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Analysis of the Phillips Curve for Turkiye: A Comparison of the Johansen Cointegration and Artificial Neural Network Models

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Abstract

This study is examined the validity of the Phillips curve hypothesis using the Johansen cointegration and artificial intelligence methods for the period of 2010-2022 in Türkiye and it is also compared the forecasting performance of these methods using coefficient of determination values and error values. Results of the study an 1% increase in unemployment in the long run leads to a 0.854% decrease in consumer prices. This result supports the Phillips Curve hypothesis for the long run. On the other hand, the error correction model shows that Phillips curve hypothesis is not valid in the short run. Besides, R2 and other error metrics namely mean absolute error, root mean square error and the mean absolute percentage error values verify the better forecasting performance of the artificial neural network model than Johansen cointegration. In this context, the findings that can be obtained as a result of artificial intelligence modeling in the management of inflation and unemployment are considered to be important.

Key words: Phillips Curve, Johansen Cointegration, Artificial Neural Networks, Error Correction Model, Python.

JEL Code: E24, E27, E31.

1. Introduction

Relationships between the unemployment rate, price levels and the production quantity had been discussed employing qualitative descriptions in the literature (Hume, 1752; Thornton, 1802; Humphrey, 1986). In 1958, William Phillips introduced the quantitative analysis method between unemployment and inflation rates which states that there is a stable and inverse relationship between these two variables (Phillips, 1958). This statement is referred to as the Phillips curve hypothesis in economics literature. Before the Phillips curve hypothesis, some quantitative findings were utilized in various studies such as in (Fisher, 1926)

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and (Tinbergen,1936) however the analyses predating the Phillips curve hypothesis did not gain much popularity and the quantitative explanation of the relationship between the inflation and the unemployment rates have taken interest with the Phillips curve analysis. Phillips studied the relationship between the wage inflation and the unemployment rate in Britain and concluded that there is an inverse relationship between the change in wages and the unemployment rate (Phillips, 1958). In addition, Samuelson and Solow (1960) used the general inflation rate instead of the change in money wages, in other words the wage inflation, hence improved the Phillips curve analysis. The Phillips curve has gained more interest after the stagflation problem appeared since 1960s since the inflation and unemployment occur simultaneously in stagflation. In this period when the monetarist approach was accepted, Friedman (1977) argued that the relationship between inflation and the unemployment was valid in the short run and that there was no relationship between these two indicators in the long run. This thesis has been presented under the conditions in which full employment is provided in the economy in the long run, which is one of the assumptions of the monetarist approach where the natural unemployment rate is experienced. In addition, according to the monetary approach which accepts the adaptive expectations assumption, the Phillips curve may change position in the short run depending on the price expectations. When adaptive individuals expect prices to rise in the future, the Phillips curve will move to the right and vice versa.

A new perspective was added to the Phillips curve under the rational expectations assumption developed by Muth (1961). According to their hypothesis, individuals do not make systematic mistakes but rational decisions using historical and current data. They argue that unpredictable policies cause individuals to make incorrect decisions. According to the new classical approach which accepts the rational expectations hypothesis, it is argued that individuals will make rational predictions regardless of short/long term distinction and that the Phillips curve will be in the form of a straight line parallel to the vertical axis at the level of full employment production volume and natural unemployment rate except in the period when an unexpected policy is applied (Lucas & Rapping, 1969). In the new Keynesian approach, which adopts the same hypothesis, the Phillips curve is accepted under the assumptions that the economy runs under assumptions of the underemployment and wage/price rigidity. Many studies have been conducted in the field of Phillips curve for different countries, periods and methods in the literature and the selected examples of these studies are presented in the literature analysis section of this study.

In this study is investigated the relationships between inflation rate and unemployment rate in Türkiye for the period of 2010:05-2022:09. In addition, the forecasting performance of the Johansen cointegration and artificial neural network models for the Phillips curve hypothesis is compared. The contribution of this study to literature is that linear and nonlinear analysis methods are employed and compared for the examination of the Phillips curve hypothesis. The linear and nonlinear models used in this study are the Johansen cointegration and artificial neural network regression methods, respectively.

