

# Learn How to Perform a KPSS Stationarity Test in R with Examples

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## The Critical Role of Stationarity in Time Series Modeling

The foundation of reliable [time series analysis](#) rests heavily on the concept of [stationarity](#). This fundamental property dictates whether the underlying statistical characteristics of the data--such as the mean, variance, and autocorrelation structure--remain constant over time. When a series exhibits stationarity, it simplifies the application of standard econometric models, which often assume that the process generating the data is invariant through time. Achieving stationarity is therefore a crucial prerequisite for accurate inference and effective [forecasting](#).

While the broader definition of stationarity encompasses various forms, practitioners frequently encounter the concept of [trend stationarity](#). A time series is classified as trend stationary if its fluctuations occur around a predictable, deterministic trend. This means that if we remove this underlying trend (a process known as detrending), the remaining residual series becomes stationary. Distinguishing trend stationary series from difference stationary series (which possess a [unit root](#) and require differencing) is essential for selecting the correct modeling approach, such as choosing between ARIMA and ARMA specifications.

To move beyond visual inspection and rigorously quantify the stationarity status of a time series, statistical tests are indispensable. One of the most powerful and widely used diagnostic tools is the [KPSS test](#), named after Kwiatkowski, Phillips, Schmidt, and Shin. This test is unique because its [null hypothesis](#) assumes stationarity, which is the inverse of the assumption used by most traditional [unit root](#) tests. This complementary approach makes the KPSS test an extremely valuable asset in the data scientist's toolkit, especially when confirming the absence of non-stationarity.

## The KPSS Test: Hypotheses and Distinctive Formulation

The [KPSS test](#) is specifically structured to determine the level of persistence in a time series, providing a clear statistical measure of whether a series is stationary around a deterministic mean or trend. This procedure is an indispensable component of the pre-modeling phase, allowing researchers to confirm that their data adheres to the fundamental assumptions required by many classical econometric techniques.

What sets the KPSS test apart from alternatives like the [Augmented Dickey-Fuller \(ADF\) test](#) is the structure of its hypotheses. While the ADF test seeks evidence for the presence of a [unit root](#) (non-stationarity), the KPSS test operates under the premise that the data is already stationary. Consequently, the interpretation of results is reversed compared to unit root tests, demanding careful attention from the analyst.

The formal statement of the hypotheses for the [KPSS test](#), when testing for [trend stationarity](#), is as follows:

**H0 (Null Hypothesis):** The time series is [trend stationary](#). This suggests that the series can be decomposed into a constant term, a linear time trend, and a stationary error component. This is the assumption we hope to retain unless strong evidence suggests otherwise.

**HA (Alternative Hypothesis):** The time series is **not** [trend stationary](#). This suggests the existence of a stochastic trend or difference stationarity, often interpreted as the presence of a unit root process.

This formulation is critical for proper interpretation: if you reject the [null hypothesis](#) (H0), you are concluding that the series is non-stationary. If you fail to reject H0, you proceed with the assumption that the series is stationary.

## Interpreting Statistical Outcomes: The P-Value Decision Rule

Interpreting the output of the [KPSS test](#) relies on comparing the calculated test statistic to critical values, or more commonly in modern statistical software, evaluating the [p-value](#) against a chosen [significance level](#) ( $\alpha$ ). The significance level represents the maximum acceptable probability of committing a Type I error--incorrectly rejecting a true null hypothesis. The standard convention in economic and scientific research is to set  $\alpha$  equal to 0.05 (5%).

The decision process is governed by a straightforward rule based on the relationship between the [p-value](#) and alpha. If the calculated [p-value](#) is smaller than the chosen [significance level](#) (e.g.,  $p < 0.05$ ), we have sufficient statistical evidence to **reject the null hypothesis**. Since the KPSS H0 posits stationarity, rejecting it means we conclude the series is non-stationary and likely contains a persistent stochastic trend.

Conversely, if the [p-value](#) is greater than or equal to the [significance level](#), we **fail to reject the null hypothesis**. In this scenario, we do not have enough evidence to conclude that the time series is non-stationary, and thus we can confidently assume that the data is [trend stationary](#). It is crucial to remember the philosophical nuance here: failing to reject H0 does not definitively prove stationarity, but rather confirms that the data does not offer statistically significant evidence against it.

## Case Study 1: Testing Stationary Data using R

To illustrate the practical application of the KPSS test, we will now perform the procedure in the statistical programming language, [R](#). This first example uses synthetically generated data that is designed to be inherently stationary, providing a baseline for expected results. We use the powerful capabilities of [R](#) to generate, visualize, and test the time series using the necessary functions from the specialized [tseries package](#).

