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The Dynamics Affecting the Export-Import Ratio in Turkey: A Hybrid Model Proposal with Econometrics and Machine Learning Approach

Türkiye'de İhracat-İthalat Oranını Etkileyen Dinamikler: Ekonometri ve Makine Öğrenmesi Yaklaşımıyla Hibrit Model Önerisi

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ABSTRACT

The indicators related to foreign trade are conventionally measured in a currency or as the ratio of the country's gross domestic products. The ratio of exports to imports, alternatively, provides more useful results when comparing the foreign trade performance of economies both over time and with other countries as a unit-free indicator. In this study, the macroeconomics and financial determinants affecting this ratio are examined both econometrically and using the machine learning method. In this context, the autoregressive distributed lag model method was first used to investigate the relationship between normalized gross domestic products, exchange rate, consumer price index, producer price index, crude oil and Turkey's ratio of exports to imports rate between 2010-2021, monthly. Long-term analysis showed that the 1% depreciation of the Turkish Liras against the US dollar increased the ratio of exports to imports rate by 0.7 points. In addition, a 1% increase in consumer price index will increase ratio of exports to imports by 1.9 points, while a 1% increase in producer price index will cause a -0.8 point decrease on the ratio of exports to imports. Then, the pattern between the variables was analyzed with quadratic support vector machine, a machine learning method. Finally, the novel ARDL-SVM hybrid method was developed, and the pattern between the variables was examined. The findings revealed that although the econometric method provided a broader scope for interpreting the relationships between variables, the developed ARDL-SVM method successfully captured patterns between variables.

Keywords: International trade, Export to import ratio, ARDL, SVM, Turkey
Jel Code: F10, F14, C13

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ÖZ

Dış ticaretle ilgili göstergeler, geleneksel olarak bir para birimi veya ülkenin gayri safi yurtiçi hasılası'nın oranı olarak ölçülmektedir. Diğer yandan, ihracatın ithalatı karşılama oranı birimsiz bir gösterge olarak, ekonomilerin hem zaman içindeki hem de diğer ülkelerle dış ticaret performanslarını karşılaştırırken daha faydalı sonuçlar vermektedir. Bu çalışmada, bu oranı etkileyen makro ekonomik ve finansal belirleyiciler hem ekonometrik olarak hem de makine öğrenmesi yöntemi kullanılarak incelenmiştir. Bu kapsamda ARDL yöntemi, ilk olarak 2010-2021 yılları arasında normalize GSYİH, döviz kuru, TÜFE, ÜFE, ham petrol ile Türkiye'nin REI oranı arasındaki ilişkiyi aylık olarak araştırmak için kullanılmıştır. Uzun vadeli analiz, TL'nin ABD doları karşısında %1'lik değer kaybının REI oranını 0,7 puan artırdığını göstermiştir. Ek olarak, TÜFE'deki %1'lik bir artış REI'yi 1,9 puan artırırken, ÜFE'deki %1'lik bir artış REI'de -0.8 puanlık bir düşüşe neden olmaktadır. Daha sonra, değişkenler arasındaki örüntü, bir makine öğrenmesi yöntemi olan ikinci dereceden destek vektör makineleri (SVM) ile analiz edilmiştir. Son olarak, yeni ARDL-SVM hibrit yöntemi geliştirilmiş ve değişkenler arasındaki örüntü incelenmiştir. Bulgular, ekonometrik yöntemin değişkenler arasındaki ilişkileri yorumlamada daha geniş bir perspektif sunmasına rağmen, geliştirilen ARDL-SVM yönteminin değişkenler arasındaki örüntüleri daha başarılı şekilde yakaladığını ortaya koymuştur.

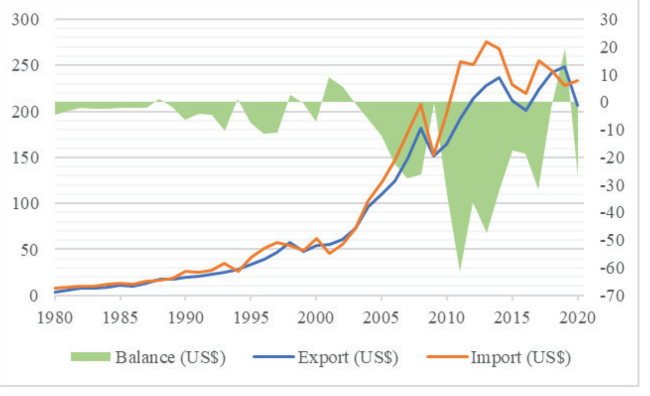
Anahtar Kelimeler: Uluslararası ticaret, İhracatın ithalata oranı, ARDL, SVM, Türkiye
Jel Code: F10, F14, C13

1. Introduction

The structure of international trade and its change over the years contain valuable information about the economic viability. This structure is followed carefully because of its effects on open economy countries' domestic and foreign economic balance. The support of international financial institutions such as the International Monetary Fund and the World Bank to liberalize trade and limit import-substitution-based development strategies has increased international trade in developing countries in recent decades. While international trade was 25% of the World's Gross Domestic Product (GDP) in 1970, this rate increased to 52% in 2020 (Worldbank, 2022). In Turkey, with the liberalization movements in the economy after 1980, especially Turkey's trade with Western Europe gained weight. In 1995, Turkey's signing of a customs union agreement in the EU accession process increased this economic cooperation. However, when foreign trade in Turkey is analyzed structurally, it is seen that imports are almost always higher than exports (See Figure 1).

The fact that imports are more than exports creates a foreign trade deficit and affects the current account balance, the most critical component of the balance of payments. The foreign trade deficit is usually measured in money or as a gross national product (GDP) ratio. This also brings some difficulties. First of all, to determine a country's foreign trade balance or deficit exactly, it is necessary to show both exports and imports in the same measure. In addition, in order to understand foreign trade in a country, it is necessary to consider not only the import and export values but also the amount. That is, the measurement of the value obtained by foreign trade in a country shows how much foreign currency the country pays when importing or how much foreign currency input it receives when exporting. On the other hand, the measurement in terms of quantity shows whether exports and imports have increased in real terms. Therefore, it is necessary to interpret these two variables while making the analysis.

Figure 1. Turkey's Export and Import (in Million Dollars)[1]



On the other hand, the ratio of the export to import (REI) coverage indicator can be used to examine the developments in the foreign trade of the countries (Mikic & Gilbert, 2009). This ratio shows how much of the import is covered by exports. Therefore, thanks to this ratio, it can be helpful to see both the trade performance of the same country over the years and its place among other countries.

Considering REI as a foreign trade measure, the critical advantage of REI is the differences in reflecting exchange rate movements on trade and GDP. While the changes in exchange rates are more similar and closer to each other in export and import prices, their reflection on the whole GDP may be different. Therefore, while the ratio of import, export, or foreign trade volume to GDP changes rapidly in sudden changes in exchange rates, REI exhibits a more limited change. This limited change puts REI in a more advantageous position regarding its ability to reflect foreign trade performance.

