Measuring technical efficiency and total factor productivity change with undesirable outputs in Stata

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Abstract. In this article, we introduce two user-written data envelopment analysis commands for measuring technical efficiency and productivity change in Stata. Over the last decades, an important theoretical progress of data envelopment analysis, a nonparametric method widely used for performance assessment of decision-making units, is the incorporating of undesirable outputs. Models with the ability to deal with undesirable outputs have been developed and applied in empirical studies for assessing the sustainability of decision-making units, and are getting more and more attention from researchers and managers. The `teddf` command developed in the present article allows users to measure technical efficiency, both radial and non-radial, when some outputs are undesirable outputs. Technical efficiency measures are obtained by solving linear programming problems. The `gtfpch` command provides tools for measuring productivity change, e.g., Malmquist-Luenberger index and Luenberger indicator. We provide a brief overview of the nonparametric efficiency and productivity measurement with the consideration of undesirable outputs, and we describe the syntax and options of the new commands. Examples are given to illustrate how to perform the technical efficiency and productivity analysis with the newly introduced commands.

Keywords: teddf, gtfpch, DEA, Malmquist-Luenberger index, Luenberger indicator, directional distance function, total fatcor productivity

1 Introduction

After the pioneering work of Farrell (1957), Debreu (1951), and Koopmans (1951), efficiency and productivity analysis have been wildly used in empirical studies assessing the performance of decision-making-units (DMUs) in term of converting inputs into outputs. Among the parametric and nonparametric frontier models that have been developed in the feild of efficiency analysis, Data Envelopment Analysis (DEA) have recevied plenty of attentions for its no needing of priori information of the production function form and capability in multiple output technologies (Färe et al. 1985, 1994). In the last decades, with the increasing demand for improving sustainability of the economic socity, scholars and managers gradually recognized that it is vital to consider undesirable output in efficiency and productivity analysis (Chung et al. 1997; Mahlberg and Sahoo 2011). Correspondingly, DEA models with the ability to deal with undesirable outputs have been developed and applied in empirical studies, e.g., (Zhou et al. 2012; Lin and Du 2015).

The estimation of nonparametric frontier models can be readily performed in Stata with some user-written commands. The `dea` command proposed in Ji and Lee (2010) provided a basic tool to estimate radial technical efficiency using DEA technique in Stata. Badunenko and Mozharovskyi (2016) extended `dea` with five new commands that allow users to do both radial and non-radial technical efficiency estimation, as well as statistical inference in nonparametric frontier models in Stata. Tauchmann (2012) introduced two commands, i.e., `orderm` and `orderalpha`, for implementing order-m, order-α, and free disposal hull efficiency analysis in Stata. These commands mentioned above, however, are limited in their capability for performing efficiency and productivity analysis with undesirable outputs.

Here, we introduce two user-written commands for measuring technical efficiency and productivity change with undesirable outputs in Stata. `teddf` estimates directional distance function with undesirable outputs for technical efficiency measurement. Both radial Debreu-Farrell and non-radial Russell measures can be calculated, under different assumptions about the production technology, e.g., window, biennial, sequential, and global production technology. `gtfpch` measures total factor productivity (TFP) change with undesirable outputs using Malmquist–Luenberger productivity index or Luenberger indicator. The new commands open up the possibility to do efficiency and productivity analysis with undesirable outputs in Stata in a very simple way, and their results can directly feed to other Stata routines for further analysis.

The remainder of this article unfolds as follows: section 2 provides a brief overview of the nonparametric efficiency and productivity measurement with the consideration of undesirable outputs; sections 3 and 4 contain the syntax and explain the options of `teddf` and `gtfpch`, respectively; section 5 presents a hypothetical example to show the usage of the two commands; and section 6 concludes the article.

2 The model

In this section, we provide a brief overview of the nonparametric efficiency and productivity measurement with the consideration of undesirable outputs. The radial and non-radial directional distance function (DDF) will be introduced firstly; followed by the description of the measurement of technical efficiency and TFP change using DDFs. The exposition here is only introductory. For more details, please refer to the cited works.

2.1 Directional distance function

Suppose that input vector $\boldsymbol{x} \in \Re_{+}^{N}$ are used to produce desirable output $\boldsymbol{y} \in \Re_{+}^{M}$, accompanied by the joint production of undesirable by-products $\boldsymbol{b} \in \Re_{+}^{H}$. This production technology can be characterized by the technology set as

$$T = \{(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) : \boldsymbol{x} \text{ can produce } (\boldsymbol{y}, \boldsymbol{b})\} \tag{1}$$

$$T = \{(\boldsymbol{x}, \boldsymbol{y}) : \boldsymbol{x} \text{ can produce } \boldsymbol{y}\} \tag{2}$$

Then, following Chung et al. (1997), the radial DDF is defined as

$$D_r(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}; \boldsymbol{g}) = \sup\{\beta : ((\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) + \beta \boldsymbol{g}) \in T\} \tag{3}$$

where $\boldsymbol{g} = (\boldsymbol{g}_x, \boldsymbol{g}_y, \boldsymbol{g}_b) \in \Re_{-}^{N} \times \Re_{+}^{M} \times \Re_{-}^{H}$ is a preassigned nonzero vector, specifying the direction in which the distance between the data point, $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b})$, and the production frontier is measured.

$$D_o(\boldsymbol{x}, \boldsymbol{y}) = \sup\{\beta : ((\boldsymbol{x}, \boldsymbol{y}) + \beta(\boldsymbol{0}, \boldsymbol{y})) \in T\} \tag{4}$$

$$D_i(\boldsymbol{x}, \boldsymbol{y}) = \sup\{\beta : ((\boldsymbol{x}, \boldsymbol{y}) + \beta(-\boldsymbol{x}, \boldsymbol{0})) \in T\} \tag{5}$$

$$D_d(\boldsymbol{x}, \boldsymbol{y}) = \sup\{\beta : ((\boldsymbol{x}, \boldsymbol{y}) + \beta(-\boldsymbol{x}, \boldsymbol{y})) \in T\} \tag{6}$$

$$D_r(\boldsymbol{x}, \boldsymbol{y}; \boldsymbol{g}) = \sup\{\beta : ((\boldsymbol{x}, \boldsymbol{y}) + \beta \boldsymbol{g}) \in T\} \tag{7}$$

