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DEBT MANAGEMENT EVALUATION THROUGH SUPPORT VECTOR MACHINES: ON THE EXAMPLE OF ITALY AND GREECE

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Abstract. The focus of this research paper is on sovereign debt management evaluation. During the first decade of the 21st century, the PIIGS countries in the EU28 were the main generator of risks in in the public finance sector, thus creating a threat for cross-border economic shocks. In 2018, Greece and Italy had the worst debt-to-GDP ratios and were earmarked as a benchmark for countries with sovereign debt problems. Greece is an example of a country with a non-systematic risk for the EU due to its low share of EU28's GDP of 1.16% (as of 2018) despite its record debt ratio of 176%. However, Italy is not only among the top 4 EU28 economies with a share of its national GDP in that of the EU28 of 11.1%, but also has a record debt ratio of 131%, which is significant for one of the top economies in the EU28 group. In view of the above, the paper is structured into three main sections. Section One presents an analysis of the efficiency of sovereign debt management as a key element of public finance management in the 28 EU Member States. Section Two presents a justification of the use of the Support Vector Machines (SVM) method for econometric analysis of macroeconomic data. Section Three presents groups and empirically tested internal and external indicators that affect the debt ratio of Italy and Greece. The analysis was conducted with quarterly time series of data for the period 2000-2018 using support vector regression (SVR) for sovereign debt testing calculated using software for interactive and functional programming - Python. The test results and their vector distribution in terms of SVR are presented as histograms. The main conclusion is that both for Greece and for Italy, there is a strong correlation between the SVM support vectors obtained through the algorithm, which is also due of the strict selection of indicators whose correlation is reformatted by the model algorithm, limiting its negative significance on the final result.

Keywords: Support Vector Machines (SVM); support vector regression (SVR); public debt to GDP ratio; Debt management

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1. Introduction

Public finance management in the EU28 is the means for allocating financial resources for implementing of the various policies of the Union based on a budgetary framework of financial relationships between net donor countries and net beneficiary countries. Despite the prioritization of macroeconomic indicators as criteria for Eurozone membership, there are some significant deviations from perhaps the most important indicator for efficiency of the national financial systems - the ratio of public debt to GDP. In 2018, Greece and Italy had the worst debt-to-GDP ratios and were earmarked as a benchmark for countries with sovereign debt problems. Greece is an example of a country with a non-systematic risk for the EU due to its low share of EU28's GDP of 1.16% (as of 2018) despite its record debt ratio of 176%. However, Italy is not only among the top 4 EU28 economies with a share of its national GDP in that of the EU28 of 11.1%, but also has a record debt ratio of 131%, which is significant for one of the top economies in the EU28 group. These facts determine the relevance of this study, which seeks to appraise and justify a technique for public debt management assessment based on the public debt-to-GDP ratio through factor regression using the Support Vector Machines (SVM) method. In view of the above, the paper is structured into three main sections. Section One presents an analysis of the efficiency of sovereign debt management as a key element of public finance management in the 28 EU Member States. Section Two presents a justification of the use of the Support Vector Machines (SVM) method for econometric analysis of macroeconomic data. Section Three presents groups of empirically tested internal and external indicators that affect the debt ratio of Italy and Greece. The analysis was conducted with quarterly time series of data for the period 2000-2018 using support vector regression (SVR) for sovereign debt testing calculated using software for interactive and functional programming - Python.