2. Literature Review

There is an extensive number of studies regarding the Phillips curve in literature. In these studies, it is seen that findings generally support the Phillips curve for different countries and periods. In addition, the literature can be divided into two categories in which the analysis of the inflation-unemployment relationship is performed using linear models or nonlinear models. This study covers both the linear and nonlinear modeling of the inflation-unemployment relationship. A short summary of the literature regarding the Phillips curve analysis is given in Table 1.

In the literature, the Phillips curve analysis is basically investigated for different countries and time frames. Some of these studies include the works of Clark and Laxton (1997) for the USA for the period of 1972-1996, Beaudry and Doyle (2000) in Canada for the period of 1980-1999, Kichian (2001) again in Canada for the period of 1972-1999, Emsen et al. (2003) in Kyrgyzstan for the period of 1992-2001, Bhattarai (2004) in OECD Countries for the period of 1970-2002, Sanchez (2006) in Japan for the period of 1973-2005, Martin and Milas (2007) in the UK for the period of 1992-2007, Abu (2019) in Malaysia for the 1980-2016 period, Chicheke (2009) in South Africa for the 1980-2008, McLeay and Tenreyro (2020) in US for period of 1957-2018, Hazell et al. (2022) in US for period of 1978-2018, Ari, Garcia-Macia & Shruti Mishra (2023) in 24 advanced economies in Europe for 2012-2019. In these studies, an inverse between the inflation and unemployment rates are observed supporting the Phillips curve hypothesis. On the other hand, Russell and Banerje (2008) obtained results rejecting the Phillips Curve in the USA for the 1952-2004 period as well as Herman (2010) in Romania for the 1990-2009 period. In the Turkish economic viewpoint, Domac (2003) studied the period of 1990-2002, Onder (2000) analysed the period of 1969-1998, Uysal and Erdogan (2003) investigated the period of 1980-2012 and Guven and Ayvaz (2016) considered the economy of Türkiye for the period of 1990-2014, and concluded that there is an inverse relationship between the inflation and unemployment rates in Türkiye for these periods supporting the Phillips curve hypothesis. On the other hand, there a few studies rejecting the Phillips curve for the Turkish economy including Agenor and Bayraktar (2003) for the 1981-2001 period, Kustepeli (2005) for the 1980-2003 period and Onder (2006) for the 1987-2004 period, Yıldırım & Sarı (2021) for the 2005-2020 period.

It is seen from the literature that linear modeling methods are generally employed in the studies regarding the Phillips curve analysis (Kichian, 2001; Domaç, 2003; Emsen et al. 2003; Kustepeli, 2005; Martin & Milas, 2007). On the other hand Tambakis (1999) emphasized the importance of the nonlinear analysis in Phillips curve. According to Tambakis (1999), if the Phillips curve is non-linear, the trade-off relationship between the unemployment and inflation rates in the short run will be interpreted differently. In other words, when the unemployment rate decreases by 1%, this may lead to a lower increase in inflation in countries with high unemployment rates compared to countries with low unemployment rates. Eliasson (1999) made estimations with linear and nonlinear models for Australia, Sweden and the USA. As a result of this study, linear Phillips curve model was rejected for Australia and Sweden where the linear Phillips curve for the US economy could not be rejected. There are studies in the literature in which the Phillips curve is estimated by nonlinear methods where Markov regime models or filtering methods are widely used (Beaudry&Doyle, 2000; Cetinkaya and Yavuz, 2002; Kuzin and Tober, 2004; Aguiar and Martins, 2005). In addition, in the study of Jalaee, Lashkary and Amin (2019), artificial neural networks are utilized for modelling in which their findings indicate the stagflation process rejecting the Phillips curve approach. A short summary of the literature regarding the Phillips curve analysis is given in Table 1.

