -.6940146   -.2691337
c.regu#c.l~p |   .0927766   .0340445     2.73   0.006      .038239    .1526358
c.prop#c.l~p |   .0777964   .0414616     1.88   0.061     .0125089    .1486909
c.judi#c.l~p |  -.0644932   .0323986    -1.99   0.047    -.1192701   -.0134126
       _cons |   2.312936   .3706691     6.24   0.000     1.701108     2.91863
-------------+----------------------------------------------------------------
      /sigma |   .2882745    .020727    13.91   0.000     .2448331    .3138336
------------------------------------------------------------------------------
. qui margins, dydx($g_list) post
. estimates store alg_2_log
```

One may not feel comfortable with using a (bias corrected) efficiency measure that conflicts with convexity of the production-possibility set; cf. Figure 1. One way of addressing this issue, is to once again envelope the non-convex bias corrected estimated frontier by a convex hull and to use the distance to this convexified bias corrected frontier as dependent variable in the regression analysis (cf. Badunenko et al. 2013, and Figure 5). The (*ref_outputs* = *ref_inputs*) specification of `teradial` allows for straightforwardly implementing this procedure; see the below Stata log and Badunenko and Mozharovskyi (2016). Compared to its direct counterpart (`simarwilson, algorithm(2)` without `invert` and `logscore`), using this once more adjusted efficiency measure changes the estimated coefficients markedly. Yet, qualitatively, the pattern of estimates remains the same.

```
. qui gen rgdpo_front = tebc_vrs_o*rgdpo
. teradial rgdpo = ck emp hc (rgdpo_front = ck emp hc) if year == 2014 & regu <
> . & prop <. & judi <. & lpop <., te(tebc_vrs_o_convex) rts(v) base(o) noprint
. simarwilson tebc_vrs_o_convex $z_list if year == 2014, reps(2000)
Simar & Wilson (2007) eff. analysis      Number of obs             =       131
(algorithm #1)                           Number of efficient DMUs  =         0
                                         Number of bootstr. reps   =      2000
                                         Wald chi2(7)              =     24.89
inefficient if tebc_vrs_o_convex > 1     Prob > chi2(7)            =    0.0008
```

Data Envelopment Analysis: externally estimated scores

inefficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [90% Conf.	Interval]
tebc_vrs_o~x						
regu	-.8525049	.351338	-2.43	0.015	-1.436492	-.2731832
prop	-1.104847	.4583591	-2.41	0.016	-1.884511	-.3711119
judi	.5759623	.3329715	1.73	0.084	.0401372	1.122519
lpop	-1.748744	.5217818	-3.35	0.001	-2.625194	-.919087
c.regu#c.l~p	.3752556	.1349932	2.78	0.005	.1569001	.5928116
c.prop#c.l~p	.2194959	.1578936	1.39	0.164	-.0314325	.4908592
c.judi#c.l~p	-.1856799	.1233833	-1.50	0.132	-.3866211	.0144541
_cons	7.956469	1.475931	5.39	0.000	5.576847	10.362
/sigma	.8986468	.0911453	9.86	0.000	.7240245	1.017877

```
. qui margins, dydx($g_list) post
. estimates store bc_convex
```

Finally, we compare the marginal effects for all specifications of `simarwilson` that we have estimated. Somewhat surprisingly, unlike the specification of reference, the specifications using the Shephard measure argue for more regulatory interference improving efficiency (p-values 0.039 and 0.096, respectively). One may, hence, speculate that `regu` not only captures detrimental but also beneficial facets of business regulation. In terms of the point estimates, all model specification yield a positive association of property right protection and GDP efficiency. Only for the Shephard measure as left-hand-side variable (without option `notwosided`) the average marginal effect of `prop` turns statistically insignificant at the 10% level.

Using the Shephard measure (option `invert`) or the option `logscore` makes interpreting the estimated marginal effect easier. According to the specification using the Shephard measure (without `notwosided`) a one unit increase in `prop` on average improves efficiency by 3.6 percentage points. According to the specification using log-inefficiency at the left-hand-side, the mean effect is a 10.7 percent reduction in inefficiency. With respect to `judi`, the estimated marginal effects are throughout statistically insignificant. In terms of estimated average marginal effects, basing the analysis on a convex estimated hull has almost no effect as compared to using the non-convex, bias corrected estimated frontier.