2. Sovereign debt and deficit financing – theoretical and practical aspects

National governments are major borrowers on both the domestic and international capital markets. On the other hand, government debt securities often constitute significant shares of institutional and individual investment portfolios. The techniques for financing government budget deficits has a strong influence on the structure and operation of the national financial markets. This influence is twofold, since any increase of the sovereign debt is a logical consequence of deficit financing decisions and, conversely, a budget surplus would allow the government to reduce the sovereign debt through active (advance repurchase of securities) or passive (redeeming callable bonds) measures. The second scenario definitely requires an assessment due to the direct relation between the regulatory requirements for the structure of the institutional investment portfolios and the availability of a sufficient number of debt securities with high credit ratings that meet the regulatory requirements. Government debt securities are therefore subject to long-term investment interest (Posner, 1999) and declines of the amount of government securities as well as shifts in their composition affect the interests of various public and private investors, such as commercial banks, insurance companies, pension funds, and the central banks of countries with a currency board. The importance of public debt management is also due to the significant and long-term consequences from debt management decisions of sovereign governments and their policy (Holcombe & Mills, 1995). This area of competence requires not only technical knowledge of the initial public offering of government securities, but most of all a thorough knowledge of the laws of macroeconomic equilibrium and the regulatory requirements for the investment portfolios of all other economic agents. For the purposes of this study, the authors have assumed that public debt management is a system of statutory activities of the Ministry of Finance in the field of initial public offering, secondary trading and redeeming callable bonds, incl. servicing of interest coupons according to ex ante deadlines. Efficient public debt management means not only to cover the government's spending needs, but also to achieve goals and meet the regulatory requirement of the national and the Community law (*acquis communautaire*). The achievement of the primary objective of public debt management relates to two groups of additional objectives, conditionally designated as technical and sectoral objectives of debt management. The first group includes objectives related to minimization of government debt service costs,

mitigation of debt management risks, minimization of the market impact on government debt operations, optimization of the maturity structure of the debt, optimization of the currency structure of the debt, establishment of an efficient system of primary dealers, etc. The second group is usually associated with the government policies on individual functions and responsibilities, such as provision of public goods with sufficient quantity and quality (Zahariev, 2012).