Table 1. Short summary of the Phillips curve literature

Author/s	**Country/Periods**	**Method**	**Phillps curve result**
Clark & Laxton (1997)	USA/ 1972-1996	Time-varying regression	Support
Eliasson (1999)	1977/1997/ Australia, Sweden and the USA.	Linear, nonlinear models	Support-US. Reject-Australia and Sweden
Beaudry & Doyle (2000)	Canada/ 1980-1999	Hodrick-Prescott Filter	Support
Gomez & Julio (2000)	Colombia/ 1990 – 1999	Kalman Filter, OLS	Support
Gagnon & Khan (2001)	US, Canada, Euro Region	GMM	Support
Kichian (2001)	Canada/ 1972-1999,	Time-varying regression	Support
Cetinkaya & Yavuz, 2002	Türkiye/ 1987-2001	Hodrick-Prescott Filter	Reject
Domaç (2003)	Türkiye/ 1990-2002	ARDL, Hodrick – Prescott Filter, Kalman Filter	Support
Emsen et al. (2003) in	KyrgyzstAN/ 1992-2001	OLS	Support

Ewing & Seyfried (2003)	ABD/ 1954 – 1999	GARCH	Support
Bhattarai (2004)	OECD Countries/ 1970-2002	Panel Cointegration and Granger causality tests	Support
Kustepeli (2005)	Türkiye/ 1980-2003	Linear, nonlinear models	Reject
Sanchez (2006)	Japan/ 1973-2005	GMM	Support
Onder (2006)	Türkiye/ 1987-2004	Markov switching multiple structural break models	Reject
Russell & Banerje (2008)	USA/ 1952-2004	GMM	Reject
Chicheke (2009)	South Africa/ 1980-2008	VECM	Reject
Herman (2010)	Romania/ 1990-2009	Correlation analysis	Reject
Bayrak & Kanca (2013)	Türkiye/ 1970-2010	Engle-Granger cointegration	Support-long run Reject-short run
Guven & Ayvaz (2016)	Türkiye/ 1990-2014	VAR, Angle-Granger	
Abu (2017)	Nigeria/ 1980-2016	ARDL, FMOLS DOLS, OLS and Canonical Cointegrating Regression (CCR)	Support
McLeay &Tenreyro (2020)	US/ 1957-2018	Dynamic Stochastic General Equilibrium (DSGE), OLS	Support
Yıldırım & Sarı (2021)	Türkiye/ 2005-2020	Dinamik OLS	Reject
Hazell et al. (2022)	US/1978-2018	Panel analysis	Support
Ari, Garcia-Macia & Shruti Mishra (2023)	24 advanced economies in Europe/2012-2019	Panel analysis	Support

In this study, the validity of the Phillips curve hypothesis is evaluated regarding Türkiye for the 2010-2022 period using both linear Johansen cointegration, error correction and nonlinear artificial neural network methods. After the linear and nonlinear modeling of the inflation-unemployment rate relationship, statistical values which allow comparing the predictive power of these modelling approaches are also benchmarked. For this aim, the error terms obtained from linear and non-linear models namely coefficient of determination (R2), mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) values are computed and compared. The study is concluded by the interpretation of the linear and nonlinear modeling assisted evaluation of the Philips curve hypothesis.

3. Methodology

This study is evaluated the validity of the Phillips curve hypothesis for the period of 2010:05-2022:09 in Türkiye utilizing linear and nonlinear modelling methods namely the Johansen cointegration, error correction model (ECM) and artificial neural networks (ANN) model. In addition, the predictive power of the Phillips Curve hypothesis of both models was compared. The dependent variable of the study is the consumer price index while the independent variables are the unemployment rate, the real effective exchange rate and the Brent oil prices. The montly consumer price index (CPI) (2003=100) was obtained from the electronic data distribution system (EDDS) of the Central Bank of Türkiye. In addition, monthly real effective exchange rate (rexc, 2003=100) and Brent oil prices supply are also obtained from the EDDS. The seasonally adjusted unemployment rate (unemp) variable is taken from the Turkish Statistical Institute (TURKSTAT). The logarithm values of all variables is employed. According to the Phillips curve approach, there is an negative relationship between the inflation rate and the unemployment rate. In addition, according to the economic theory, it is expected that there would be a positive relationship between the real effective exchange rate, money supply and the inflation rate.

From the stationarity point of view, the Augmented Dickey-Fuller (ADF) test may be insufficient if structural breaks are present in the data. Structural break unit root tests are used for the determination of the break points if any breakpoint exists. The Minimized Dickey-Fuller test is a structural break unit root test and is applied when the history of the structural break is unknown. In this approach, the null hypothesis is represented by Model 0 as given in the following expression (Peron, 1997):

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Model 0: non-trending data with intercept break:

$$y_t = \mu + \theta DU(T_b) + \omega D_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} \Delta y_{t-1} + \mu_t \quad (1)$$

$DU(T_b)$ is an intercept break variable, $D_t(T_b)$ is a trend break variable, coefficient β and γ to zero yields a test of a random walk against a trend stationary model with the intercept break.

