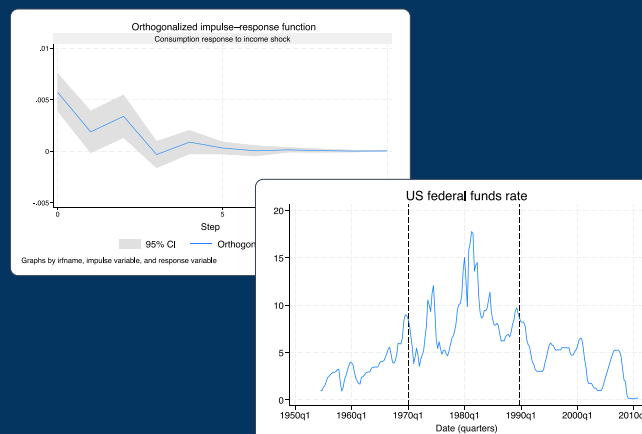


Time series

Handle all the statistical challenges inherent in time-series data—autocorrelations, common factors, autoregressive conditional heteroskedasticity, unit roots, cointegration, and much more. From graphing and filtering to fitting complex multivariate models, let Stata reveal the structure in your time-series data.



• Filters and smoothers

- Hodrick–Prescott and Butterworth high-pass filters
- Baxter–King and Christiano–Fitzgerald band-pass filters
- Single and double exponential smoothers
- Holt–Winters seasonal and nonseasonal exponential filters

• Univariate time series

- ARIMA and ARFIMA
- ARCH, GARCH, APARCH, EGARCH, NARCH, and more
- Dynamic and autoregressive Markov-switching models
- Threshold regression
- Unobserved component models
- Cochrane–Orcutt/Prais–Winsten models

• Multivariate time series

- VAR (vector autoregressive) models
- Local projections for IRFs **New**
- Structural VAR
- Instrument-variables structural VAR **StataNow**
- VEC (vector error-correction) models
- Dynamic-factor models
- State-space models
- Multivariate GARCH models
- Linear and nonlinear DSGEs

• Tests and diagnostics

- Dickey–Fuller (DF), modified DF, augmented DF, Phillips–Perron, unit-root tests
- Granger causality tests
- Eigenvalue stability conditions
- Tests for known and unknown structural breaks
- Lag-order selection and lag-exclusion statistics **Updated**
- Pormanteau’s test

• Forecasting

- One or two equations or thousands of equations
- Dynamic and static forecasts
- Simulation for prediction intervals

• Graphical and tabular analysis

- Impulse–response functions
- Autocorrelations and partial autocorrelations
- Spectral densities
- Periodograms
- Eigenvalue stability condition
- Markov transition probabilities

• Time-series functions

- Lag, lead, difference, and seasonal operators
- Business calendars
- String conversion for clock-time, daily, weekly, monthly, quarterly, half-yearly, and yearly dates
- High-frequency data with millisecond resolution

• Importing and exporting data

- Excel
- SAS and SPSS **Updated**
- CSV
- ODBC
- JDBC
- Oracle
- SQL Server and MySQL
- Access
- Haver Analytic databases
- FRED

• Bayesian analysis

- VAR models
- DSGEs

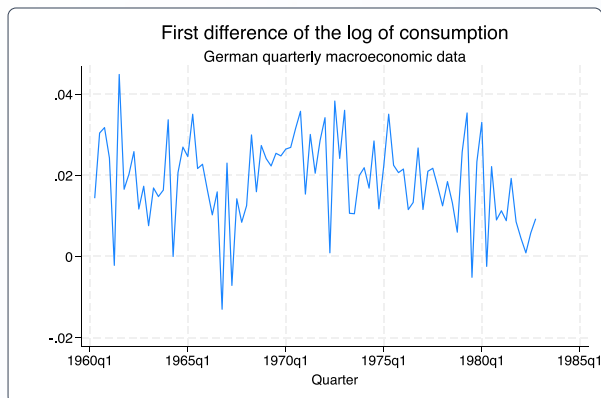
Seamlessly incorporate time-series operators like leads, lags, differences, and seasonal differences in Stata commands without having to generate new variables.

