

pperron — Phillips–Perron unit-root test

Description	Quick start	Menu	Syntax
Options	Remarks and examples	Stored results	Methods and formulas
References	Also see		

Description

`pperron` performs the Phillips–Perron (1988) test that a variable has a unit root. The null hypothesis is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process. `pperron` uses Newey–West (1987) standard errors to account for serial correlation, whereas the augmented Dickey–Fuller test implemented in `dfuller` (see [TS] `dfuller`) uses additional lags of the first-differenced variable.

Quick start

Phillips–Perron unit-root test for `y` using `tsset` data

```
pperron y
```

As above, and include a trend in the specification

```
pperron y, trend
```

As above, but use 10 lags when calculating Newey–West standard errors

```
pperron y, trend lags(10)
```

As above, but without a trend or constant in the specification

```
pperron y, lags(10) noconstant
```

Menu

Statistics > Time series > Tests > Phillips–Perron unit-root test

Syntax

```
pperron varname [if] [in] [, options]
```

<i>options</i>	Description
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Main

<code>noconstant</code>	suppress constant term
<code>trend</code>	include trend term in regression
<code>regress</code>	display regression table
<code>lags(#)</code>	use # Newey–West lags

You must `tsset` your data before using `pperron`; see [TS] `tsset`.

varname may contain time-series operators; see [U] 11.4.4 Time-series varlists.

`collect` is allowed; see [U] 11.1.10 Prefix commands.

Options

Main

`noconstant` suppresses the constant term (intercept) in the model.

`trend` specifies that a trend term be included in the associated regression. This option may not be specified if `noconstant` is specified.

`regress` specifies that the associated regression table appear in the output. By default, the regression table is not produced.

`lags(#)` specifies the number of Newey–West lags to use in calculating the standard error. The default is to use $\text{int} \left\{ 4(T/100)^{2/9} \right\}$ lags.

Remarks and examples

[stata.com](https://www.stata.com)

As noted in [TS] `dfuller`, the Dickey–Fuller test involves fitting the regression model

$$y_t = \alpha + \rho y_{t-1} + \delta t + u_t \quad (1)$$

by ordinary least squares (OLS), but serial correlation will present a problem. To account for this, the augmented Dickey–Fuller test’s regression includes lags of the first differences of y_t .

The Phillips–Perron test involves fitting (1), and the results are used to calculate the test statistics. Phillips and Perron (1988) proposed two alternative statistics, which `pperron` presents. Phillips and Perron’s test statistics can be viewed as Dickey–Fuller statistics that have been made robust to serial correlation by using the Newey–West (1987) heteroskedasticity- and autocorrelation-consistent covariance matrix estimator.

Hamilton (1994, chap. 17) and [TS] `dfuller` discuss four different cases into which unit-root tests can be classified. The Phillips–Perron test applies to cases one, two, and four but not to case three. Cases one and two assume that the variable has a unit root without drift under the null hypothesis, the only difference being whether the constant term α is included in regression (1). Case four assumes that the variable has a random walk, with or without drift, under the null hypothesis. Case three, which assumes that the variable has a random walk with drift under the null hypothesis, is just a special case of case four, so the fact that the Phillips–Perron test does not apply is not restrictive. The table below summarizes the relevant cases:

Case	Process under null hypothesis	Regression restrictions	<code>dfuller</code> option
1	Random walk without drift	$\alpha = 0, \delta = 0$	<code>noconstant</code>
2	Random walk without drift	$\delta = 0$	(default)
4	Random walk with or without drift	(none)	<code>trend</code>

The critical values for the Phillips–Perron test are the same as those for the augmented Dickey–Fuller test. See Hamilton (1994, chap. 17) for more information.

► Example 1

Here we use the international airline passengers dataset (Box, Jenkins, and Reinsel 2008, Series G). This dataset has 144 observations on the monthly number of international airline passengers from 1949 through 1960. Because the data exhibit a clear upward trend over time, we will use the `trend` option.

```
. use https://www.stata-press.com/data/r17/air2
(TIMESLAB: Airline passengers)
. pperron air, lags(4) trend regress
Phillips-Perron test for unit root      Number of obs   = 143
Variable: air                          Newey-West lags = 4
H0: Random walk with or without drift
```

Test statistic	Dickey-Fuller critical value		
	1%	5%	10%
Z(rho)	-46.405	-27.687	-20.872
Z(t)	-5.049	-4.026	-3.444

MacKinnon approximate p -value for $Z(t) = 0.0002$.

