Geliş Tarihi:
16.10.2023
Kabul Tarihi:
13.11.2024
Yayımlanma Tarihi:
28.12.2024

Kaynakça Gösterimi: Kara, A. 2024, Support vector machine-based and crisis-pertaining forecasts of a subset of foreign currency-denominated bank deposits in Türkiye. *İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi, 23*(51), 2069-2087, doi: 10.46928/iticusbe.1376808

SUPPORT VECTOR MACHINE-BASED AND CRISIS-PERTAINING FORECASTS OF A SUBSET OF FOREIGN CURRENCY-DENOMINATED BANK DEPOSITS IN TÜRKİYE

Araştırma

Ahmet Kara
Sorumlu Yazar (Correspondence)
İstanbul Ticaret Üniversitesi
kara2010@ticaret.edu.tr

Ahmet Kara, İstanbul Ticaret Üniversitesi ekonomi profesörüdür. İktisat teorisi ve uygulamalı iktisat alanlarında dersler vermekte ve bu alanlarda araştırmalar yayınlamaktadır.

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Ahmet Kara
kara2010@ticaret.edu.tr

Abstract

This paper presents support vector machine-based forecasts of a subset of the banking system's foreign currency-denominated deposit-growth for a crisis-inclusive period in Türkiye. Forecasts concerning such periods pose challenges that may not always be efficiently handled within the confines of conventional statistical methods. This brings out a need to make recourse to alternative methods, one of which is employed in this paper. The method employed in the paper belongs to a particular group of machine learning/artificial intelligence algorithms known as support vector machines, which could yield successful results in a wide range of cases. We demonstrate that proper employment of support vector machines leads to a reasonably high degree of accuracy in forecasting and produces, with a small margin of error, real-value-replicating trajectories of the target variable in question. Accurate forecasts of foreign currency-denominated deposit growth rates at crisis-inclusive junctures could be of practical significance to the policy designers attempting to limit, in an optimal manner, the magnitudes or growths of the foreign currency-denominated deposits within the banking system. This article shows how the objective of practical significance in question could be achieved with an alternative method.

Keywords: Foreign currency-denominated deposits, support vector machines, forecasting, Türkiye.

JEL Code: G01, G17.

BİR KRİZ DÖNEMİ TÜRKİYE'SİNDEKİ DÖVİZ CİNSİNDEN MEVDUATLARIN BİR ALT KÜMESİNİN DESTEK VEKTÖR MAKİNELERİ İLE TAHMİNİ

Özet

Bu makale, döviz cinsinden mevduatların, Türkiye'nin iktisadi ve siyasi tarihinin kriz içeren bir konjonktüründeki büyüme hızlarını tahmin etmeye çalışmaktadır. Bu tür konjonktürlerin tahmin süreçleri için yarattığı sorunların, geleneksel istatistiksel yöntemlerin sınırları içinde her zaman etkin bir şeklide çözülememesi, alternatif yöntem kullanımı ihtiyacını ortaya çıkarmaktadır. Bu makale, tahmin için alternatif bir yöntem denemektedir. Kullanılan yöntem, bir makine öğrenmesi/yapay zekâ algoritmaları demeti olan destek vektör makineleridir. Destek vektör makineleri, geniş bir yelpazede başarılı sonuçlar üretebilmektedir. Destek vektör makinelerinin uygun bir kullanımının, makaledeki hedef değişkenin yüksek doğruluk derecesine sahip tahminine ve gerçek değerlerle küçük bir hata marjıyla örtüşen bir yörünge türetimine yol açtığı gösterilmektedir. Döviz cinsinden mevduatların büyüme hızlarının, kriz içeren konjonktürlerde doğru tahmini, ilgili mevduatların miktarlarını ya da büyüme hızlarını optimal bir tarzda sınırlamak isteyen politika yapıcılar için pratik önem taşımaktadır. Bu makale, pratik önem ve değer taşıyan bir amaca, alternatif bir yöntemle nasıl ulaşılabileceğini göstermektedir.