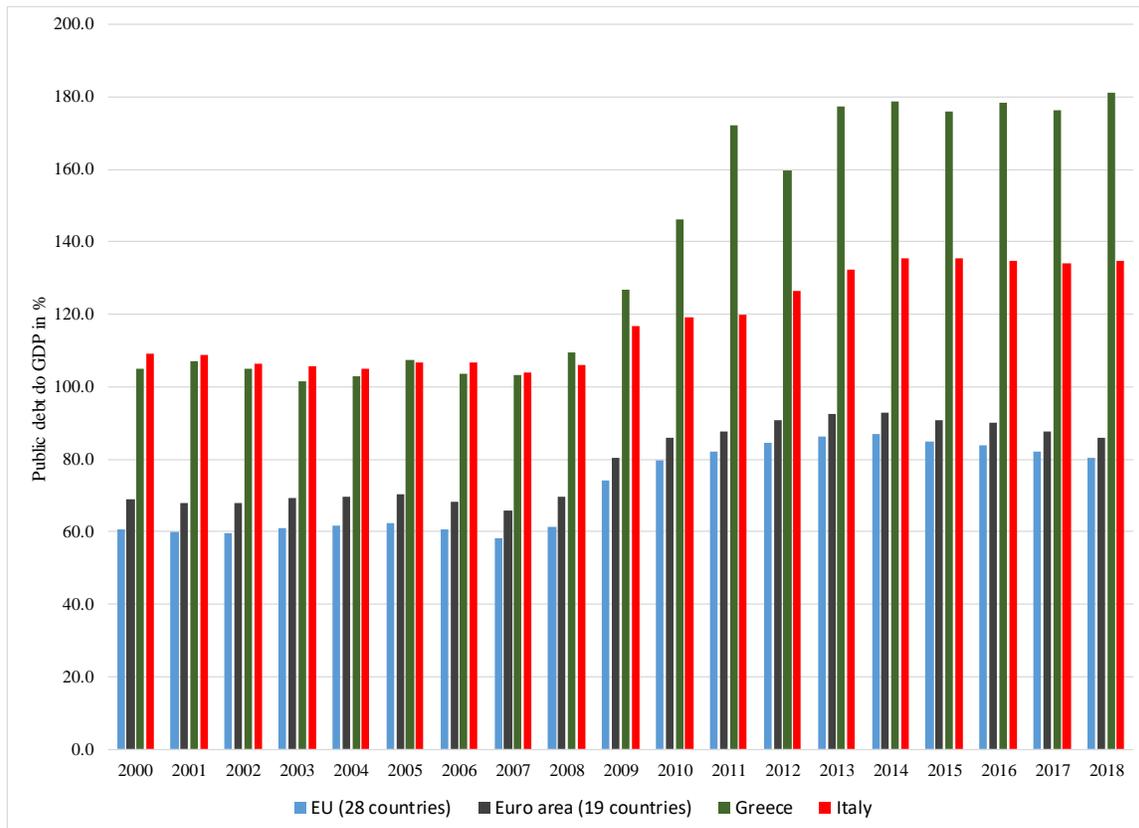


Figure 1. Public debt to GDP ratio of Italy, Greece and EU (2000 – 2018)

Source: compiled by the authors based on information from Eurostat

Any increase of a central government’s budget deficit requires specific decisions on what debt securities should be issued and in what currency, at what interest rate, for what period, and whether the IPO should be discount or premium-based. Regardless of the requirements and expectations of institutional investors in government securities, the macroeconomic framework and the medium-term prospects for the economic development of the country are equally important for the Ministry of Finance in terms of sovereign debt management. According to the Maastricht criteria for Eurozone membership, there is direct correlation between the criteria for the maximum debt level, central budget deficit, and long-term convergence interest rates that can dramatically upset the balance between budget revenues and budget expenditures when decisions are made to revolve government budget deficits and there is demand for increasing risk premiums from the primary dealers. In such circumstances, the interest burden on the existing debt can result in long-term destabilization of the economy (Zahariev, 2000) and block the phases of the debt cycle, equalizing the absorption of the economy with the income generated at a certain interest rate levels on the outstanding debt. Such a debt crisis situation occurred in Greece in 2010, when for a period of only two years the country’s debt ratio boomed from 109% (in 2008) to 172% (in 2011) and continued to increase to reach 181% in 2018. A similar situation was observed in Italy (see Figure 1), where the pre-crisis debt ratio of 106% increased to 135% from 2014 through 2018 compared to EU28 average of 80.4%

and Euro Area 19 average of 86% in 2018 The inability of the two countries to reduce their sovereign debt shows that the reforms undertaken by their governments can only maintain the debt ratio at a stable level, thus hindering the growth of their economies by reducing the GDP with the amount of the redeemed callable debt, which is usually revolved by issuing new debt securities. It is therefore important to study the dynamics of the debt ratio with econometric analysis technology that takes into account multiple factors in order to establish statistically significant regression dependence for Italy and Greece.

3. The Support Vector Machines (SVMs) technology as a tool for digital econometric analysis of macroeconomic data

Commonly known as a "black box" technology, the **Support Vector Machines (SVMs)** are generally supervised machine learning models with associated learning algorithms. SVMs are based on a large set of complex mathematical calculations. SVM software is written in some of the popular programming languages, incl. "R", "Python", "Eviews", "Matlab", etc. The support-vector clustering algorithm is a relatively new approach developed by Professor Siegelmann (Dr. Hava Siegelmann, 2019), a world leader in the field of machine learning and the University of Colombia's professor of computer science and statistics Vladimir Vapnik (Vapnik, Vladimir, 2019.) It applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabeled data and can be used both to the analysis of the relationship between large amounts of statistical data and to classification and regression analyses. SVMs are based on supervised machine learning methods that analyse the data and identify the models. They construct a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks.

SVMs are largely reduced to choosing a kernel and a support vector machine. The method (Boser, Guyon, & Vapnik, 1992) generally works based on finding an oriented hyperplane that maximizes the closest distance between observations while minimizing the amount of error in the experiments performed. An SVM model (Ben-Hur, Horn, Siegelmann, & Vapnik, 2001) is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible from the kernel. New examples are then mapped into that same space and predicted to belong to a category based on the side of the gap on which they fall. In this way, a better generalizability of the function obtained and the ability to interpret the regression results are achieved. The performance of an SVM depends largely on the choice of its parameters. Its estimation consists of a description of unknown dependencies in the observed data set. These dependencies may be linear or non-linear.

