Package ‘PredictiveDGP’

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Title Predictive DGPs exhibiting various distributions, contemporaneous correlations and persistency

Version 1.0.0

Description This package generates the data vectors Y and X using a simple predictive regression model with no intercept and a single regressor. The regressor follows an AR(1) process with no trend and intercept. This framework was initially studied by Mankiw and Shapiro (1986). For each R function, the predictor's errors are distributed according to a standard Normal distribution, whereas the disturbances of the predictive regression are changed according to the function of choice. The degree of contemporaneous correlaion and persistency of the regressors is in the hands of the investigator.

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RdMacros Rdpack

License GPL (>= 3)

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R topics documented:

BIVDGP *Normal errors with break in variance*

Description

The processes y and x are generated by a predictive regression of the form $y_t = \beta x_{t-1} + \varepsilon_t$ for $t = 1, \cdots, T$, in which the regressors follow an AR(1) process - i.e. $x_t = \theta x_{t-1} + u_t$. The predictor's errors are distributed according to $u_t \sim N(0, 1)$, whereas the disturbances of the predictive regression, ε_t, are distributed $\varepsilon_t \sim N(0, 1)$ for $t \neq T/2$ and $\varepsilon_t \sim 1000N(0, 1)$ for $t = T/2$ respectively. An example of standard Normal disturbances with break in variance can be found in Dufour and Taamouti (2010). The initial value of the process x is generated by $x_0 = \frac{w_0}{\sqrt{1-\theta^2}}$, where $w_t \sim N(0, 1)$. Finally, the contemporaneous correlation between the disturbances ε_t and u_t is captured by $u_t = \rho\varepsilon_t + w_t\sqrt{1 - \rho^2}$.

Usage

```
BIVDGP(n, beta, theta, rho)
```

Arguments

n	the number of observations.
beta	the regressor coefficient of the predictive regression.
theta	the autocorrelation coefficient of the predictor.
rho	the contemporaneous correlation coefficient.

References

Jean-Marie Dufour, Abderrahim Taamouti (2010). "Exact optimal inference in regression models under heteroskedasticity and non-normality of unknown form." *Computational Statistics \& Data Analysis*, **54**(11), 2532–2553.

Examples

```
BIVDGP(50,0.5,0.999,0.9)
```

CauchyDGP *Cauchy errors*

Description

The processes y and x are generated by a predictive regression of the form $y_t = \beta x_{t-1} + \varepsilon_t$ for $t = 1, \cdots, T$, in which the regressors follow an AR(1) process - i.e. $x_t = \theta x_{t-1} + u_t$. The predictor's errors are distributed according to $u_t \sim N(0, 1)$, whereas the disturbances of the predictive regression, ε_t, are distributed $\varepsilon_t \sim Cauchy$. An example of a predictive regression DGP with Cauchy perturbations can be found in Campbell and Dufour (1995). The initial value of the process x is generated by $x_0 = \frac{w_0}{\sqrt{1-\theta^2}}$, where $w_t \sim N(0, 1)$. Finally, the contemporaneous correlation between the disturbances ε_t and u_t is captured by $u_t = \rho\varepsilon_t + w_t\sqrt{1 - \rho^2}$.

Usage

```
CauchyDGP(n, beta, theta, rho)
```

Arguments

`n`	the number of observations.
`beta`	the regressor coefficient of the predictive regression.
`theta`	the autocorrelation coefficient of the predictor.
`rho`	the contemporaneous correlation coefficient.

References

Bryan Campbell, Jean–Marie Dufour (1995). “Exact nonparametric orthogonality and random walk tests.” *The Review of Economics and Statistics*, **77**(1), 1–16.

