BETA
Bureau
d'économie
théorique
et appliquée

Documents de travail

«Forecasting the Stability and Growth Pact compliance using Machine Learning»

Auteurs

Kéa Baret, Amélie Barbier-Gauchard, Théophilos Papadimitriou

Document de Travail n° 2021 – 01

(Version révisée du WP 2019-48)

Janvier 2021

Bureau d'Économie Théorique et Appliquée BETA

www.beta-umr7522.fr

@beta_economics

Contact :
jaoulgrammare@beta-cnrs.unistra.fr

Forecasting the Stability and Growth Pact compliance using Machine Learning

Kéa BARET,[1] Amélie BARBIER-GAUCHARD,[2] and Théophilos PAPADIMITRIOU[3]

[1] *Corresponding Author*: BETA CNRS UMR 7522, University of Strasbourg, France. Email: k.baret@unistra.fr

[2]BETA CNRS UMR 7522, University of Strasbourg, France. Email: abarbier@unistra.fr

[3]Democritus University of Thrace, Department of Economics, Komotini, Greece. Email: papadimi@econ.duth.gr

Abstract

Since the reinforcement of the Stability and Growth Pact (1996), the European Commission closely monitors public finance in the EU members. A failure to comply with the 3% limit rule on the public deficit by a country triggers an audit. In this paper, we present a Machine Learning based forecasting model for the compliance with the 3% limit rule. To do so, we use data spanning the period from 2006 to 2018 (a turbulent period including the Global Financial Crisis and the Sovereign Debt Crisis) for the 28 EU Member States. A set of eight features are identified as predictors from 141 variables through a feature selection procedure. The forecasting is performed using the Support Vector Machines (SVM). The proposed model reached 91.7% forecasting accuracy and outperformed the Logit model that we used as benchmark.

Keywords: Fiscal Rules; Fiscal Compliance; Stability and Growth Pact; Machine learning.

JEL Codes: E62, H11, H60, H68.

Acknowledgements: We want to thank Xavier Debrun for all his support and relevant comments during UCA-CNRS-IRD-CERDI International Workshop on the Policy Mix , January 30-31, 2020. The paper also benefited from valuable discussions and comments from Alexandru Minea, Piotr Stanek, António Afonso, Stefano Bianchini and participants in the GEBA 2019, ERMEES international workshop 2019 and UCA-CNRS-IRD-CERDI International Workshop on the Policy Mix 2020. All remaining errors are our own.

1 Introduction

For almost 20 years, enhancing fiscal discipline in the Eurozone has become the bone of contention between the European authorities and the EU Member States. Widely criticized and several times reformed, the European supranational fiscal discipline introduced by the so-called Stability and Growth Pact (1996) -SGP thereafter-[1] is facing a new challenge. This fiscal rule aims at two complementary objectives: the "stability" of public finance on the one hand, requiring Eurozone countries to pursue sound management of public finance, and "economic growth" in the EMU on the other, ensuring that national governments have enough leeway to intervene if necessary (especially if a cyclical shock occurs). To achieve these two objectives, the Pact offers two types of instruments: the "dissuasive" arm intended to ensure strict compliance with the rule[2] and the "preventive" arm designed to encourage Member States to present balanced and sound public finance over the medium term[3]

Despite this supranational fiscal rule, the Eurozone has experienced several periods of turbulence[4], that have systematically questioned the fiscal discipline that has been implemented. Each time, the SGP was considered far from perfect and was reformed. These successive reforms led to the creation of a stack of indicators that Member States are expected to respect, without in-depth reflection on the real reasons of the fiscal discipline failures in the Euro area. Following the reforms of 2005, 2011 and 2013, the fiscal rule in force in the Eurozone has turned into a catalog of indicators to monitor, failing to ensure real coercive disciplinary power over the Member States, and not enabling a real monitoring of the efficient management of national public finance.