Like any other classification technique, SVM has its advantages and disadvantages, which are more or less important depending on the data being analysed and are thus relatively important. The advantages of the SVM technique are that it:

- guarantees optimal results;
- minimizes the error;
- is equally applicable for both linear and non-linear classifiers;
- is versatile in terms of format selection and model structure;

The main disadvantage of the SVM technique is the lack of transparency of results and requires bulky computations. Interpretation of results relies on graphical visualization of the score. An analysis of the graphs gives an important input about the direction towards which the score should be optimized.

The SVM technique is applicable to various types of data and for various purposes. It was used by many researchers, such as Marček and Marček (n.d), who used the technique to investigate the quantifying of statistical

structural model parameters of inflation in Slovak economy. They used dynamic and SVM modelling approaches and concluded that the Support Vector Regression (SVR) models deserve to be integrated in the range of methodologies used by data mining techniques, particularly for control applications or short-term forecasting where they can advantageously replace traditional techniques. The SVM technique was used by Nalbantov, Bioch, and Groenen (2005) to evaluate the dichotomous variable of interest and thus assess the effect of manipulating some marketing instruments on the probability of a certain choice between two alternatives. Grigoryan (2018) focuses on financial time series prediction problem. He proposes an integrated prediction model based on support vector machines (SVM) for stock market prediction of stocks traded on the Baltic Stock Exchange and the Bucharest Stock Exchange. The proposed prediction framework consists of two stages. In the first stage, the ICA technique is used to extract information from research data and then the SVM technique is applied to forecast the stock prices. Tay & Cao (2001) apply the neural network technique (SVM) to financial time series forecasting. They compare the SVM with a multi-layer back-propagation (BP) neural network. Their experiment proved that SVM outperforms the BP neural network based on the criteria of error and directional symmetry and proved that it is advantageous to apply SVMs to forecast financial time series. Panigrahi & Mantri (2014) performed a comparative analysis of the prediction efficiency of a Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) in the field of financial time series analysis considering the importance of economic growth, macroeconomic stability, and the minimization of the stock price volatility in India. Their study proved SVM as a better alternative to MLP for forecasting of non-stationary, non-linear and inherently chaotic financial time series. Divya & Agarwal (2011) used an enhanced SVM - Fuzzy Support Vector Machine“ (FSVM) - to classify 70 countries in terms of their macroeconomic variables. The result of their experiment shows that the used classifier has a good accuracy. Auria & Moro (2008) examined the SVM statistical technique as an alternative considered by the Deutsche Bundesbank for company rating. They pay special attention to the features of the SVM which provide a higher accuracy of company classification compared with more traditional approaches such as logistic regression and discriminant analysis with data of annual income statements and balance sheets of German companies. The out-of-sample accuracy tests confirm that the SVM outperforms both traditional techniques.

The above brief review of theoretical concepts and publications leads to the conclusion that SVMs outperform most of the other classification techniques because they provide a good out-of-sample generalization. When used for forecasting and cluster distribution, they minimize the error, which is an essential feature of the classification results.

Therefore, we can conclude that SVMs are an advanced technique for digital econometric analysis of time series. They deliver a unique solution for flexibility in the choice of the form of the threshold, good classification results in the case of non-regularity in the data, and minimization of the statistical error. These features were considered essential for our research on the problems and challenges of sovereign debt management of Greece and Italy, whose economies are important for the stability of the European economic and monetary union.

In statistical learning theory, the supervised “learning” of data, which underlies the SVMs, was defined by (Vapnik, 1998) as: We are given a set of training data (z_1, y_1) according to unknown probability distribution $P(z, y)$ and a loss function $V(y, f(z))$ that measures the error done when, for a given z , $f(z)$ is predicted instead of the actual value of y . The problem consists in finding a function f that minimizes the expectation of the error on, i.e. find a function that minimizes the expected error:

$$\int V(y, f(z)) P(z, y) dz dy$$

Since $P(z, y)$ is unknown, we need to use some induction principle to infer from the available training examples a function that minimizes the expected error, which is written as minimizing the empirical error:

$$\frac{1}{l} \sum_{i=1}^l V(y_i, f(x_i))$$

An important question is how close the empirical error of the solution is to the minimum of the expected error. A central result of the theory states the conditions under which the two errors are close to each other, and provides probabilistic bounds on the distance between empirical and expected errors.