Model 1: trending data with intercept break:

$$y_t = \mu + \beta t + \theta DU(T_b) + \omega D_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-1} + \mu_t \quad (2)$$

Model 2: trending data with intercept and trend break:

$$y_t = \mu + \beta t + \theta DU(T_b) + \gamma DT_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-1} + \mu_t \quad (3)$$

Model 3: trending data with trend break:

$$y_t = \mu + \beta t + \gamma DT_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-1} + u_t \quad (4)$$

According to Model 2, 3 and 4, if the calculated t-test value is greater than the critical t-test value, the null hypothesis is rejected. This shows that there is structural break in the data.

In econometric models, the long-term coexistence of two or more non-stationary series analyzed by cointegration tests. If the relationship between the variables is in the long run, after taking the differences of the non-stationary series, they are made stationary at the same level and analyzed using Engle-Granger or Johansen-Juselius (JJ) cointegration tests (Barisik and Demircioglu, 2006). In this study, Johansen cointegration technique was used, which allows us to examine the cointegration relationship and to estimate the long-term relationship between the series.

In order to apply cointegration tests, it is necessary to look at the stationarity degrees of the series. If the stationarity degrees of the series are the same, the existence of cointegration between the series can be measured by the cointegration test developed by Johansen in 1988 (Akpolat and Altintas, 2013). The hypothesis used for the Johansen cointegration test is as follows:

H_0: There is no cointegration relationship between the variables.

H_1: There is a cointegration relationship between the variables.

The Johansen cointegration test equation system is as follows:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-1} + \beta X_t + u_t \quad (5)$$

If the X_t and Yt level values given in Equation (5) are not stationary and it is necessary to take their first difference, the first difference of the equation should be rearranged as in Equation (6).

$$Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \tau_i Y_{t-1} + \beta X_t + v_t \quad (6)$$

In Equation (6), the auxiliary variables are defined as follows:

$$\pi = \sum_{i=1}^{p-1} A_i - I \text{ ve } \tau_i = \sum_{i=1}^{p} A_j \quad (7)$$

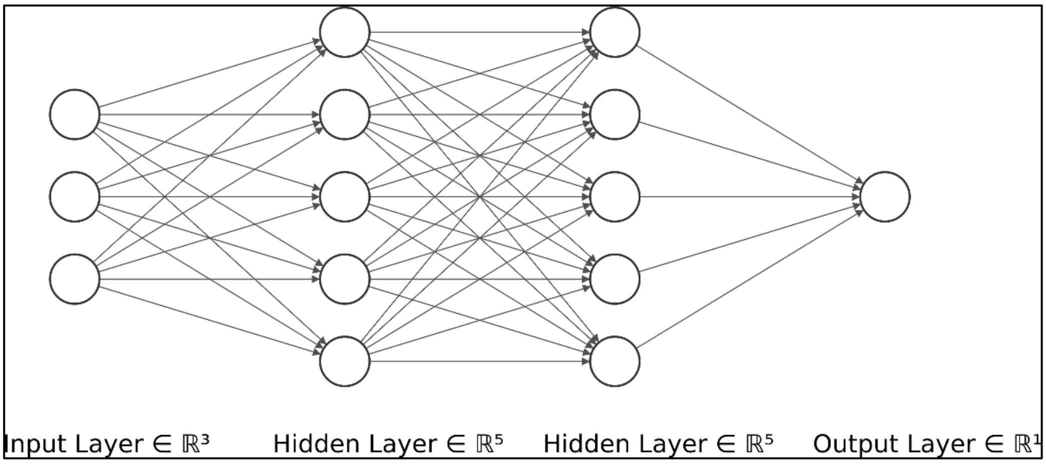
After determining the cointegration relationship between the variables, the error correction model (ECM) is applied between the series in which the cointegrated relationship was detected. The equation of the error correction model is as follows given in Equation (8).

$$\Delta Y_t = \alpha_1 + \sum_{i=1}^{p} \beta_{li} \Delta X_{t-1} + \sum_{i=1}^{p} Y_{li} \Delta Y_{t-1} + \varphi ecm_{t-1} + \mu_{1t} \quad (8)$$

In Equation (8), ecm represents the error correction term and p represents the optimum delay length. The fact that the coefficient of ecm is negative and statistically significant indicates that the short-term deviations between the series with a cointegration relationship in the long-term disappear and the series approach the long-term equilibrium (Gocer et al., 213).