To better understand the strengths and weaknesses of fiscal discipline in the Euro area, it is essential to refer to the seminal paper of Kopits and Symansky [1998] on the features of an ideal fiscal rule. The authors propose eight properties to be for a "good" fiscal rule. One constitutes a hotspot in the debate on fiscal rules efficiency: the credibility property of fiscal rules, which corresponds to enforceability (also appearing in the "fiscal rules trilemma"[5]) and refers to compliance with the fiscal rule. Fiscal rule compliance could be defined as the ability of the relevant fiscal aggregates (the budget balance, the debt-to-GDP ratio or government expenditure) to reach, in purely quantitative terms, the target set by the fiscal rules. In other words, compliance assesses whether or not the rule has been complied with[6].

The purpose of this paper is neither to question the justification of fiscal rules nor to discuss the threshold used to control compliance[7]. In addition, the aim of this paper is neither to assess fiscal rules effectiveness[8] nor to propose new fiscal rules[9]. This paper tries to fill a gap in the fiscal

[1] The rule of the Stability and Growth Pact (1996) succeeds the public finance criteria (public debt below 60% of GDP and public deficit below 3% of GDP) introduced by the Maastricht Treaty (1992) as one of the conditions to be met in order to be an eligible member country for the European monetary union.

[2] The disuasive arm consists in public deficit ceiling with sanctions imposed in case of non-compliance, and exceptions to the rule in very specific economic circumstances.

[3] The preventive arm corresponds to a multilateral surveillance procedure with "stability programs", multi-annual programs setting fiscal guidelines over 3 years and making it possible to have visibility on public finance for the next 3 years in order to reach budget balance in the medium term.

[4] The first crisis in 2004, the Great Recession from 2007 to 2009 with the Subprime crisis which was followed by the sovereign debt crisis, then the COVID 19 pandemic crisis.

[5] Debrun and Jonung [2019]

[6] In most cases, this assessment does not take into account escape clauses.

[7] See for instance Debrun et al. [2008] or Wyplosz [2012] for a general overview of the main reasons to introduce fiscal rules.

[8] See, for instance, Foremny [2014], Sacchi and Salotti [2015], Bergman et al. [2016], or also Barbier-Gauchard et al. [2021].

[9] As such, see papers on the second generation of fiscal rules as underlined by Eyraud et al. [2018] and Caselli et al. [2018] and also Darvas et al. [2018], Hauptmeier and Kamps [2020] or Debrun and Jonung [2019].

rules compliance literature by proposing the use of the groundwork on compliance to strengthen the preventive arm of the Stability and Growth Pact (1996) in the Euro area.

Indeed, on the one hand, a wide field of fiscal rules compliance literature focuses on the compliance score and the main determinants of fiscal rules compliance. Delgado-Téllez et al. [2017] for Spain regions using first-difference General Method of Moments or Reuter [2019] for EU Member States and Nandelenga and Ellyne [2020] for sub-Saharan African countries, both used a logistic model and the highlighted determinants are mainly rule-related[10]. Larch and Santacroce [2020] provide highlights on correlations between the fiscal rules included in the SGP and various macroeconomic variables such as the market volatility index, the output gap, the nominal GDP growth or the quality of governance. While the studies by Reuter [2019] and Nandelenga and Ellyne [2020] are seeking for causality, Larch and Santacroce [2020] propose a simple correlation analysis, that differ from forecasting. All these approaches use contemporaneous information in the variable set and cannot be used for forecasting. Moreover, Reuter [2019] and Nandelenga and Ellyne [2020] created a universal model to investigate the compliance with a set of varying rules: some countries set a limit on the structural balance, others on the overall balance or the balance excluding public investment etc[11]. Since such variation in the dependent variable isn't possible in forecasting, we will focus on the "3 % limit on public deficit" which is applied to all the European Union Member States.