The main feature of SVMs is that it finds the optimal hyperplane as a solution to the problem. The simplest SVM is linear, whereby the hyperplane lies on the input data space z . In this case, the hypothesis plane is a subset of all hyperplanes.

$$f(z)=w.z+b$$

In their most general formulation, SVM find a hyperplane in a space different from that of the input data z . It is a hyperplane in a feature space induced by a kernel K , through which the hypothesis space is defined as a set of "hyperplanes" in the feature space induced by K . So, the hypothesis space used by SVM is a subset of the set of hyperplanes defined in some space written as: (Evgeniou & Pontil, 2001):

$$\{f: |f|_K^2 < \infty\}$$

where:

K is the kernel.

We have to distinguish between SVM classifiers and SVM regressors. For classification ideally the misclassification error needs to be minimized, so a loss function of the form $\text{sign}(-yf(z))$ should be used (in classification y takes binary values ± 1 , and classification is done by taking the sign of function $f(z)$). Because of scaling as well as computational reasons (Vapnik, 1998), the actual loss function used for SVM classification is:

$$|1 - yf(z)|, \text{ i.e. } 0 \text{ if } 1-yf(z)<0 \text{ and } 1-yf(z) \text{ e } >0.$$

This is also called the *soft margin* loss function. The margin is an important geometric quantity associated with SVM classification. For regression the loss function used is the so-called *epsilon-insensitive loss function*:

$$|y - f(z)|\epsilon, \text{ which is equal to } |y - f(z)| - \epsilon,$$

if $|y - f(z)| < \epsilon$, and 0 otherwise.

To summarize, SVM are learning machines that minimize the empirical error while taking into account the "complexity" of the hypothesis space used by also minimizing the kernel norm of the solution. SVM in practice minimize a trade-off between empirical error and complexity of hypothesis space. Formally this is done by solving the following minimization problems:

$$\begin{aligned} & \min |f|_K^2 + C \sum_{i=1}^i |1 - y_i f(x_i)| \\ & \text{for SVM classification, and} \\ & \min |f|_K^2 + C \sum_{i=1}^i |1 - y_i f(x_i)|\epsilon \\ & \text{for SVM regression (SVR),} \end{aligned}$$

where C is a so called "regularization parameter" that controls the trade-off between empirical error and complexity of the hypothesis space used.

SVRs must be adjusted for each particular application depending on the type of data, the approach used and the desired results. Many SVRs use unbalanced data and parameter optimization. Scaling data of independent variables is important for summarizing the results of parameter optimization. In this particular case, the SVR is used to model the relationship between the main subject of monitoring by the European institutions –

“government debt as a percentage of gross domestic product” (sovereign debt ratio) and the main factors that affect the ratio, which are components of indicators tracked by the financial institutions in the Euro Area. Subsequently, the model is used to distinguish the factors that have an adverse effect on the debt management of Italy and Greece. This presents, through a different approach, the challenges that governments need to address in order to improve the fiscal discipline in these countries and take preventative measures against the risk of volatility in the Euro Area. The SVR evaluation of government debt management was computed with an interactive and functional programming software written in Python.

4. SVR evaluation of the sovereign debt management of Italy and Greece in the period 2000 – 2018

The SVR model uses data for factors with direct and indirect effect on the debt management of Greece and Italy. Quarterly data for the period from 2000 to 2018 (a total of 76 observations of the indicators and the resulting ratios) are used, which have a low degree of correlation with government debt to gross domestic product ratio (*The use of the government debt to gross domestic product ratio as a target variable is due to the fact that this indicator is subject to statutory requirement for a fixed threshold limit of 60% and thus allows objective comparison of the two countries in terms of their sovereign debt*). The data was optimized to derive a total of indicators classified conventionally in two groups as internal and external indicators.