Another method used in this study is the nonlinear artificial neural networks (ANN) model. Artificial neural networks are utilized in a wide range of application areas such as curve fitting (regression), classification and pattern recognition. Artificial neural networks are also employed in economics as a nonlinear regression method (Lashkary, 2019). The general structure of artificial neural networks is shown in Graph 1. There are three inputs to the input layer, two hidden layers consisting of five neurons each and one output node are present in the artificial neural network shown in Graph 1. It is worth noting that the number of hidden layers and the number of neurons in these hidden layers have to be optimized depending on the regression problem.

Graph 1. The general ANN model



4. Results

This study is utilized to the structural unit root test (Minimized Dickey-Fuller test) for determining the stationarity levels of the variables. Table 2 presents the results of minimized Dickey Fuller stationarity test and it show that inf, unemp, rexc and oil variables are stationary at the first difference.

Table 2. Results of the structural breakpoint unit root test (Minimized Dickey-Fuller test)

Variables	Breakpoint	Lag	Constant	t-statistic	Prob.
Inf (Level)	2021M09	2	-2.576	-5.348	0.979
Inf (First Difference)	2021M11	8	-10.823*	-5.347	0.010

Unemp (Level)	2021M05	2	-4.083	-5.347	0.321
Unemp (First Difference)	2021M06	2	-13.460*	-5.347	0.010
Rexc (Level)	2014M03	2	-3.832	-5.347	0.480
Rexc (First Difference	2018M08	1	-10.381*	-5.347	0.010
Oil (Level)	2014M09	1	-4.518	-5.347	0.124
Oil (First Difference	2020M03	3	-12.670*	-5.347	0.010

Note: * indicates the rejection of the null hypothesis at the 1% level.
Source: Authors' calculations

Table 4 shows that all variables are stationary at I(I) level, consequently Johansen Cointegration model was used for estimating Phillips curve. According to this analysis at the first stage, a VAR model (Information criteria of this model for lag length and AR graph is presented in Appendices 1 and 2) respectively). At the second stage is estimated Johansen cointegration model which is obtained Trace and Eigenvalue tests. Table 3. is shown that Trace and Eigenvalue tests values.

Table 3. Johansen Cointegration Results

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.189816	59.91397	47.85613	0.0025
At most 1	0.133418	28.97138	29.79707	0.0620
At most 2	0.039692	7.921216	15.49471	0.4739
At most 3	0.013296	1.967551	3.841466	0.1607
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level * denotes rejection of the hypothesis at the 0.05 level **MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.189816	30.94259	27.58434	0.0178
At most 1	0.133418	21.05017	21.13162	0.0513
At most 2	0.039692	5.953665	14.26460	0.6192
At most 3	0.013296	1.967551	3.841466	0.1607
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level * denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

$$LINF = -0.854LUNEMP - 0.155LECX + 0.416LOIL \quad (9)$$

t statistic	2.140	0.398	2.286
Stan.Eror	(0.399)	(0.389)	(0.182)

The cointegration equation shows that there is a statistically significant and negative relationship between unemployment rate and inflation. An 1% increase in unemployment rate leads to a 0.854% decrease in consumer prices. Similarly, the exchange rate does not affect inflation in the long run. On the other side, oil prices are other effective indicator on inflation rate at the long run. An 1% increase in oil prices causes inflation to increase by 2.29%.