To explain another advantage of REI with an example, let us take two different countries. Let the ratio of exports and imports to GDP be 30% and 40% in the first country, and 20% and 30% in the second country. The foreign trade deficit in both countries is at the level of 10% of GDP. However, while the REI was 0.75 in the first country, this rate was 0.67 in the

[1] While the left axis of Figure 1 shows the change in exports and imports in million dollars according to years, the right axis indicates the foreign trade difference over the years.

second country. As a demonstration, the foreign trade deficit does not allow a clear distinction between the two countries; on the contrary, it can be said that with REI, the trade volume of the first country is higher, and therefore there is greater integration with the outside world. Therefore, when there is an increase in the exports of the first country or a decrease in the imports, it can be interpreted that the foreign trade deficit can be closed more quickly than in the second country. It would be more challenging to close the foreign trade deficit at the same rate in the second country.

In this context, REI offers a normalized and de-united measure of the foreign trade deficit. The coverage ratio of a country in year t is shown as:

$$Z_t = \frac{X_t}{M_t} \tag{1}$$

In Equation 1, X_t represents the country's exports in year t, and M_t its imports. In the normalization created by dividing the foreign trade deficit by GDP, as stated above, countries differ in terms of openness. Therefore, a foreign trade deficit of a certain percentage of GDP has different meanings for different countries.

In this research, the export-import coverage ratio is examined as a foreign trade measure, and the effects of changes in the exchange rate, Brent petroleum, consumer and producer price indices, and finally, the GDP on REI are investigated. First, the most suitable econometric method was determined for the research, and analyses were made in this direction. Later, the machine learning method, which is generally much more successful in solving non-linear relations, was used, and a new hybrid method was introduced, especially for predicting the future.

In this study, firstly, REI, which is not frequently analyzed in the economic literature in Turkey, will be analyzed in the light of econometric models. As it is known, certain assumptions and tests are made while performing an econometric analysis. If the prepared data cannot pass these tests and assumptions, either a different method is used or a different time interval, and the variable group is selected. All these bring some problems with econometric analysis. In recent years, Bayesian analysis methods and, more importantly, machine learning methods have been used as an alternative to these methods. The purpose of applying two different methods to the same model is to compare the econometric and machine learning method in terms of the predictive power of features.

Moreover, and importantly, in this research, the machine learning method was built on the outputs obtained after the econometric method, and a hybrid one was developed. With this advanced method, estimation was made, and all results were compared. Therefore, this study is unique because it uses the export-import coverage ratio to measure foreign trade and analyzes it using both econometric and machine learning methods, and it is thought to contribute to the economic literature.

2. Literature

In this study, the elasticity of import coverage ratio according to national income, exchange rate, and Brent oil price, which affect the input price of production, will be examined. When the literature is reviewed, it is observed that the studies on REI in Turkey are limited. In other respect, although the studies on the dependent variable are limited in the literature, when it is examined in terms of the econometric method, it can be mentioned that there are studies that can make inferences indirectly (on import-export, trade balance).

Vita and Abbott (2004) investigated the effect of exchange rate variation on US exports using the ARDL bounds test. The study's findings showed the existence of a cointegration relationship between some international economic determinants. Furthermore, while the sign and magnitude of this effect vary depending on the case, the data show that US exports have been significantly affected by exchange rate volatility.

Using Pakistani data, Waliullah, Kakar, Kakar and Khan (2010) investigated the short and long-run relationships among the trade balance and other macroeconomic variables. Using annual data from 1970 to 2005, researchers investigated a long-term balance link between the variables by the trade balance using the ARDL approach. The boundary test claims that the trade balance and other variables have a stable long-run connection. The estimation results support the Marshall Lerner condition, indicating that exchange rate depreciation is positively related to long-run and short-run trade balances. According to the study's findings, money supply and income play an important role in determining trade balance. Growth and monetary policy have a more significant impact on trade balance than the exchange rate.

Altıntaş (2013) aims to estimate Turkey's export function with the ARDL method and causality tests using exports, foreign real income, real exchange rate, real oil prices, and relative export price with quarterly data for the 1987-2010 period. The estimation result revealed a long-term relationship between exports and defined variables. While the relative export price has no long-term significance, the absolute oil price seems to positively and considerably impact exports. Granger Causality Test Results showed the existence of a one-way relationship from relative export price to exports, from real exchange rate to foreign income, from foreign income to real oil price. Furthermore, a bidirectional link between exports and foreign income, relative export price, and real oil price.

Thao and Jian Hua (2016) looked at the impact of trade policy reforms on Vietnam's foreign trade and weighed in on the benefits and drawbacks resulting from the changes. In addition, the scope and application method of trade policy reform in Vietnam are discussed in detail. ARDL test and error correction model (ECM) were applied in the study. In addition, the stability of the model used was tested with CUSUM and CUSUMSQ. The cointegration findings revealed that the response and explanatory variables had a long-term relationship. It is concluded that the trade policy reform in Vietnam has a positive impact on foreign trade activity, economic development, and people's living standards.

Mukhtar, Adamu, Ibrahim Abdullahi, Shehu and Buba (2022) examined the elements that influence Nigerian exports. For the years 1989 to 2019, financial, macro and international economics determinants were all tracked. The impacts of supply, physical capital, and government expenditures on exports were explored utilizing the ARDL model. Interest rate, domestic credit, openness to trade, income per capita, agricultural output, and manufacturing all favorably affect exports, while inflation, exchange rate, foreign direct investment, and government expenditures all negatively affect exports, according to the findings.

Other recent studies in the literature examine the impact of international trade on growth. Raghuramapatruni and Reddy (2020) utilized ARDL to explore into the hands of global trade on India's economic growth. The outcome of this research imply that exports and domestic investments get a significantly positive impact on GDP. It was discovered that there is a negative and statistically significant association between imports and exchange rates and GDP. The results of the short-term relationship estimation indicated a strong positive relation between exports and domestic investments, and also a negative but statistically irrelevant association amongst imports and exchange rates.

Bardi and Hfaiedh (2021) examined the effect of trade openness on the economic growth of Mediterranean countries using the ARDL panel method for eight countries between 1975 and 2016. The findings revealed that economic development and trade openness have a one-way causal relationship. Furthermore, financial openness contributes to economic growth. Changes in the financial sector have less impact on economic growth in the nations studied than other factors, and the human capital and investment ratios encourage economic growth.

Ahmed, Zhang and Cary (2021) researched Japan to explore the relation between environmental variables and macroeconomics indicators. The researchers used Narayan-Popp and CMR unit root tests to determine cointegration and long-term linkages while also asymmetric and symmetric ARDL techniques. The outcomes of this research revealed that there had been simultaneously symmetrical and asymmetrical long-term relations between the variables. Consequently, economic globalization and financial growth increase the ecological footprint, with such an improvement in financial development raising the footprint more effectively. Furthermore, environmental consequences and environmental issues will arise once energy consumption improves.

Few studies in the literature examine foreign trade with hybrid models. Yu, Wang and Lai (2008) propose a novel kernel-based ensemble learning approach that combines econometric and artificial intelligence (AI) models to forecast China's foreign trade volume. The experimental results show that the hybrid econometric-AI ensemble learning approach outperforms the other linear and nonlinear models in this study in terms of prediction performance.

Sun, Zhang and Wang (2020) researched a novel hierarchical model to forecast China's foreign trade because hierarchies naturally organize economic systems. First, international trade data are separated in this paper from the perspectives of trading partners and trading products, with total exports and imports as target variables. The bottom time series are then modeled by corresponding control variables based on trading theories. The results show that this forecasting model outperforms benchmark models and generates consistent forecasts for total imports and exports.

