

## Title

**time series** — Introduction to time-series commands

## Description

The *Time-Series Reference Manual* organizes the commands alphabetically, which makes it easy to find individual command entries if you know the name of the command. This overview organizes and presents the commands conceptually, that is, according to the similarities in the functions that they perform.

The commands listed under the heading **Data management tools and time-series operators** help you prepare your data for further analysis. The commands listed under the heading **Univariate time series** are grouped together because they are either estimators or filters designed for univariate time series or pre-estimation or postestimation commands that are conceptually related to one or more univariate time-series estimators. The commands listed under the heading **Multivariate time series** are similarly grouped together because they are either estimators designed for use with multivariate time series or pre-estimation or postestimation commands conceptually related to one or more multivariate time-series estimators. Within these three broad categories, similar commands have been grouped together.

*(Continued on next page)*

**Data management tools and time-series operators**

<code>tsset</code>	Declare a dataset to be time-series data
<code>tsfill</code>	Fill in missing times with missing observations in time-series data
<code>tsappend</code>	Add observations to a time-series dataset
<code>tsreport</code>	Report time-series aspects of a dataset or estimation sample
<code>tsrevar</code>	Time-series operator programming command
<code>haver</code>	Load data from Haver Analytics database
<code>rolling</code>	Rolling window and recursive estimation

**Univariate time series****Estimators**

<code>arima</code>	ARIMA, ARMAX, and other dynamic regression models
<code>arima postestimation</code>	Postestimation tools for arima
<code>arch</code>	Autoregressive conditional heteroskedasticity (ARCH) family of estimators
<code>arch postestimation</code>	Postestimation tools for arch
<code>newey</code>	Regression with Newey–West standard errors
<code>newey postestimation</code>	Postestimation tools for newey
<code>prais</code>	Prais–Winsten and Cochrane–Orcutt regression
<code>prais postestimation</code>	Postestimation tools for prais

**Time-series smoothers and filters**

<code>tssmooth ma</code>	Moving-average filter
<code>tssmooth dexponential</code>	Double-exponential smoothing
<code>tssmooth exponential</code>	Single-exponential smoothing
<code>tssmooth hwinters</code>	Holt–Winters nonseasonal smoothing
<code>tssmooth shwinters</code>	Holt–Winters seasonal smoothing
<code>tssmooth nl</code>	Nonlinear filter

**Diagnostic tools**

<code>corrgram</code>	Tabulate and graph autocorrelations
<code>xcorr</code>	Cross-correlogram for bivariate time series
<code>cumsp</code>	Cumulative spectral distribution
<code>pergram</code>	Periodogram
<code>dfgls</code>	DF-GLS unit-root test
<code>dfuller</code>	Augmented Dickey–Fuller unit-root test
<code>pperron</code>	Phillips–Perron unit-root test
<code>estat dwatson</code>	Durbin–Watson $d$ statistic
<code>estat durbinalt</code>	Durbin’s alternative test for serial correlation
<code>estat bgodfrey</code>	Breusch–Godfrey test for higher-order serial correlation
<code>estat archlm</code>	Engle’s LM test for the presence of autoregressive conditional heteroskedasticity
<code>wntestb</code>	Bartlett’s periodogram-based test for white noise
<code>wntestq</code>	Portmanteau (Q) test for white noise

**Multivariate time series****Estimators**

<code>var</code>	Vector autoregression models
<code>var postestimation</code>	Postestimation tools for <code>var</code>
<code>svar</code>	Structural vector autoregression models
<code>svar postestimation</code>	Postestimation tools for <code>svar</code>
<code>varbasic</code>	Fit a simple VAR and graph impulse–response functions
<code>vec</code>	Vector error-correction models