Table 4. Results of the OLS model for the ECM

Dependent Variable: LINF

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.56267	0.502797	26.97444	0.0000
LUNEMP	0.000848	0.102463	0.008277	0.9934
LOIL	-0.044113	0.032069	-1.375551	0.1711
LEXC	-1.704081	0.051362	-33.17814	0.0000

R-squared	0.927848	Mean dependent var	5.750038
Adjusted R-squared	0.926355	S.D. dependent var	0.436953
S.E. of regression	0.118579	Akaike info criterion	-1.399998
Sum squared resid	2.038838	Schwarz criterion	-1.319355
Log likelihood	108.2998	Hannan-Quinn criter.	-1.367234
F-statistic	621.5450	Durbin-Watson stat	0.227696
Prob(F-statistic)	0.000000		

Source: Authors' calculations

The stationarity analysis of the error terms obtained from Table 4 is presented in Table 5.

The error correction model (ECM) is a model used in time series analysis to eliminate the imbalance between the short and long run relationship and to test the short and long run causality between cointegrating variables. The ECM is also used to distinguish between the long-run equilibrium and short-term dynamics among the variables and to determine the short-term dynamics. For ECM analysis, the relationships between the variables are estimated using the OLS method in the first step. With OLS, the level values of all variables are used in the estimation phase. The error term series of the OLS model is obtained. The stationarity structure of the error term is examined. For ECM analysis, this series should be stationary at the level. In Table 4, the results of the OLS model, which is the first stage of ECM analysis, are presented. The stationarity analysis of the error terms obtained from Table 4 is presented in Table 5.

Table 5. Stationarity analysis of the error terms

Break Date: 2022M06			
Break Selection: Minimize Dickey-Fuller t-statistic			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.887973	0.0461
Test critical values:	1% level	-5.347598	
	5% level	-4.859812	
	10% level	-4.607324	

Source: Authors' calculations

Table 5 shows that error terms are level stationary therefore, the ECM estimation has been performed whose parameters are given in Table 6.

In Table 6, the sign of the term ecm(-1) is negative and its value is between zero and one. This result indicates that the error correction mechanism works in the model, the error disappears by -0.034% for each period, and the model stabilizes in the long run. However, it has been determined that there is no statistically significant relationship between the consumer prices and the unemployment rate in the short run. In this context, ECM results reject to the Phillips curve hypothesis in the short run.

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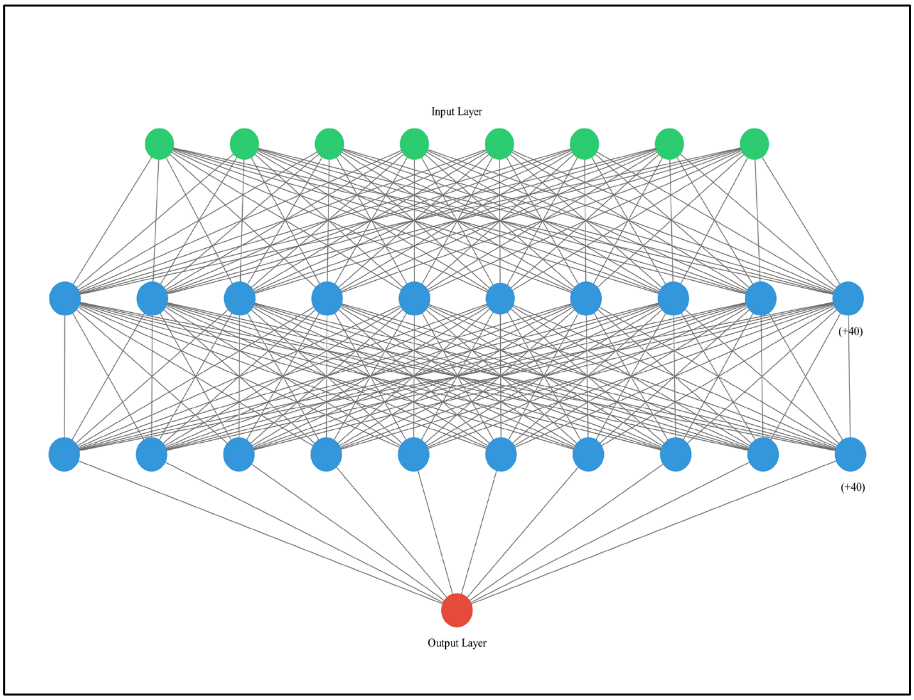
Table 6. ECM estimation results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001536	0.002347	-0.654434	0.5139
D(LUNEMP)	0.013053	0.029212	0.446850	0.6557
D(LOIL)	0.010205	0.008445	1.208373	0.2289
D(LEXC)	-0.065487	0.036754	-1.781753	0.0769
@TREND	0.000179	2.73E-05	6.536943	0.0000
ecm(-1)	-0.033740	0.010039	-3.360776	0.0010
R-squared	0.293159	Mean dependent var		0.012073
Adjusted R-squared	0.268270	S.D. dependent var		0.016569
S.E. of regression	0.014174	Akaike info criterion		-5.635189
Sum squared resid	0.028526	Schwarz criterion		-5.513681
Log likelihood	423.0040	Hannan-Quinn criter.		-5.585821
F-statistic	11.77875	Durbin-Watson stat		0.920184
Prob(F-statistic)	0.000000			