Finally, although economic studies using ARDL and SVM methods are not common in the literature, it is seen that other machine learning methods and ARDL methods have been used in the last few years. Wu et al. (2020) analyzed the interaction involving financial development and economic growth for Asian nations between 1960 and 2016. They used ARDL and machine learning approaches. Even though there is no long-run cointegration among real GDP and private credit, the outcomes indicate that the three Asian economies assessed have short-run causality.

Bakshi, Jaiswal and Jaiswal (2021) monitored the efficiency of the Indian crude oil futures market by cointegration tests with the ARDL model. In the study, besides the ARDL model to estimate crude oil futures prices, support vector regression from machine learning algorithms and XGBoost were used to make comparisons. ARDL model obtained more accurate prediction results than machine learning models.

3. Methodology

In the research, the REI, which shows Turkey's foreign trade with other countries, and its sensitivity to exchange rate, national income, consumer and producer price index, and Brent oil prices, are examined with econometrics and machine learning analyses.

First, the econometric method that analyzes the relationship between dependent and independent variables in the most appropriate way is selected, and the results are interpreted.

Then, the non-linear relationship between these variables will then be analyzed using the machine learning method. Moreover finally, a hybrid method will be applied using the machine learning method with the results obtained by econometric analysis. As a result, the method that best shows the relationship between the variables will be reported.

3.1. Data

In the analyses, export and import data, normalized GDP, exchange rate, Consumer price index (CPI), Producer price index (PPI), and Brent oil data were used for 2010-2021 at a monthly frequency. The data sets and details used for these variables are shown below.

Table 1: Definition of the Variables

Variable	Symbol	Data Sources
The ratio of Export to Import	REI	UNCTAD
Normalized GDP	GDP	FRED
Exchange Rate (USDTRY)	EXC	Turkstat
Consumer Price Index	CPI	Turkstat
Producer Price Index	PPI	Turkstat
Brent Crude Oil Price	BRENT	FRED

While building the data set, The United Nations Conference on Trade and Development (UNCTAD) was used to prepare the data for the REI variable. For independent variables, the data set presented by the Organization for Economic Cooperation and Development (OECD) for GDP under the title of Main Economic Indicator; Turkish Statistical Institute (TURKSTAT) was used for EXC, CPI, and PPI, and Federal Reserve Economic Data (FRED) was used for BRENT in Table 2.

Table 2: The statistical description of the Data Set

	REI	GDP	EXC	CPI	PPI	BRENT
Mean	0,699	99,856	3,338	289,254	290,448	75,825
Maximum	0,507	101,611	8,030	517,960	590,520	126,590
Minimum	1,011	93,560	1,427	174,070	164,936	14,850
Std. Dev.	0,103	1,198	1,844	95,756	111,276	27,508
Skewness	0,656	-1,983	0,957	0,765	1,011	0,140
Kurtosis	3,096	9,598	2,683	2,421	2,800	1,801
Observation	134	134	134	134	134	134

In Table 2, the REI variable shows the ratio of exports to imports. According to this variable, while the lowest value of REI in Turkey was in September 2011, it reached the highest rate in October 2018. First independent indicator is GDP which is normalized[2]. The 93.56 value in the table shows the year May 2002, while the highest value of 101.6 shows

[2] The series are normalized by using the formula, which is, $\frac{(x-mean)}{(\sum|x-mean|/T)}$, where x indicates the series and T indicates the sample size (OECD, 2022).

the data for February 2018. EXC is the TL equivalent of the dollar in nominal terms. CPI, PPI, and Brent petroleum are also included in the data collected from data sources. In more detail, the change of the variables in the historical process is shown in Figure 2.

3.2. Econometric Approach: Autoregressive Distributed Lag Models

Non-stationary economic time series are particularly prevalent (Johansen & Juselius, 2009). A spurious regression problem may arise in non-stationary time series analyses (Granger & Newbold, 1974). The methods developed by Engle and Granger (1987), Johansen (1988) and Johansen and Juselius (2009) can be widely used to determine the cointegration relationship between series. However, Engle and Granger's methods are not preferred because there may be more than one cointegration relationship in cases where there are more than two inputs. Furthermore, in the Johansen, Johansen, and Juselius tests, all series should not be stationary in level and should be stationary when the difference is taken to the same degree. These limitations in classical cointegration tests led to the ARDL bounds test approach.

In this context, the ARDL bounds test approach has some advantages over alternative cointegration tests. The most significant benefit is that it can be used notwithstanding whether the analysis parameters are I(0) or I(1). This feature of ARDL analysis eliminates the necessity of determining the integration degrees of the variables a priori. Furthermore, when the power of unit root tests is low, there is a chance that the pretest will produce questionable results. Another benefit of the bounds test methodology in this perspective is that it has better statistical properties than the Engle-Granger method when the unconstrained error correction model (UECM) is used. Another significant advantage is that it works well with small or limited sample sets. Since it produces more reliable results when the number of observations is low compared to the Engle-Granger and Johansen cointegration tests (Morley, 2006).

The ARDL bounds testing approach is divided into three stages. The first stage determines whether the variables included in the analysis have a long-term relationship. If the variables have a cointegration relationship, long and short-term elasticity is obtained in the following stages (Odhiambo, 2009). The UECM, created in the first stage for the ARDL bounds test approach, is included in Equation 2. Finally, the model in question is expressed in its adapted form to this research.

$$\Delta REI_t = \alpha_0 + \theta_1 REI_{t-1} + \theta_2 GDP_{t-1} + \theta_3 EXC_{t-1} + \theta_4 CPI_{t-1} + \theta_5 PPI_{t-1} + \theta_6 BRENT_{t-1} + \sum_{i=1}^{p} \beta_{1i} \Delta REI_{t-i} + \sum_{j=0}^{p} \beta_{2j} \Delta GDP_{t-j} + \sum_{j=0}^{p} \beta_{3j} \Delta EXC_{t-j} + \sum_{j=0}^{p} \beta_{4j} \Delta CPI_{t-j} + \sum_{j=0}^{p} \beta_{5j} \Delta PPI_{t-j} + \sum_{j=0}^{p} \beta_{6j} \Delta BRENT_{t-j} + \varepsilon \tag{2}$$

The p-value in the model in Equation 2 represents the appropriate lag length. Information criteria are used to decide the p-value. The null hypothesis H_0: $\theta_1=\theta_2=\theta_3=\theta_4=\theta_5=\theta_6=0$ is tested using the F test after determining the lag length in the ARDL bounds test approach to investigate the existence of a cointegration relationship between the variables included in the analysis (Narayan, 2005). The standard F test, used to test the null hypothesis, has a non-standard distribution in a few cases (Narayan & Smyth, 2006). These situations include whether the ARDL model's variables are I(0) or I(1), the number of variables and whether the ARDL model contains constant terms and/or trends. As a result, Pesaran et al. (2001) tabulated the critical values compared with the test statistics.