Examples

```
CauchyDGP(50,0.5,0.999,0.9)
```

`ExpVarDGP` *Normal errors with exponential variance*

Description

The processes y and x are generated by a predictive regression of the form $y_t = \beta x_{t-1} + \varepsilon_t$ for $t = 1, \cdots, T$, in which the regressors follow an AR(1) process - i.e. $x_t = \theta x_{t-1} + u_t$. The predictor's errors are distributed according to $u_t \sim N(0, 1)$, whereas the disturbances of the predictive regression, ε_t, are distributed $\varepsilon_t \sim N(0, \sigma_t^2)$, where $\sigma_t = \exp(0.5t)$. Examples of DGPs with Normal disturbances and exponential variance can be found in Dufour and Taamouti (2010) and Coudin and Dufour (2009). The initial value of the process x is generated by $x_0 = \frac{w_0}{\sqrt{1-\theta^2}}$, where $w_t \sim N(0, 1)$. Finally, the contemporaneous correlation between the disturbances ε_t and u_t is captured by $u_t = \rho\varepsilon_t + w_t\sqrt{1 - \rho^2}$.

Usage

```
ExpVarDGP(n, beta, theta, rho)
```

Arguments

`n`	the number of observations.
`beta`	the regressor coefficient of the predictive regression.
`theta`	the autocorrelation coefficient of the predictor.
`rho`	the contemporaneous correlation coefficient.

References

Elise Coudin, Jean-Marie Dufour (2009). "Finite-sample distribution-free inference in linear median regressions under heteroscedasticity and non-linear dependence of unknown form." *The Econometrics Journal*, **12**, S19–S49.

Jean-Marie Dufour, Abderrahim Taamouti (2010). "Exact optimal inference in regression models under heteroskedasticity and non-normality of unknown form." *Computational Statistics \& Data Analysis*, **54**(11), 2532–2553.

Examples

```
ExpVarDGP(50,0.5,0.999,0.9)
```

GarchDGP — *Normal errors with stationary GARCH(1,1) variance*

Description

The processes y and x are generated by a predictive regression of the form $y_t = \beta x_{t-1} + \varepsilon_t$ for $t = 1, \cdots, T$, in which the regressors follow an AR(1) process - i.e. $x_t = \theta x_{t-1} + u_t$. The predictor's errors are distributed according to $u_t \sim N(0,1)$, whereas the disturbances of the predictive regression, ε_t, are distributed $\varepsilon_t \sim N(0, \sigma_t^2)$, where $\sigma_t^2 = 0.00037 + 0.0888\varepsilon_{t-1}^2 + 0.9024\sigma_{t-1}^2$. Examples of DGPs with Normal disturbances and stationary GARCH(1,1) variance can be found in Dufour and Taamouti (2010) and Coudin and Dufour (2009). The initial value of the process x is generated by $x_0 = \frac{w_0}{\sqrt{1-\theta^2}}$, where $w_t \sim N(0,1)$. Finally, the contemporaneous correlation between the disturbances ε_t and u_t is captured by $u_t = \rho\varepsilon_t + w_t\sqrt{1-\rho^2}$.

Usage

```
GarchDGP(n, beta, theta, rho)
```

Arguments

`n`	the number of observations.
`beta`	the regressor coefficient of the predictive regression.
`theta`	the autocorrelation coefficient of the predictor.
`rho`	the contemporaneous correlation coefficient.

References

Elise Coudin, Jean-Marie Dufour (2009). "Finite-sample distribution-free inference in linear median regressions under heteroscedasticity and non-linear dependence of unknown form." *The Econometrics Journal*, **12**, S19–S49.

Jean-Marie Dufour, Abderrahim Taamouti (2010). "Exact optimal inference in regression models under heteroskedasticity and non-normality of unknown form." *Computational Statistics \& Data Analysis*, **54**(11), 2532–2553.

Examples

```
GarchDGP(50,0.5,0.999,0.9)
```

MixtureDGP *Mixture of Cauchy and Normal errors*

Description

The processes y and x are generated by a predictive regression of the form $y_t = \beta x_{t-1} + \varepsilon_t$ for $t = 1, \cdots, T$, in which the regressors follow an AR(1) process - i.e. $x_t = \theta x_{t-1} + u_t$. The predictor's errors are distributed according to $u_t \sim N(0,1)$, whereas the disturbances of the predictive regression, ε_t, are distributed $\varepsilon_t \sim s_t|\varepsilon_t^C| - (1-s_t)|\varepsilon_t^N|$, where $P(s_t = 0) = P(s_t = 1) = 0.5$ for all t. An example of a DGP with mixture perturbations can be found in Dufour and Taamouti (2010). The initial value of the process x is generated by $x_0 = \frac{w_0}{\sqrt{1-\theta^2}}$, where $w_t \sim N(0,1)$. Finally, the contemporaneous correlation between the disturbances ε_t and u_t is captured by $u_t = \rho\varepsilon_t + w_t\sqrt{1-\rho^2}$.

