

# Package ‘snfa’

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**Title** Smooth Non-Parametric Frontier Analysis

**Version** 0.0.1

**Description** Fitting of non-parametric production frontiers for use in efficiency analysis. Methods are provided for both a smooth analogue of Data Envelopment Analysis (DEA) and a non-parametric analogue of Stochastic Frontier Analysis (SFA). Frontiers are constructed for multiple inputs and a single output using constrained kernel smoothing as in Racine et al. (2009), which allow for the imposition of monotonicity and concavity constraints on the estimated frontier.

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allocative. efficiency *Allocative efficiency estimation*

---

## Description

Fits frontier to data and estimates technical and allocative efficiency

## Usage

```
allocative. efficiency(X, y, X. price, y. price, X. constrained = NA,
  H. inv = NA, H. mult = 1, model = "br", method = "u",
  scale. constraints = TRUE)
```

## Arguments

X	Matrix of inputs
y	Vector of outputs
X. price	Matrix of input prices
y. price	Vector of output prices
X. constrained	Matrix of inputs where constraints apply
H. inv	Inverse of the smoothing matrix (must be positive definite); defaults to rule of thumb
H. mult	Scaling factor for rule of thumb smoothing matrix
model	Type of frontier to use; "br" for boundary regression, "sf" for stochastic frontier
method	Constraints to apply; "u" for unconstrained, "m" for monotonically increasing, and "mc" for monotonically increasing and concave
scale. constraints	Boolean, whether to scale constraints by their average value, can help with convergence

## Details

This function estimates allocative inefficiency using the methodology in McKenzie (2018). The estimation process is a non-parametric analogue of Schmidt and Lovell (1979). First, the frontier is fit using either a boundary regression or stochastic frontier as in Racine et al. (2009), from which technical efficiency is estimated. Then, gradients and price ratios are computed for each observation and compared to determine the extent of misallocation. Specifically, log-overallocation is computed as

$$\log\left(\frac{w_i^j}{p_i}\right) - \log\left(\phi_i \frac{\partial f(x_i)}{\partial x^j}\right),$$

where  $\phi_i$  is the efficiency of observation  $i$ ,  $\partial f(x_i)/\partial x^j$  is the marginal productivity of input  $j$  at observation  $i$ ,  $w_i^j$  is the cost of input  $j$  for observation  $i$ , and  $p_i$  is the price of output for observation  $i$ .

## Value

Returns a list with the following elements

<code>y.fit</code>	Estimated value of the frontier at X.fit
<code>gradient.fit</code>	Estimated gradient of the frontier at X.fit
<code>technical. efficiency</code>	Estimated technical efficiency
<code>log. overallocation</code>	Estimated log-overallocation of each input for each observation
<code>X. eval</code>	Matrix of inputs used for fitting
<code>X. constrained</code>	Matrix of inputs where constraints apply
<code>H. inv</code>	Inverse smoothing matrix used in fitting
<code>method</code>	Method used to fit frontier
<code>scaling. factor</code>	Factor by which constraints are multiplied before quadratic programming

## References

Aigner D, Lovell CK, Schmidt P (1977). "Formulation and estimation of stochastic frontier production function models." *Journal of econometrics*, **6**(1), 21–37.

McKenzie T (2018). "Semi-Parametric Estimation of Allocative Inefficiency Using Smooth Non-Parametric Frontier Analysis." Working Paper.

Racine JS, Parmeter CF, Du P (2009). "Constrained nonparametric kernel regression: Estimation and inference." Working paper.

Schmidt P, Lovell CK (1979). "Estimating technical and allocative inefficiency relative to stochastic production and cost frontiers." *Journal of econometrics*, **9**(3), 343–366.