Anahtar Kelimeler: Döviz cinsinden mevduatlar, destek vektör makineleri, tahmin, Türkiye.

JEL Kodu: G01, G17.

INTRODUCTION

The magnitudes, shares and/or growths of foreign currency-denominated deposits could be indicative of or related to some of the crisis-prone tendencies within a financial system and, as such, may deserve particular attention. In view of its possible intricate role in the patterns of interdependencies characterizing some of the key financial processes, accurate forecasts of the magnitudes or growths of the deposits in question are of considerable importance. There are multiple statistical/econometric and artificial intelligence/machine learning methods we can employ to forecast the relevant trajectories. The performance of these methods is contingent upon the nature and complexity of the case study under consideration. The particular type of complexity that is of interest here is the pattern of fluctuations that may arise during the crisis periods. Those fluctuations may be prone to instability and even chaos and may not lend themselves to easy modeling and analysis. Some of the relatively new and promising methods may play an instrumental role in addressing some of the problems that may arise at such junctures. We will use one of those methods, namely support vector machines, to forecast, with a reasonably high degree of accuracy, the trajectory of the foreign currency-denominated deposit-growths within the conventional Turkish banking system during a world financial crisis-influenced period in Türkiye.

Forecasting economic and financial processes with a high degree of accuracy is of considerable practical significance to both microeconomic and macroeconomic decision-making processes. The optimality of microeconomic decision-making under conditions of risk and/or manageable uncertainty would depend on the accuracy of predicting, with a fair amount of success, of the multiple possibilities that are relevant to the possible outcomes of the decisions. For instance, the reasonably correct forecasting of the currency-denominated deposit-growth that we will deal with in this paper could be crucial to the optimal currency positions of the banks at the microeconomic level. Similarly, the forecasting of the dynamic trajectory of the relative fraction of the currency-denominated deposits in the entire financial system could be important for the stability and optimal growth paths of the overall macroeconomic system. This paper will demonstrate, with a particular example, the extent to which one can undertake successful predictions of such processes based on support vector machines.

The second section of the paper presents a brief review of the literature. The third section describes the method and the theoretical framework. The fourth section gives the results. The discussion and concluding remarks follow in the final section.

THE LITERATURE REVIEW

There are many works in the literature exploring the issues associated with financial forecasting in particular and analyses of financial processes in general. Among these works are Nair & Mohandas (2015) and Popkava & Parakhina (2019), which provide a general account of the use of artificial intelligence in financial forecasting and financial systems. The first of these articles presents a survey of 100 articles and points out that artificial intelligence-based methods are better than traditional ones in financial forecasting. Within the general terrain of the artificial intelligence-based techniques concerning financial processes and systems, some works focus on selected sub-issues such as intelligent feature selection (Vaiyapuri et al.,2022), machine leaning-based bank classification (Herrera & Dominquez,2020), bankruptcy forecasting (Pawelek & Grochowina,2017) and stock trend or market prediction (Yin et al.,2023; Chopra & Sharma, 2021). Here, especially, artificial intelligence-based stock market analyses at both aggregated and disaggregated levels, which could be related to microeconomic and macroeconomic dynamics of the sectors and the overall economy, which may be of particular interest to the researchers of practical orientation.

Nevertheless, the treatments of the issues are not limited to the topics of practical interest. There are treatments of the saddle issues such as forecasting performance of wavelet neural networks and other neural network topologies (Vogl, Rötzel & Homes,2022), particle swarm optimization for forecasting financial time series (Chen, Huang & Hsu, YC, 2009), development of prediction models for bank deposit subscription (Hou et. al., 2022) and genetic algorithms in forecasting commercial banks deposit (Chiraphadhanakul, Dangprasert & Avatchanakorn, 1997). In view of its relevance to the deposit forecasting which we will also deal with in this paper, we should underline the promising potential of the genetic algorithms in this area. Indeed, as verified by Chiraphadhanakul, Dangprasert & Avatchanakorn (1997), genetic algorithms could indeed lead to accurate forecasts without restricting the form of the objective function.