These critical values are divided into two parts. First, the variables being I(0) and I(1) were used to calculate critical values for the lower and upper limits. Assume the calculated F statistical value is greater than the critical value's upper limit. In that case, the null hypothesis, which states no long-term relationship between the variables, is rejected. However, the null hypothesis cannot be rejected if the calculated F statistical value is less than the lower limit of the critical value. Suppose that the calculated F statistical value falls between the lower and upper bounds. In that case, no decision can be made, and other cointegration tests that take the stationarity levels of the variables into account are recommended. The next step in the ARDL bounds test approach is rejecting the null hypothesis due to the F test. This stage is divided into two parts. First, the appropriate lag length for the long-term ARDL model in Equation 2 is determined by taking the Akaike Information Criterion into account (AIC). The following section estimates the model in question using the ordinary least squares technique (Narayan, 2005).

$$REI_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} REI_{t-i} + \sum_{i=0}^{n} \alpha_{2i} GDP_{t-i} + \sum_{i=0}^{n} \alpha_{3i} EXC_{t-i} + \sum_{i=0}^{n} \alpha_{4i} CPI_{t-i} + \sum_{i=0}^{n} \alpha_{5i} PPI_{t-i} + \sum_{i=0}^{n} \alpha_{6i} BRENT_{t-i} + \varepsilon_t \tag{3}$$

In the third and final stage of the ARDL bounds test approach, the ARDL model in Equation 3 is estimated for the short-term relationship between the variables.

$$\Delta REI_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} \Delta REI_{t-i} + \sum_{i=0}^{n} \alpha_{2i} \Delta GDP_{t-i} + \sum_{i=0}^{n} \alpha_{3i} \Delta EXC_{t-i} + \sum_{i=0}^{n} \alpha_{4i} \Delta CPI_{t-i} + \sum_{i=0}^{n} \alpha_{5i} \Delta PPI_{t-i} + \sum_{i=0}^{n} \alpha_{6i} \Delta BRENT_{t-i} + \varphi ECT_{t-1} + \varepsilon_t \tag{4}$$

The variable ECT_{t-1}expressed as the error correction term in Equation 4 is the value of the residue series obtained from the long-term ARDL model one period ago. The coefficient φ belonging to the variable in the equation shows how much of the short-term imbalance can be corrected in the long term.

3.3. Machine Learning Approach: Support Vector Machine

Econometric analyses provide a robust analysis method for explaining the relationships between variables. However, many basic assumptions and tests (variable variance, autocorrelation, the correlation between units, etc.) must be provided for the analyses to be performed reliably. In cases where these assumptions are not met, different methods may be used for the analysis, but this may decrease the reliability of the analysis. On the other hand, machine learning is a set of methods that enable learning specific patterns from past data observations.

Cortes and Vapnik (1995) used the Support Vector Machine (SVM) approach for the first time. Both classification and regression issues can be solved using the SVM approach called Support vector regression (SVR) for regression problems. For continuous data, the goal of SVR is to minimize the variance between the target values and the generated hyperplane. To detect non-linear relationships among data, SVR employs kernel functions. These functions used data as input and reshaping it into the required form for processing data. Table 3 lists the most frequently utilized kernel functions (Rüping, 2001). Furthermore, increasing the number of input variables does not affect the difficulty of solving the task. Therefore, the SVR model is preferable compared to other machine learning models (Guleryuz, 2022; Ozden & Guleryuz, 2021).

Table 3: Mathematical formulations of SVR kernel functions (Rüping, 2001)

Kernel Function	Expression
Linear	$K(x_i, x_j) = (x_i, x_j)$
Polynomial	$K(x_i, x_j) = (\langle x_i, x_j \rangle + 1)^d$
Gaussian	$K(x_i, x_j) = e^{(-\frac{\|x_i - x\|^2}{2\gamma^2})}$
Sigmoid	$K(x_i, x_j) = tanh(\gamma\langle x_i, x_j \rangle + 1)^d$

Equation 5 shows the mathematical formulation of SVR, which includes the objective function and constraints.

$$\text{maximize} \begin{cases} \frac{1}{2}\sum_{i=1}^{j}(\omega_i - \omega_i^{*})(\omega_i - \omega_i^{*})\, K\langle x_i, x_j \rangle \\ -\epsilon\sum_{i=1}^{j}(\omega_i + \omega_i^{*}) + \sum_{i=1}^{j} y_i(\omega_i - \omega_i^{*}) \end{cases}$$

$$\begin{cases} \sum_{i=1}^{k}(\omega_i - \omega_i^{*}) = 0 \; and \; \omega_i, \omega_i^{*} \in [0, C] \\ .\mathrm{t} \\ 0 \leq \omega_i, \omega_i^{*} \leq \frac{C}{j} \\ i = 1,2, \ldots, j \end{cases} \tag{5}$$

In Equation 5, x_i depicts current data, j represents the dataset volume, C denotes the penalty coefficient, ϵ denotes the penalty dimension, and K (x_i, x_j) is the kernel function. Adjust the $\omega = [\omega_1, \omega_1^*, \ldots, \omega_j, \omega_j^*]^T$ to attain the optimum values, and SVR can be defined as Equation 6.

$$f(x) = \sum_{i=1}^{j}(\omega_i - \omega_i^{*})\, K(\omega_i - \omega_j) + b^{*} \tag{6}$$

3.4. Model Performance Evaluation

By calculating and comparing performance metrics criteria, the accuracy of the research's econometric and machine learning models can be determined. Therefore, Mean Absolute

Error (MAE), Mean Square Error (RMSE), and coefficient of determination (R^2) values were calculated to check the accuracy of the models. As a result, equations of performance evaluation criteria are seen between Equation 7 and Equation 9, respectively (Guleryuz & Ozden, 2020; Wang et al., 2015).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|REI_i^{observed} - REI_i^{predicted}\right| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(REI_i^{observed} - REI_i^{predicted})^2} \tag{8}$$

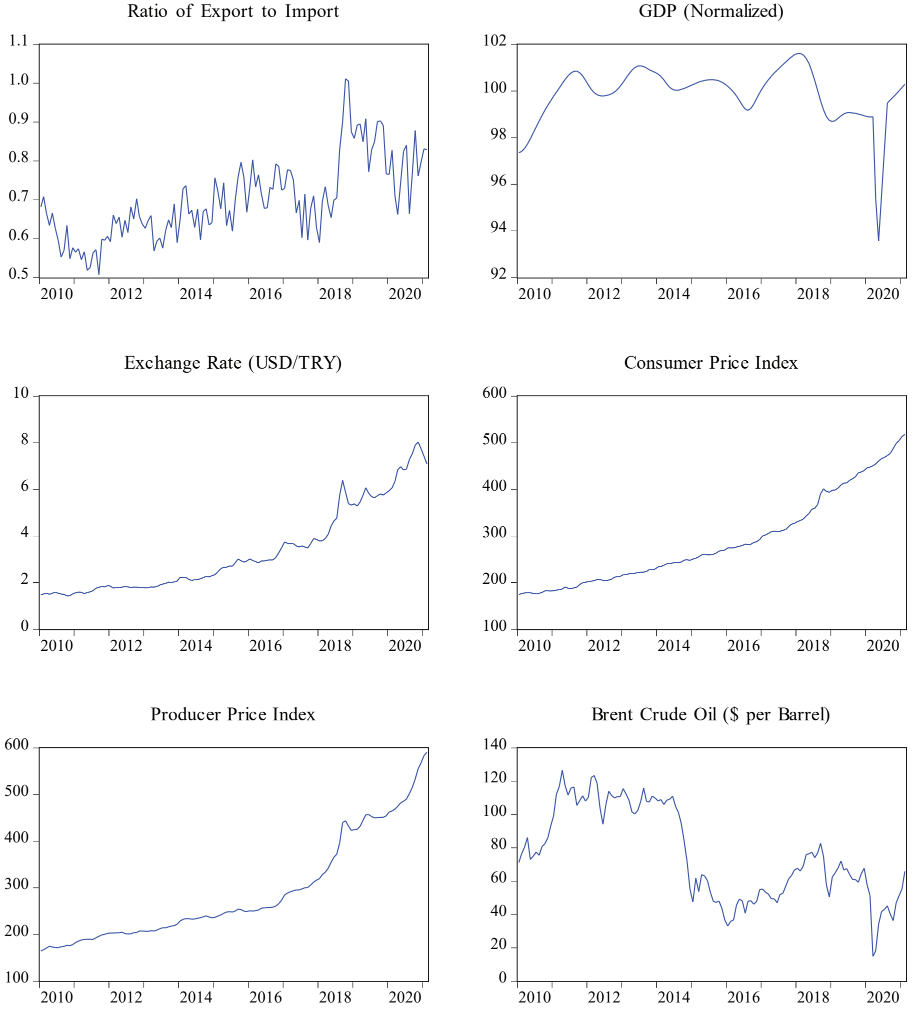
$$R^2 = \left(\frac{\sum_{i=1}^{n}(REI_i^{observed} - \overline{REI_i^{observed}})\,(REI_i^{predicted} - \overline{REI_i^{predicted}})}{\sqrt{\sum_{i=1}^{n}(REI_i^{observed} - \overline{REI_i^{observed}})^2\,(REI_i^{predicted} - \overline{REI_i^{predicted}})^2}}\right)^2 \tag{9}$$