On the other hand, the latest reform of the Stability and Growth Pact undertaken with the Six Pack (2011) modified in depth the preventive arm by introducing the Macroeconomic Imbalance Scoreboard (MIP). The purpose of this scoreboard is to monitor a wide range of indicators used to identify any risk of internal and external imbalances that could destabilize public finance for a long time. In addition, a few years earlier, in 2010, the implementation of the European Semester was already a milestone towards more efficient monitoring of public finance. While it is true that the SGP reforms introduced some powerful tools for close and thorough monitoring of public finance, these tools created an undesired complication for the countries : an excessively complex framework aiming at the prevention of non-compliance with the fiscal rule. Rather than replacing the SGP, an alternative may be the simplification of the monitoring process[12]. Simplifying monitoring procedure by proposing a new alert mechanism could be interpreted as making the preventive arm less complex, but it could simultaneously strengthen the dissuasive arm. In other words, strengthening the preventive arm would enable to reduce the number of situations where there is a risk of an excessive deficit and thus strengthen the dissuasive arm. Following this idea, in this paper, we propose a model to forecast the compliance with the 3% limit of public deficit. The model is created using Machine Learning, a methodological path rather unexplored in Macroeconomics, that often outperforms traditional Econometrics (see Ince and Trafalis [2006], Plakandaras et al. [2013]).

This paper offers an original contribution in several ways : a) we focus on the European supranational fiscal rules introduced with the Stability and Growth Pact (1996), not on national fiscal rules, b) we use only past information modeled as lagged instances of our variable set[13] and c) we try to forecast[14] the same supranational rule in every case (the 3% deficit rule of SGP). Our analysis focuses on the 28 EU Member States over the period 2006-2018. We choose not to study the 60% public debt rule, since its non-compliance is the result of a succession of public

[10] The features that could strenghten fiscal rules compliance: registration in the law, level of rigor, degree of public finance coverage, etc.

[11] For example, Denmark and the United Kingdom set a budget balance rule in 2005. However, the UK introduced a Golden rule, whereas Denmark set a general 2% GDP threshold on general government surpluses.

[12] The simplification of the fiscal framework is advocated by the European Commission [2020] or the European Fiscal Board [2020].

[13] This use is inherent to the next point c .

[14] This isn't the same as causality approach.

deficits that mechanically increase the stock of public debt over time and usually this status remains stable for many years (for example according to the Fiscal Compliance Tracker of Larch and Santacroce [2020], France hasn't complied with the 60% public debt rule since 2008 and the same finding appears for several others members, such as Belgium or Portugal).

The rest of the paper is structured as follows. Section 2 presents the literature review. Section 3 exposes the data and the descriptive statistics. Section 4 describes the empirical strategy and Section 5 exposes robustness approaches. Finally Section 6 reports the benchmark results and Section 7 concludes the paper.

2 Literature review

The literature on fiscal rules compliance assessment dates back to the work of Reuter [2015]. However, it is closely linked to an older literature initiated by the seminal work of Kopits and Symansky [1998], which deals with the qualities that fiscal rules should have. Very quickly, many authors stressed that is was impossible to define a fiscal rule that satisfies all these criteria simultaneously. In particular, Debrun and Jonung [2019] highlight the "fiscal rules trilemma". They show that with the current fiscal rules it is impossible to reconcile simultaneously three of Kopits and Symansky's criteria: (i) simplicity, (ii) flexibility, (iii) compliance.

A widespread litterature focuses on the performance assessment of fiscal rules. Indeed, fiscal rules constitute a major tool to control fiscal discipline[15]. The starting point for fiscal rules assessment comes from Kopits and Symansky [1998]'s "ideal fiscal rule"[16]. Since fiscal rules are really heterogenous through their design and their application, they also present heterogenous effect and compliance. Following Kopits and Symansky [1998], some papers proposed a ranking of fiscal policy rules based on these ideal properties[17], and many others such Debrun et al. [2008] used empirical strategy and showed that national fiscal rules seem correlated to government fiscal performance (see also IMF [2009]). This theory is supported by other empirical studies, like Reuter [2015] using Least Square Dummy Variable, Bergman et al. [2016] with the system-GMM, or Tapsoba [2012] and Barbier-Gauchard et al. [2021] with the Propensity-Score Matching method. Similar conclusions were found on subnational level in Foremny [2014]. Fiscal rules performance is also relative to their macro-stabilizing power. For instance, Sacchi and Salotti [2015] highlighted that national fiscal rules contributed to the GDP stabilization. Guerguil et al. [2017] showed that flexible budget balance rules supported public expenditure stabilization (for standard definition of flexible rules see Schick [2010], Dabán [2011] or Caselli et al. [2018]). Numerous papers studied the impact of the supranational fiscal rule of the SGP on the counter-cyclical feature of national fiscal policy, as recently shown by Larch et al. [2020].

