Iraqi Statisticians Journal / Vol. 2 (2025): Special issue for ICSA2025 : 197-205

IRAQI STATISTICIANS JOURNAL

https://isj.edu.iq/index.php/isj

ISSN: 3007-1658 (Online)

Nonparametric Estimation For Nonstationary Time Series Models

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ARTICLE INFO

Article history:
Received 13/11/2024
Revised 16/11/2024
Accepted 14/1/2025
Available online 15/5/2025

Keywords:
Spline
Engle and Granger
Cointegration
Philips-Perron
Lowess Smoother
ECM

ABSTRACT

This paper aimed to use some nonparametric methods in estimating nonstationary time series through the application of the cointegration regression methodology. The research employed both descriptive and econometric methods to construct the standard ECM (Error Correction Model) for monthly time series data for the period 2010-2015. The results relied on the Phillips-Perron unit root test to ascertain the stationarity of the time series and the Engle and Granger cointegration test to examine the existence of a long-run relationship. The application focused on the use of two nonparametric methods, in order to compare and identify the best method for estimating time series models in the light of the cointegration regression methodology. The results proved the superiority of the Lowess method over the cubic Spline method, as it achieved the shortest period and the highest adjustment ratio for disturbances occurring in the short run, with the aim of returning to the long run

1. Introduction

Traditional economic research seeks to build mathematical models and formulas that illustrate the interrelations between the economic variables under investigation. This process involves the practical application of economic theory and Mathematical Economics, in which theoretical concepts and mathematical structures are used to analyze real-world economic phenomena. The primary goal is to represent these phenomena through mathematical modeling-the formulation of problems using equations or inequalities that capture quantitative relationships between relevant factors and conditions. Such representations facilitate the application of well-established mathematical techniques to derive meaningful solutions and insights.

The present research seeks to employ two non-parametric estimation methodologies to model the error correction mechanism within a cointegration regression framework, specifically examining the dynamic relationship between bank deposits and money supply.

This analytical endeavor is predicated on the understanding that robust economic analysis necessitates consideration of the historical evolution and influential factors shaping the phenomena under investigation. Characterizing the temporal trajectory of such phenomena typically involves the acquisition and analysis of statistical data presented as time series.

Many studies, such as Irizarry (2004) [17] demonstrated the application of periodic smoothing Splines in modeling data exhibiting underlying circadian patterns, establishing a connection to REACT estimators. Similarly, Nchor and Adamec (2016) [21] identified key determinants of real money aggregates in Ghana, revealing the long-run impact of GDP

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https://doi.org/10.62933/bs07mq83

and the short-run influence of interest rates. Hmood and Burhan (2018) [14] evaluated the efficacy of non-parametric techniques, including Local Linear Regression and Cubic Smoothing Splines, alongside semi-parametric Single Index models in estimating transfer functions, concluding the superiority of their proposed estimator. Adams and Adeyemi Ipinyomi (2019) [3] compared various methods for estimating the smoothness of Spline smoothing techniques in time series data, aiming to identify the most effective and consistent approach for smoothing parameter estimation.

Furthermore, Fernandez and Fernández (2018) [8] analyzed the interplay between foreign direct investment, exports, and economic growth in Spain utilizing an error correction model (ECM) and vector error correction model (VECM) Granger causality approach, confirming a long-run relationship among the variables.

Finally, Makawi M. (2020) [20] investigated the factors affecting Algeria's gross domestic product through simultaneous integration, multiple linear regression, and Granger causality tests, following an assessment of data stationarity.

The current research contributes to this literature by focusing on the specific relationship between bank deposits and money supply, utilizing nonparametric estimation techniques to provide insights into their dynamic interaction and potential for error correction.

2. Cointegration

Cointegration analysis represents a contemporary statistical methodology specifically designed to investigate long-run relationships between variables, even in instances where short-term deviations from equilibrium occur.

While differencing techniques can induce stationarity in time series data, they inherently lead to a loss of crucial information regarding the underlying long-term dynamics of the variables under consideration.

Granger's contributions significantly elucidated the concept of cointegration between two or more statistical variables, suggesting a long-run equilibrium relationship among them.

This methodological approach has become particularly useful in cases where long-run relationships affect the present value of the variable under study, emphasizing the importance of cointegration in time series analysis.

Moreover, cointegration has played a pivotal role in making economic relations more measurable and quantifiable, in line with contemporary trends in the econometrics of time series

To ascertain the presence of unit roots in time series data, a variety of diagnostic tests have been developed, among which the Phillips-Perron test (Phillips & Perron, 1988) stands as a notable example.