```
. estimates table alg_1 alg_2 alg_2_inv alg_2_notwo alg_2_log bc_convex, title(
> Estimated Mean Marginal Effects) p b(%5.4f) p(%4.3f)
Estimated Mean Marginal Effects
```

Variable	alg_1	alg_2	alg_2~v	alg_2~o	alg_2~g	bc_co~x
regu	0.0400	0.0412	-0.0378	-0.0358	0.0074	0.0210
	0.661	0.681	0.039	0.096	0.861	0.848
prop	-0.3340	-0.3393	0.0359	0.0532	-0.1067	-0.3541
	0.004	0.011	0.139	0.063	0.056	0.015
judi	0.0880	0.0670	0.0310	0.0256	0.0020	0.0828
	0.332	0.520	0.104	0.253	0.964	0.455

legend: b/p

4.2 Effect heterogeneity

We complete our application by analyzing possible heterogeneity in the efficiency effects of 'burden of government regulation', 'property rights protection', and 'judicial independence'. In doing this, we focus on `simarwilson, algorithm(2)` without `invert` and `logscore` as our preferred estimation method. The estimated mean marginal effects from this model suggest that only the protection of property rights matters for efficiency. However, this result might just be an artifact of averaging heterogenous effects. We graphically examine possible effect heterogeneity using [R] **marginsplot** command; see [R] **marginsplot** and the Stata log below. We consider two dimensions of heterogeneity: heterogeneity with respect to country size measured by `lpop` (Fig. 2, right panel), and heterogeneity with respect to the respective considered dimension of governance quality (Fig. 2, left panel).

```
. estimates restore alg_2_raw
(results alg_2_raw are active now)
. local h_list "$g_list lpop"
. foreach h of varlist `h_list´ {
  2.         qui sum `h´ if e(sample)
  3.         local mymin = r(min)*0.98
  4.         local myxmin = ceil(`mymin´)
  5.         local mymax = r(max)*1.02
  6.         local myxmax = floor(`mymax´)
  7.         local mystep = (`mymax´-`mymin´)/25
  8.         foreach g of varlist `h_list´ {
  9.                 local r_list : list h_list - h
 10.                 qui margins if e(sample), dydx(`g´) at(`h´=(`mymin´(`myste
> p´)`mymax´) (asobserved) `r_list´)