where the number of observed values are shown via n, $REI_i^{observed}$ is the observed value at time i and $REI_i^{predicted}$ is the estimating value at time i.

4. Empirical Results and Discussion

In the research, while examining the relationship between the export coverage ratio and the fundamental macroeconomic and financial indicators, it is necessary to examine the movement of the variables over time. Figure 2 shows the oscillations of the variables between the years 2010-2021.

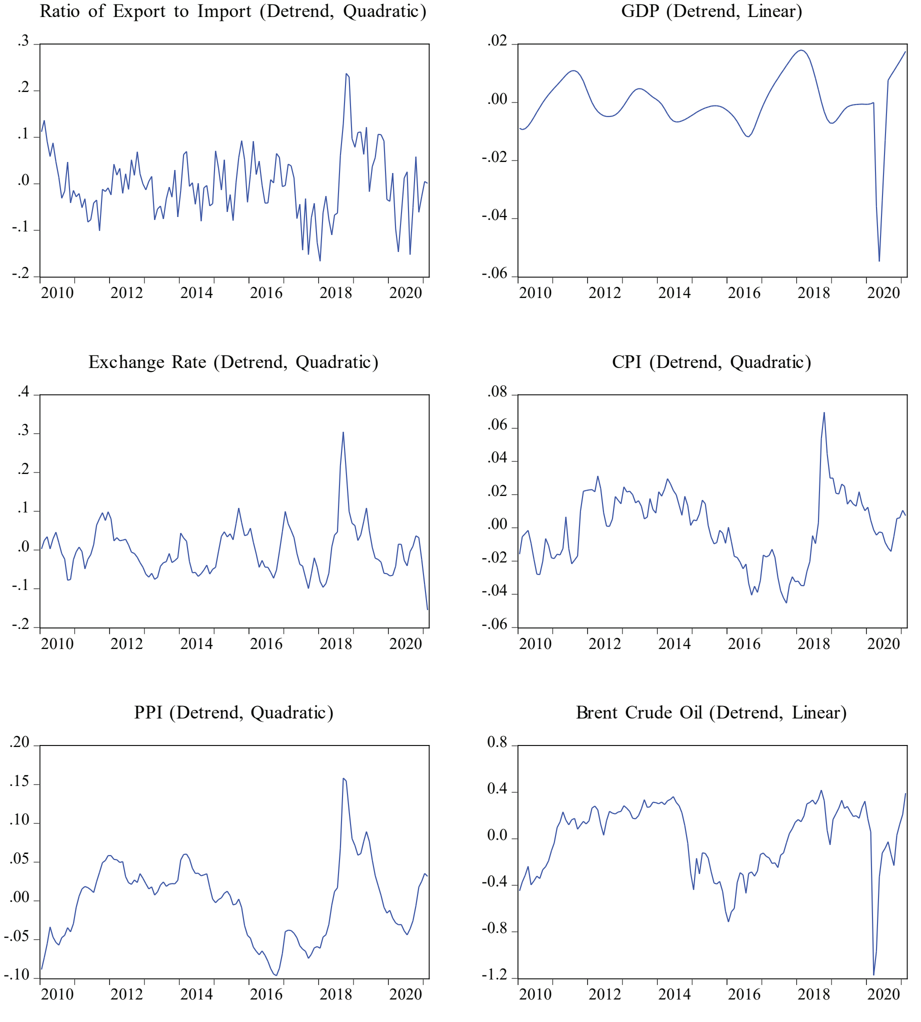
Figure 2. Trends of Variables for the Period 2010-2021



When Figure 2 is examined, it is seen that REI has high volatility over time but has a rising trend in the long run. Therefore, at first glance, the REI has increased over the years, which can be considered favorable for Turkey. Another variable, GDP, is already normalized in the dataset, so it does not contain a trend, and in this respect, the changes can be quickly followed. The effects of COVID-19, which affected the whole world in March 2020, are also clearly seen in the GDP chart. On the other hand, there is a clear rising trend of Exchange rate, CPI, and PPI. On the other hand, Brent oil prices followed a fluctuating course, but they are in a decreasing trend in the long run.

These trends can lead to misleading results (false regression) when examining the relationships between variables. Therefore, before examining the relationship between the variables, it is crucial to separate the variables from the trends and test their stability. When it comes to decoupling from trends, it is generally assumed that the variables are in a linear trend, and a decomposition method is applied accordingly. However, the variables can be linear, quadratic, or even trending to a higher degree. In this respect, this should be taken into account when detrending the variables. Figure 3 shows the graphs of the detrended variables.

Figure 3. Trends of Detrended Variables for the Period 2010-2021



When the analysis was made for the variables, it was determined that the dependent variables, REI and Brent Petroleum, had a linear (first-order) trend and were detrended. For other variables, the quadratic trend of Exchange rate, CPI, PPI was detected and detrended, and finally, the third-order trend of GDP was detected and detrended. Looking at Figure 3, the changes in the variables can be seen more clearly.

Detrending also controls the stationarity of the variables. However, they were tested with the most commonly used Augmented Dickey Fuller (ADF) and Philips-Perron (PP) unit root tests to ensure whether the variables contain unit roots. The results are presented in Table 4.

Table 4: The ADF and PP Unit Root Tests at the Level

		Variables					
Unit Root Tests		**dtREI**	**dtGDP**	**dtEXC**	**dtCPI**	**dtPPI**	**dtBRENT**
ADF	t-Stat.	-5,771***	-3,008***	-4,023***	-2,464**	-2,911***	-2,888***
	Prob.	0,000	0,003	0,000	0,014	0,004	0,004
PP	t-Stat.	-5,857***	-3,145***	-3,542***	-2,676***	-2,561**	-3,091***
	Prob.	0,000	0,002	0,001	0,008	0,011	0,002

Notes: a: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1% and (no) Not Significant, b: Lag Length based on AIC, c: Prob. based on MacKinnon (1996) one-sided p-values.