## Examples

```
data(USMacro)

USMacro <- USMacro[complete.cases(USMacro), ]

#Extract data
X <- as.matrix(USMacro[,c("K", "L")])
y <- USMacro$Y
```

```

X.price <- as.matrix(USMacro[,c("K.price", "L.price")])
y.price <- rep(1e9, nrow(USMacro)) #Price of $1 billion of output is $1 billion

#Run model
efficiency.model <- allocative.efficiency(X, y,
                                          X.price, y.price,
                                          X.constrained = X,
                                          model = "br",
                                          method = "mc")

#Plot technical/allocative efficiency over time
library(ggplot2)

technical.df <- data.frame(Year = USMacro$Year,
                          Efficiency = efficiency.model$technical.efficiency)

ggplot(technical.df, aes(Year, Efficiency)) +
  geom_line()

allocative.df <- data.frame(Year = rep(USMacro$Year, times = 2),
                          log.overallocation = c(efficiency.model$log.overallocation[,1],
                                                  efficiency.model$log.overallocation[,2]),
                          Variable = rep(c("K", "L"), each = nrow(USMacro)))

ggplot(allocative.df, aes(Year, log.overallocation)) +
  geom_line(aes(color = Variable))

#Estimate average overallocation across sample period
lm.model <- lm(log.overallocation ~ 0 + Variable, allocative.df)
summary(lm.model)

```

---

fit.boundary

*Multivariate smooth boundary fitting with additional constraints*


---

## Description

Fits boundary of data with kernel smoothing, imposing monotonicity and/or concavity constraints.

## Usage

```

fit.boundary(X.eval, y.eval, X.bounded, y.bounded, X.constrained = NA,
            X.fit = NA, y.fit.observed = NA, H.inv = NA, H.mult = 1,
            method = "u", scale.constraints = TRUE)

```

## Arguments

X.eval	Matrix of inputs used for fitting
y.eval	Vector of outputs used for fitting

X.bounded	Matrix of inputs where bounding constraints apply
y.bounded	Vector of outputs where bounding constraints apply
X.constrained	Matrix of inputs where monotonicity/concavity constraints apply
X.fit	Matrix of inputs where curve is fit; defaults to X.constrained
y.fit.observed	Vector of outputs corresponding to observations in X.fit; used for efficiency calculation
H.inv	Inverse of the smoothing matrix (must be positive definite); defaults to rule of thumb
H.mult	Scaling factor for rule of thumb smoothing matrix
method	Constraints to apply; "u" for unconstrained, "m" for monotonically increasing, and "mc" for monotonically increasing and concave
scale.constraints	Boolean, whether to scale constraints by their average value, can help with convergence

## Details

This method fits a smooth boundary of the data (with all data points below the boundary) while imposing specified monotonicity and concavity constraints. The procedure is derived from Racine et al. (2009), which develops kernel smoothing methods with bounding, monotonicity and concavity constraints. Specifically, the smoothing procedure involves finding optimal weights for a Nadaraya-Watson estimator of the form

$$\hat{y} = m(x) = \sum_{i=1}^N p_i A(x, x_i) y_i,$$

where  $x$  are inputs,  $y$  are outputs,  $p$  are weights, subscripts index observations, and

$$A(x, x_i) = \frac{K(x, x_i)}{\sum_{h=1}^N K(x, x_h)}$$

for a kernel  $K$ . This method uses a multivariate normal kernel of the form

$$K(x, x_h) = \exp\left(-\frac{1}{2}(x - x_h)' H^{-1}(x - x_h)\right),$$

where  $H$  is a bandwidth matrix. Bandwidth selection is performed via Silverman's (1986) rule-of-thumb, in the function `H.inv.select`.