 11.                 qui marginsplot, xlabel(`myxmin´(1)`myxmax´) recast(line)
> recastci(rarea) scheme(s2manual)
 12.                 *qui graph export "${figures}marginsplot_aso_`g´_`h´_${dat
> e}.eps", as(eps) preview(off) replace fontface(Times)
.                 qui graph export "marginsplot_aso_`g´_`h´_${date}.eps", as(ep
> s) preview(off) replace fontface(Times)
 13.         }
 14. }
```

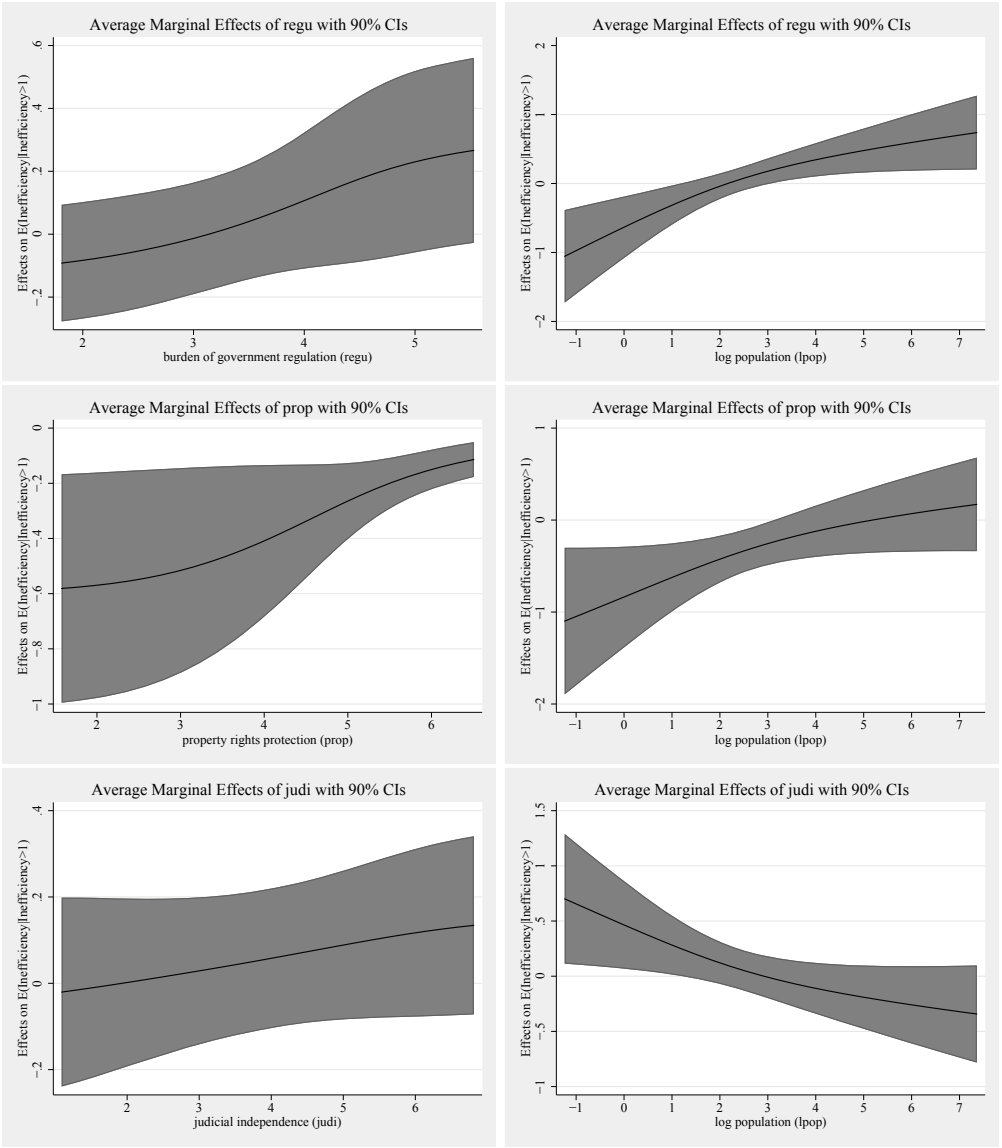

Figure 2: Estimated marginal effects of **governance quality indices** on inefficiency by country size (right column) and its respective own value (left column). *Notes*: Farrell output oriented efficiency as dependent variable; Simar and Wilson (2007), algorithm #2 used for estimation; 90% confidence bands indicated by shaded areas. *Source*: Own calculations based on Penn World Table and World Economic Forum Global Competitiveness Report data.

The left panel of Fig. 2 does not suggest that effect heterogeneity with respect to the respective category of governance quality is a big issue, at least qualitatively. The effects of both, 'burden of government regulation' and 'judicial independence' on inefficiency are statistically insignificant at any level of `regu` and `judi`. This is perfectly in line with the small and statistically insignificant estimated mean effects. Yet, if one focuses on the point estimates of the marginal effect of `regu` and for a moment ignores statistical significance, then Fig. 2 points to relaxing government regulation being beneficial, if the regulator burden is high but exerting a negative effect on efficiency, if it is already small. This pattern arguably makes much sense. The pattern for 'property rights protection' does also not conflict with what we found for the mean effect. Here we find a significant inefficiency reducing effect of better property rights protection over the entire range of `prop`. Yet, the effect seems to be much stronger for low levels of property rights protection, though the estimated marginal effect gets increasingly noisy for small values of `prop`.