Source: Authors' calculations

Artificial neural network modelling is performed using the Python programming language thanks to its powerful libraries. The MLP Regressor class from the scikit-learn library is used for neural network modelling. The number of hidden layers is selected as three while each hidden layer contains fifty neurons. The optimum number of layers are determined using a looping technique where the coefficient of determination between the actual inflation rate and the modelled rate is maximized. The activation functions are selected as hyperbolic tangent function, which provides the required nonlinearity for the neural network. The standard sampling percentage of 70% is used as the training data where the remaining 30% constitutes the test data. The coefficient of determination, mean absolute error, root mean square error and mean absolute percentage errors are also computed using the relevant methods of the spicy library. The structure of the developed artificial neural network is shown in Graph 2 in which the ann_visualizer library of Python is utilized.

Graph 2. The ANN model constructed in Python



The developed ANN model is trained using training data. It is worth noting that the training phase is in fact the optimization of the weights of the individual nodes, in other words neurons, in the ANN model. After the training phase, the inflation data is computed by employing the developed artificial neural network model. The actual inflation data, the data obtained using the linear Johansen modeling and the results of the nonlinear ANN model are plotted on the same axes as shown in Graph 3. Then, the performance metrics of the Johansen and ANN model forecasts, which are the coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE) and the mean absolute percentage error (MAPE) are calculated in the Python programming language. The obtained performance parameters of the linear Johansen and nonlinear ANN model results are presented in Table 7.

Table 7. Error Parameters of the Johansen Cointegration and ANN Model

MODEL	**MAE**	**RMSE**	**MAPE**	**R^2**
Johansen cointegration	0.15	0.17	0.02	0.83
ANN	0.07	0.09	0.01	0.95

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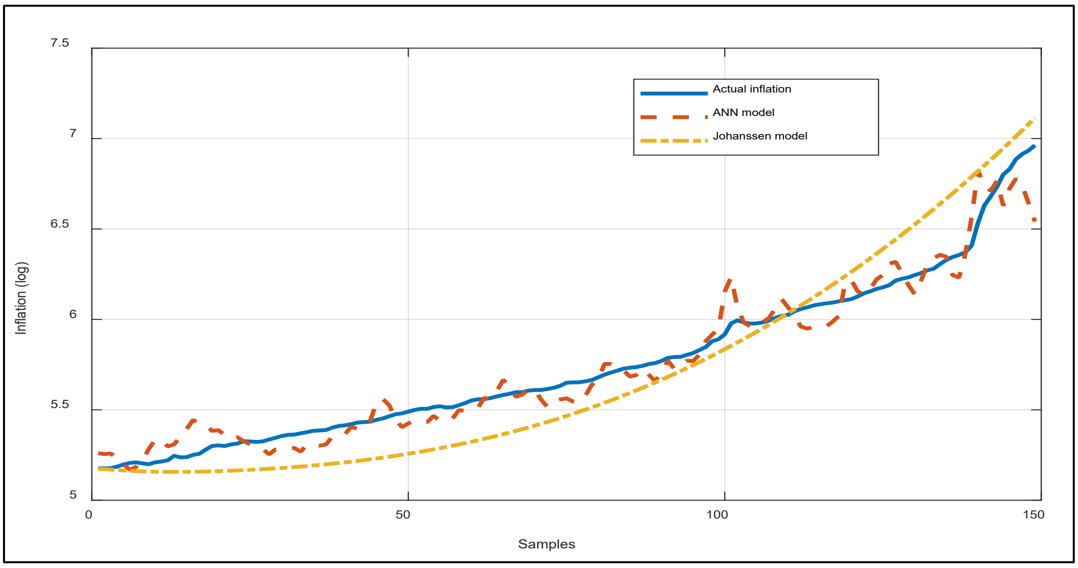
According to Table 7, the coefficient of determination between the results obtained by the actual inflation data and the Johansen cointegration modeling is found to be 0.83 while the same parameter is observed as 0.95 for the actual data and the data obtained using ANN. Moreover, mean absolute error (MAE), the root of mean squared error (RMSE) and (MAPE) were also calculated for Johansen cointegration and ANN model results. In this context, the nonlinear ANN model has better performance over the linear Johansen cointegration model in the analysis of the Phillips curve within the scope of the error parameters given in Table 7.