Optimal weights  $\hat{p}$  are selected by solving the quadratic programming problem

$$\min_p -\mathbf{1}'p + \frac{1}{2}p'p.$$

This method always imposes bounding constraints as specified points, given by

$$m(x_i) - y_i = \sum_{h=1}^N p_h A(x_i, x_h) y_h - y_i \geq 0 \quad \forall i.$$

Additionally, monotonicity constraints of the following form can be imposed at specified points:

$$\frac{\partial m(x)}{\partial x^j} = \sum_{h=1}^N p_h \frac{\partial A(x, x_h)}{\partial x^j} y_h \geq 0 \quad \forall x, j,$$

where superscripts index inputs. Finally concavity constraints of the following form can also be imposed using Afriat's (1967) conditions:

$$m(x) - m(z) \leq \nabla_x m(z) \cdot (x - z) \quad \forall x, z.$$

The gradient of the frontier at a point  $x$  is given by

$$\nabla_x m(x) = \sum_{i=1}^N \hat{p}_i \nabla_x A(x, x_i) y_i,$$

where  $\hat{p}_i$  are estimated weights.

## Value

Returns a list with the following elements

<code>y.fit</code>	Estimated value of the frontier at <code>X.fit</code>
<code>gradient.fit</code>	Estimated gradient of the frontier at <code>X.fit</code>
<code>efficiency</code>	Estimated efficiencies of <code>y.fit.observ</code>
<code>solution</code>	Boolean; TRUE if frontier successfully estimated
<code>X.eval</code>	Matrix of inputs used for fitting
<code>X.constrained</code>	Matrix of inputs where monotonicity/concavity constraints apply
<code>X.fit</code>	Matrix of inputs where curve is fit
<code>H.inv</code>	Inverse smoothing matrix used in fitting
<code>method</code>	Method used to fit frontier
<code>scaling.factor</code>	Factor by which constraints are multiplied before quadratic programming

## References

Racine JS, Parmeter CF, Du P (2009). "Constrained nonparametric kernel regression: Estimation and inference." Working paper.

**Examples**

```
data(univariate)

#Set up data for fitting

X <- as.matrix(univariate$x)
y <- univariate$y

N.fit <- 100
X.fit <- as.matrix(seq(min(X), max(X), length.out = N.fit))

#Reflect data for fitting
reflected.data <- reflect.data(X, y)
X.eval <- reflected.data$X
y.eval <- reflected.data$y

#Fit frontiers
frontier.u <- fit.boundary(X.eval, y.eval,
                          X.bounded = X, y.bounded = y,
                          X.constrained = X.fit,
                          X.fit = X.fit,
                          method = "u")

frontier.m <- fit.boundary(X.eval, y.eval,
                          X.bounded = X, y.bounded = y,
                          X.constrained = X.fit,
                          X.fit = X.fit,
                          method = "m")

frontier.mc <- fit.boundary(X.eval, y.eval,
                           X.bounded = X, y.bounded = y,
                           X.constrained = X.fit,
                           X.fit = X.fit,
                           method = "mc")

#Plot frontier
library(ggplot2)

frontier.df <- data.frame(X = rep(X.fit, times = 3),
                         y = c(frontier.u$y.fit, frontier.m$y.fit, frontier.mc$y.fit),
                         model = rep(c("u", "m", "mc"), each = N.fit))

ggplot(univariate, aes(X, y)) +
  geom_point() +
  geom_line(data = frontier.df, aes(color = model))

#Plot slopes
slope.df <- data.frame(X = rep(X.fit, times = 3),
                      slope = c(frontier.u$gradient.fit,
                                frontier.m$gradient.fit,
                                frontier.mc$gradient.fit),
                      model = rep(c("u", "m", "mc"), each = N.fit))
```

```
ggplot(slope.df, aes(X, slope)) +
  geom_line(aes(color = model))
```

---

fit.mean

*Kernel smoothing with additional constraints*


---

### Description

Fits conditional mean of data with kernel smoothing, imposing monotonicity and/or concavity constraints.