Another field of research for the fiscal rule investigates ways to resolve the "fiscal rules trilemma". This litterature gives birth to the second generation of fiscal rules as underlined by Eyraud et al. [2018] and Caselli et al. [2018] which promote rule-based on fiscal frameworks and stronger incentives to reach compliance. The "fiscal Taylor rule" proposal by Debrun and Jonung [2019] offers an illustration of what a second generation of fiscal rule could be. In the same vein, Blanchard et al. [2020] propose to shift from fiscal rules to "enforceable fiscal standards."

At the same time, other studies focus on existing fiscal rules and consider the enforceability criteria (also appearing in the "fiscal rules trilemma"), which ultimately influences the degree of

[15] Fiscal discipline is a wide concept including the whole fiscal framework. It should promote sound management of public finance. Fiscal discipline could be established through various fiscal rules.

[16] Indeed, Kopits and Symansky [1998] defined the "ideal fiscal rule" that must satisfy all these properties: (1) Suitability for the intended objective, (2) Clear definition, (3) General consistency, (4) Robust analytical foundations, (5) Transparency, (6) Simplicity, (7) Flexibility, (8) Credibility.

[17] See Creel [2003] for an attempt to evaluate these properties.

credibility attributed to the fiscal rules and refers to compliance with the fiscal rule. This paper takes its place in this field of literature, which implicitly assumes that: (i) the existence of fiscal rules is justified (see for instance Debrun et al. [2008] or Wyplosz [2012] for a general overview of the main reasons to introduce fiscal rules), (ii) the numerical limits defined are optimal. It is not the purpose of this paper to question these two hypotheses.

The studies on fiscal rules compliance are numerous. Some papers try to assess the compliance with fiscal rules based on the numerical fiscal rules databases published by the European Commission [2017] and by the IMF (2016)[18]. These databases provide information in terms of description and definition of the fiscal rule and its coverage, its statutory base, monitoring bodies, correction mechanisms in case of deviation from the rule, as well as experience with the respect of the rule.

Thanks to this information, composite indicators are defined to assess the potential coercive power of fiscal rules: the Fiscal Rule Index (FRI) proposed by the European Commission [19] or by the IMF. However, to be able to assess the effective coercive power of the fiscal rule (ie the effective compliance), effective level of relevant fiscal aggregates should be compared to the numerical limit of fiscal rules. Reuter [2015] or Larch and Santacroce [2020] show that numerical fiscal rules are generally respected in only 50% of cases. In the same vein, Delgado-Téllez et al. [2017] analyse the compliance on the subnational level in Spain and Cordes et al. [2015] focus on public expenditure rules compliance in advanced and emerging countries.

Other studies analyse the key determinants of fiscal rules compliance. Reuter [2019] looks at the determinants of fiscal rules compliance in the European Union from 1995 to 2005. This study shows in particular that the rule specific features (in particular its legal basis and the existence of independent monitoring and enforcement authorities), the degree of government fragmentation or the political cycle have a significant influence on whether or not the national fiscal rule is respected. Nandelenga and Ellyne [2020] implemented a similar analysis for the sub-Saharan African countries. However, neither the economic environment of the country (output gap, inflation rate, public debt or interest payments) nor the position in the economic cycle seem to play a role in national fiscal rule compliance. Moreover, combinations of fiscal rules (at national level or in addition with fiscal rules at regional or local level) do not significantly affect the compliance. Larch and Santacroce [2020] study the determinants of compliance with the supranational fiscal rule that exists in the European Union, introduced since the Stability and Growth Pact (1996). The European fiscal rules, which have been reformed several times, present different targets in terms of fiscal aggregates (deficit rule, debt rule, structural balance and expenditure). Their study covers the European Union countries from 1998 to 2019 and brings to light stark and persistent differences across countries. Their results reveals noteworthy links between numerical compliance in the one hand and some key macroeconomic variables (especially episodes of pro-cyclical fiscal policy) and that quality of governing institutions on the other (countries with “watchdogs”(Debrun et al. [2019]), i.e. national independent fiscal institutions). Nevertheless, as suggested by Reuter [2015], fiscal rules could be considered as a tool “to force governments to adjust their budgetary plans in such a way that the constrained variable is moving in the direction of the constraint”. In this case, the compliance degree and the factors explaining compliance may be considered as elements that make it possible to predict whether or not the fiscal rules will be complied with or not.