According to the unit root tests, it has been tested that the variables are stationary at the level. However, even if they are not stationary at the level, that is, some of the variables are stationary at the level [I(0)] and some of them are first-order integrated [I(1)], the autoregressive distributed lag model (ARDL) bounds test can be applied.

The problem of multicollinearity between explanatory variables is another basic assumption that must be tested. This problem arises when there is a high correlation between variables, which leads to unreliable and unstable regression coefficient estimates. One of the most widely used methods to examine this problem is the variance inflation factor (VIF).

Table 5: Multicollinearity Test

Variable	**VIF**	**1/VIF**
dtPPI	4,89	0,2045
dtCPI	4,17	0,2398
dtBRENT	2,76	0,3624
dtREI	1,79	0,5590
dtGDP	1,56	0,6406
Mean VIF	3,034	

As shown in Table 5, the average VIF value of the model was 3,034. Some studies have pointed out that values of five and above can cause problems (Menard, 1995; O'Brien, 2007). However, the VIF value below five shows no multicollinearity problem in this research.

4.1. ARDL Cointegration Analysis with Boundary Test:

The ARDL approach is divided into two stages. The unconstrained ECM is used in the first stage to investigate the cointegration relationship between the variables in the model. The second stage involves estimating the model's short and long-run coefficients based on a cointegration relationship between the variables.

The optimal lag length must first be determined for the first step of the ARDL approach. The critical values of Akaike, Schwarz, and Hannan-Quinn are then calculated to determine lag lengths. The model's lag length is then determined to be the lag length that produces the smallest critical value. Finally, the optimal lag number of the model was tested considering the minimum AIC value, and Table 6 displays the best results.

Table 6: The determination of lag lengths for ARDL

Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
12375	**210,392**	**-3,1137**	**-2,9373**	**-3,0420**	0,471926	**ARDL(1, 0, 1, 0, 0, 0)**
12250	211,355	-3,1132	-2,9146	-3,0325	0,475395	ARDL(1, 0, 2, 0, 0, 0)
12000	213,324	-3,1127	-2,8700	-3,0141	**0,482497**	ARDL(1, 0, 4, 0, 0, 0)
12374	211,269	-3,1118	-2,9133	-3,0312	0,474702	ARDL(1, 0, 1, 0, 0, 1)
11999	214,203	-3,1108	-2,8461	-3,0033	0,485120	ARDL(1, 0, 4, 0, 0, 1)

According to Table 6, the model with the smallest AIC was selected. At the same time, ARDL(1,0,1,0,0,0) was determined as the best model according to other valuation criteria, except adjusted R-sq. In this chosen model, the model in which the dependent variable (REI) itself has a one-period lag. In addition, the exchange rate has a one-period lag is the most appropriate model.

After determining the lag length, the cointegration relationship is determined by applying the F test or Wald test to the coefficients of the first lags of the dependent and independent variables and testing their significance. The null hypotheses expressing the absence of cointegration between the variables are set as H_0: $\theta_{REI}=\theta_{REI(-1)}=\theta_{GDP}=\theta_{EXC}=\theta_{EXC(-1)}=\theta_{CPI}=\theta_{PPI}=\theta_{BRENT}=0$, and the alternative hypotheses expressing the existence of cointegration between the variables are set as H_0: $\theta_{REI}\neq\theta_{REI(-1)}\neq\theta_{GDP}\neq\theta_{EXC}\neq\theta_{EXC(-1)}\neq\theta_{CPI}\neq\theta_{PPI}\neq\theta_{BRENT}\neq 0$.

Pesaran and Shin (1997) and Pesaran et al. (2001) developed a set of critical values that included lower and upper bound values for various significance levels. The lower bound value assumes that all variables are I(0), while the upper bounds are based on the assumption that all variables are I(1). If the calculated test statistic exceeds the upper bound critical value, the null hypothesis indicating no cointegration among the variables in the model is rejected. Suppose the calculated test statistic is less than the lower bound critical value. In that case, the null hypothesis is accepted, stating that there is no cointegration between the variables included in the model. At this stage of the ARDL analysis, the F-statistic value should be determined and interpreted. F-Bounds test results are given in Table 7.

Table 7: F-Bounds Test Results

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	**12.67194**	10%	1.81	2.93
k	5	5%	2.14	3.34
		2.5%	2.44	3.71
		1%	**2.82**	**4.21**

Table 7 shows that the null hypothesis that the F-statistic value is greater than the calculated F-statistic value at the 1% significance level (12.67 > 4.21) was rejected, and it was decided that there is a long-term relationship between the series, that is, there is cointegration.

After determining the existence of a long-term relationship between the series with the ARDL Boundary Test, the long-term parameters of the series were estimated. The estimation results of the established ARDL(1,0,1,0,0,0) model are given in Table 8.

Table 8: The Long-run Analysis Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
dtREI(-1)	0,3715	0,0757	4,910	0,0000
dtBRENT	0,0336	0,0239	1,407	0,1620
dtEXC	0,1332	0,1338	0,995	0,3216
dtEXC(-1)	0,3059	0,1431	2,139	0,0344
dtGDP	-0,7723	0,5462	-1,414	0,1598
dtCPI	1,1982	0,5200	2,304	0,0228
dtPPI	-0,4995	0,2689	-1,857	0,0656
R-sq.	0,517	Jarque-Bera Norm Test		2,582 (0,2750)
Adj. R-sq	0,494	Breusch-Godfrey LM		0,9989 (0,3484)

*Note: p-values and any subsequent tests do not account for model selection.

The findings obtained from Table 8, which includes the estimation results of the ARDL(1,0,1,0,0,0) model, reveal the compatibility of the diagnostic test results of the model. It proves that the model has a normal distribution, constant variance, and no autocorrelation problem and model building error. It is essential to determine whether there is a structural break in the established model during the analysis period. CUSUM and CUSUMSQ structural break tests were performed to see whether there is a structural break in ARDL long-term findings.

Figure 4. Structural Break Analyzes

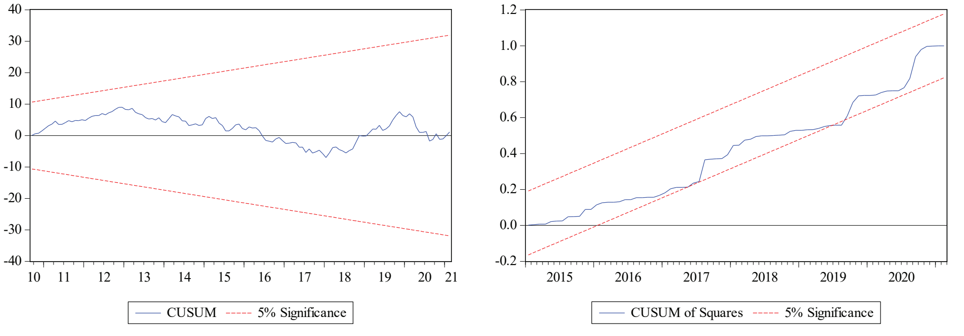


Figure 4 shows the CUSUM and CUSUMSQ tests for the ARDL long-run model. Although it was observed that the CUSUMSQ test went outside the limits in the last months of 2019, this situation lasted for a short time and returned within limits in an average of two months. In this respect, it can be stated that the estimated long-term ARDL coefficients are stable. However, a short-term analysis is required to interpret the long-term results better. The results of the short-term test are given in the table below.