### Usage

```
fit.mean(X.eval, y.eval, X.constrained = NA, X.fit = NA, H.inv = NA,
  H.mult = 1, method = "u", scale.constraints = TRUE)
```

### Arguments

X.eval	Matrix of inputs used for fitting
y.eval	Vector of outputs used for fitting
X.constrained	Matrix of inputs where constraints apply
X.fit	Matrix of inputs where curve is fit; defaults to X.constrained
H.inv	Inverse of the smoothing matrix (must be positive definite); defaults to rule of thumb
H.mult	Scaling factor for rule of thumb smoothing matrix
method	Constraints to apply; "u" for unconstrained, "m" for monotonically increasing, and "mc" for monotonically increasing and concave
scale.constraints	Boolean, whether to scale constraints by their average value, can help with convergence

### Details

This method uses kernel smoothing to fit the mean of the data while imposing specified monotonicity and concavity constraints. The procedure is derived from Racine et al. (2009), which develops kernel smoothing methods with bounding, monotonicity and concavity constraints. Specifically, the smoothing procedure involves finding optimal weights for a Nadaraya-Watson estimator of the form

$$\hat{y} = m(x) = \sum_{i=1}^N p_i A(x, x_i) y_i,$$

where  $x$  are inputs,  $y$  are outputs,  $p$  are weights, subscripts index observations, and

$$A(x, x_i) = \frac{K(x, x_i)}{\sum_{h=1}^N K(x, x_h)}$$

for a kernel  $K$ . This method uses a multivariate normal kernel of the form

$$K(x, x_h) = \exp\left(-\frac{1}{2}(x - x_h)'H^{-1}(x - x_h)\right),$$

where  $H$  is a bandwidth matrix. Bandwidth selection is performed via Silverman's (1986) rule-of-thumb, in the function `H.inv.select`.

Optimal weights  $\hat{p}$  are selected by solving the quadratic programming problem

$$\min_p -\mathbf{1}'p + \frac{1}{2}p'p.$$

Monotonicity constraints of the following form can be imposed at specified points:

$$\frac{\partial m(x)}{\partial x^j} = \sum_{h=1}^N p_h \frac{\partial A(x, x_h)}{\partial x^j} y_h \geq 0 \quad \forall x, j,$$

where superscripts index inputs. Finally concavity constraints of the following form can also be imposed using Afriat's (1967) conditions:

$$m(x) - m(z) \leq \nabla_x m(z) \cdot (x - z) \quad \forall x, z.$$

The gradient of the estimated curve at a point  $x$  is given by

$$\nabla_x m(x) = \sum_{i=1}^N \hat{p}_i \nabla_x A(x, x_i) y_i,$$

where  $\hat{p}_i$  are estimated weights.

## Value

Returns a list with the following elements

<code>y.fit</code>	Estimated value of the frontier at <code>X.fit</code>
<code>gradient.fit</code>	Estimated gradient of the frontier at <code>X.fit</code>
<code>solution</code>	Boolean; TRUE if frontier successfully estimated
<code>X.eval</code>	Matrix of inputs used for fitting
<code>X.constrained</code>	Matrix of inputs where constraints apply
<code>X.fit</code>	Matrix of inputs where curve is fit
<code>H.inv</code>	Inverse smoothing matrix used in fitting
<code>method</code>	Method used to fit frontier
<code>scaling.factor</code>	Factor by which constraints are multiplied before quadratic programming

## References

Racine JS, Parmeter CF, Du P (2009). “Constrained nonparametric kernel regression: Estimation and inference.” Working paper.

## Examples

```
data(USMacro)

USMacro <- USMacro[complete.cases(USMacro),]

#Extract data
X <- as.matrix(USMacro[,c("K", "L")])
y <- USMacro$Y

#Reflect data for fitting
reflected.data <- reflect.data(X, y)
X.eval <- reflected.data$X
y.eval <- reflected.data$y

#Fit frontier
fit.mc <- fit.mean(X.eval, y.eval,
                  X.constrained = X,
                  X.fit = X,
                  method = "mc")

#Plot input productivities over time
library(ggplot2)
plot.df <- data.frame(Year = rep(USMacro$Year, times = 2),
                    Elasticity = c(fit.mc$gradient.fit[,1] * X[,1] / y,
                                   fit.mc$gradient.fit[,2] * X[,2] / y),
                    Variable = rep(c("Capital", "Labor"), each = nrow(USMacro)))

ggplot(plot.df, aes(Year, Elasticity)) +
  geom_line() +
  facet_grid(Variable ~ ., scales = "free_y")
```

---

fit.sf

*Non-parametric stochastic frontier*

---

## Description

Fits stochastic frontier of data with kernel smoothing, imposing monotonicity and/or concavity constraints.