A regression of y on the lag of x_1 , the difference of x_2 , and the lagged difference of x_3 is as easy as typing

```
. regress y l.x1 d.x2 ld.x3
```

Performing other time-series analyses is just as easy. Let's look at a few examples with real data. We have German quarterly macroeconomic data from the first quarter of 1960 to the fourth quarter of 1982. We want to analyze the first difference of the log of consumption ($d.ln_consump$). First, we graph the series:

```
. tsline d.ln_consump ...
```



We test for the presence of a unit root using `dfgls` to perform a modified Dickey-Fuller t test.

```
Viewer - view ts1.smcl
view ts1.smcl
. dfgls d.ln_consump, maxlag(2)

DF-GLS test for unit root          Number of obs = 88
Variable: D.ln_consump
Lag selection: User specified      Maximum lag = 2

[lags]  DF-GLS tau      Critical value
        1%           5%           10%
-----
2       -3.200       -3.614       -3.019       -2.729
1       -5.264       -3.614       -3.037       -2.745

Opt lag (Ng-Perron seq t) = 2 with RMSE = .0100464
Min SIC = -9.048438 at lag 2 with RMSE = .0100464
Min MAIC = -8.495085 at lag 2 with RMSE = .0100464
```

A unit root is not a concern.

The volatility of the series seems to change with time. We fit a model with a first-order ARCH component and first- and second-order GARCH components.

```
Viewer - view ts2.smcl
view ts2.smcl
. arch d.ln_consump, arch(1) garch(1 2)

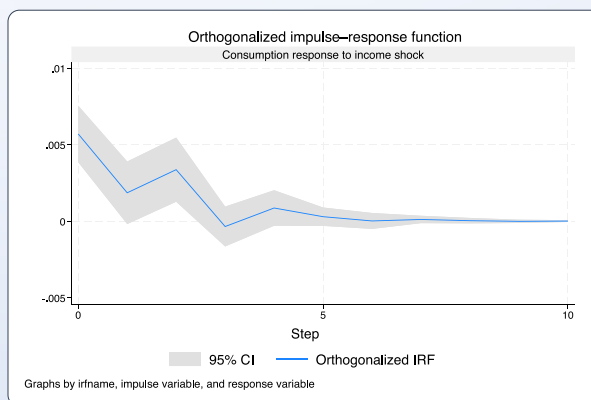
ARCH family regression
Sample: 1960q2 thru 1982q4          Number of obs = 91
Log likelihood = 284.5086           Wald chi2(.) = .
                                      Prob > chi2 = .

D.ln_consump
+-----+-----+-----+-----+-----+
| Coefficient | OPG   | z     | P>|z| | [95% conf. interval] |
|-----|-----|-----|-----|-----|
| ln_consump | .0177286 | .0010575 | 16.76 | 0.000 | .0156559 | .0198013 |
+-----+-----+-----+-----+-----+
ARCH
+-----+-----+-----+-----+-----+
| arch      |         |         |         |         |         |
| L1.       | -.0100908 | .0143674 | -0.70 | 0.482 | -.0382504 | .0180688 |
+-----+-----+-----+-----+-----+
| garch    |         |         |         |         |         | |
| L1.      | 1.881504 | .0228932 | 82.19 | 0.000 | 1.836634 | 1.926373 |
| L2.      | -1.040618 | .0260518 | -39.94 | 0.000 | -1.091679 | -.9895574 |
+-----+-----+-----+-----+-----+
| _cons    | .0000193 | 3.33e-06 | 5.80  | 0.000 | .0000128 | .0000258 |
+-----+-----+-----+-----+-----+
```

Now, we want to analyze a group of series. We can fit a VAR model using the first difference of the log of income and consumption by typing

```
. var d.ln_inc d.ln_consump
```

We now obtain an orthogonalized impulse-response function for a shock of income on consumption.



Finally, we perform a pairwise Granger causality test.

```
Viewer - view ts3.smcl
view ts3.smcl
. vargranger

Granger causality Wald tests
+-----+-----+-----+-----+-----+
| Equation | Excluded | chi2 | df | Prob > chi2 |
+-----+-----+-----+-----+-----+
| D_ln_inc | D.ln_consump | 6.392 | 2 | 0.041 |
| D_ln_inc | ALL          | 6.392 | 2 | 0.041 |
+-----+-----+-----+-----+-----+
| D_ln_consump | D.ln_inc | 16.677 | 2 | 0.000 |
| D_ln_consump | ALL          | 16.677 | 2 | 0.000 |
+-----+-----+-----+-----+-----+
```

This is just a glimpse of what Stata can do. Stata has all the tools you need to conduct time-series analysis.