Equation (7) gives out the most general form of the DDF. One can define the distance between the DMU and the production frontier in a specific direction through set different $\boldsymbol{g}$. By way of illustration, we consider the cases of $\boldsymbol{g}_1 = (\boldsymbol{0}, \boldsymbol{y}, \boldsymbol{0})$, $\boldsymbol{g}_2 = (\boldsymbol{0}, \boldsymbol{0}, -\boldsymbol{b})$, $\boldsymbol{g}_3 = (\boldsymbol{0}, \boldsymbol{y}, -\boldsymbol{b})$, which is wildly used in literature. Figure 1 present hypothetical one-desirable output (e.g., GDP) one-undesirable output (e.g., CO_2) production processes. Conceptually, in Fig. 1, $\overline{EI}$ and $\overline{EF}$ represent the distance when the direction is $\boldsymbol{g}_1 = (\boldsymbol{0}, \boldsymbol{y}, \boldsymbol{0})$ and $\boldsymbol{g}_2 = (\boldsymbol{0}, \boldsymbol{0}, -\boldsymbol{b})$, respectively. The former focuses on economic prosperity, while the latter focuses on environmental protection. Similarly, $\overline{EH}$ is the distance when the direction is $\boldsymbol{g}_3 = (\boldsymbol{0}, \boldsymbol{y}, -\boldsymbol{b})$, which describes the maximum increase of desirable output while simultaneously reducing the undesirable output along the direction $(\boldsymbol{y}, -\boldsymbol{b})$. Intuitively, the smaller the distance, the closer the DMU is next to the production

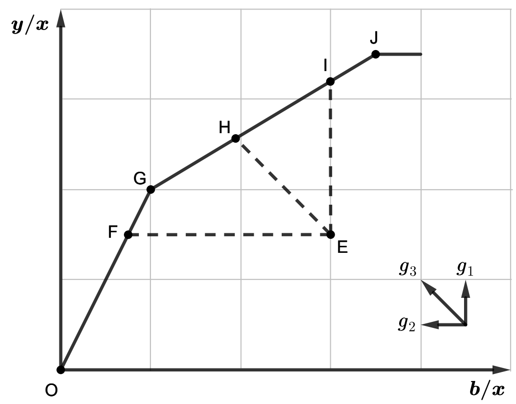

Figure 1: A graphical illustration of directional distance functions

frontier, and the distance is 0 for the DMU which operates on the production frontier.

The radial measure expands (shrinks) all outputs or/and inputs proportionally until the production frontier is reached. At the reached frontier point, some but not all outputs (inputs) can be expanded (shrunk) while remaining feasible. If such possibility is available for a given decision-making units for some outputs (inputs), then the reference point is said to have slacks in output (input). Non-radial measures, i.e., the Russell measure, accommodate such slacks (Chambers 2002; Färe and Grosskopf 2010; Zhou et al. 2012).

The non-radial DDF is defined as

$$D_{nr}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}; \boldsymbol{g}) = \sup\{\boldsymbol{w}^T\boldsymbol{\beta} : ((\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) + diag(\boldsymbol{\beta}) \cdot \boldsymbol{g}) \in T\} \tag{8}$$

where $\boldsymbol{w}$ denotes a normalized weight vector that is relevant to the numbers of inputs and outputs, and $\boldsymbol{\beta} = (\boldsymbol{\beta}_x, \boldsymbol{\beta}_y, \boldsymbol{\beta}_b) \in \Re^N \times \Re^M \times \Re^H$ denotes the vector of the scaling factors. Clearly, the non-radial DDF measure allows the inputs and outputs to be adjusted non-proportionally. Compared with the radial measure in Fig. 1, instead of use a fixed point, e.g., I, F or H, as the reference point, if the non-radial directional distance function is used, the reference point would be located at any point of the polygonal line FGHI. It is worth pointing out that, the slacks-based measure (SBM) proposed by Tone (2001, 2003) is a special case of the non-radial DDF approach (Färe and Grosskopf 2010).

$$D_{nr}(\boldsymbol{x}, \boldsymbol{y}; \boldsymbol{g}) = \sup\{\boldsymbol{w}^T\boldsymbol{\beta} : ((\boldsymbol{x}, \boldsymbol{y}) + diag(\boldsymbol{\beta}) \cdot \boldsymbol{g}) \in T\} \tag{9}$$

2.2 Measurement of technical efficiency

To estimate the DDF measure of technical efficiency using nonparametric programming technique, the production technology set is derived from observed data as

$$T = \left\{ (\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) : \sum_{j=1}^{J} \lambda_j \boldsymbol{x}_j \leq \boldsymbol{x}, \sum_{j=1}^{J} \lambda_j \boldsymbol{y}_j \geq \boldsymbol{y}, \sum_{j=1}^{J} \lambda_j \boldsymbol{b}_j = \boldsymbol{b}, \& \boldsymbol{\lambda} \geq 0 \right\} \tag{10}$$

Then, the radial DDF measure of inefficiency can be estimated by solving the following linear programming problem,

$$\begin{aligned} D_r(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}; \boldsymbol{g}) = & \max_{\beta, \boldsymbol{\lambda}} \beta \\ & \text{s.t.} \sum_{j=1}^{J} \lambda_j \boldsymbol{x}_j \leq \boldsymbol{x} + \beta \boldsymbol{g}_x, \\ & \sum_{j=1}^{J} \lambda_j \boldsymbol{y}_j \geq \boldsymbol{y} + \beta \boldsymbol{g}_y, \\ & \sum_{j=1}^{J} \lambda_j \boldsymbol{b}_j = \boldsymbol{b} + \beta \boldsymbol{g}_b, \\ & \lambda_j \geq 0, j = 1, ..., J. \end{aligned} \tag{11}$$

Similarly, the non-redial DDF measure of inefficiency can be estimated by solving the following linear programming problem,

$$\begin{aligned} D_{nr}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}; \boldsymbol{g}) = & \max_{\boldsymbol{\beta}, \boldsymbol{\lambda}} \boldsymbol{w}^T \boldsymbol{\beta} \\ & \text{s.t.} \sum_{j=1}^{J} \lambda_j \boldsymbol{x}_j \leq \boldsymbol{x} + diag(\boldsymbol{\beta}_x) \cdot \boldsymbol{g}_x, \\ & \sum_{j=1}^{J} \lambda_j \boldsymbol{y}_j \geq \boldsymbol{y} + diag(\boldsymbol{\beta}_y) \cdot \boldsymbol{g}_y, \\ & \sum_{j=1}^{J} \lambda_j \boldsymbol{b}_j = \boldsymbol{b} + diag(\boldsymbol{\beta}_b) \cdot \boldsymbol{g}_b, \\ & \boldsymbol{\beta} \geq 0; \lambda_j \geq 0, j = 1, ..., J. \end{aligned} \tag{12}$$

2.3 Measurement of total factor productivity change

The measurement of productivity change has traditionally focused on measuring marketable (desirable) outputs of DMUs relative to paid factors of production. This approach, which typically ignores the production of by-products such as pollution, can yield biased measures of productivity growth Chung et al. (1997). For example, firms in industries that face environmental regulations would typically find that their productivity is adversely affected since the costs of abatement capital would typically be included on the input side, but no account would be made of the reduction in pollutants on the output side.