Table 9: The Short-run Analysis Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DTEXC)	0.133179	0.119105	1.118162	0.2656
CointEq(-1)*	-0.628457	0.070685	-8.890938	0.0000

* p-value incompatible with t-Bounds distribution.

The variable coefficient showing the one-term lagged value of the series of error terms obtained from the long-term relationship, namely the error correction coefficients, has a negative sign and is statistically significant, as expected, according to Table 9. This means that short-run deviations will approach the equilibrium in the long run. For example, in this study, the data set was used monthly; therefore, it is interpreted monthly. To determine how long a possible short-term shock takes to reach equilibrium, we divide the error correction coefficient value by 1 to get the result. Accordingly, a short-term deviation reaches long-term equilibrium after an average of 1.6 (1/0,63) months.

As a result of these analyses, ARDL long-term parameters can be estimated, and the variables' relationships can be examined. The results of the long-term estimation parameters are given in Table 10.

Table 10: The Long-run Relationship Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DtBRENT	0.053427	0.038546	1.386054	0.1682
DtEXC	0.698723	0.158559	4.406705	0.0000
DtGDP	-1.228918	0.878266	-1.399256	0.1642
DtCPI	1.906614	0.780819	2.441814	0.0160
DtPPI	-0.794738	0.404703	-1.963758	0.0492

Table 10 shows that while exchange rate, CPI, and PPI derive a statistically significant relationship, Brent Oil and GDP do not have a statistically significant relationship. If we interpret the variables that will be statistically significant, a 1% increase in the exchange rate (the depreciation of the TL against the US dollar) will increase the REI rate by 0.7 points on average. A 1% increase in CPI will increase REI by 1.9 points, while a 1% increase in PPI will cause a -0.8 point decrease in REI. In economic theory, the rise in the general level of prices has an increasing effect on imports. In the results, it is seen that the opposite is the case at first glance. In the analysis period, although imports increased, there was an increase in the REI since there was a minor increase compared to exports. The reasons for the increase in CPI should be examined to understand this fact. For Turkey, when examined in the historical process, the increase in inflation is cost inflation rather than demand inflation, so the increase in CPI positively affects REI. In addition, exports were more positively affected by the rapid depreciation of the local currency. In Table 10, the depreciation of the TL against the dollar is significant in that it positively affects exports while limiting imports. In terms of PPI, the opposite is the case. As the production costs of the producers' increase, this situation is reflected in the prices. That is why the prices of the exported products also increase. Therefore, even if total imports remain constant, ceteris paribus, REI will be adversely affected as exports decrease.

4.2. SVM Analysis:

SVR is mainly used in time series. In SVM, on the other hand, various kernel functions are used to expand the field of independent variables towards a feature field with a more complex dimension. This research obtained results by applying SVM analyzes in two different stages. In the first stage, a direct SVM analysis was performed on the available data set. In this analysis, the quadratic kernel was chosen as the best kernel. In the second stage, an SVM analysis was applied to the ARDL analysis's outputs. The aim is to make a confident prediction with the econometric method and create a hybrid model by applying an ML method to this prediction, rather than directly applying the machine learning method to the data set. This way, unlike the other SVM applied time series, a more robust pattern was tried to be caught among the data. Therefore, more detailed analyzes can be made on the variables used thanks to econometrics, while more reliable estimates are obtained thanks to the ML and hybrid models.

4.3. Comparison of ARDL and SVM Analysis

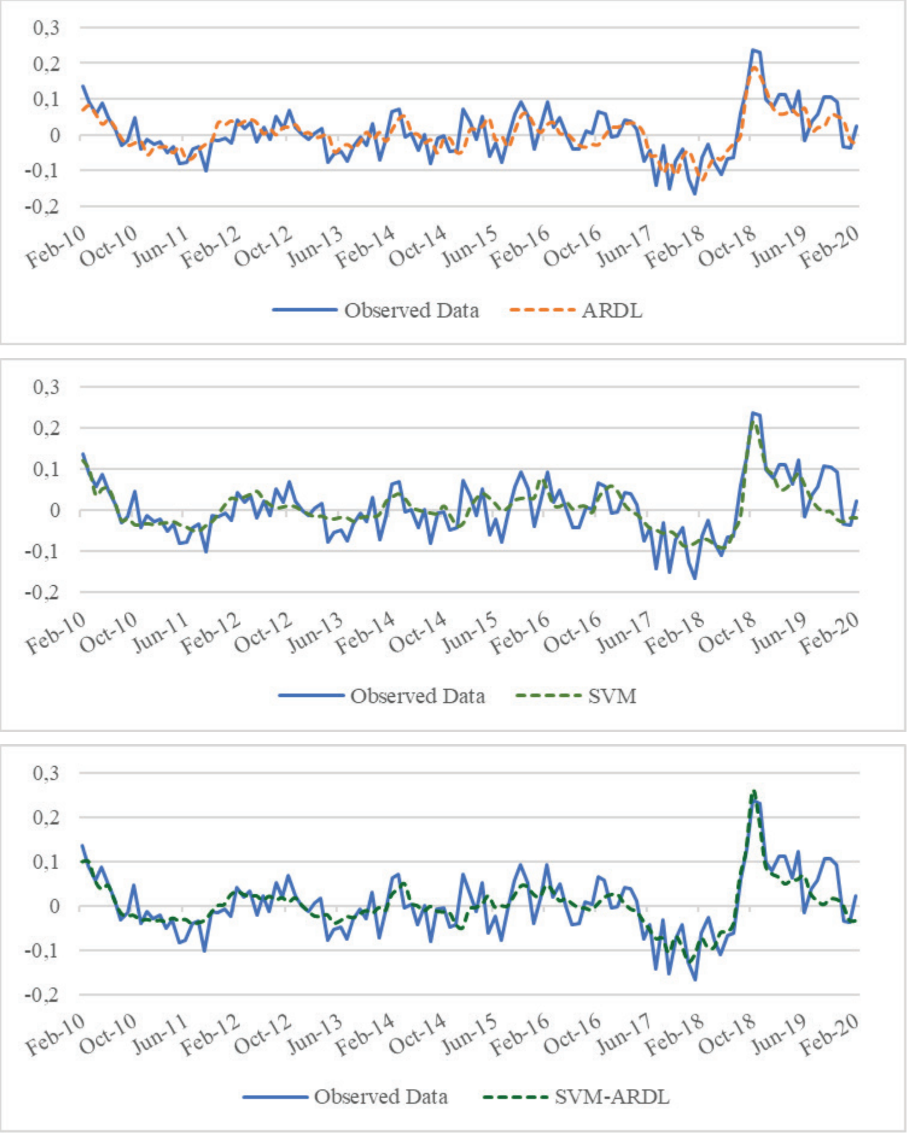
The training set is used to analyze and then predict the pattern among the variables for the particular model architecture. Finally, the test set is used to see the method's estimation power and compare it with other models. Table 11 summarizes the econometric and machine learning models to predict accuracy.