The literature contains many other intricate issues, the detailed description of which goes beyond the scope of this paper. Among these are refining financial analysts' forecasts by predicting earnings forecasts error (Fedyk, 2017), panel data modeling of bank deposits (Costa et.al, 2020) and forecasting financial times series with generalized long memory processes (Ferrara & Guegan, 2000).

In an intersecting strand of literature, there are also works exploring issues of similar complexity in a simulative framework. Kassem & Salih (2005) and Scholten (2016) present simulations of financial crisis in a system dynamics framework, the general structure of which is informatively described in Steerman (2000). Xiao & Wang (2020) and Cao & Chen (2012) undertake agent-based simulations of financial processes. Various issues of stability or efficiency are examined by Kara (2000, 2001,2023a), Samitas, Polyzas & Siriopoulas (2018) and Minsky (2008).

Among these strands of works, our paper is methodologically most related to a particular class of artificial intelligence/machine learning algorithms called support vector machines which have a wide range of applications such as stock market forecasting (Ding, 2012; Kara, 2023b), credit operation (Teles et. al.,2021) and financial crisis analysis (Hsu & Pai, 2013). Our paper will employ the support vector regression technique in the forecasting of the trajectories of the growths of foreign currency-denominated deposits at a crisis-inclusive juncture in Turkey.

THE METHOD AND THE MATERIAL

Among the available methods in the literature, we will use support vector machines (SVM) which are a sub-class of artificial intelligence/machine learning algorithms. We will undertake SVM-based forecasting of a subset of the banking system's foreign currency-denominated deposit-growths for a crisis-inclusive period in Turkey. Support vector machines are machine learning algorithms that can be used for the purpose of classification and regression. The main logic behind the method is to find the optimal hyperplane separating the data points belonging to different classes by maximizing the margin between the closest points in different classes. Here we will make use of the algorithm for regression-related tasks. We will not delve into the intricate details of the inner structure of the algorithm; instead, we will make use of a way in which the algorithm could be used to forecast the financial process under consideration with the help of a program called "Waikato Environment for Knowledge Analysis (WEKA). There are some works in the literature describing and teaching the program in question such as Witten (2022a, 2022b). Other programs such as R could be used for the same purpose as well.

Our reasons for using the support vector machines in this work reside in their versatility and accuracy. SVM could be considered a versatile method that can be used in both low and high dimensional cases. Moreover, SMV could produce highly accurate results, as we will demonstrate in this paper in the context of the study we will undertake.

For forecasting purposes, we will construct a set-up where the growth of the relevant part of the banking system's foreign currency denominated deposits (y-growth) is the target variable, which is assumed to be influenced by a subset of variables such as the stock market averages (x1), the bond rates (x2), the dollar-denominated interest rates (x3) and the Euro-denominated interest rates (x4), which could be properly called the "overlay variables" within the forecasting module of the program WEKA (The non-stationary variables such as x1, x2, x3 and x4 are transformed so as to make them stationary.) We will add the growth-related autocorrelation and HP-filter extracted cycle to the list of overlay variables. There are of course other micro-level and macro-related variables that can influence the chosen target variable. In cases where the influences in question are non-negligibly explanatory-power-enhancing, one can add the variables in question to the model.

As indicated, some of the variables in the model are not stationary. For conventional reasons, we transform the non-stationary variables so as to make them stationary.

During the process of forecasting, the algorithm will automatically select, in an optimal manner, a subset of the overlay variables as well as some of the explanatorily influential past values of the target variables and construct some new time-dependent artificial variables or variables out of the existing ones.