Chung et al. (1997) has introduced a productivity index based the radial DDF measure, called the Malmquist-Luenberger productivity index, which credits the reduction of undesirable outputs, e.g., pollution, while simultaneously crediting increases in desirable outputs. Considering two adjacent period, denoted as s and t. respectively. If we choose the direction to be $\boldsymbol{g} = (\boldsymbol{0}, \boldsymbol{y}, -\boldsymbol{b})$, the output-oriented Malmquist-Luenberger productivity index with undesirable outputs is defined as

$$ML = \left[\frac{1 + D_r^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g})}{1 + D_r^s(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})} \times \frac{1 + D_r^t(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g})}{1 + D_r^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})}\right]^{1/2} \tag{13}$$

To avoid an arbitrary choice between base years, an geometric mean of a fraction-based Malmquist-Luenberger productivity index in base year t (first fraction) and s (second fraction) has been taken. The Malmquist–Luenberger measure indicates productivity improvements if their values are greater than one and decreases in productivity if the values are less than one.

The Malmquist-Luenberger productivity index can be decomposed into two components (Chung et al. 1997), one accounting for efficiency change (*MLEFFCH*), and one measuring technology change (*MLTECH*):

$$MLEFFCH = \frac{1 + D_r^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g})}{1 + D_r^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})} \tag{14}$$

and,

$$MLTECH = \left[\frac{1 + D_r^t(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g})}{1 + D_r^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g})} \times \frac{1 + D_r^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})}{1 + D_r^s(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})}\right]^{1/2} \tag{15}$$

Based on the pioneering work in Chambers (2002), another productivity measure, called the Luenberger productivity indicator, is also wildly used to account productivity change. The Luenberger productivity indicator based on radial DDF measures is defined as

$$\begin{aligned} L = &\left[(D_r^t(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g}) - D_r^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})\right] \times \frac{1}{2} \\ &+ \left[D_r^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g}) - D_r^s(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g}))\right] \times \frac{1}{2} \end{aligned} \tag{16}$$

Again, to avoid an arbitrary choice between base years, an arithmetic mean of a difference based Luenberger productivity index in base year t (first difference) and s (second difference) has been taken. Productivity improvements are indicated by positive values and declines by negative values.

In the spirit of decomposition of Malmquist–Luenberger productivity index, the Luenberger productivity indicator based on radial DDFs can also be decomposed into two component measures, i.e., an efficiency change component (Mahlberg and Sahoo 2011),

$$LEFFCH = D_r^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g}) - D_r^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g}) \tag{17}$$

and a technical change component,

$$
\begin{aligned}
LTECH = & \left[D_r^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g}) - D_r^s(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})\right] \times \frac{1}{2} \\
& + \left[(D_r^t(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g}) - D_r^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g})\right] \times \frac{1}{2}
\end{aligned} \tag{18}
$$

The Luenberger indicator based on radial DDFs is expressed as the sum of *LEFFCH* and *LTECH*. *LEFFCH* captures the average gain/loss due to difference in technical efficiency from period s to period t. *LTECH* captures the average gain/loss due to shift in technology from period s to period t.

Like any radial measure of efficiency estimated using DEA technologies, DDF overestimates the efficiency of a firm when there are non-zero slacks that remained in the constraints after the full radial efficiency is achieved. To account for these slacks, Färe and Grosskopf (2010) proposed a slacks-based measure of efficiency based on non-radial directional distance function. Another type of Luenberger indicator, called non-proportional Luenberger indicator, can be constructed based on the non-radial DDFs (Mahlberg and Sahoo 2011).

The Luenberger productivity indicator based on non-radial DDFs is defined as

$$
\begin{aligned}
L = & \left[(D_{nr}^t(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g}) - D_{nr}^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})\right] \times \frac{1}{2} \\
& + \left[D_{nr}^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g}) - D_{nr}^s(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g}))\right] \times \frac{1}{2}
\end{aligned} \tag{19}
$$

The non-proportional Luenberger productivity indicator can also be decomposed into two parts (Mahlberg and Sahoo 2011). An efficiency change component,

$$
LEFFCH = D_{nr}^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g}) - D_{nr}^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g}) \tag{20}
$$

and a technical change component,

$$
\begin{aligned}
LTECH = & \left[D_{nr}^t(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g}) - D_{nr}^s(\boldsymbol{x}^t, \boldsymbol{y}^t, \boldsymbol{b}^t; \boldsymbol{g})\right] \times \frac{1}{2} \\
& + \left[(D_{nr}^t(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g}) - D_{nr}^s(\boldsymbol{x}^s, \boldsymbol{y}^s, \boldsymbol{b}^s; \boldsymbol{g})\right] \times \frac{1}{2}
\end{aligned} \tag{21}
$$

3 The teddf command

`teddf` estimates directional distance function with undesirable outputs for technical efficiency measurement.

3.1 Syntax

```
teddf Xvarlist = Yvarlist:Bvarlist [if] [in], dmu(varname) [
   time(varname) gx(varlist) gy(varlist) gb(varlist) nonradial
   wmat(name) vrs rf(varname) window(#) biennial sequential
   global tol(real) maxiter(#) saving(filename[,replace]) ]
```

3.2 Options

`dmu(`*varname*`)` specifies names of DMUs. It is required.

`time(`*varname*`)` specifies the time variable for panel data.

`gx(`*varlist*`)` specifies direction components for input adjustment. The order of variables specified in gx() should as the same in *Xvarlist*. The default is gx=(0,..,0) for all assessed DMUs.

`gy(`*varlist*`)` specifies direction components for desirable output adjustment. The order of variables specified in gy() should as the same in *Yvarlist*. The default is gy=*Yvarlist*.

`gb(`*varlist*`)` specifies direction components for undesirable output adjustment. The order of variables specified in gb() should as the same in *Bvarlist*. The default is gb=-*Bvarlist*.

`nonradial` specifies using the nonradial directional distance measure.