This test offers a refinement over earlier unit root tests by incorporating a nonparametric adjustment to the model variance, effectively correcting for the potential autocorrelation present in the residuals of the test equation.

By accounting for the Autocorrelation structure of the error term without relying on specific parametric assumptions, the Phillips-Perron test addresses the limitations associated with residual autocorrelation and heteroscedasticity often encountered in the conventional Dickey-Fuller test.

The implementation of the Phillips-Perron test typically involves four distinct stages.

1. Estimation of the three basic models for the Augmented Dickey-Fuller test using ordinary least squares, with calculating the associated statistics.

2. Estimating the short-run variance:

$\sigma^2 = \frac{1}{n}\sum_{t=0}^{n} e_t{}^2$, where e_t represents the residual term.

3. Estimating the long-run correction factor, s^2, that can be determined from the residual variance:

$$S_t^2 = \frac{1}{n}\sum_{i=1}^{n} e_t^2 \ + 2\sum_{i=1}^{n}\left(1-\frac{i}{t-1}\right)\frac{1}{n}\sum_{t=i+1}^{n} e_t\, e_{t-1} \tag{1}$$

This type of variance estimation requires the knowledge of the number of lags, determined by the number of observations (n).

4. Calculate the Phillips-Perron statistic:

$$ppt_{\emptyset}^{*} = \sqrt{K} \times \frac{(\emptyset - 1)}{\sigma_{\emptyset 1}} + \frac{n(K-1)\sigma_{\emptyset 1}}{\sqrt{K}} \tag{2}$$

Where $K = \frac{\sigma^2}{S_t{}^2}$ (which equals one in the approximate case if e_t represents white noise).

Subsequently, this test statistic is evaluated against critical values obtained from the Mackinnon (1991) distribution tables.

Consequently, if the computed Phillips-Perron statistic exceeds the tabulated critical values at a chosen significance level, this provides evidence to suggest the presence of a unit root within the time series, thereby indicating its nonstationary nature.

3. Engle and Granger Methodology

According to this methodology, the cointegration test is based on the algorithm proposed by Engle and Granger (1987), which consists of two stages [2][6]:

1)Testing the degree of integration of variables.

2) Estimating the long-run relationship.

To test the null hypothesis that both Y_t and X_t do not share a common level of integration within the framework of the Engle-Granger (EG) model, a test is conducted assuming that the residuals is integrated at the I(0) level. [25]

4. Error Correction Model (ECM)

Economic variables characterized by long-run cointegration tend towards stability or equilibrium. However, due to temporary shocks, these variables may temporarily deviate from their path. Therefore, the Error Correction Model (ECM) is used to account for the fitting between the long-run and short-run behaviors of economic relationships. [1]

The ECM represents an adjustment mechanism that allows the incorporation of short-run changes into the long-run relationship. The name "Error Correction Model" signifies its ability to correct short-run deviations from the long-run trend. The ECM enables us to examine and analyze the behavior of variables in the short run to achieve equilibrium in the long run. According to Engle and Granger (1987), the long-run residuals of the relationship are introduced as a lagged independent variable to estimate the ECM.

To estimate the ECM according to Engle and Granger, the following steps are required:

1) Verify the stationarity of the model variables and determine the order of integration of each variable separately by testing for unit roots.

2) Ensure a balanced relationship between the variables of the model through cointegration testing.

5. Cubic Spline Smoother

Smoothing Spline is a statistical method aimed to estimate the nonparametric regression function to establish a nonlinear relationship between pairs of random variables and to discover patterns or structures in data without the need for a parametric model. The method of Splines is a commonly used smoothing technique that relies on the residual sum of squares (RSS) as a measure of the goodness of fit of the function $f(.)$ to the data. The RSS is defined as follows: [14]

$$RSS = \sum_{t=1}^{n}\{Y_t - f(X_t)\}^2 \tag{3}$$

The necessary condition for the function $f(X_t)$ is that it must be twice differentiable, allowing the second derivative to be obtained.

In Spline smoothing, the number of knots is equal to the number of observations in the time series studied, i.e., knots = n). Non-smoothed penalty solution methods have been proposed to calculate the non-smoothed part.

If we have n observations of the time series values such as $X_1, X_2, \dots, X_n$, represented over the time interval [a, b], then the function f indicates a cubic Spline if the following conditions are met: [9]

1. The function f is a Cubic Polynomial Spline with multiple boundaries in the intervals $(a, X_1), (X_1, X_2), \dots, (X_n, b)$.