Our chosen forecasting period, which extends from January 2006 to December 2009, includes both a sub-period with early signs of the world financial crisis as well as the crisis period itself. We can undertake both "in-period" as well as "beyond-period" forecasts of growth rates of a subset of the conventional banking foreign currency-denominated deposits. The data concerning the period is publicly available and could be obtained from the Central Bank of Turkey and from a variety of data-providing institutions. No preprocessing is needed. The only thing that needs to be done in the pre-estimation stage is to put the data in the ARFF format, which is exactly what we have done. Then we have used the program, WEKA, to run the support vector machine algorithm (with an attribute selected classifier) to forecast the target variable. Among the performance metrics that can be used for the purpose of measuring the accuracy of the forecasting, we have used the "the normalized root mean squared error" ($NRMSE_{y*}$), which could be defined, for our purposes, as the root mean squared error (RMSE) of the growth-values divided by the range of the deposit-growth-values (y*), for the testing period,

$$NRMSE_{y*} = \frac{RMSE}{y*} \tag{1}$$

Let N denote the number of observations and $y*_n$ and $y*_n^p$ represent the actual and forecasted values for n=1,…, N. RMSE is the square root of the sum, from 1 to N, of all $(y*_n-y*_n^p)^2$ divided by N.

We have used the metric $NRMSE_{y*}$ to measure the forecasting performance of the support vector machine algorithm. Since lower $NRMSE_{y*}$-values indicate better performance, we use the following alternative as a performance metric, which can be called the "degree of forecasting accuracy" (d).

$$d = 1 - NRMSE_{y*} \tag{2}$$

d will be used to assess the forecasting results in the following section.

Another metric, which is less frequently used, is the "mean absolute error" (MAE), which is the sum of the absolute errors (i.e., the difference between the actual and the predicted values). We will report all these metrics in the results section.

THE RESULTS

70 % of the data is used for training purposes and 30 % is used for testing. The root mean squared error (RMSE) is 0.0042 while the mean absolute error is (MAE) is 0.034. Since these values by themselves may not be sufficiently indicative of the forecasting accuracy, we will also report what might be called the normalized root mean squared

error (NRMSE) and the degree of forecasting accuracy (d). The testing data-based $NRMSE_{y*}$ value for the support vector machine algorithm is 0.0449, which yields a d value of 0.9551, indicating a high degree of forecasting accuracy, i.e., the forecasting success is over 95 %.

The obtained predictions/forecasts are presented in Table 1, Table 2 and Table 3 below.

Table 1. Predictions of the Target Variable for the Training Data

Instance no	actual	predicted	error
13	-0.0086	-0.0013	0.0074
14	0.0087	0.0155	0.0068
15	0.0086	0.018	0.0093
16	0	0.0127	0.0127
17	0	0.0136	0.0136
18	0.0085	0.0191	0.0106
19	0.0085	0.0235	0.015
20	-0.0168	-0.0043	0.0125
21	-0.0085	0.0014	0.0099
22	0	0.0099	0.0099
23	0	0.0078	0.0078
24	0.0259	0.0348	0.0089
25	0.0084	0.0083	-0.0001
26	0.0333	0.0334	0
27	0.0645	0.056	-0.0085
28	0.0152	0.0108	-0.0044
29	0	-0.0002	-0.0002
30	0.0149	0.0055	-0.0094
31	-0.0294	-0.0326	-0.0032
32	0.0152	0.0098	-0.005445

Table 1 displays the results obtained with training data for the actual and predicted values and errors concerning the target variable. A few points concerning the results are of practical significance. First, the errors representing the difference between the actual and predicted values are, on average, reasonably small, signifying the accuracy of the predictions. Second, there are considerable fluctuations in the value of the target variable over time, indicating the possible effects of the global financial crisis that occurred in the middle of the sample period. Third, the use of an attributed selected classifier has helped improve the accuracy of predictions by selecting the features yielding the best results.