`wmat(name)` specifies a weight matrix for adjustment of input and output variable for the nonradial directional distance measure. The default is wmat= (1,...,1).

`vrs` specifies production technology with variable returns to scale. By default, production technology with constant returns to scale is assumed.

`rf(`*varname*`)` specifies the indicator variable that defines which data points of outputs and inputs form the technology reference set.

`window(#)` specifies using window production technology with the #-period bandwidth.

`biennial` specifies using biennial production technology.

`sequential` specifies using sequential production technology.

`global` specifies using global production technology.

`tol(real)` specifies the convergence-criterion tolerance for LinearProgram(). The default value of tol is 1e-8.

`maxiter(#)` specifies the maximum number of iterations for LinearProgram(). The default value of maxiter is 16000.

`saving(filename[,replace])` specifies that the results be saved in filename.dta.

4 The gtfpch command

`gtfpch` measures total factor productivity change with undesirable outputs using Malmquist–Luenberger productivity index or Luenberger indicator.

4.1 Syntax

```
gtfpch Xvarlist = Yvarlist:Bvarlist [if] [in] , [ dmu(varname)
   luenberger ort(string) gx(varlist) gy(varlist) gb(varlist) nonradial
   wmat(name) window(#) biennial sequential global fgnz rd
   tol(real) maxiter(#) saving(filename[,replace]) ]
```

4.2 Options

`dmu(`*varname*`)` specifies names of DMUs.

`luenberger` specifies estimating Luenberger productivity indicator. The default is Malmquist–Luenberger productivity index based on the radial directional distance function.

`ort(`*string*`)` specifies the oriention. The default is ort(input), meaning the input oriented productivity index/indicator. ort(output) means the output oriented productivity index/indicator. ort(hybrid) means the hybrid-direction productivity index/indicator.

`gx(`*varlist*`)` specifies direction components for input adjustment. The order of variables specified in gx() should as the same in *Xvarlist*. By default, gx=(0,..,0) for ort(output);gx=-*Xvarlist* for ort(input) and ort(hybird).

`gy(`*varlist*`)` specifies direction components for desirable output adjustment. The order of variables specified in gy() should as the same in *Yvarlist*. By default, gy=(0,..,0) for ort(input);gy=*Yvarlist* for ort(output) and ort(hybird).

`gb(`*varlist*`)` specifies direction components for undesirable output adjustment. The order of variables specified in gb() should as the same in *Bvarlist*. By default, gb=(0,..,0) for ort(input);gb=-*Bvarlist* for ort(output) and ort(hybird).

`nonradial` specifies using the non-radial directional distance measure.

`wmat(name)` specifies a weight matrix for adjustment of input and output variable for the nonradial directional distance measure. The default is wmat=(1,...,1).

`window(#)` specifies using window production technology with the #-period bandwidth.

`biennial` specifies using biennial production technology.

`sequential` specifies using sequential production technology.

`global` specifies using global production technology.

`fgnz` specifies specifies decomposing TFP change following the spirit of Färe et al. (1994) method.

`rd` specifies decomposing TFP change following the spirit of Ray and Desli (1997) method.

`tol(real)` specifies the convergence-criterion tolerance for LinearProgram(). The default value of tol is 1e-8.

`maxiter(#)` specifies the maximum number of iterations for LinearProgram(). The default value of maxiter is 16000.

`saving(filename[,replace])` specifies that the results be saved in filename.dta.

5 Example

To exemplify the use of the commands described above, we use a input-output data set of China's provinces for the period of 2013-2015 which is obtained from a recent publication, Yan et al. (2020). The dataset includes three input variables (capital, labor and energy), one desirable output (real GDP), and one undesirable output (CO_2 emissions). The data is described as follows.

.

```
. use example.dta

.
. describe
Contains data from example.dta
  obs:            90
 vars:             7                 6 Aug 2020 12:12
---------------------------------------------------------------------------------------
              storage   display
variable name   type    format       variable label
---------------------------------------------------------------------------------------
Province        str12   %12s         province name
year            int     %10.0g       year
K               float   %9.0g        capital stock (in 100 million 1997 CNY)
L               double  %10.0g       employment (in 10 thousand persons)
E               double  %10.0g       energy consumption (in million tons of standard coal)
Y               float   %9.0g        real GDP (in 100 million 1997 CNY)
CO2             float   %15.1f       carbon dioxide emission (in kg)
---------------------------------------------------------------------------------------
Sorted by:
.
```

5.1 Application of teddf

The estimation of the directional distance function model proposed by Chung et al. (1997) as follows. The corresponding results are displayed below the executed command. The Dval variable stores the values of the directional distance function of the DMUs. The technical efficiency can be further calculated as $1 - Dval$. Note that the sav(ex1res) option saves the results in a new data file named as ex1res.dta.

```
.
. teddf K L= Y: CO2, dmu( Province ) time(year) sav(ex1result,replace)
 The diectional vector is (-K -L Y -CO2)

  Directional Distance Function Results:
    (Row: Row # in the original data; Dval: Estimated value of DDF.)
```

	Row	Province	year	Dval
1.	1	Anhui	2013	0.2917
2.	2	Anhui	2014	0.3589
3.	3	Anhui	2015	0.3735
4.	4	Beijing	2013	-0.0000
5.	5	Beijing	2014	-0.0000
6.	6	Beijing	2015	-0.0000
7.	7	Chongqing	2013	0.2068
8.	8	Chongqing	2014	0.2362
9.	9	Chongqing	2015	0.2570
10.	10	Fujian	2013	0.0877
11.	11	Fujian	2014	0.1423
12.	12	Fujian	2015	0.1482
13.	13	Gansu	2013	0.2894
14.	14	Gansu	2014	0.3679
15.	15	Gansu	2015	0.4425
16.	16	Guangdong	2013	-0.0000
17.	17	Guangdong	2014	0.0372