2. The piecewise polynomial with multiple boundaries is appropriate at point X_t for the first and second derivatives of the function f, and it is continuous at the points X_t, i.e., f is continuous in the interval [a, b].

The concept behind Spline smoothing is to place a knot at each data point, aligning perfectly with the number of observations. However, parameter estimation is achieved by minimizing the sum of squares, in addition to the penalty term. Cubic Splines are represented as a continuous curve, and the idea of this method is to find a smoothing estimator that minimizes the sum of squared penalized residuals, along with a roughness penalty.

$$\sum_{t=1}^{n}[Y_t - f(X_t)]^2 + \lambda \int [f''(X)]^2 dx \qquad (4)$$

We can use the Reinsch algorithm to calculate the estimator [Green and Silverman 1994]. [9]

Regarding the selection of the penalty parameter h, the penalty parameter plays an important role in balancing between the goodness of fit and the roughness penalty. [4]

One of the techniques for estimating this parameter is Generalized Cross Validation (GCV). This approach can be summarized by the following formula: [3]

$$GCV(\lambda) = \frac{1\sum_{t=1}^{n}\{Y_t - \hat{f}_\lambda(X_t)\}^2}{n\left\{1 - \frac{1}{n}\mathrm{Trace}(S_\lambda)\right\}^2} = \frac{\frac{1}{n}\|(1 - S_\lambda)Y\|^2}{\left[\frac{1}{n}\mathrm{Trace}(1 - S_\lambda)\right]^2} \qquad (5)$$

Given that:

n: Refers to the number of pairs of observations (X_t, Y_t).

λ: Represents the penalty parameter.

S_λ: Denotes the hat matrix, defined as $(X'\grave{W}X)^{-1}X'\grave{W}$.

Trace: Represents the trace of the matrix.

6. Locally Weighted Scatter plot Smoothing (LOWESS)

A method of nonparametric smoothing, fortified based on the idea of local polynomial regression, starts by minimizing the squared errors of the local polynomial and then refines them by adopting a weight function from the local linear estimator (Local Linear Estimation). The method can be clarified according to the following algorithm: [10]

1. Find the nearest value adjacent to X_t, i.e., find the coefficients that minimize the following value as much as possible $\{\beta_j\}_{j=0}^{p}$

$$n^{-1}\sum_{t=1}^{n} W_{Kt}(x)\left(Y_t - \sum_{j=0}^{p}\beta_j x_j\right)^2 \qquad (6)$$

Whereas:

$W_{Kt}(x)$: represents the weights in Local Linear Smoothing (LLS).

2. Calculate the value of $\hat{\sigma}$ after estimating the residuals$\{\hat{\varepsilon}_i\}$, and then compute δi.

Whereas:

$$\hat{\sigma} = \ \mathrm{med}\{|\hat{\varepsilon}_t|\}$$

$$\delta_t = K(\hat{\varepsilon}_I/6\hat{\sigma})$$

Here, K represents a Gaussian function.

3. Estimate the regression function as in the first step, but now using the following weight function:$\{\delta_t\, W_{Kt}(x)\}$, this represents the weight function of the Local Linear Regression Smoother (LLS), proposed by Fan in 1993 and Fan and Gijbels in 1992 and 1996. It is considered one of the best estimators in nonparametric regression as it corrects some of the defects found in kernel estimators.

Based on this, assuming that the second derivative of the unknown nonparametric regression function f(x) exists, and to estimate the parameters a and b, we minimize the following expression. [11]

$$\sum_{t=1}^{n}\left(Y_t - \alpha - b(x - X_t)\right)^2 K\left(\frac{x - X_t}{h}\right) \qquad (7)$$

Assuming that the solution to the problem of weighted least squares is represented by the estimators $\hat{\alpha}, \hat{b}$, and by performing some simple calculations, the Local Linear Smoothing (LLS) can be written as follows:

$$\hat{\alpha} = \hat{f}(x) = \frac{\sum_{t=1}^{n} W_t Y_t}{\sum_{t=1}^{n} W_t}$$

Whereas

$$W_t = K\left(\frac{x - X_t}{h}\right)\left(S_{n.2} - (x - X_t)\right)S_{n.1})$$

$$S_{n.1} = \sum_{t=1}^{n} K\left(\frac{x - X_t}{h}\right)\ (x - X_t)^l\ ,\ \ l = 1,2$$

The smoothing parameter can be determined

using the CV method

7. Results and discussion

In order to evaluate the influence of fluctuations in bank deposits on the money supply, we conducted an analysis utilizing data sourced from the Central Bank of Iraq's database, spanning the years 2010 to 2015. MATLAB 2018 and EViews 12 were employed for data analysis purposes. The investigation focused on assessing the relationship between the variables using the Engle-Granger methodology. A crucial aspect of this methodology involves confirming the degree of integration within the time series. This validation process was executed through the application of Unit Roots tests, with particular emphasis placed on the Philips-Perron test.