Table 2. Predictions of the Target Variable for the Test Data (1-step ahead)

Instance no	actual	predicted	error
33	0.0746	0.0684	-0.0062
34	0.0417	0.0345	-0.0072
35	0	-0.0063	-0.0063
36	0.02	0.0152	-0.0048
37	0	-0.0016	-0.0016
38	0.0392	0.0349	-0.0043
39	-0.0189	-0.0194	-0.0006
40	-0.0064	-0.0059	0.0005
41	0	0.0022	0.0022
42	0	0.0001	0.0001
43	0.0194	0.0201	0.0007
44	0.0127	0.0154	0.0028
45	0.0063	0.0107	0.0044
46	0.0062	0.0122	0.0059

Table 2 displays the results with the testing data. Again, the errors are small, indicating a high degree of accuracy reported by the RMSE and NRMSE and MAE values reported above. Fluctuations representing the effects of financial crisis are apparent in the testing period as well. Using an attributed selected classifier appeared to have helped improve the degree of accuracy.

Table 3. Future predictions from the end of training data for the target variable (y-growth)

Instance no	y-growth	Instance no	y-growth
1	0.0065	18	0.0085
2	0.0071	19	0.0085
3	-0.0212	20	-0.0168
4	0.0644	21	-0.0085
5	0.1338	22	0
6	-0.0196	23	0
7	0	24	0.0259

8	0.04	25	0.0084
9	0.0385	26	0.0333
10	0.0185	27	0.0645
11	0.0273	28	0.0152
12	0.0265	29	0
13	-0.0086	30	0.0149
14	0.0087	31	-0.0294
15	0.0086	32	0.0152
16	0	33*	0.0684
17	0		

Having obtained a high degree of accuracy in forecasting, we can reasonably expect that an upcoming value of the target variable would be accurately predicted with a small margin of error.

The associated trajectories of the target variable (the growth of the relevant subset of set of the banking system's foreign currency-denominated deposits) are given in Figure 1, Figure 2 and Figure 3.

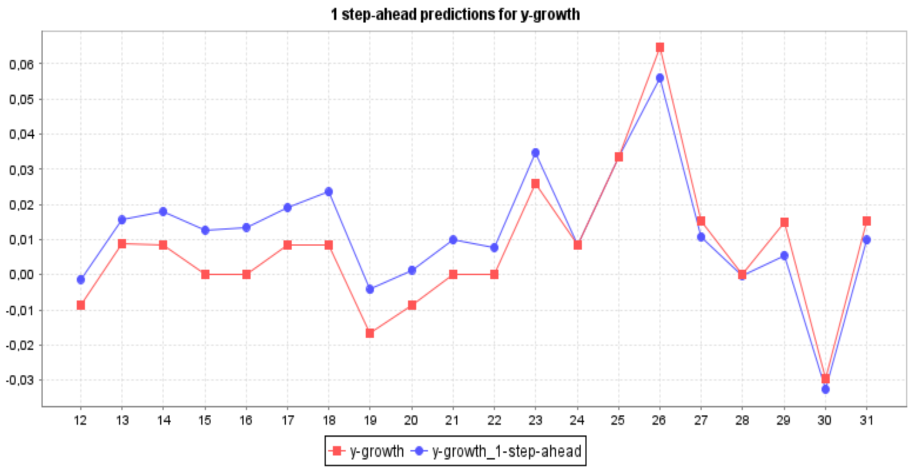

Figure 1. Predictions for the target variable (y-growth) with the training data

Clearly, for the training data set, the actual and predicted values are close. The average prediction error is small.