Internal indicators refer to the ratios of the main structural components of government debt to total government debt as follows: *currency and deposits to government debt (gg_curr_deposits_from_debt); debt securities to government debt (gg_debt_sec_from_debt); short-term debt securities to government debt (shortt_debt_sec_from_debt); long-term debt securities to government debt (longtt_debt_sec_from_debt); short-term debt securities to long-term debt securities (shortt_debt_sec_from_longtt_debt_sec); government loans to government debt (loans_debt); short-term loans to government debt (shortt_loans_from_debt); long-term loans to government debt (longtt_loans_from_debt); short-term loans to long-term loans (shortt_loans_from_longtt_loans); the amount of outstanding international debt securities to government debt (gg_int_outst_amount_from_debt); real effective exchange rate (real_eff_exch_rate); the amount of outstanding international debt securities due within one year to government debt (gg_1yr_amount_from_debt).*

External factors affect indirectly the measure of government debt to gross domestic product and are part of the statutory criteria for monitoring the financial stability of the EU member states by the monetary institutions of the EU. They include: *the exchange rate of the Euro to the USD (local_ccy_to_usd); consumer price index (cons_price_index); 3-month (90-day) interbank interest rate (3m_int_rate); consumer price index change from the previous reporting period (cons_price_growth_index); exports to imports rate (export_import); government debt to active population (aged 25-54) (debt_active_population); government debt to working age population (debt_working_age_population); unemployment rate of the population aged 15-74 (unempl_rate); net lending to GDP (net_lend_from_gdp), production of total industry (prod_of_total_industry).*

The data in the SVR model are trained using the parameters listed in Table 1 below.

Table 1. Training parameters in SVR

Parameter	Value	Parameter	Value
GREECE			
Coefficient	0.0	Gamma	0.0001
Degree	3	Max. Iteration	-1
Epsilon	1e-05	Model Score	0.9878092
ITALY			
Coefficient	0.0	Gamma	0.0001
Degree	3	Max. Iteration	-1
Epsilon	1e-05	Model Score	0.9901414

Source: compiled by the authors

The table clearly shows the statistical similarity between the two structured algorithms. The only difference between the models is the accuracy value (*model score*), which is significant for both countries. With values of 0.98780% for Greece and 0.99014% for Italy, the algorithm is used to determine the degree of influence of the selected indicators on the government debt to gross domestic product ratio of the two countries in the period 2000-2018.

The original and predicted data sets and vector distribution of the SVR results are presented graphically as histograms in Figure 2 below. The dots (original) represent the raw data and the stripes (predicted) represent the predicted values shown as vector functions and the relations thereby.

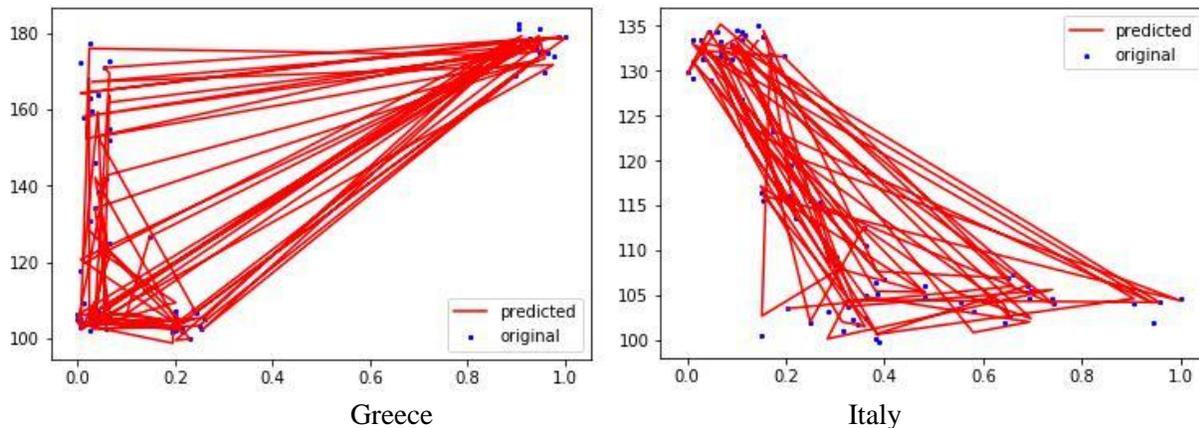


Figure 2. Vector histogram for the period 2000-2018.