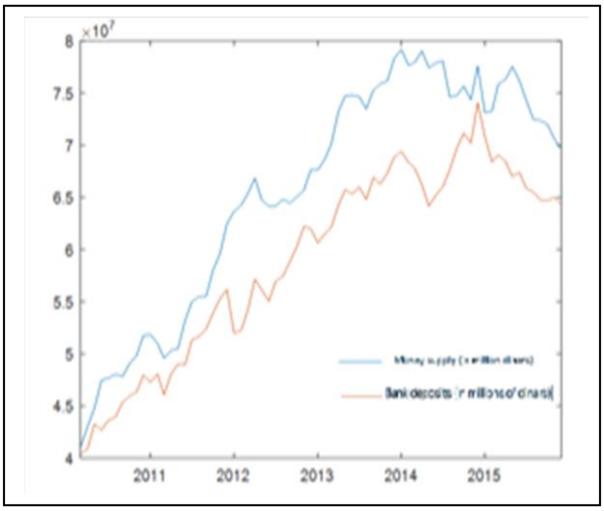

Figure 1: The time series of Deposit Banks and Money Supply (in million dinars)

Through the plotting of the time series for the study variables, it is evident that they exhibit nonstationary at level zero, i.e., I(0).

To confirm this status, unit root tests are conducted, both at level I(0) and first differences I(1), utilizing the Phillips-Perron test. Table (1) presents the results of this test for the money supply at I(0) and I(1) levels, respectively.

The results in Table (1) indicate that the time series for the Money Supply variable is nonstationary at the level I(0), revealing the presence of a unit root in this variable.

So that after applying the first difference I(1), the analysis shows that the Money Supply variable becomes stationary. Similarly, the series of bank deposits is evaluated in Table (2), which presents the test results for both I(0) and I(1).

Table (1): Philips-Perron Test Results for Unit Root under 5% Significance Level for the Money Supply

	Without Intercept and trend		Intercept		Intercept and Trend	
Money Supply	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
Statistic	1.49	-7.05	-2.78	-7.36	-0.16	-8.16
P-Value	0.97	0.00	0.07	0.00	0.99	0.00
Decision	**NS**	**S**	**NS**	**S**	**NS**	**S**

Table (2): Philips-Perron Test Results for Unit Root under 5% Significance Level for the Bank Deposits variable

	Without Intercept and trend		Intercept		Intercept and Trend	
Bank Deposits	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
Statistic	1.59	-7.97	-2.24	-8.34	-0.73	-9.02
P-Value	0.97	0.00	0.20	0.00	0.97	0.00
Decision	**NS**	**S**	**NS**	**S**	**NS**	**S**

Observing the results in the aforementioned tables reveals that the variables are integrated at the first-difference level I(1), which allows for the application of the Engle-Granger cointegration test methodology.

The stationarity analysis of the variables reveals that all variables are initially nonstationary, as they exhibit a unit root, with computed values significantly below the MacKinnon critical values.

However, after first differencing the time series, the variables achieve stationarity, indicating first-order integration, I(1).

The Engle-Granger cointegration test requires that the time series be nonstationary at the level I(0) but integrated at the same order. Once this condition is confirmed, i.e., the series achieve stationarity at the first difference I(1), the Engle-Granger test can be applied to determine the presence of a long-term equilibrium relationship between the money supply and bank deposits. Traditionally, this relationship is estimated using Ordinary Least Squares (OLS) regression; however, our research will employ two nonparametric estimation methods for a more robust analysis.

Table (3): The results of the Phillips-Perron test for residuals at level I(0).

Method	**Lowess**	**Cubic Spline**
Phillips-Perron test Statistic	-4.6716	-3.5269
1% level	-2.5989	-2.5989
5% level	-1.9456	-1.9456
10% level	-1.6137	-1.6137
P-value	0.0000	0.0006

Table (3) shows that the test statistic (t) values for both methods exceed the critical values at all significance levels. As a result, the null hypothesis of a unit root in the residual series is rejected, implying that the error series is stationary at the level I(0).

In other words, the variables are integrated at the first order I(1), confirming cointegration among the time series variables and indicating a long-term equilibrium relationship between them.