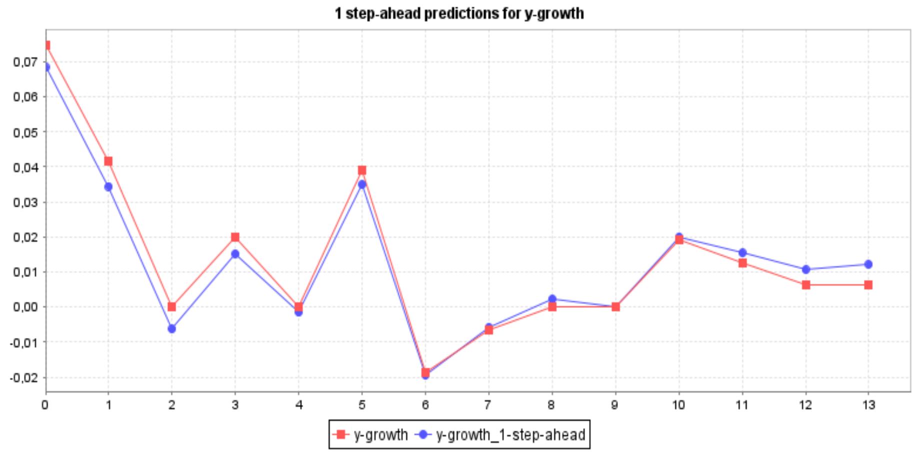

Figure 2. Predictions for the target variable (y-growth) with the testing data

The trajectories displayed in Figure 2 indicate a small average prediction error for testing data as well. The actual and predicted trajectories are quite close.

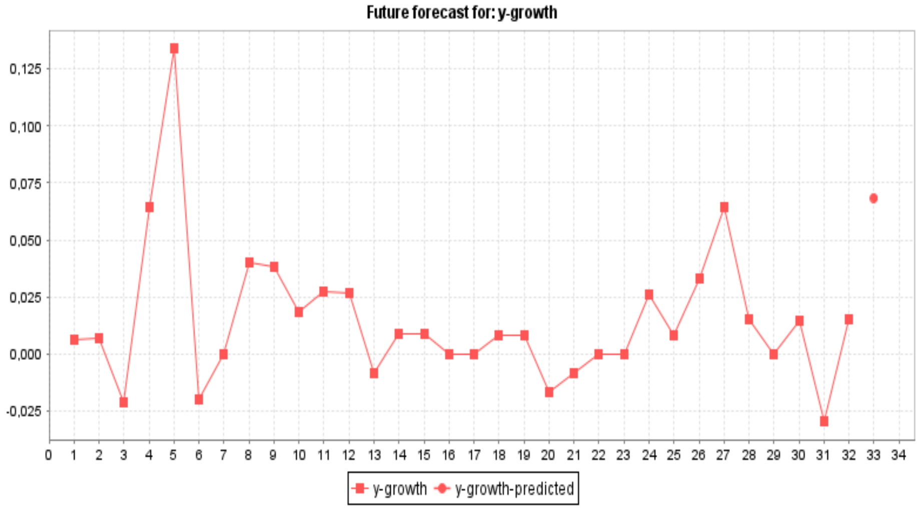

Figure 3. Future forecast for the target variable (y-growth) with training data

The results above reflect the effects of the variables, including the overlay variables, which are relevant to the forecasting of the target variable. Their effects are evident in, for instance, the degree of forecasting accuracy. If we were to remove the overlay variables from the model, the value of d would be reduced from 95.5 % to about 75 %. The resulting trajectories in the absence of overlay variables are given in Figure 4, Figure 5 and Figure 6.