Source: compiled by the authors

The histograms show a strong correlation between the support vectors obtained by the algorithm for both countries. This is due, on the one hand, to the rigorous selection of indicators whose correlation relationship is reformatted by the algorithm and its negative significance to the end result is limited.

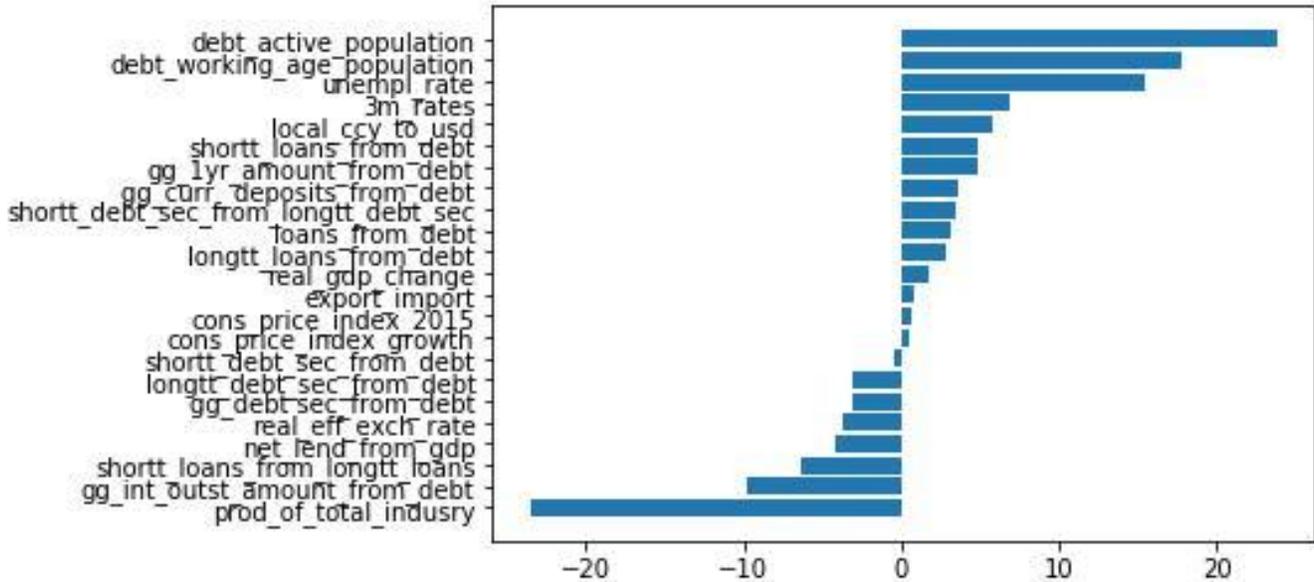
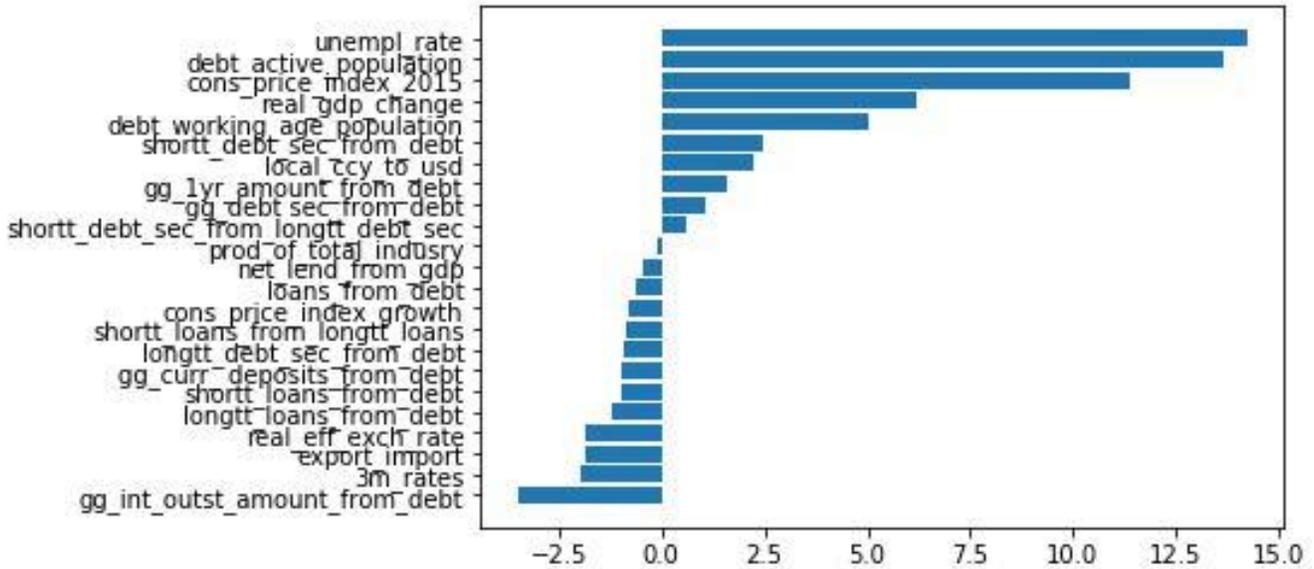