Regression table

air	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
air						
L1.	.7318116	.0578092	12.66	0.000	.6175196	.8461035
_trend	.7107559	.1670563	4.25	0.000	.3804767	1.041035
_cons	25.95168	7.325951	3.54	0.001	11.46788	40.43547

Just as in the example in [TS] `dfuller`, we reject the null hypothesis of a unit root at all common significance levels. The interpolated critical values for Z_t differ slightly from those shown in the example in [TS] `dfuller` because the sample sizes are different: with the augmented Dickey–Fuller regression we lose observations because of the inclusion of lagged difference terms as regressors.

Stored results

`pperron` stores the following in `r()`:

Scalars

<code>r(N)</code>	number of observations
<code>r(lags)</code>	number of lagged differences used
<code>r(pval)</code>	MacKinnon approximate p -value (not included if <code>noconstant</code> specified)
<code>r(Zt)</code>	Phillips–Perron τ test statistic
<code>r(Zrho)</code>	Phillips–Perron ρ test statistic
<code>r(level)</code>	confidence level

Matrices

<code>r(table)</code>	matrix of regression results
<code>r(cvalues)</code>	test statistic and critical values

Methods and formulas

In the OLS estimation of an AR(1) process with Gaussian errors,

$$y_i = \rho y_{i-1} + \epsilon_i$$

where ϵ_i are independent and identically distributed as $N(0, \sigma^2)$ and $y_0 = 0$, the OLS estimate (based on an n -observation time series) of the autocorrelation parameter ρ is given by

$$\hat{\rho}_n = \frac{\sum_{i=1}^n y_{i-1} y_i}{\sum_{i=1}^n y_i^2}$$

If $|\rho| < 1$, then $\sqrt{n}(\hat{\rho}_n - \rho) \rightarrow N(0, 1 - \rho^2)$. If this result were valid for when $\rho = 1$, then the resulting distribution would have a variance of zero. When $\rho = 1$, the OLS estimate $\hat{\rho}$ still converges to one, though we need to find a nondegenerate distribution so that we can test $H_0: \rho = 1$. See [Hamilton \(1994, chap. 17\)](#).

The Phillips–Perron test involves fitting the regression

$$y_i = \alpha + \rho y_{i-1} + \epsilon_i$$

where we may exclude the constant or include a trend term. There are two statistics, Z_ρ and Z_τ , calculated as

$$\begin{aligned} Z_\rho &= n(\hat{\rho}_n - 1) - \frac{1}{2} \frac{n^2 \hat{\sigma}^2}{s_n^2} (\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}) \\ Z_\tau &= \sqrt{\frac{\hat{\gamma}_{0,n} \hat{\rho}_n - 1}{\hat{\lambda}_n^2}} \frac{\hat{\rho}_n - 1}{\hat{\sigma}} - \frac{1}{2} (\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}) \frac{1}{\hat{\lambda}_n} \frac{n \hat{\sigma}}{s_n} \\ \hat{\gamma}_{j,n} &= \frac{1}{n} \sum_{i=j+1}^n \hat{u}_i \hat{u}_{i-j} \\ \hat{\lambda}_n^2 &= \hat{\gamma}_{0,n} + 2 \sum_{j=1}^q \left(1 - \frac{j}{q+1}\right) \hat{\gamma}_{j,n} \\ s_n^2 &= \frac{1}{n-k} \sum_{i=1}^n \hat{u}_i^2 \end{aligned}$$

where u_i is the OLS residual, k is the number of covariates in the regression, q is the number of Newey–West lags to use in calculating $\widehat{\lambda}_n^2$, and $\widehat{\sigma}$ is the OLS standard error of $\widehat{\rho}$.

The critical values, which have the same distribution as the Dickey–Fuller statistic (see Dickey and Fuller 1979) included in the output, are linearly interpolated from the table of values that appear in Fuller (1996), and the MacKinnon approximate p -values use the regression surface published in MacKinnon (1994).

Peter Charles Bonest Phillips (1948–) was born in Weymouth, England, and earned degrees in economics at the University of Auckland in New Zealand, and the London School of Economics. After periods at the Universities of Essex and Birmingham, Phillips moved to Yale in 1979. He also holds appointments at the University of Auckland and the University of York. His main research interests are in econometric theory, financial econometrics, time-series and panel-data econometrics, and applied macroeconomics.

Pierre Perron (1959–) was born in Québec, Canada, and earned degrees at McGill, Queen’s, and Yale in economics. After posts at Princeton and the Université de Montréal, he joined Boston University in 1997. His research interests include time-series analysis, econometrics, and applied macroeconomics.

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Also see

[TS] **dfgls** — DF-GLS unit-root test

[TS] **dfuller** — Augmented Dickey–Fuller unit-root test

[TS] **tsset** — Declare data to be time-series data

[XT] **xtunitroot** — Panel-data unit-root tests