**Diagnostic tools**

<code>varlmar</code>	Obtain LM statistics for residual autocorrelation after <code>var</code> or <code>svar</code>
<code>varnorm</code>	Test for normally distributed disturbances after <code>var</code> or <code>svar</code>
<code>varsoc</code>	Obtain lag-order selection statistics for VARs and VECMs
<code>varstable</code>	Check the stability condition of VAR or SVAR estimates
<code>varwle</code>	Obtain Wald lag-exclusion statistics after <code>var</code> or <code>svar</code>
<code>veclmar</code>	Obtain LM statistics for residual autocorrelation after <code>vec</code>
<code>vecnorm</code>	Test for normally distributed disturbances after <code>vec</code>
<code>vecrank</code>	Estimate the cointegrating rank using Johansen’s framework
<code>vecstable</code>	Check the stability condition of VECM estimates

**Forecasting, inference, and interpretation**

<code>irf create</code>	Obtain impulse–response functions and FEVDs
<code>fcast compute</code>	Compute dynamic forecasts of dependent variables after <code>var</code> , <code>svar</code> , or <code>vec</code>
<code>vargranger</code>	Perform pairwise Granger causality tests after <code>var</code> or <code>svar</code>

**Graphs and tables**

<code>corrgram</code>	Tabulate and graph autocorrelations
<code>xcorr</code>	Cross-correlogram for bivariate time series
<code>pergram</code>	Periodogram
<code>irf graph</code>	Graph impulse–response functions and FEVDs
<code>irf cgraph</code>	Combine graphs of impulse–response functions and FEVDs
<code>irf ograph</code>	Graph overlaid impulse–response functions and FEVDs
<code>irf table</code>	Create tables of impulse–response functions and FEVDs
<code>irf ctable</code>	Combine tables of impulse–response functions and FEVDs
<code>fcast graph</code>	Graph forecasts of variables computed by <code>fcast compute</code>
<code>tsline</code>	Time-series line plot
<code>tsrline</code>	Time-series range plot with lines
<code>varstable</code>	Check the stability condition of VAR or SVAR estimates
<code>vecstable</code>	Check the stability condition of VECM estimates
<code>wntestb</code>	Bartlett’s periodogram-based test for white noise

**Results management tools**

<code>irf add</code>	Add results from an IRF file to the active IRF file
<code>irf describe</code>	Describe an IRF file
<code>irf drop</code>	Drop IRF results from the active IRF file
<code>irf rename</code>	Rename an IRF result in an IRF file
<code>irf set</code>	Set the active IRF file

## Remarks

Remarks are presented under the headings

- Data management tools and time-series operators*
- Univariate time series*
  - Estimators*
  - Time-series smoothers and filters*
  - Diagnostic tools*
- Multivariate time series*
  - Estimators*
  - Diagnostic tools*

## Data management tools and time-series operators

Since time-series estimators are, by definition, a function of the temporal ordering of the observations in the estimation sample, Stata's time-series commands require the data to be sorted and indexed by time, using the `tsset` command, before they can be used. `tsset` is simply a way for you to tell Stata which variable in your dataset represents time; `tsset` then sorts and indexes the data appropriately for use with the time-series commands. Once your dataset has been `tsset`, you can use Stata's time-series operators in data manipulation or programming using that dataset and when specifying the syntax for most time-series commands. Stata has time-series operators for representing the lags, leads, differences, and seasonal differences of a variable. The time-series operators are documented in [TS] `tsset`.

`tsset` can also be used to declare that your dataset contains cross-sectional time-series data, often referred to as panel data. When you use `tsset` to declare your dataset to contain panel data, you specify a variable that identifies the panels, as well as identifying the time variable. Once your dataset has been `tsset` as panel data, the time-series operators work appropriately for the data.

`tsfill`, which is documented in [TS] `tsfill`, can be used after `tsset` to fill in missing times with missing observations. `tsset` will report any gaps in your data, and `tsreport` will provide additional details about the gaps. `tsappend` adds observations to a time-series dataset using the information set by `tsset`. This can be particularly useful when you wish to predict out of sample after fitting a model with a time-series estimator. `tsrevar` is a programmer's command that provides a way to use *varlists* that contain time-series operators with commands that do not otherwise support time-series operators.