Usage

```
MixtureDGP(n, beta, theta, rho)
```

Arguments

`n`	the number of observations.
`beta`	the regressor coefficient of the predictive regression.
`theta`	the autocorrelation coefficient of the predictor.
`rho`	the contemporaneous correlation coefficient.

References

Jean-Marie Dufour, Abderrahim Taamouti (2010). "Exact optimal inference in regression models under heteroskedasticity and non-normality of unknown form." *Computational Statistics \& Data Analysis*, **54**(11), 2532–2553.

Examples

```
MixtureDGP(50,0.5,0.999,0.9)
```

NormalDGP *Standard Normal errors*

Description

The processes y and x are generated by a predictive regression of the form $y_t = \beta x_{t-1} + \varepsilon_t$ for $t = 1, \cdots, T$, in which the regressors follow an AR(1) process - i.e. $x_t = \theta x_{t-1} + u_t$. The predictor's errors are distributed according to $u_t \sim N(0, 1)$, whereas the disturbances of the predictive regression, ε_t, are distributed $\varepsilon_t \sim N(0, 1)$. The initial value of the process x is generated by $x_0 = \frac{w_0}{\sqrt{1-\theta^2}}$, where $w_t \sim N(0, 1)$. Finally, the contemporaneous correlation between the disturbances ε_t and u_t is captured by $u_t = \rho\varepsilon_t + w_t\sqrt{1 - \rho^2}$.

Usage

```
NormalDGP(n, beta, theta, rho)
```

Arguments

`n`	the number of observations.
`beta`	the regressor coefficient of the predictive regression.
`theta`	the autocorrelation coefficient of the predictor.
`rho`	the contemporaneous correlation coefficient.

References

There are no references for Rd macro \insertAllCites on this help page.

Examples

```
NormalDGP(50,0.5,0.999,0.9)
```

StudentDGP *Student's $t(2)$ errors*

Description

The processes y and x are generated by a predictive regression of the form $y_t = \beta x_{t-1} + \varepsilon_t$ for $t = 1, \cdots, T$, in which the regressors follow an AR(1) process - i.e. $x_t = \theta x_{t-1} + u_t$. The predictor's errors are distributed according to $u_t \sim N(0, 1)$, whereas the disturbances of the predictive regression, ε_t, are distributed $\varepsilon_t \sim t(2)$. An example of a predictive regression DGP with $t(3)$ perturbations can be found in Campbell and Dufour (1995). Outside a predictive regression framework, $t(2)$ disturbances have further been considered in Dufour and Taamouti (2010). The initial value of the process x is generated by $x_0 = \frac{w_0}{\sqrt{1-\theta^2}}$, where $w_t \sim N(0, 1)$. Finally, the contemporaneous correlation between the disturbances ε_t and u_t is captured by $u_t = \rho\varepsilon_t + w_t\sqrt{1 - \rho^2}$.

Usage

```
StudentDGP(n, beta, theta, rho)
```

Arguments

`n`	the number of observations.
`beta`	the regressor coefficient of the predictive regression.
`theta`	the autocorrelation coefficient of the predictor.
`rho`	the contemporaneous correlation coefficient.

References

Bryan Campbell, Jean–Marie Dufour (1995). "Exact nonparametric orthogonality and random walk tests." *The Review of Economics and Statistics*, **77**(1), 1–16.

Jean-Marie Dufour, Abderrahim Taamouti (2010). "Exact optimal inference in regression models under heteroskedasticity and non-normality of unknown form." *Computational Statistics \& Data Analysis*, **54**(11), 2532–2553.

Examples

```
StudentDGP(50,0.5,0.999,0.9)
```

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