## Usage

```
fit.sf(X, y, X.constrained = NA, H.inv = NA, H.mult = 1,
       method = "u", scale.constraints = TRUE)
```

**Arguments**

X	Matrix of inputs
y	Vector of outputs
X.constrained	Matrix of inputs where constraints apply
H.inv	Inverse of the smoothing matrix (must be positive definite); defaults to rule of thumb
H.mult	Scaling factor for rule of thumb smoothing matrix
method	Constraints to apply; "u" for unconstrained, "m" for monotonically increasing, and "mc" for monotonically increasing and concave
scale.constraints	Boolean, whether to scale constraints by their average value, can help with convergence

**Details**

This method fits non-parametric stochastic frontier models. The data-generating process is assumed to be of the form

$$\ln y_i = \ln f(x_i) + v_i - u_i,$$

where  $y_i$  is the  $i$ th observation of output,  $f$  is a continuous function,  $x_i$  is the  $i$ th observation of input,  $v_i$  is a normally-distributed error term ( $v_i \sim N(0, \sigma_v^2)$ ), and  $u_i$  is a normally-distributed error term truncated below at zero ( $u_i \sim N^+(0, \sigma_u)$ ). Aigner et al. developed methods to decompose  $\varepsilon_i = v_i - u_i$  into its basic components.

This procedure first fits the mean of the data using `fit.mean`, producing estimates of output  $\hat{y}$ . Log-proportional errors are calculated as

$$\varepsilon_i = \ln(y_i/\hat{y}_i).$$

Following Aigner et al. (1977), parameters of one- and two-sided error distributions are estimated via maximum likelihood. First,

$$\hat{\sigma}^2 = \frac{1}{N} \sum_{i=1}^N \varepsilon_i^2.$$

Then,  $\hat{\lambda}$  is estimated by solving

$$\frac{1}{\hat{\sigma}^2} \sum_{i=1}^N \varepsilon_i \hat{y}_i + \frac{\hat{\lambda}}{\hat{\sigma}} \sum_{i=1}^N \frac{f_i^*}{1 - F_i^*} y_i = 0,$$

where  $f_i^*$  and  $F_i^*$  are standard normal density and distribution function, respectively, evaluated at  $\varepsilon_i \hat{\lambda} \hat{\sigma}^{-1}$ . Parameters of the one- and two-sided distributions are found by solving the identities

$$\sigma^2 = \sigma_u^2 + \sigma_v^2$$

$$\lambda = \frac{\sigma_u}{\sigma_v}.$$

Mean efficiency over the sample is given by

$$\exp\left(-\frac{\sqrt{2}}{\sqrt{\pi}}\right)\sigma_u,$$

and modal efficiency for each observation is given by

$$-\varepsilon(\sigma_u^2/\sigma^2).$$

### Value

Returns a list with the following elements

y.fit	Estimated value of the frontier at X.fit
gradient.fit	Estimated gradient of the frontier at X.fit
mean. efficiency	Average efficiency for X, y as a whole
mode. efficiency	Modal efficiencies for each observation in X, y
X.eval	Matrix of inputs used for fitting
X.constrained	Matrix of inputs where constraints apply
X.fit	Matrix of inputs where curve is fit
H.inv	Inverse smoothing matrix used in fitting
method	Method used to fit frontier
scaling.factor	Factor by which constraints are multiplied before quadratic programming

### References

Aigner D, Lovell CK, Schmidt P (1977). "Formulation and estimation of stochastic frontier production function models." *Journal of econometrics*, **6**(1), 21–37.

Racine JS, Parmeter CF, Du P (2009). "Constrained nonparametric kernel regression: Estimation and inference." Working paper.

