Package ‘dynlm’

July 22, 2025

Version 0.3-6

Date 2019-01-06

Title Dynamic Linear Regression

Description Dynamic linear models and time series regression.

Depends R (>= 2.10.0), zoo

Suggests datasets, sandwich, strucchange, TSA

Imports stats, car (>= 2.0-0), lmtest

LazyLoad yes

LazyData yes

License GPL-2 | GPL-3

NeedsCompilation no

Author Achim Zeileis [aut, cre] (ORCID: <https://orcid.org/0000-0003-0918-3766>)

Maintainer Achim Zeileis <Achim.Zeileis@R-project.org>

Repository CRAN

Date/Publication 2019-01-06 20:12:56 UTC

Contents

dynlm *Dynamic Linear Models and Time Series Regression*

Description

Interface to lm.wfit for fitting dynamic linear models and time series regression relationships.

Usage

```
dynlm(formula, data, subset, weights, na.action, method = "qr",
  model = TRUE, x = FALSE, y = FALSE, qr = TRUE, singular.ok = TRUE,
  contrasts = NULL, offset, start = NULL, end = NULL, ...)
```

Arguments

formula	a "formula" describing the linear model to be fit. For details see below and lm.
data	an optional "data.frame" or time series object (e.g., "ts" or "zoo"), containing the variables in the model. If not found in data, the variables are taken from environment(formula), typically the environment from which lm is called.
subset	an optional vector specifying a subset of observations to be used in the fitting process.
weights	an optional vector of weights to be used in the fitting process. If specified, weighted least squares is used with weights weights (that is, minimizing sum(w*e^2)); otherwise ordinary least squares is used.
na.action	a function which indicates what should happen when the data contain NAs. The default is set by the na.action setting of options, and is na.fail if that is unset. The “factory-fresh” default is na.omit. Another possible value is NULL, no action. Note, that for time series regression special methods like na.contiguous, na.locf and na.approx are available.
method	the method to be used; for fitting, currently only method = "qr" is supported; method = "model.frame" returns the model frame (the same as with model = TRUE, see below).
model, x, y, qr	logicals. If TRUE the corresponding components of the fit (the model frame, the model matrix, the response, the QR decomposition) are returned.
singular.ok	logical. If FALSE (the default in S but not in R) a singular fit is an error.
contrasts	an optional list. See the contrasts.arg of model.matrix.default.
offset	this can be used to specify an *a priori* known component to be included in the linear predictor during fitting. An offset term can be included in the formula instead or as well, and if both are specified their sum is used.
start	start of the time period which should be used for fitting the model.
end	end of the time period which should be used for fitting the model.
...	additional arguments to be passed to the low level regression fitting functions.

Details

The interface and internals of dynlm are very similar to lm, but currently dynlm offers three advantages over the direct use of lm: 1. extended formula processing, 2. preservation of time series attributes, 3. instrumental variables regression (via two-stage least squares).

For specifying the formula of the model to be fitted, there are additional functions available which allow for convenient specification of dynamics (via d() and L()) or linear/cyclical patterns (via trend(), season(), and harmon()). All new formula functions require that their arguments are time series objects (i.e., "ts" or "zoo").

Dynamic models: An example would be d(y) ~ L(y, 2), where d(x, k) is diff(x, lag = k) and L(x, k) is lag(x, lag = -k), note the difference in sign. The default for k is in both cases 1. For L(), it can also be vector-valued, e.g., y ~ L(y, 1:4).

Trends: y ~ trend(y) specifies a linear time trend where (1:n)/freq is used by default as the regressor. n is the number of observations and freq is the frequency of the series (if any, otherwise freq = 1). Alternatively, trend(y, scale = FALSE) would employ 1:n and time(y) would employ the original time index.

Seasonal/cyclical patterns: Seasonal patterns can be specified via season(x, ref = NULL) and harmonic patterns via harmon(x, order = 1). season(x, ref = NULL) creates a factor with levels for each cycle of the season. Using the ref argument, the reference level can be changed from the default first level to any other. harmon(x, order = 1) creates a matrix of regressors corresponding to cos(2 * o * pi * time(x)) and sin(2 * o * pi * time(x)) where o is chosen from 1:order.

See below for examples and M1Germany for a more elaborate application.

Furthermore, a nuisance when working with lm is that it offers only limited support for time series data, hence a major aim of dynlm is to preserve time series properties of the data. Explicit support is currently available for "ts" and "zoo" series. Internally, the data is kept as a "zoo" series and coerced back to "ts" if the original dependent variable was of that class (and no internal NAs were created by the na.action).

To specify a set of instruments, formulas of type y ~ x1 + x2 | z1 + z2 can be used where z1 and z2 represent the instruments. Again, the extended formula processing described above can be employed for all variables in the model.