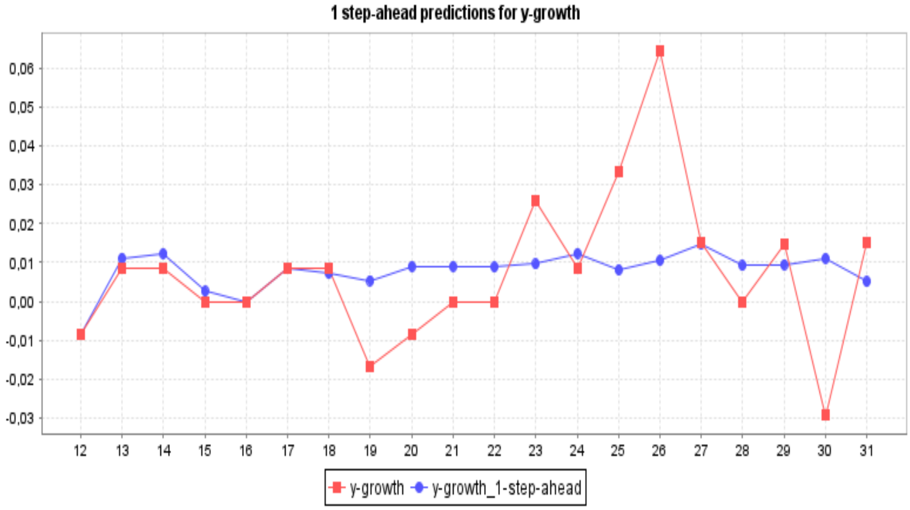

Figure 4. Predictions for the target variable (y-growth) with the training data in the absence of overlay variables

As reflected in Figure 4, the discrepancy between the actual and predicted trajectories is significant in the absence of overlay variables.

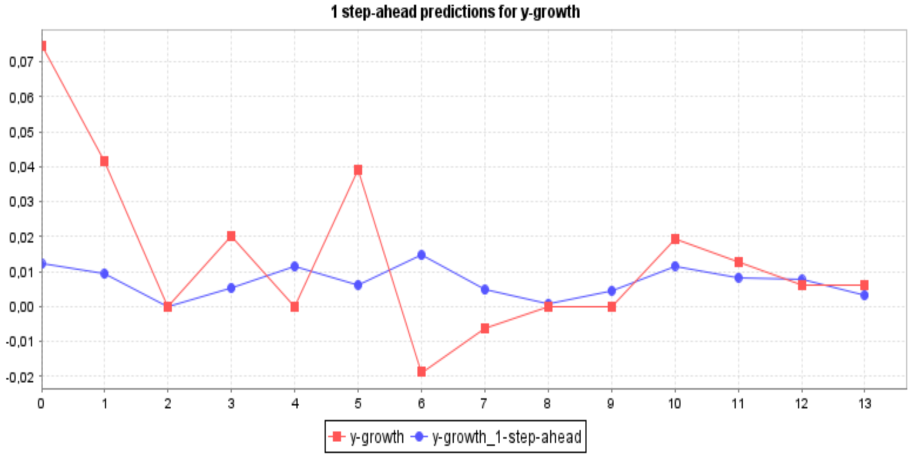

Figure 5. Predictions for the target variable (y-growth) with the testing data in the absence of overlay variables

The discrepancy between the actual and predicted values in the absence of overlay variables is, on average, significant for the testing data as well.

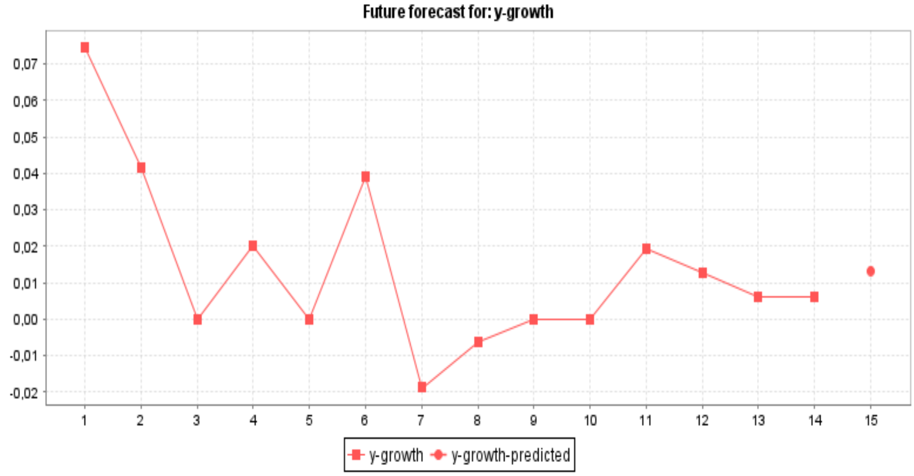

Figure 6. Future forecast for the target variable (y-growth) with training data in the absence of overlay variables