### Examples

```
data(USMacro)

USMacro <- USMacro[complete.cases(USMacro),]

#Extract data
X <- as.matrix(USMacro[,c("K", "L")])
y <- USMacro$Y

#Fit frontier
```

```

fit.sf <- fit.sf(X, y,
                X.constrained = X,
                method = "mc")

print(fit.sf$mean. efficiency)
# [1] 0.9772484

#Plot efficiency over time
library(ggplot2)

plot.df <- data.frame(Year = USMacro$Year,
                      Efficiency = fit.sf$mode. efficiency)

ggplot(plot.df, aes(Year, Efficiency)) +
  geom_line()

```

---

H.inv.select

*Bandwidth matrix selection*


---

### Description

Computes inverse of bandwidth matrix using rule-of-thumb from Silverman (1986).

### Usage

```
H.inv.select(X, H.mult = 1)
```

### Arguments

X	Matrix of inputs
H.mult	Scaling factor for rule-of-thumb smoothing matrix

### Details

This method performs selection of (inverse) multivariate bandwidth matrices using Silverman's (1986) rule-of-thumb. Specifically, Silverman recommends setting the bandwidth matrix to

$$H_{jj}^{1/2} = \left( \frac{4}{M+2} \right)^{1/(M+4)} \times N^{-1/(M+4)} \times \text{sd}(x^j) \quad \text{for } j = 1, \dots, M$$

$$H_{ab} = 0 \quad \text{for } a \neq b$$

where  $M$  is the number of inputs,  $N$  is the number of observations, and  $\text{sd}(x^j)$  is the sample standard deviation of input  $j$ .

### Value

Returns inverse bandwidth matrix

## References

Silverman BW (1986). *Density estimation for statistics and data analysis*, volume 26. CRC press.

## Examples

```
data(USMacro)

USMacro <- USMacro[complete.cases(USMacro),]

#Extract data
X <- as.matrix(USMacro[,c("K", "L")])

#Generate bandwidth matrix
print(H.inv.select(X))
#           [,1]      [,2]
# [1,] 3.642704e-08 0.000000e+00
# [2,] 0.000000e+00 1.215789e-08
```

---

panel.production      *Randomly generated panel of production data*

---

## Description

A dataset for illustrating technical and efficiency changes using smooth non-parametric frontiers.

## Usage

```
panel.production
```

## Format

A data frame with 200 observations of six variables.

**Firm** Firm identifier

**Year** Year of observation

**X.1** Input 1

**X.2** Input 2

**X.3** Input 3

**y** Output

**Details**

Generated with the following code:

```
set.seed(100)

num.firms <- 20
num.inputs <- 3
num.years <- 10

beta <- runif(num.inputs, 0, 1)
TFP.trend = 0.25
TFP <- cumsum(rnorm(num.years)) + TFP.trend * (1:num.years)

sd.measurement <- 0.05
sd.inefficiency <- 0.01

f <- function(X){
  return(TFP + X
}
gen.firm.data <- function(i){
  X = matrix(runif(num.years * num.inputs, 1, 10), ncol = num.inputs)
  y = f(X) +
    rnorm(num.years, sd = sd.measurement) -
    abs(rnorm(num.years, sd = sd.inefficiency))
  firm.df <- data.frame(Firm = i,
                        Year = 1:num.years,
                        X = exp(X),
                        y = exp(y))
}

panel.production = Reduce(rbind, lapply(1:num.firms, gen.firm.data))
panel.production$Firm = as.factor(panel.production$Firm)
```

---

reflect.data

*Data reflection for kernel smoothing*

---

**Description**

This function reflects data below minimum and above maximum for use in reducing endpoint bias in kernel smoothing.