The overall picture is somewhat different for heterogeneity with respect to country size (Fig. 2, right panel). There, the marginal effect of all three governance indicators exhibits substantial heterogeneity. While focusing on mean marginal effects suggested that the level of regulation was immaterial for national efficiency, considering effect heterogeneity challenges this finding. More specifically, Fig. 2 suggests that relaxing government regulation reduces inefficiency in small countries. Yet in big countries, it seems to exerts a negative effect on national efficiency. This pattern corroborates our earlier hypothesis of 'regulatory burden' being an ambiguous concept, since in certain circumstances some regulation may be well required for efficient production. A similar pattern of heterogeneity is found for the effect of `prop`. In small countries, improving the protection of property rights is clearly beneficial for efficiency of GDP production, while for big counties such effect is not found in the data. The reverse pattern of heterogeneity is found with respect to judicial independence. While the effect of `judi` on efficiency is statistically insignificant for a wide range of values of `lpop`, Fig. 2 suggests a statistically significant, efficiency reducing effect for very small countries. This somewhat surprising finding has, however, to be interpreted with caution. Near collinearity might be a technical explanation for the mirror inverted patterns found for `prop` and `judi`. Both variables are strongly correlated (0.903) in the estimation sample, while their respective correlations with `regu` (0.506 and 0.448) are much weaker.

4.3 The gciget command

As mentioned in Section 4.1 importing the indices from the Global Competitiveness Report that we used in our empirical study is not straightforward. We have developed the new Stata command `gciget` to get the indices directly into the memory of Stata from the World Economic Forum's Global Competitiveness Report.

`gciget` proceeds in three steps. First it downloads the excel file GCI_Dataset_2007-2017.xlsx from the The Global Competitiveness Report section (http://wef.ch/gcr17) of the World Economic Forum website. The user can optionally indicate the path to the excel file `GCI_Dataset_2007-2017.xlsx` stored locally. Second, `gciget` imports the

excel file. See [D] **import excel** regarding the requirement for the version of Stata. Third, `gciget` processes the variables that use has specified after `gciget`. The resulting data are in a long format and are by default declared to be panel data, see [XT] **xtset**.

The syntax for `gciget` reads as follows:

`gciget [varlist] [, options]`

The user can optionally specify the `varlist` from the list of indices in the Global Competitiveness Report (see the excel file GCI_Dataset_2007-2017.xlsx for the possible names). If no valid name of the index is specified, all indices will be processed.

The following options are available:

`clear` replace data in memory

`noxtset` do not declare the loaded data to be panel data

`noquery` suppress summary calculations by xtset

`panelvar(`*newvarname*`)` generate numeric panelvar *newvarname*

`url(filename)` download link

`sheet(``sheetname'')` excel worksheet to load

`cellrange([start][:end])` excel cell range to load

`nowarnings` do not display warnings

`gciget` only helps user get the data from the World Economic Forum into Stata. Thus any liability for the data or its usage is disclaimed. That the data comes from the World Economic Forum, also puts restriction on the data availability and the terms and conditions under which the data can be used. As of this writing the data are available for 2007–2017. The following code illustrate a simple import of four indices and plotting GCI index for four countries.

```
. gciget EOSQ048 EOSQ051 GCI GCI.A.02.01, clear
DISCLAIMER: The World Economic Forum is the provider of the Global
  Competitiveness Index 2017-2018, a framework and a corresponding set of
  indicators for 137 economies. The software gciget.ado provides a practical
  way to read the indicators into Stata (R). The responsibility of complying
  with the terms and conditions of use under which the owner of the data
  grants access to the indicators is entirely with the user but not with the
  authors of the software gciget.ado. Any user of gciget.ado is responsible
  for making him or herself familiar with the terms of use under which she or
  he is allowed to work with the data of the Global Competitiveness Index. For
  more information and methodology, please see http://wef.ch/gcr17. In no
  event will the authors, owners, and creators of gciget.ado, or their
  employers or any other party who may modify and/or redistribute this
  software, accept liability for any loss or damage suffered as a result of
  using the gciget.ado software.