Figure 3. Profile of the degree and direction of influence of the factors on the target variable for Greece

Source: compiled by the authors



Фигура 4. Profile of the degree and direction of influence of the factors on the target variable for Italy

Source: compiled by the authors

The individual components of the aggregate indicators used in the EU do not indicate explicitly the fiscal implications of long-term and short-term government liabilities, nor do they identify the threats associated with sustainable sovereign indebtedness. On the other hand, European regulations do not have provisions for a “sudden cease” in the movement of capitals among the Euro Area Member States and the emergence of cross-border effects. The huge bail-out cost of the counter-cyclical fiscal policies undermine the creditworthiness of most Euro Area Member States, most notably of Greece and Italy.

The simple debt-related rule which states that the greater the sovereign debt, the greater is the risk of difficulties related to its management and servicing is especially obvious in the case of Greece and Italy. The level of sovereign debt ratio depends on the particular circumstances and the effects of various factors. The effect of the indicators on the target variable is graphically presented in Figure 3 for Greece and Figure 4 for Italy. In the case of Italy, 13 of the factors (of which 4 with high intensity) have a negative effect for the debt ratio (i.e. they decrease the target government debt-to-GDP ratio) and the remaining 9 factors (all of them with low intensity) have a positive effect. In the case of Greece, there are 14 factors with negative effect (among which 3 with high intensity) and 8 factors with a positive effect. The significance of each indicator in terms of the degree of its effect on the sovereign debt-to-GDP ratio evaluated using the SVR, shows that the “external” indicators have higher intensity than the “internal” ones. This, in turn, could contribute to finding an optimal solution to the sovereign debt problems experienced by Greece and Italy.

Conclusions

The application of the SVM method to model the dependence of the debt ratio of Italy and Greece on two groups of factors confirms the analytical and research utility of the method in two aspects. First, the technique proves that, both in Greece and Italy, there is a strong correlation between the support vectors obtained with the SVM algorithm, which is also due to the strict selection of indicators whose correlation is reformatted by the model algorithm to limit their negative significance for the final result. Secondly, the SVR test results and their vector distribution represented as histograms confirm that the correlation between the factor indicators and the debt ratio of Italy, whose economy is significant for the EU28, indicates that it has better chances to overcome its debt crisis. This is also due to Italy's highly diversified economy, which invariably generates over 10% of the GDP of EU28. Nevertheless, the governments of both countries will face many challenges, especially when the European Central Bank abandons its zero interest rate policy and sets a positive interest rate. Such a decision will inevitably increase the cost of servicing the sovereign debts of Italy and Greece and they will remain, at least for a while, the countries with the most critical levels of public debt-to-GDP ratio.

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