Graph 3. Actual inflation data and inflation data obtained from the linear Johansen cointegration and nonlinear ANN models



The plots shown in Graph 3 also allow the comparison of the predictive performance of the ANN and Johansen cointegration models. It is exposed that the inflation data estimated by the ANN model predicts the actual inflation data with lower error than the Johansen cointegration model.

5. Conclusion

This paper is examined the Phillips curve for the 2014-2019 period in Türkiye by linear and nonlinear modelling methods which are Johansen cointegration analysis and artificial neural network analysis. According to the Johansen cointegration analysis there is a negative relationship between inflation rate and unemployment rates in the long-term. This result leads to the conclusion that the policies implemented to prevent inflation affect unemployment inversely. Identifying this process in Türkiye within the scope of the Phillips curve approach is in line with the study of Jalaee, Lashkary, and Amin (2019) in which Iranian economics was studied. In addition, the ECM analysis shows that the short-term imbalance in the model would decrease by 0.034 percent in each month and disappear in the long-term. According to the ECM, the Phillips Curve is rejected in the short run. Inflation is affected by the exchange rate in the short run. On the other hand, oil prices are another effective indicator on the inflation rate in the long run. These results are compatible with Bayrak and Kanca (2013). Besides, results of the forecasting linear and non-linear analysis models show R2, MAE, RMSE and MAPE values of the ANN model are lower than the Johansen cointegration model. Depending on these results, ANN model can more effectively results in policy recommendations than the Johansen cointegration model in this topic. Therefore, it can be recommended that the policy makers may choose to use ANN modeling methods to analyze the relationship between inflation and unemployment rates and then arrange the oil prices and exchange rate policies by taking these effects into consideration.

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Appendix

The VAR model is estimated for the Johansen Cointegration analysis. In Table A1 below, it is indicated that the appropriate lag length for the VAR model is two periods according to the information criteria FPE, AIC, SC and HQ.

Table A1. VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-138.8200	NA	9.45e-05	2.084964	2.170219	2.119609
1	1008.826	2211.523	6.32e-12	-14.43542	-14.00914	-14.26219
2	**1065.029**	**105.0216**	**3.52e-12***	**-15.02232***	**-14.25503***	**-14.71051***
3	1074.343	16.85997	3.88e-12	-14.92471	-13.81640	-14.47432
4	1087.386	22.84964	4.07e-12	-14.88155	-13.43222	-14.29258
5	1097.196	16.61282	4.47e-12	-14.79119	-13.00084	-14.06363
6	1105.553	13.66360	5.04e-12	-14.67961	-12.54824	-13.81347
7	1120.008	22.79005	5.20e-12	-14.65705	-12.18466	-13.65233
8	1139.520	29.62394*	5.00e-12	-14.70832	-11.89491	-13.56502
9	1146.908	10.78533	5.77e-12	-14.58260	-11.42816	-13.30071
10	1164.871	25.17409	5.72e-12	-14.61125	-11.11580	-13.19078
11	1180.352	20.79266	5.91e-12	-14.60368	-10.76721	-13.04463
12	1192.957	16.19362	6.41e-12	-14.55412	-10.37663	-12.85649

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Graph A1. Inverse roots of AR characteristic polynomial