See Also

zoo, merge.zoo

Examples

```
###########################
## Dynamic Linear Models ##
###########################

## multiplicative SARIMA(1,0,0)(1,0,0)_12 model fitted
## to UK seatbelt data
data("UKDriverDeaths", package = "datasets")
uk <- log10(UKDriverDeaths)
dfm <- dynlm(uk ~ L(uk, 1) + L(uk, 12))
dfm
## explicitly set start and end
```

```
dfm <- dynlm(uk ~ L(uk, 1) + L(uk, 12), start = c(1975, 1), end = c(1982, 12))
dfm

## remove lag 12
dfm0 <- update(dfm, . ~ . - L(uk, 12))
anova(dfm0, dfm)

## add season term
dfm1 <- dynlm(uk ~ 1, start = c(1975, 1), end = c(1982, 12))
dfm2 <- dynlm(uk ~ season(uk), start = c(1975, 1), end = c(1982, 12))
anova(dfm1, dfm2)

plot(uk)
lines(fitted(dfm0), col = 2)
lines(fitted(dfm2), col = 4)

## regression on multiple lags in a single L() call
dfm3 <- dynlm(uk ~ L(uk, c(1, 11, 12)), start = c(1975, 1), end = c(1982, 12))
anova(dfm, dfm3)

## Examples 7.11/7.12 from Greene (1993)
data("USDistLag", package = "lmtest")
dfm1 <- dynlm(consumption ~ gnp + L(consumption), data = USDistLag)
dfm2 <- dynlm(consumption ~ gnp + L(gnp), data = USDistLag)
plot(USDistLag[, "consumption"])
lines(fitted(dfm1), col = 2)
lines(fitted(dfm2), col = 4)
if(require("lmtest")) encomptest(dfm1, dfm2)


###############################
## Time Series Decomposition ##
###############################

## airline data
data("AirPassengers", package = "datasets")
ap <- log(AirPassengers)
ap_fm <- dynlm(ap ~ trend(ap) + season(ap))
summary(ap_fm)

## Alternative time trend specifications:
##   time(ap)                  1949 + (0, 1, ..., 143)/12
##   trend(ap)                 (1, 2, ..., 144)/12
##   trend(ap, scale = FALSE)  (1, 2, ..., 144)

## Exhibit 3.5/3.6 from Cryer & Chan (2008)
if(require("TSA")) {
data("tempdub", package = "TSA")
td_lm <- dynlm(tempdub ~ harmon(tempdub))
summary(td_lm)
plot(tempdub, type = "p")
lines(fitted(td_lm), col = 2)
}
```

`M1Germany` *German M1 Money Demand*

Description

German M1 money demand.

Usage

```
data(M1Germany)
```

Format

`M1Germany` is a `"zoo"` series containing 4 quarterly time series from 1960(1) to 1996(3).

logm1 logarithm of real M1 per capita,

logprice logarithm of a price index,

loggnp logarithm of real per capita gross national product,

interest long-run interest rate,

Details

This is essentially the same data set as `GermanM1`, the important difference is that it is stored as a `zoo` series and not as a data frame. It does not contain differenced and lagged versions of the variables (as `GermanM1`) does, because these do not have to be computed explicitly before applying `dynlm`.

The (short) story behind the data is the following (for more detailed information see `GermanM1`): Lütkepohl et al. (1999) investigate the linearity and stability of German M1 money demand: they find a stable regression relation for the time before the monetary union on 1990-06-01 but a clear structural instability afterwards. Zeileis et al. (2005) re-analyze this data set in a monitoring situation.

Source

The data is provided by the German central bank and is available online in the data archive of the Journal of Applied Econometrics `http://qed.econ.queensu.ca/jae/1999-v14.5/lutkepohl-terasvirta-wolters/`.

References

Lütkepohl H., Teräsvirta T., Wolters J. (1999), Investigating Stability and Linearity of a German M1 Money Demand Function, *Journal of Applied Econometrics*, **14**, 511–525.

Zeileis A., Leisch F., Kleiber C., Hornik K. (2005), Monitoring Structural Change in Dynamic Econometric Models, *Journal of Applied Econometrics*, **20**, 99–121.

See Also

`GermanM1`

Examples

```
data("M1Germany")
## fit the model of Luetkepohl et al. (1999) on the history period
## before the monetary unification
histfm <- dynlm(d(logm1) ~ d(L(loggnp, 2)) + d(interest) + d(L(interest)) + d(logprice) +
                           L(logm1) + L(loggnp) + L(interest) +
                           season(logm1, ref = 4),
                data = M1Germany, start = c(1961, 1), end = c(1990, 2))

## fit on extended sample period
fm <- update(histfm, end = c(1995, 4))

if(require("strucchange")) {
  scus <- gefp(fm, fit = NULL)
  plot(scus, functional = supLM(0.1))
}
```

Index