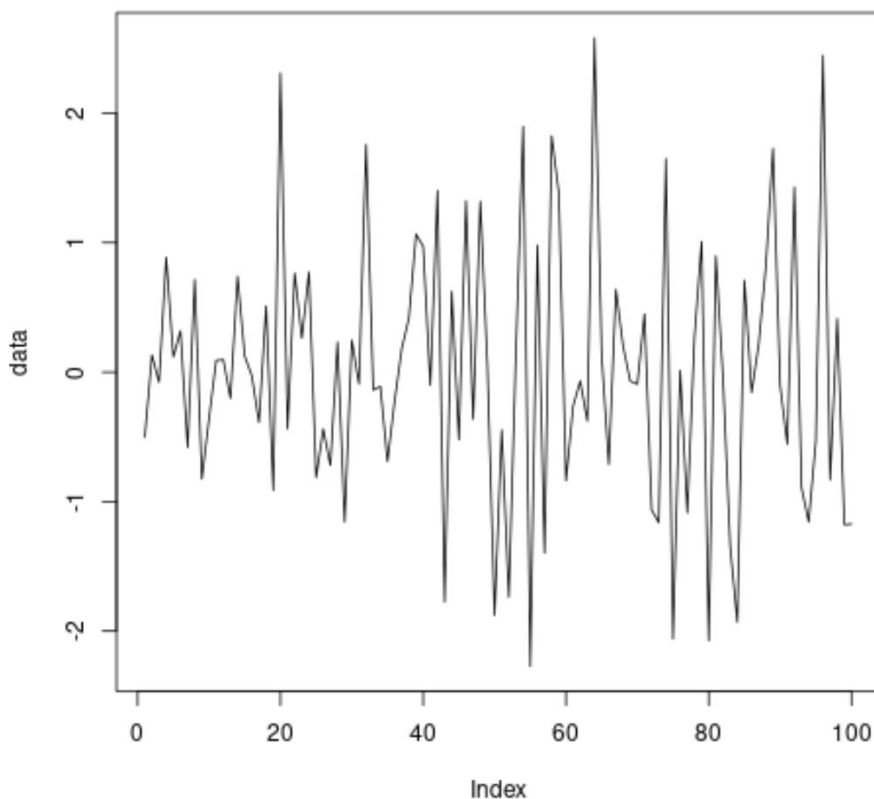
We begin by creating a series of 100 observations drawn from a standard normal distribution

(mean 0, variance 1). Data generated this way exhibits classic stationary behavior. We set a seed for reproducibility, create the data vector, and then visualize the results using a simple line plot.

```
# Ensure the example is reproducible by setting a seed  
set.seed(100)
```

```
# Create stationary time series data (100 observations from N(0, 1))  
data<-rnorm(100)
```

```
# Plot the time series data as a line plot for visual inspection  
plot(data, type='l')
```



Visual inspection of the plot confirms our data generation strategy: the time series fluctuates consistently around a zero mean, lacking any discernible trend, which strongly suggests stationarity. We now formally apply the test using the `kpss.test()` function. By specifying `null="Trend"`, we instruct the test to assess stationarity around a deterministic trend.

```
library(tseries)
```

```
# Perform KPSS test for trend stationarity  
kpss.test(data, null="Trend")
```

## KPSS Test for Trend Stationarity

data: data

KPSS Trend = 0.034563, Truncation lag parameter = 4, p-value = 0.1

Warning message:

In kpss.test(data, null = "Trend") : p-value greater than printed p-value

The resulting [p-value](#) is reported as **0.1**. Comparing this to our standard [significance level](#) of  $\alpha = 0.05$ , we see that 0.1 is not less than 0.05. According to the decision rule, we **fail to reject the null hypothesis**. This statistically validates our expectation: the generated time series is deemed [trend stationary](#). Note that the warning message simply indicates that the function's internal table limits the reported p-value to 0.1 for highly stationary results, which only strengthens our conclusion.

## Case Study 2: Detecting Non-Stationarity in R

In contrast to the previous example, this second case study focuses on a time series that clearly exhibits non-stationary behavior, specifically a pronounced, increasing stochastic trend. By applying the same [KPSS test](#) methodology, we aim to demonstrate how the test successfully identifies the lack of stationarity in challenging data structures.

We generate a synthetic dataset in [R](#) designed to simulate a process with drift, similar to a simple [random walk](#). This type of series typically displays a variance that increases with time and a mean that drifts away from the starting point, making it non-stationary.