As indicated above, the discrepancy between the actual and forecasted trajectories are visible in Figure 4 and 5. Accordingly the forecasting (with a lower degree of accuracy) displayed in Figure 6 is less successful than the one in Figure 3. Clearly the overlay variables such as the stock market averages, the bond rates, the dollar-denominated interest rates and the Euro-denominated interest rates play a considerable role in the forecasting of the relevant part of the banking system's foreign currency denominated deposit-growth (y-growth), which is the chosen target variable in the model.

DISCUSSION AND CONCLUDING REMARKS

The analysis in this paper clearly indicates that certain artificial intelligence/machine learning algorithms could, depending on the context, yield highly accurate forecasts of the patterns of dynamic processes such as deposit-growths in a modern financial system. Moreover, a high degree of accuracy could be achieved even at financial crisis junctures, as we have shown in the paper. Artificial intelligence/machine learning algorithms may have some additional advantages over the traditional methods plagued by certain problems, the nature of which could not be explored in sufficient detail within the confines of this paper. We should, however, indicate that some of those problems could be satisfactorily addressed through proper transforming of the variables during the forecasting process and retransforming them back to their original form in the end. Nevertheless, for more concrete comparisons, it would be worthwhile to inquire, in future works, about whether or to what extent the artificial intelligence/machine learning algorithms of flexible/versatile structure that yield good results are less susceptible to the kind of complications/problems plaguing the traditional methods.

In this paper, we have focused on the performance of a particular class of algorithms called support vector machines. We have first demonstrated that, via this algorithm, we can obtain small forecasting errors representing the difference between the actual and predicted values of the target variable, signifying a high degree forecasting accuracy. Second, we have shown that there are considerable fluctuations in the value of the target variable over time, indicating the possible effects of the global financial crisis that occurred in the chosen period. Third, the use of support vector machines with an attributed selected classifier has helped improve accuracy by selecting the features yielding the best results.

In our empirical study, the degree of forecasting accuracy has turned out to be high, making the method one of the likely candidates for the analysis and practical management of the financial crisis. During crisis periods, the tendency of some of the economic actors to maintain a higher fraction of their assets in the form of foreign currency-denominated deposits could increase. This has ramifications for the confidence in the national currency, which could trigger a chain of actions and interactions forming feedback loops that need not always have desirable economic outcomes. Keeping the fraction or magnitudes of the foreign denominated deposits or their growth rates within certain bounds may well be a sub-policy target serving higher level targets in the economy. In any case, accurate forecasts of the magnitudes or growth rates in question are of practical significance as far as the economy-wide-policy making is concerned. This significance of practical nature also holds true for microeconomic decision-making, which could benefit from the accurate predictions of the patterns of economic or financial variables that could be relevant to the microeconomic performance of the economic actors. For instance, correctly predicting the deposit-growth under different conditions inclusive of crisis junctures would be extremely valuable to bank managers trying to formulate optimal policies targeting the bank’s relevant goals.

Besides support vector regression, there are many other artificial intelligence algorithms, such as deep learning, random forests, random subspace, input mapped classifier, bagging, vote and stacking etc. which could be of productive use for forecasting purposes. Additionally, artificial intelligence-based forecasting methods could be combined with certain simulation methods, such as system dynamics and agent-based modeling, so as to more effectively and comprehensively address many of the real-life complexities of interdependent, strategic and stochastic nature.

Ethics Committee Report: The article does not require any ethics committee report. The data used in the article are publicly available.

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