Table 11: The predictive accuracy of all models

		ARDL	SVM	Hybrid ARDL-SVM
Training Phase	RMSE	0,0449	0,0432	0,0400
	MAE	0,0362	0,0330	0,0305
	R^2	0,5633	0,5989	0,6558
		ARDL	**SVM**	**Hybrid ARDL-SVM**
Testing Phase	RMSE	0,0709	0,0455	0,0432
	MAE	0,0569	0,0254	0,0237
	R^2	0,0055	0,4976	0,5518

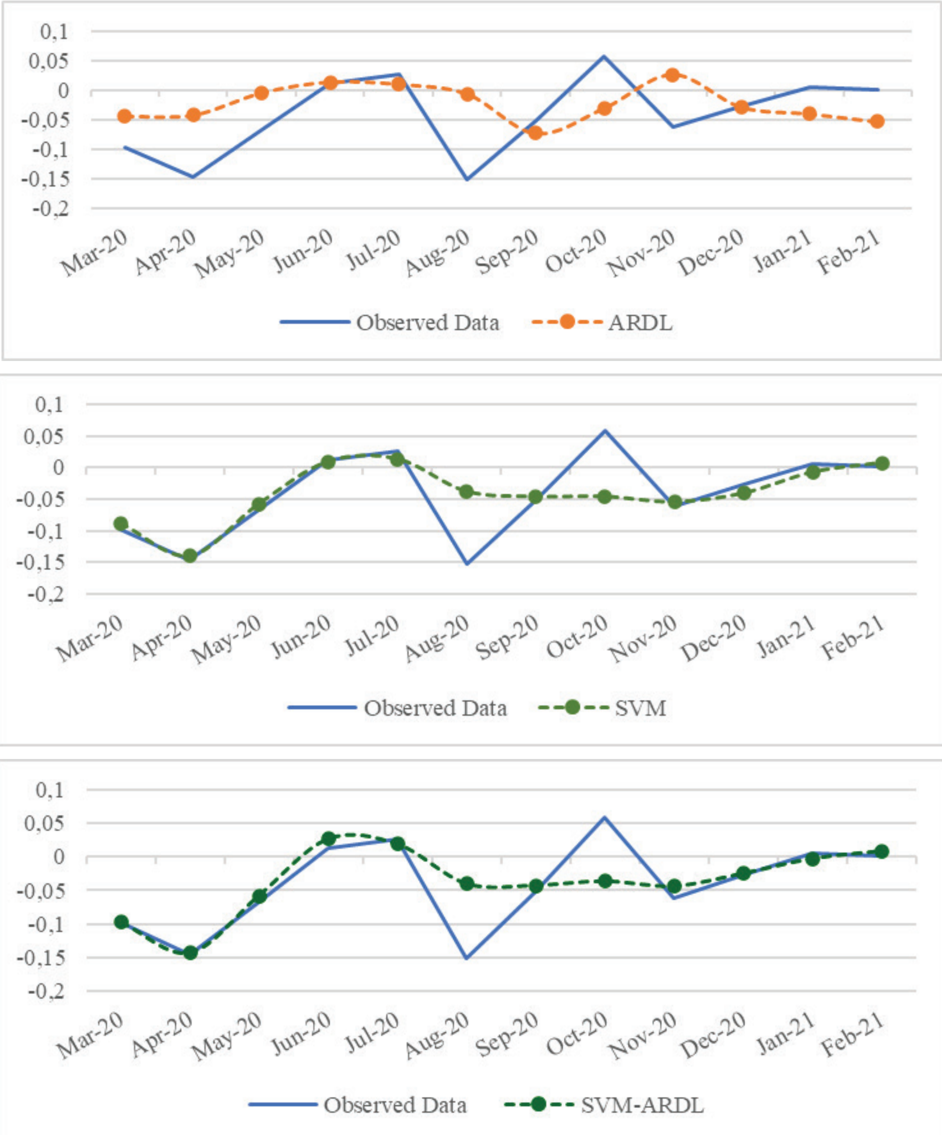
Regarding performance criteria, the low values for RMSE and MAE show that that model is more suitable for estimation. For example, in Table 11, the RMSE value of the ARDL model for the training set was 0.0449, while this value was 0.0432 for the SVM and 0.04 for the hybrid ARDL-SVM. Similarly, lower values are encountered for the SVM-ARDL model when looking at the MAE. Figure 5 shows the estimation performances of ARDL, SVM, and hybrid ARDL-SVM models for training set in detail, in separate graphs, respectively.

Figure 5. Observed and Estimated REI for Training Set via ARDL, SVM, and SVM-ARDL models



On the other hand, the test set is valuable in seeing how accurate the trained models can perform in the future by analyzing the relationship between the variables. The hybrid ARDL-SVM model fits with higher accuracy for REI estimation according to all evaluations considering the performance criteria of the test set in Table 11. Figure 6 indicates the prediction performances of ARDL, SVM, and hybrid ARDL-SVM models for the test set.

Figure 6. Observed and Estimated REI for Test Set via ARDL, SVM, and SVM-ARDL models



In Figure 6, the predictive performance of the developed hybrid SVM-ARDL model is especially successful compared to the classical econometric model. In summary, the developed ARDL-SVM model in the research produces a more suitable model than both the traditionally used econometric ARDL model and the basic SVM model.

Conclusion

The economic literature analyzes the export and import rates of a country in order to evaluate the foreign trade performance of a country. Indicators for foreign trade are traditionally measured as a currency or a ratio of the country's GDP. Although the results show differences between countries, insufficient and biased inferences can be made against these analyses. The ratio of imports to exports, on the other hand, is more convenient to make comparisons between countries and between times as a unit-free indicator.

In this research, two different methods were used methodologically. The ratio of exports to imports is considered the dependent variable in examining Turkey's foreign trade performance. The independent variables, such as GDP, exchange rate, CPI, PPI, and crude Brent oil, effects on Turkey's REI between 2010-2021 monthly, were analyzed using the ARDL bounds test method. The literature that makes direct estimates of the coverage ratio in Turkey is very limited. Therefore, the results of the study can only be indirectly compared. In terms of the results, it was determined that the exchange rate positively affected the REI. Therefore, when the studies are examined, it is seen that they are compatible with the literature (Aldan et al., 2012; Ekinci & Kilinc, 2013; Thorbecke, 2011). In the study, increases in CPI and PPI affect REI positively and negatively, respectively. In order to be able to compare with the literature, studies on inflation and balance of trade were examined. In this regard, studies are showing that the increase in inflation has positive effects on the balance of trade (Güneş & Konur, 2013; Thomas, 2012), and studies are showing the opposite (Cooke, 2010; Lin, 2011). In addition, in multi-country studies, some studies show both positive and negative effects on these variables by country (Martinez & Iyer, 2013).

In the paper, machine learning was used as another method. At this stage, the SVM method was used, which best analyzes the pattern among the variables in the dataset, and the results were compared with the econometric method. Then, the outputs obtained from the econometric analysis and the SVM method were combined, a hybrid method was created, and the results were compared for all three methods. The results showed that although the econometric method provides researchers with a broader scope for interpreting the relationships between the variables, the machine learning method is more successful in capturing the patterns between the variables. In addition, the developed hybrid method can predict this pattern much better.

This research is unique in using the export-import coverage ratio to measure foreign trade and analyzing this variable with both econometric and machine learning. In future studies, since the dependent variable used is comparable to other countries, a panel analysis can be made to compare this research's outputs. In addition, novel hybrid methods can be created in future studies to better reveal the pattern between the variables by using different machine learning applications.

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