**Usage**

```
reflect.data(X, y)
```

**Arguments**

X                    Matrix of inputs  
y                    Vector of outputs

**Value**

Returns a list with the following elements

X.reflected        Reflected values of X  
y.reflected        Reflected values of y

**Examples**

```
data(univariate)

#Extract data
X <- as.matrix(univariate$x)
y <- univariate$y

#Reflect data
reflected.data <- reflect.data(X, y)

X.reflected <- reflected.data$X
y.reflected <- reflected.data$y

#Plot
library(ggplot2)

plot.df <- data.frame(X = X.reflected,
                      y = y.reflected,
                      data = rep(c("reflected", "actual", "reflected"), each = nrow(X)))

ggplot(plot.df, aes(X, y)) +
  geom_point(aes(color = data))
```

---

technical. efficiency.change  
*Technical and efficiency change estimation*

---

**Description**

Estimates technical and efficiency change using SNFA

**Usage**

```
technical. efficiency.change(df, input.var.names, output.var.name,  
                             firm.var.name, time.var.name, method = "u")
```

**Arguments**

df	Data frame with variables used in estimation
input.var.names	Names of input variables; must appear in df
output.var.name	Name of output variable; must appear in df
firm.var.name	Name of firm variable; must appear in df
time.var.name	Name of time variable; must appear in df
method	Constraints to apply; "u" for unconstrained, "m" for monotonically increasing, and "mc" for monotonically increasing and concave

**Details**

This function decomposes change in productivity into efficiency and technical change, as in Fare et al. (1994), using smooth non-parametric frontier analysis. Denoting  $D_s(x_t, y_t)$  as the efficiency of the production plan in year t relative to the production frontier in year s, efficiency change for a given firm in year t is calculated as

$$\frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)},$$

and technical change is given by

$$\left( \frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_t(x_t, y_t)}{D_{t+1}(x_t, y_t)} \right)^{1/2}.$$

**Value**

Returns a data.frame with the following columns

firm.var.name	Column of firm name data
time.var.name	Column of time period data
efficiency.change	Average annual efficiency change since the previous period in data
technical.change	Average annual technical change since the previous period in data
productivity.change	Average annual productivity change since the previous period in data

**References**

Fare R, Grosskopf S, Norris M, Zhang Z (1994). "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries." *The American Economic Review*, **84**(1), 66-83.

## Examples

```
data(panel.production)

results.df <- technical.encychange(df = panel.production,
                                  input.var.names = c("X.1", "X.2", "X.3"),
                                  output.var.name = "y",
                                  firm.var.name = "Firm",
                                  time.var.name = "Year")

#Plot changes over time by firm
library(ggplot2)

ggplot(results.df, aes(Year, technical.change)) +
  geom_line(aes(color = Firm))
ggplot(results.df, aes(Year, efficiency.change)) +
  geom_line(aes(color = Firm))
ggplot(results.df, aes(Year, productivity.change)) +
  geom_line(aes(color = Firm))
```

---

univariate

*Randomly generated univariate data*

---

## Description

A dataset for illustrating univariate non-parametric boundary regressions and various constraints.

## Usage

```
univariate
```

## Format

A data frame with 50 observations of two variables.

**x** Input

**y** Output

## Details

Generated with the following code:

```
set.seed(100)

N <- 50
x <- runif(N, 10, 100)
y <- sapply(x, function(x) 500 * x^0.25 - dnorm(x, mean = 70, sd = 10) * 8000) - abs(rnorm(N, sd = 20))
y <- y - min(y) + 10
df <- data.frame(x, y)
```

---

USMacro

*US Macroeconomic Data*

---

**Description**

A dataset of real output, labor force, capital stock, wages, and interest rates for the U.S. between 1929 and 2014, as available. All nominal values converted to 2010 U.S. dollars using GDP price deflator.

**Usage**

USMacro

**Format**

A data frame with 89 observations of four variables.

**Year** Year

**Y** Real GDP, in billions of dollars

**K** Capital stock, in billions of dollars

**K.price** Annual cost of \$1 billion of capital, using 10-year treasury

**L** Labor force, in thousands of people

**L.price** Annual wage for one thousand people

**Source**

<https://fred.stlouisfed.org/>

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