Downloading the GCI_Dataset_2007-2017.xlsx file
Importing the GCI_Dataset_2007-2017.xlsx file
Processing EOSQ048:  1.09 Burden of government regulation, 1-7 (best)
```

```
Processing EOSQ051:  1.01 Property rights, 1-7 (best)
Processing GCI:  Global Competitiveness Index
Processing GCI_A_02_01:  A. Transport infrastructure
. xtline GCI if countrycode == "USA" | countrycode == "DEU" | countrycode == "F
> RA" | countrycode == "GBR", overlay i(country) t(year) scheme(sj) xlabel(2007
> (2)2017)
. qui graph export "GCI_four_cns.eps", as(eps) preview(off) replace fontface(Ti
> mes)
```

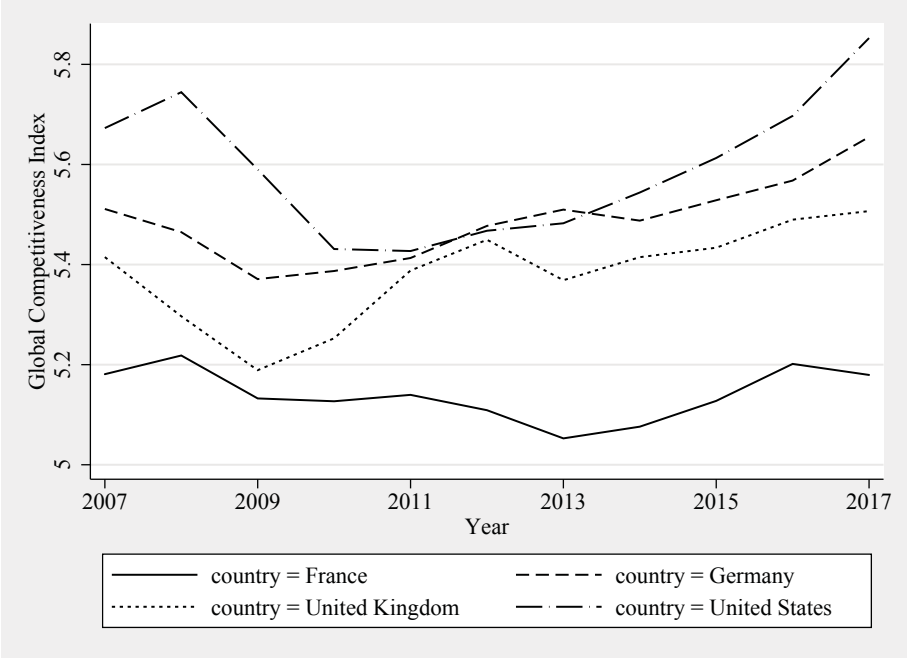

Figure 3: Global Competitiveness Index for Fracne, Germany, the UK and the USA. *Source*: World Economic Forum's Global Competitiveness Report.

5 Summary and conclusions

In this article, the new user written Stata command `simarwilson` was introduced that implements Simar and Wilson (2007) two-stage efficiency analysis. This estimator has substantial value for applied efficiency analysis as it puts regression analysis of DEA scores on firm statistical ground. The new Stata command extends the originally proposed procedure in some (minor) respects, which increases its applicability in applied empirical work. `simarwilson` complements the contributions of Ji and Lee (2010), Tauchmann (2012), and in particular Badunenko and Mozharovskyi (2016), who have already made related methods of non-parametric efficiency analysis available to Stata users.

6 Acknowledgements

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7 Supplementary Figures

The figures below graphically illustrate the concepts of a 'restricted reference set' (Figure 4) and a 'convexified frontier' (Figure 5) that were referred to in this article, using the same artificial data that was used to illustrate DEA in Figure 1.