18.	18	Guangdong	2015	0.0487
19.	19	Guangxi	2013	0.2495
20.	20	Guangxi	2014	0.2751
21.	21	Guangxi	2015	0.2877
22.	22	Guizhou	2013	0.2795
23.	23	Guizhou	2014	0.3660
24.	24	Guizhou	2015	0.4460
25.	25	Hainan	2013	0.1920
26.	26	Hainan	2014	0.2533
27.	27	Hainan	2015	0.3076
28.	28	Hebei	2013	0.2237
29.	29	Hebei	2014	0.2913
30.	30	Hebei	2015	0.3486
31.	31	Heilongjiang	2013	0.1191
32.	32	Heilongjiang	2014	0.1401
33.	33	Heilongjiang	2015	0.1579
34.	34	Henan	2013	0.3024
35.	35	Henan	2014	0.3473
36.	36	Henan	2015	0.3597
37.	37	Hubei	2013	0.1463
38.	38	Hubei	2014	0.1870
39.	39	Hubei	2015	0.2051
40.	40	Hunan	2013	0.1579
41.	41	Hunan	2014	0.1891
42.	42	Hunan	2015	0.2286
43.	43	Inner Mongolia	2013	-0.0000
44.	44	Inner Mongolia	2014	-0.0000
45.	45	Inner Mongolia	2015	0.0000
46.	46	Jiangsu	2013	0.1451
47.	47	Jiangsu	2014	0.1613
48.	48	Jiangsu	2015	0.1549
49.	49	Jiangxi	2013	0.2358
50.	50	Jiangxi	2014	0.2748
51.	51	Jiangxi	2015	0.3122
52.	52	Jilin	2013	0.3361
53.	53	Jilin	2014	0.3433
54.	54	Jilin	2015	0.3663
55.	55	Liaoning	2013	0.1794
56.	56	Liaoning	2014	0.1832
57.	57	Liaoning	2015	0.1711
58.	58	Ningxia	2013	-0.0000
59.	59	Ningxia	2014	0.0000
60.	60	Ningxia	2015	-0.0000
61.	61	Qinghai	2013	0.4524
62.	62	Qinghai	2014	0.4928
63.	63	Qinghai	2015	0.5074
64.	64	Shaanxi	2013	0.4054
65.	65	Shaanxi	2014	0.4547
66.	66	Shaanxi	2015	0.4914
67.	67	Shandong	2013	0.1372
68.	68	Shandong	2014	0.1767
69.	69	Shandong	2015	0.2197
70.	70	Shanghai	2013	-0.0000
71.	71	Shanghai	2014	-0.0000
72.	72	Shanghai	2015	-0.0000
73.	73	Shanxi	2013	-0.0000
74.	74	Shanxi	2014	-0.0000
75.	75	Shanxi	2015	0.0269
76.	76	Sichuan	2013	0.1667
77.	77	Sichuan	2014	0.2008
78.	78	Sichuan	2015	0.2048

```
 79. | 79          Tianjin   2013   -0.0000 |
 80. | 80          Tianjin   2014   -0.0000 |
 81. | 81          Tianjin   2015    0.0116 |
 82. | 82         Xinjiang   2013    0.2433 |
 83. | 83         Xinjiang   2014    0.2511 |
 84. | 84         Xinjiang   2015    0.2397 |
 85. | 85           Yunnan   2013    0.2680 |
 86. | 86           Yunnan   2014    0.3446 |
 87. | 87           Yunnan   2015    0.3416 |
 88. | 88         Zhejiang   2013    0.1197 |
 89. | 89         Zhejiang   2014    0.1540 |
 90. | 90         Zhejiang   2015    0.1732 |
     +-------------------------------------+

Note: missing value indicates infeasible problem.
file ex1result.dta saved

Estimated Results are saved in ex1result.dta.

.
```

Additionally, We show an application of teddf to estimate the non-radial directional distance function model as follows. The Dval variable stores the values of the non-radial directional distance function of the DMUs.B_K,B_L, B_E, B_CO2, and B_Y variables stores the reduction proportion of inputs (K,L, E) and undesirable outputs ($CO2$), and the expansion proportion of desirable output (Y), respectively. The sav(ex2res) option saves the results in a new data file named as ex2res.dta.

```
.
. teddf K L= Y: CO2, dmu( Province ) time(year) nonr sav(ex2result,replace)
 The weight vector is (1 1 1 1)
 The diectional vector is (-K -L Y -CO2)

 Non-raidal Directional Distance Function Results:
    (Row: Row # in the original data; Dval: Estimated value of DDF.)
```

	Row	Province	year	Dval	B_K	B_L	B_Y	B_CO2
1.	1	Anhui	2013	1.6710	0.4594	0.7225	0.0000	0.4890
2.	2	Anhui	2014	1.7823	0.5293	0.7198	0.0000	0.5331
3.	3	Anhui	2015	1.8210	0.5827	0.7181	0.0000	0.5202
4.	4	Beijing	2013	0.0000	0.0000	0.0000	0.0000	0.0000
5.	5	Beijing	2014	0.0000	0.0000	0.0000	0.0000	0.0000
6.	6	Beijing	2015	0.0000	0.0000	0.0000	0.0000	0.0000
7.	7	Chongqing	2013	1.3031	0.4994	0.5887	0.0000	0.2149
8.	8	Chongqing	2014	1.3988	0.5415	0.5781	0.0000	0.2792
9.	9	Chongqing	2015	1.3936	0.5777	0.5661	0.0000	0.2499
10.	10	Fujian	2013	0.7968	0.3578	0.4363	0.0000	0.0026
11.	11	Fujian	2014	1.0092	0.4289	0.4426	0.0000	0.1377
12.	12	Fujian	2015	0.9997	0.4915	0.4581	0.0000	0.0500
13.	13	Gansu	2013	1.9927	0.5204	0.7853	0.0000	0.6869
14.	14	Gansu	2014	2.2088	0.0000	0.4725	1.4444	0.2920
15.	15	Gansu	2015	2.3532	0.0000	0.3980	1.7971	0.1580
16.	16	Guangdong	2013	0.0000	0.0000	0.0000	0.0000	0.0000
17.	17	Guangdong	2014	0.6215	0.1373	0.4425	0.0000	0.0417
18.	18	Guangdong	2015	0.6649	0.1980	0.4420	0.0000	0.0250
19.	19	Guangxi	2013	1.5334	0.4916	0.7061	0.0000	0.3357