The `haver` commands documented in [TS] `haver` allow you to load and describe the contents of a Haver Analytics ([www.haver.com](http://www.haver.com)) file.

`rolling` performs rolling regressions, recursive regressions, and reverse recursive regressions. Any command that saves results in `e()` or `r()` can be used with `rolling`.

## Univariate time series

### Estimators

The four univariate time-series estimators currently available in Stata are `arima`, `arch`, `newey`, and `prais`. The latter two, `prais` and `newey`, are really just extensions to ordinary linear regression. When you fit a linear regression on time-series data via ordinary least squares, if the disturbances are autocorrelated, the parameter estimates are usually consistent, but the estimated standard errors tend to be biased downward. A number of estimators have been developed to deal with this problem. One strategy is to use OLS for estimating the regression parameters and use a different estimator for the variances, one that is consistent in the presence of autocorrelated disturbances, such as the

Newey–West estimator that is implemented in `newey`. An alternative strategy is to attempt to model the dynamics of the disturbances. The estimators found in `prais`, `arima`, and `arch` are based on such a strategy.

`prais` implements two such estimators: the Prais–Winsten and the Cochrane–Orcutt GLS estimators. These estimators are generalized least-squares estimators, but they are fairly restrictive in that they permit only first-order autocorrelation in the disturbances. While they have certain pedagogical and historical value, they are somewhat obsolete. Faster computers with more memory have made it possible to implement Full Information Maximum Likelihood (FIML) estimators, such as Stata's `arima` command. These estimators permit much greater flexibility when modeling the disturbances and are more efficient estimators.

`arima` provides the means to fit linear models with autoregressive moving-average (ARMA) disturbances, or in the absence of linear predictors, autoregressive integrated moving-average (ARIMA) models. This means that, whether you think that your data are best represented as a distributed-lag model, a transfer-function model, or a stochastic difference equation, or you simply wish to apply a Box–Jenkins type filter to your data, the model can be fitted using `arima`. `arch`, a conditional maximum likelihood estimator, has similar modeling capabilities for the mean of the time series but can also model autoregressive conditional heteroskedasticity in the disturbances with a wide variety of specifications for the variance equation.

## Time-series smoothers and filters

In addition to the estimators mentioned above, Stata also provides six time-series filters or smoothers. Included are a simple, uniformly weighted, moving-average filter with unit weights; a weighted moving-average filter in which you can specify the weights; single- and double-exponential smoothers; Holt–Winters seasonal and nonseasonal smoothers; and a nonlinear smoother.

Most of these smoothers were originally developed as *ad hoc* procedures and are used for reducing the noise in a time series (smoothing) or forecasting. While they have limited application for signal extraction, these smoothers have all been found to be optimal for some underlying modern time-series model.

## Diagnostic tools

Stata's time-series commands also include a number of pre-estimation and postestimation diagnostic commands. `corrgram` estimates the autocorrelation function and partial autocorrelation function of a univariate time series, as well as  $Q$  statistics. These functions and statistics are often used to determine the appropriate model specification before fitting ARIMA models. `corrgram` can also be used with `wntestb` and `wntestq` to examine the residuals after fitting a model for evidence of model misspecification. Stata's time-series commands also include the commands `pergram` and `cumsp`, which provide the log-standardized periodogram and the cumulative sample spectral distribution, respectively, for time-series analysts who prefer to estimate in the frequency domain rather than the time domain.

`xcorr` estimates the cross-correlogram for bivariate time series and can similarly be used both for pre-estimation and postestimation. For example, the cross-correlogram can be used before fitting a transfer-function model to produce initial estimates of the impulse–response function. This estimate can then be used to determine the optimal lag length of the input series to include in the model specification. It can also be used as a postestimation tool after fitting a transfer function. The cross-correlogram between the residual from a transfer-function model and the pre-whitened input series of the model can be examined for evidence of model misspecification.