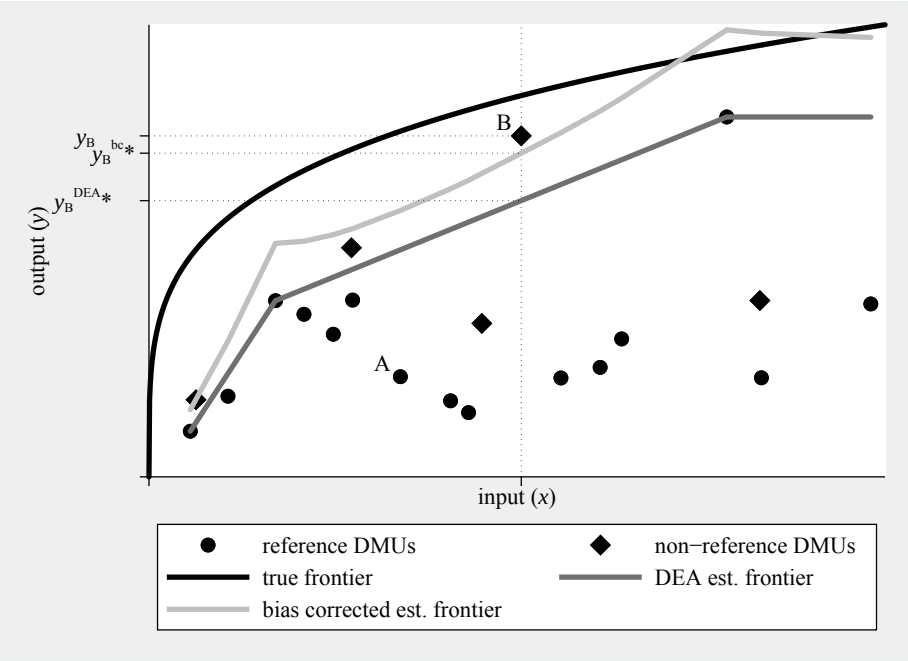

Figure 4: **Estimated inefficiency for sub-sample of DMUs used as reference**. Considering only as sub-sample of DMUs as reference set renders DMU B seemingly super-efficient, both according to conventional DEA ($\widehat{\theta_{\mathrm{B}}} = y_{\mathrm{B}}^{\mathrm{DEA}*}/y_{\mathrm{B}} < 1$) and according to bias corrected DEA ($\widehat{\theta_{\mathrm{B}}^{\mathrm{bc}}} = y_{\mathrm{B}}^{\mathrm{bc}*}/y_{\mathrm{B}} < 1$). DMU A, is still estimated to be inefficient, cf. Figure 1. Yet, the magnitude of estimated inefficiency is somewhat smaller. *Note*: Artificial data generated in the same way as for Figure 1. *Source*: Own calculations.

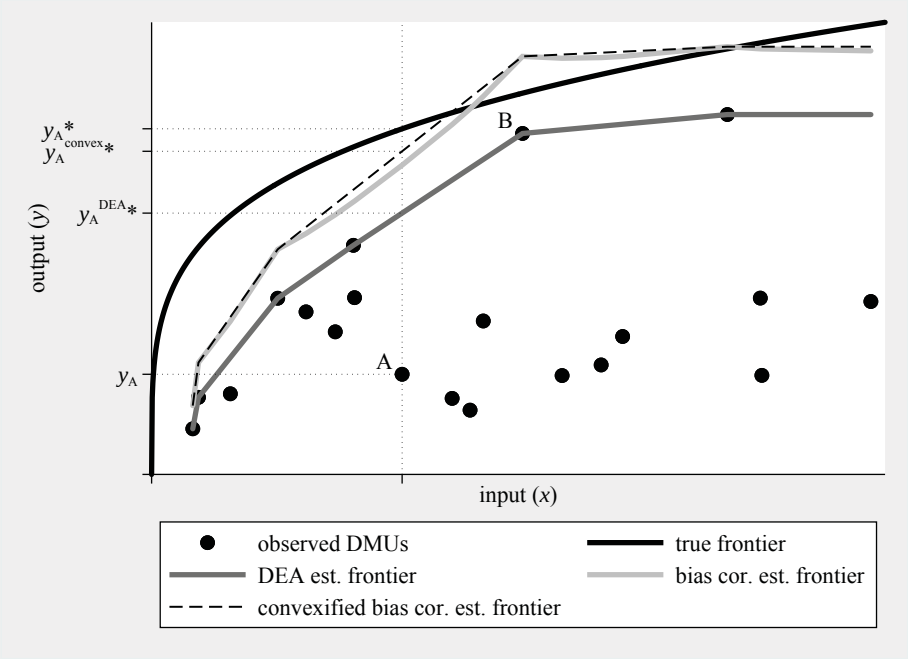

Figure 5: **Convexified bias corrected estimated frontier**. Measuring inefficiency relative to the convexified bias corrected frontier either does not affect estimated bias corrected inefficiency (e.g. DMU B) or increases estimated bias corrected inefficiency (e.g. DMU A). *Note*: Artificial data generated in the same way as for Figure 1. *Source*: Own calculations.

8 Software availability

The ado-files `simarwilson.ado` and `gciget.ado` and the accompanying help-files are available from `ssc`. Type

```
ssc install simarwilson
```

and

```
ssc install gciget
```

to install the ado-files on your machine.

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