20.	20	Guangxi	2014	1.6170	0.5515	0.7041	0.0000	0.3613
21.	21	Guangxi	2015	1.6090	0.6022	0.7043	0.0000	0.3025
22.	22	Guizhou	2013	2.3695	0.0000	0.5540	1.3240	0.4915
23.	23	Guizhou	2014	2.5997	0.0000	0.4772	1.7013	0.4212
24.	24	Guizhou	2015	2.7821	0.0000	0.3915	2.1054	0.2852
25.	25	Hainan	2013	1.3403	0.4746	0.6643	0.0000	0.2013
26.	26	Hainan	2014	1.5403	0.5388	0.6783	0.0000	0.3231
27.	27	Hainan	2015	1.6483	0.5871	0.6841	0.0000	0.3771
28.	28	Hebei	2013	1.7228	0.4579	0.6047	0.0000	0.6603
29.	29	Hebei	2014	1.8109	0.5240	0.6092	0.0000	0.6777
30.	30	Hebei	2015	1.8541	0.5731	0.6118	0.0000	0.6692
31.	31	Heilongjiang	2013	1.1895	0.2710	0.4781	0.0000	0.4404
32.	32	Heilongjiang	2014	1.3255	0.3249	0.4909	0.0000	0.5098
33.	33	Heilongjiang	2015	1.3640	0.3629	0.4874	0.0000	0.5137
34.	34	Henan	2013	1.6570	0.4861	0.7193	0.0000	0.4516
35.	35	Henan	2014	1.7660	0.5408	0.7209	0.0000	0.5043
36.	36	Henan	2015	1.8019	0.5890	0.7232	0.0000	0.4897
37.	37	Hubei	2013	1.1084	0.3302	0.5707	0.0000	0.2075
38.	38	Hubei	2014	1.2365	0.4089	0.5605	0.0000	0.2672
39.	39	Hubei	2015	1.2621	0.4735	0.5504	0.0000	0.2382
40.	40	Hunan	2013	1.2374	0.3551	0.6629	0.0000	0.2194
41.	41	Hunan	2014	1.3441	0.4279	0.6566	0.0000	0.2596
42.	42	Hunan	2015	1.4214	0.4905	0.6471	0.0000	0.2839
43.	43	Inner Mongolia	2013	1.7859	0.5261	0.4361	0.0000	0.8237
44.	44	Inner Mongolia	2014	1.8903	0.5853	0.4627	0.0000	0.8423
45.	45	Inner Mongolia	2015	1.8930	0.6002	0.4526	0.0000	0.8402
46.	46	Jiangsu	2013	0.8171	0.2965	0.2874	0.0000	0.2332
47.	47	Jiangsu	2014	0.9144	0.3588	0.2780	0.0000	0.2776
48.	48	Jiangsu	2015	0.9532	0.4106	0.2691	0.0000	0.2736
49.	49	Jiangxi	2013	1.4948	0.4929	0.7009	0.0000	0.3011
50.	50	Jiangxi	2014	1.6075	0.5492	0.6958	0.0000	0.3626
51.	51	Jiangxi	2015	1.6652	0.5977	0.6920	0.0000	0.3755
52.	52	Jilin	2013	1.6010	0.5369	0.5118	0.0000	0.5523
53.	53	Jilin	2014	1.6964	0.5795	0.5259	0.0000	0.5911
54.	54	Jilin	2015	1.7212	0.6167	0.5408	0.0000	0.5637
55.	55	Liaoning	2013	1.3721	0.4781	0.3567	0.0000	0.5373
56.	56	Liaoning	2014	1.4933	0.5313	0.3762	0.0000	0.5858
57.	57	Liaoning	2015	1.5003	0.5517	0.3631	0.0000	0.5855
58.	58	Ningxia	2013	3.1219	0.0000	0.1265	2.3015	0.6939
59.	59	Ningxia	2014	3.4828	0.0000	0.0072	2.7891	0.6864
60.	60	Ningxia	2015	3.6264	0.0954	0.0000	2.8435	0.6875
61.	61	Qinghai	2013	1.9420	0.6348	0.6909	0.0000	0.6163
62.	62	Qinghai	2014	2.0615	0.0977	0.1108	1.8529	0.0000
63.	63	Qinghai	2015	2.2182	0.1745	0.0802	1.9635	0.0000
64.	64	Shaanxi	2013	1.9274	0.5964	0.6706	0.0000	0.6604
65.	65	Shaanxi	2014	1.9953	0.6413	0.6646	0.0000	0.6894
66.	66	Shaanxi	2015	2.0757	0.0399	0.0000	1.9710	0.0648
67.	67	Shandong	2013	1.2119	0.2871	0.4964	0.0000	0.4285
68.	68	Shandong	2014	1.3313	0.3519	0.4916	0.0000	0.4878
69.	69	Shandong	2015	1.4087	0.4106	0.4904	0.0000	0.5077
70.	70	Shanghai	2013	0.0000	0.0000	0.0000	0.0000	0.0000
71.	71	Shanghai	2014	0.0000	0.0000	0.0000	0.0000	0.0000
72.	72	Shanghai	2015	0.0000	0.0000	0.0000	0.0000	0.0000
73.	73	Shanxi	2013	2.0539	0.0000	0.2748	1.0972	0.6818
74.	74	Shanxi	2014	2.3002	0.0000	0.1839	1.4368	0.6795
75.	75	Shanxi	2015	2.5450	0.0000	0.0894	1.8447	0.6109
76.	76	Sichuan	2013	1.2849	0.4147	0.6779	0.0000	0.1923
77.	77	Sichuan	2014	1.4019	0.4715	0.6752	0.0000	0.2551
78.	78	Sichuan	2015	1.3719	0.5171	0.6742	0.0000	0.1806
79.	79	Tianjin	2013	0.6668	0.3760	0.0466	0.0000	0.2441
80.	80	Tianjin	2014	0.7531	0.4253	0.0551	0.0000	0.2727

81.	81	Tianjin	2015	0.7349	0.4665	0.0581	0.0000	0.2103
82.	82	Xinjiang	2013	2.0085	0.0000	0.1794	1.2920	0.5370
83.	83	Xinjiang	2014	2.2392	0.0000	0.0731	1.6136	0.5526
84.	84	Xinjiang	2015	2.4689	0.0096	0.0000	1.9262	0.5330
85.	85	Yunnan	2013	1.7617	0.4480	0.7814	0.0000	0.5323
86.	86	Yunnan	2014	1.8300	0.5165	0.7834	0.0000	0.5301
87.	87	Yunnan	2015	1.8184	0.5696	0.7790	0.0000	0.4698
88.	88	Zhejiang	2013	0.8887	0.2696	0.4386	0.0000	0.1805
89.	89	Zhejiang	2014	1.0078	0.3364	0.4375	0.0000	0.2340
90.	90	Zhejiang	2015	1.0589	0.3912	0.4368	0.0000	0.2309

```
Note: missing value indicates infeasible problem.
file ex2result.dta saved
Estimated Results are saved in ex2result.dta.
.
```