Consequently, an Error Correction Model (ECM) can be estimated to confirm the joint integration, demonstrating a long-term equilibrium relationship between the money supply and bank deposits, as established by Engle and Granger (1987). This ECM framework allows for testing and estimating both the long-term relationship and the directionality of this relationship in both the short and long runs.

The Error Correction Term (ECT), or Speed of Adjustment, indicates the magnitude of change in the dependent variable resulting from deviations in the independent variable from its equilibrium value in the short term. This coefficient is expected to be negative, reflecting the rate at which the short-term dynamics converge towards the long-term equilibrium. The other coefficients represent the short-term relationship direction.

Table (4) below presents the results of estimating the Error Correction Model using the Engle-Granger methodology.

Table (4): Estimation of the Error Correction Model (ECM) using Cubic Spline Smoother.

Variable	Coeff.	Std. Error	t-Statistic	P-Value
C	0.252	2.154	1.636	0.107
D(X)	0.500	0.102	4.889	0.000
U(t-1)	-0.240	0.073	-3.305	0.002
R-Squared	0.331	Mean Dependent Variable		4.414
Adjusted R-Squared	0.3107	Sum Squared Residual		1.02E+14
F-Statistic	16.326	Akaike Info. Criterion (AIC)		30.948
P-Value	0.000002	Durbin-Watson (D.W.)		1.394

Table (5): Estimation of the Error Correction Model (ECM) using Lowess method.

Variable	Coeff.	Std. Error	t-Statistic	P-Value
C	2.247	0.159	1.553	0.125
D(X)	0.506	0.1061	4.767	0.000
U(t-1)	-0.247	0.099	-2.476	0.016
R-Squared	0.286	Mean Dependent Variable		4.414
Adjusted R-Squared	0.265	Sum Squared Residual		1.09E+14
F-Statistic	13.250	Akaike Info. Criterion (AIC)		31.012
P-Value	0.000015	Durbin-Watson (D.W.)		1.610

Based on the results in Table (4), the Error Correction Term (ECT) coefficient for the Cubic Spline Smoother is negative and statistically significant, with a probability of 0.002, this suggests a speed of adjustment of approximately 24% per month, indicating that short-term disequilibrium corrects towards long-term equilibrium at this rate.

In other words, the estimated ECM implies that roughly 24% of any deviation in the relationship between money supply and bank deposits is corrected within a month. Thus, following a shock in the bank deposits variable, it would take approximately $\frac{1}{-0.240} = -4.1322$ months for the money supply to return to its long-run equilibrium, assuming other factors remain constant.

For the Lowess smoother in table (5), the Error Correction Term (ECT) coefficient is negative and statistically significant, with a P-value of 0.016 and a coefficient of -0.247. This indicates that approximately 25% of any short-term disequilibrium adjusts towards the long-term equilibrium each month.

In other words, about 25% of the discrepancy in the relationship between money supply and bank deposits is corrected within a month. Therefore, it would take an estimated $\frac{1}{-0.247} = -4.049$ months for the money supply to return to its long-run equilibrium level after a shock in the bank deposits variable, assuming other factors remain constant.

Examining the coefficients of the model for both estimators reveals the following observations:

- There is a positive and statistically significant effect of bank deposits on the money supply in the short term. Specifically, an increase in bank deposits by one unit results in an increase in the money supply by approximately 0.500 and 0.506 units, respectively, for each estimator.
- The coefficient of determination (R-squared) values are 0.331 and 0.286, indicating that approximately 33% and 29% of the variations in the money supply are explained by the bank deposits variable in the model. This means that the remaining 67% and 71%, respectively, can be attributed to errors or other unaccounted variables.
- The Durbin-Watson statistics (DW) are 1.394 and 1.610, suggesting that there are

no significant autocorrelation issues among the residuals of the model.

8. Conclusions

1. Unit Root tests indicated that the variables in the model (Money Supply and Bank Deposits) were not stationary at level I(0), but became stationary after first differencing, indicating integration of the first degree I(1).

2. Engle-Granger cointegration test revealed a long-run equilibrium relationship between Money Supply and Bank Deposits, indicating similar behavior of these variables in the long run.

3. There was a statistically significant positive relationship between both Money Supply and Bank Deposits for both methods.

4. The estimation results of the Error Correction Model (ECM) for short-run Money Supply using the Engle-Granger methodology showed that Bank Deposits explained 33% of the variations in Money Supply using the Cubic Spline Smoother and 29% using the Lowess Smoother.

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