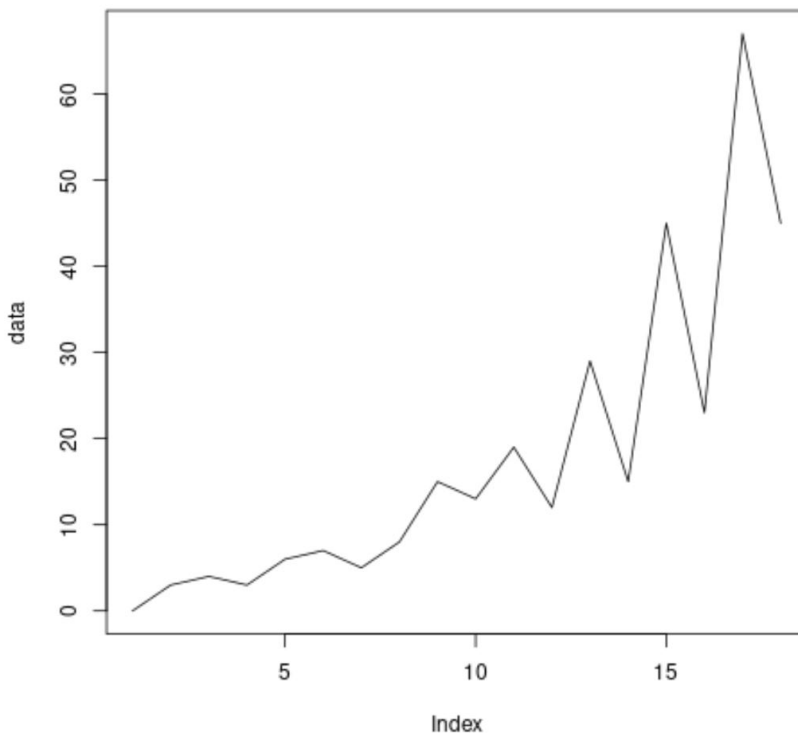
### # Ensure the example is reproducible

```
# Create non-stationary time series data with an upward trend
```

```
data <-c(0, 3, 4, 3, 6, 7, 5, 8, 15, 13, 19, 12, 29, 15, 45, 23, 67, 45)
```

```
# Plot the time series data as a line plot
```

```
plot(data, type='l')
```



The visual evidence from the line plot is striking: the values increase dramatically over time, confirming the presence of a strong upward trend and increasing volatility. This series clearly violates the assumptions of stationarity. We now use the `kpss.test()` function, sourced from the reliable [tseries package](#), to obtain a formal statistical assessment of its trend stationarity.

### **library(tseries)**

```
# Perform KPSS test for trend stationarity  
kpss.test(data, null="Trend")
```

KPSS Test for Trend Stationarity

data: data

KPSS Trend = 0.149, Truncation lag parameter = 2, p-value = 0.04751

The output provides a [p-value](#) of **0.04751**. When measured against the standard [significance level](#) of  $\alpha = 0.05$ , we observe that  $0.04751 < 0.05$ . This result is statistically significant and compels us to **reject the [null hypothesis](#)**.

Rejecting  $H_0$  means concluding that the time series is **not [trend stationary](#)**. The KPSS test has thus correctly identified the non-stationary nature of the data, reinforcing the visual evidence of a stochastic upward trend. This successful diagnosis highlights the test's utility in confirming the

need for transformation (such as differencing) before proceeding with subsequent [time series analysis](#).

## Summary of Findings and Future Directions

The [KPSS test](#) stands as a powerful and essential instrument for accurately diagnosing the [stationarity](#) of a time series, particularly when assessing [trend stationarity](#). Its unique formulation, where the [null hypothesis](#) asserts stationarity, offers a crucial complementary perspective to tests like the [ADF test](#), which focus on detecting non-stationarity (a unit root). Identifying whether a time series is stationary is not merely an academic exercise; it is a vital prerequisite for constructing reliable models and producing trustworthy [forecasting](#) results.

Through our detailed examples, we demonstrated the step-by-step implementation of the KPSS test in [R](#), utilizing the dedicated `kpss.test()` function within the robust [tseries package](#). We successfully interpreted the [p-value](#) to correctly distinguish between a simulated stationary series (where we failed to reject H0) and a non-stationary series with a pronounced trend (where we rejected H0).

We encourage readers to utilize the KPSS test alongside other diagnostic tools to gain a comprehensive understanding of their data's statistical behavior. For those interested in advancing their expertise in this domain, consider exploring the following advanced topics:

Comparison and application of other time series stationarity tests.

Techniques for transforming non-stationary data into a stationary form, such as applying differencing operators.

The development and optimization of Autoregressive Integrated Moving Average (ARIMA) models for advanced [time series analysis](#).