5.2 Application of gtfpch

We first apply gtfpch to estimate the Malmquist–Luenberger productivity index (MLPI) to measure the green total-factor productivity growth of China's provinces. Regarding the results, TFPCH stores the values of MLPI; TECH and TECCH are the two decomposition terms of MLPI, describing technical efficiency change and technological change, respectively. Note that we implement the estimation based on the global technology benchmark by specifying the *global* option.

```
.
. egen id=group(Province)
. xtset id year
       panel variable:  id (strongly balanced)
        time variable:  year, 2013 to 2015
                delta:  1 unit
. gtfpch K L= Y: CO2, dmu( Province ) global sav(ex3result,replace)
 The diectional vector is (0 0 Y -CO2)

 Total Factor Productivity Change:Malmquist-Luenberger Productivity Index
    (Row: Row # in the original data; Pdwise: periodwise)
```

	Row	Province	id	Pdwise	TFPCH	TECH	TECCH
1.	2	Anhui	1	2013~2014	0.9832	0.9179	1.0711
2.	3	Anhui	1	2014~2015	0.9853	0.9027	1.0916
3.	5	Beijing	2	2013~2014	1.0383	1.0000	1.0383
4.	6	Beijing	2	2014~2015	1.0620	1.0000	1.0620
5.	8	Chongqing	3	2013~2014	1.0029	0.9788	1.0246
6.	9	Chongqing	3	2014~2015	1.0476	0.9348	1.1207
7.	11	Fujian	4	2013~2014	0.9707	0.9248	1.0496
8.	12	Fujian	4	2014~2015	1.0327	0.9665	1.0685
9.	14	Gansu	5	2013~2014	0.9721	0.9011	1.0788
10.	15	Gansu	5	2014~2015	0.9791	0.8768	1.1167
11.	17	Guangdong	6	2013~2014	1.0221	0.9556	1.0695
12.	18	Guangdong	6	2014~2015	1.0175	0.9823	1.0358
13.	20	Guangxi	7	2013~2014	1.0076	0.9709	1.0378
14.	21	Guangxi	7	2014~2015	1.0750	0.9640	1.1152

```
 15. | 23          Guizhou   8   2013~2014   1.0101   0.9364   1.0787
 16. | 24          Guizhou   8   2014~2015   1.0565   0.9253   1.1418
 17. | 26           Hainan   9   2013~2014   0.9417   0.9099   1.0350
 18. | 27           Hainan   9   2014~2015   0.9470   0.8566   1.1055
 19. | 29            Hebei  10   2013~2014   1.0212   0.9316   1.0963
 20. | 30            Hebei  10   2014~2015   1.0010   0.9203   1.0877
 21. | 32     Heilongjiang  11   2013~2014   1.0015   0.9123   1.0978
 22. | 33     Heilongjiang  11   2014~2015   1.0160   0.9686   1.0489
 23. | 35            Henan  12   2013~2014   0.9872   0.9264   1.0656
 24. | 36            Henan  12   2014~2015   0.9892   0.9024   1.0962
 25. | 38            Hubei  13   2013~2014   1.0035   0.9420   1.0652
 26. | 39            Hubei  13   2014~2015   1.0026   0.9426   1.0637
 27. | 41            Hunan  14   2013~2014   1.0165   0.9555   1.0638
 28. | 42            Hunan  14   2014~2015   0.9670   0.9059   1.0674
 29. | 44   Inner Mongolia  15   2013~2014   1.0573   0.8995   1.1753
 30. | 45   Inner Mongolia  15   2014~2015   1.1133   1.0124   1.0997
 31. | 47          Jiangsu  16   2013~2014   1.0478   0.9845   1.0643
 32. | 48          Jiangsu  16   2014~2015   1.0623   0.9963   1.0662
 33. | 50          Jiangxi  17   2013~2014   0.9837   0.9468   1.0390
 34. | 51          Jiangxi  17   2014~2015   0.9927   0.8935   1.1110
 35. | 53            Jilin  18   2013~2014   1.0231   0.9590   1.0668
 36. | 54            Jilin  18   2014~2015   1.1073   0.9765   1.1339
 37. | 56         Liaoning  19   2013~2014   1.0534   0.9316   1.1308
 38. | 57         Liaoning  19   2014~2015   1.0798   0.9993   1.0805
 39. | 59          Ningxia  20   2013~2014   1.0492   0.9476   1.1071
 40. | 60          Ningxia  20   2014~2015   1.0404   0.8599   1.2099
 41. | 62          Qinghai  21   2013~2014   1.0628   0.9735   1.0917
 42. | 63          Qinghai  21   2014~2015   1.0176   0.8650   1.1765
 43. | 65          Shaanxi  22   2013~2014   0.9909   0.9619   1.0302
 44. | 66          Shaanxi  22   2014~2015   1.0624   0.8997   1.1808
 45. | 68         Shandong  23   2013~2014   1.0072   0.9213   1.0932
 46. | 69         Shandong  23   2014~2015   0.9817   0.9326   1.0527
 47. | 71         Shanghai  24   2013~2014   0.9954   1.0000   0.9954
 48. | 72         Shanghai  24   2014~2015   1.0154   1.0000   1.0154
 49. | 74           Shanxi  25   2013~2014   0.9358   0.8411   1.1126
 50. | 75           Shanxi  25   2014~2015   0.9671   0.8692   1.1126
 51. | 77          Sichuan  26   2013~2014   1.0051   0.9515   1.0563
 52. | 78          Sichuan  26   2014~2015   1.0349   0.9608   1.0771
 53. | 80          Tianjin  27   2013~2014   1.0921   1.0000   1.0921
 54. | 81          Tianjin  27   2014~2015   1.0801   0.9692   1.1144
 55. | 83         Xinjiang  28   2013~2014   0.9204   0.8438   1.0907
 56. | 84         Xinjiang  28   2014~2015   0.8992   0.7948   1.1313
 57. | 86           Yunnan  29   2013~2014   1.0489   0.9720   1.0791
 58. | 87           Yunnan  29   2014~2015   1.0442   0.9604   1.0872
 59. | 89         Zhejiang  30   2013~2014   1.0234   0.9548   1.0718
 60. | 90         Zhejiang  30   2014~2015   1.0044   0.9539   1.0529

Note: missing value indicates infeasible problem.
file ex3result.dta saved
Estimated Results are saved in ex3result.dta.
.
```

Alternatively, gtfpch can be employed to estimate the Luenberger productivity indicator. We present an example as follows.

```
.
. gtfpch K L= Y: CO2, dmu( Province ) nonr  global sav(ex4result,replace)
 The weight vector is (0 0 1 1)
```

The diectional vector is (0 0 Y -CO2)

Total Factor Productivity Change:Luenberger Productivity Index (based on nonrial DDF)
(Row: Row # in the original data; Pdwise: periodwise)