When you fit ARMA or ARIMA models, the dependent variable being modeled must be covariance-stationary (ARMA models), or the order of integration must be known (ARIMA models). Stata has three commands that can test for the presence of a unit root in a time-series variable: `dfuller` performs the augmented Dickey–Fuller test, `pperron` performs the Phillips–Perron test, and `dfgls` performs a modified Dickey–Fuller test.

The remaining diagnostic tools for univariate time-series are for use after fitting a linear model via OLS with Stata’s `regress` command. They are documented collectively in [R] **regress postestimation time series**. They include `estat dwatson`, `estat durbinalt`, `estat bgodfrey`, and `estat archlm`. `estat dwatson` computes the Durbin–Watson  $d$  statistic to test for the presence of first-order autocorrelation in the OLS residuals. `estat durbinalt` likewise tests for the presence of autocorrelation in the residuals. By comparison, however, Durbin’s alternative test is more general and easier to use than the Durbin–Watson test. With `estat durbinalt`, you can test for higher orders of autocorrelation, the assumption that the covariates in the model are strictly exogenous is relaxed, and there is no need to consult tables to compute rejection regions, as you must with the Durbin–Watson test. `estat bgodfrey` computes the Breusch–Godfrey test for autocorrelation in the residuals, and while the computations are different, the test in `estat bgodfrey` is asymptotically equivalent to the test in `estat durbinalt`. Finally, `estat archlm` performs Engle’s LM test for the presence of autoregressive conditional heteroskedasticity.

## Multivariate time series

### Estimators

Stata provides commands for fitting the most widely applied multivariate time-series models. `var` and `svar` fit vector autoregressions and structural vector autoregressions to stationary data. `vec` fits cointegrating vector error-correction models.

### Diagnostic tools

Before fitting a multivariate time-series model, you must specify the number of lags to include. `varsoc` produces statistics for determining the order of a VAR, SVAR, or VECM.

Several postestimation commands perform the most common specification analysis on a previously fitted VAR or SVAR. You can use `varlmar` to check for serial correlation in the residuals, `varnorm` to test the null hypothesis that the disturbances come from a multivariate normal distribution, and `varstable` to see if the fitted VAR or SVAR is stable. Two common types of inference about VAR models are whether one variable Granger-causes another and whether a set of lags can be excluded from the model. `vargranger` reports Wald tests of Granger causation, and `varwle` reports Wald lag exclusion tests.

Similarly, several postestimation commands perform the most common specification analysis on a previously fitted VECM. You can use `vec1mar` to check for serial correlation in the residuals, `vecnorm` to test the null hypothesis that the disturbances come from a multivariate normal distribution, and `vecstable` to analyze the stability of the previously fitted VECM.

VARs and VECMs are frequently fitted to produce baseline forecasts. `fcast` produces dynamic forecasts from previously fitted VARs and VECMs.

Many researchers fit VARs, SVARs, and VECMs because they want to analyze how unexpected shocks affect the dynamic paths of the variables. Stata has a suite of `irf` commands for estimating IRF functions and interpreting, presenting, and managing these estimates; see [TS] `irf`.

## References

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- Lütkepohl, H. 1993. *Introduction to Multiple Time Series Analysis*. 2nd ed. New York: Springer.
- Pisati, M. 2001. sg162: Tools for spatial data analysis. *Stata Technical Bulletin* 60: 21–37. Reprinted in *Stata Technical Bulletin Reprints*, vol. 10, pp. 277–298. College Station, TX: Stata Press.
- Stock, J. H. and M. W. Watson. 2001. Vector autoregressions. *Journal of Economic Perspectives* 15(4): 101–115.

## Also See

**Complementary:**    [U] [1.3 What's new](#)

**Background:**        [R] [intro](#)