	Row	Province	id	Pdwise	TFPCH	TECH	TECCH
1.	2	Anhui	1	2013~2014	-0.0676	-0.2281	0.1605
2.	3	Anhui	1	2014~2015	0.0214	-0.0597	0.0811
3.	5	Beijing	2	2013~2014	0.0832	-0.0000	0.0832
4.	6	Beijing	2	2014~2015	0.1705	0.0000	0.1705
5.	8	Chongqing	3	2013~2014	0.0175	-0.0564	0.0738
6.	9	Chongqing	3	2014~2015	0.0178	-0.1079	0.1257
7.	11	Fujian	4	2013~2014	-0.0378	-0.0947	0.0569
8.	12	Fujian	4	2014~2015	0.0640	-0.0590	0.1230
9.	14	Gansu	5	2013~2014	-0.1748	-0.3039	0.1291
10.	15	Gansu	5	2014~2015	-0.1423	-0.2188	0.0765
11.	17	Guangdong	6	2013~2014	0.0372	-0.1043	0.1416
12.	18	Guangdong	6	2014~2015	0.0316	-0.0483	0.0799
13.	20	Guangxi	7	2013~2014	0.0701	-0.0935	0.1636
14.	21	Guangxi	7	2014~2015	0.0463	-0.0685	0.1149
15.	23	Guizhou	8	2013~2014	-0.1899	-0.3070	0.1171
16.	24	Guizhou	8	2014~2015	-0.1913	-0.2681	0.0767
17.	26	Hainan	9	2013~2014	-0.0770	-0.1506	0.0736
18.	27	Hainan	9	2014~2015	-0.0974	-0.2098	0.1124
19.	29	Hebei	10	2013~2014	-0.0842	-0.2057	0.1215
20.	30	Hebei	10	2014~2015	-0.0754	-0.1438	0.0684
21.	32	Heilongjiang	11	2013~2014	-0.0189	-0.1510	0.1321
22.	33	Heilongjiang	11	2014~2015	0.0066	-0.0513	0.0579
23.	35	Henan	12	2013~2014	-0.0239	-0.1969	0.1731
24.	36	Henan	12	2014~2015	0.0449	-0.0597	0.1046
25.	38	Hubei	13	2013~2014	-0.0002	-0.0640	0.0638
26.	39	Hubei	13	2014~2015	-0.0045	-0.1038	0.0993
27.	41	Hunan	14	2013~2014	0.0227	-0.0417	0.0644
28.	42	Hunan	14	2014~2015	-0.0449	-0.1487	0.1037
29.	44	Inner Mongolia	15	2013~2014	0.0528	-0.1069	0.1598
30.	45	Inner Mongolia	15	2014~2015	0.1649	0.0329	0.1320
31.	47	Jiangsu	16	2013~2014	0.0605	-0.0053	0.0657
32.	48	Jiangsu	16	2014~2015	0.0831	-0.0268	0.1100
33.	50	Jiangxi	17	2013~2014	0.0129	-0.1216	0.1345
34.	51	Jiangxi	17	2014~2015	-0.0358	-0.1499	0.1141
35.	53	Jilin	18	2013~2014	0.0620	-0.1153	0.1773
36.	54	Jilin	18	2014~2015	0.1629	0.0191	0.1438
37.	56	Liaoning	19	2013~2014	0.0780	-0.1039	0.1820
38.	57	Liaoning	19	2014~2015	0.1291	0.0198	0.1092
39.	59	Ningxia	20	2013~2014	-0.3604	-0.4801	0.1197
40.	60	Ningxia	20	2014~2015	0.0329	-0.0555	0.0884
41.	62	Qinghai	21	2013~2014	-0.1070	-0.2903	0.1833
42.	63	Qinghai	21	2014~2015	0.0362	-0.1169	0.1531
43.	65	Shaanxi	22	2013~2014	-0.1201	-0.2856	0.1655
44.	66	Shaanxi	22	2014~2015	-0.0245	-0.1140	0.0896
45.	68	Shandong	23	2013~2014	-0.0162	-0.1516	0.1353
46.	69	Shandong	23	2014~2015	-0.0472	-0.1088	0.0616
47.	71	Shanghai	24	2013~2014	0.1528	0.0000	0.1528
48.	72	Shanghai	24	2014~2015	0.0676	-0.0000	0.0676
49.	74	Shanxi	25	2013~2014	-0.2466	-0.3373	0.0907
50.	75	Shanxi	25	2014~2015	-0.2778	-0.3393	0.0614
51.	77	Sichuan	26	2013~2014	-0.0004	-0.0521	0.0518
52.	78	Sichuan	26	2014~2015	0.0495	-0.0636	0.1131
53.	80	Tianjin	27	2013~2014	0.1075	-0.0275	0.1350
54.	81	Tianjin	27	2014~2015	0.1303	0.0530	0.0774

```
 55. | 83         Xinjiang   28   2013~2014   -0.2221   -0.3371   0.1150 |
 56. | 84         Xinjiang   28   2014~2015   -0.2232   -0.2931   0.0699 |
 57. | 86           Yunnan   29   2013~2014    0.0128   -0.1320   0.1448 |
 58. | 87           Yunnan   29   2014~2015    0.1378    0.0586   0.0792 |
 59. | 89         Zhejiang   30   2013~2014    0.0119   -0.0558   0.0677 |
 60. | 90         Zhejiang   30   2014~2015   -0.0092   -0.0996   0.0903 |
     +--------------------------------------------------------------------+

Note: missing value indicates infeasible problem.
file ex4result.dta saved
Estimated Results are saved in ex4result.dta.
.
```

6 Conclusion

With the increasing demand for improving sustainability at the macro and micro level, scholars and managers recognized that it is becoming more and more important to consider undesirable output in efficiency and productivity analysis. Stata, as one of the leading packages for economic analysis, however, has not provided comprehensive tools to measure technical efficiency and total factor productivity change when considering undesirable outputs. Here, as an attempt to fill this gap, we introduced two new Stata commands that perform estimations for nonparametric frontier models with undesirable outputs.

`teddf` estimates directional distance function with undesirable outputs for technical efficiency measurement. Both radial Debreu-Farrell and non-radial Russell measures can be calculated, under different assumptions about the production technology, e.g., window, biennial, sequential, and global production technology. `gtfpch` measures total factor productivity change with undesirable outputs using Malmquist–Luenberger productivity index or Luenberger indicator. Two types of specification of decomposing total factor productivity change were given. A empirical example have been presented to show the usage of the two commands.

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