The aim of this paper is to offer an additional insight into the preventive arm of the fiscal rules in the Eurozone. We propose to deepen the analysis in this direction and are thus interested

[18] Schaechter et al. [2016].

[19] The Fiscal Rule Index (FRI) of the European Commission is calculated taking into account five criteria : 1) legal base, 2) binding character, 3) bodies monitoring compliance, 4) correction mechanisms, and 5) resilience to shocks.

in identifying the determinants of the SGP compliance and use them to forecasting it. We are therefore working on the preventive arm of SGP. To the best of our knowledge, there is no similar empirical study on the supranational fiscal rules compliance. These topics and questioning have never been approached in the literature. The adopted methodology has never been used to treat public finance problems. Indeed, in this study we propose a new machine learning model that can be used as a trigger to an alerting mechanism.

Machine learning methodologies are increasingly applied for classification and forecasting in Economics. Gogas et al. [2015] were interested in the ability of the yield curve to forecast economic activity. They forecasted the positive and negative derivations of the real US GDP from its long-run trend over the period going from 1976 to 2014. Results showed that the best SVM model outperformed the econometric one (probit model). Gogas et al. [2018] used SVM in Forecasting U.S. Bank Failures and obtained a striking 99.22% overall forecasting accuracy, outperforming the well-established Ohlson's score. Härdle et al. [2009] studied the default risk of companies with SVM and Huang et al. [2004] used SVM in forecasting corporate credit ratings for the U.S. and Taiwan. They compared SVM to back propagation neural networks (BPNN); in every case the linear SVM outperformed the competition. We are thus interested in extending the application range of Machine Learning to Public Policy Issues.

3 Data and descriptive statistics

3.1 Compliance with the Supranational Fiscal Rule in the European Union and Public Finance Statistics

In the European context, the concept of supranational fiscal rule appears in the Maastricht Treaty (1992) which launched the project of the creation of the Monetary Union and set the conditions to be satisfied to achieve it. Some of these relate to the stability of public finance that any candidate country should achieve to be accepted in the Eurozone: a) the public deficit should not exceed the 3% of the GDP and b) the pubic debt should not exceed the 60% of GDP. As soon as a candidate country is admitted to the Eurozone, it must satisfy the rules of the Stability and Growth Pact (1996) which initially only related to the threshold of 3% for the public deficit[20]. In the early 2000s, despite the supranational rules, some countries presented excessive deficits as shown by Table 1. Deficit procedures were launched against Portugal (in 2002), France and Germany (in 2003) but sanctions never applied.

[20]Nevertheless, EU-members (both Eurozone and non-Eurozone members) are concerned by SGP compliance since the European Commission requests them multiannual programs on public finance. This program provides a forecast of the level and nature of public finance for the next 3 years. Countries that belong to EU but not the Eurozone, are expected to provide "stability programs" every year; countries belonging to the Eurozone must provide "convergence programs". Public finance of all EU countries are thus monitored. In the event of bad public finance trajectories, the European Commission will provide recommendations so that the States rectify the deficiencies. No deadline was initially imposed for these programs and monitoring was not as thorough as in the SGP's latest version.

Table 1: **Public budget balance in EMU members from 1999 to 2004 (in % of GDP)**

Countries	1999	2000	2001	2002	2003	2004
Austria	-2,6	-2,4	-0,7	-1,4	-1,8	**-4,8**
Germany	-1,7	-1,6	-3,0	**-3,9**	**-3,7**	**-3,3**
Belgium	-0,6	-0,1	0,2	0,0	-1,9	0,2
Spain	-1,2	-1,2	-0,5	-0,3	-0,4	-0,1
Finland	1,7	6,9	5,0	4,1	2,4	2,2
France	-1,6	-1,3	-1,4	**-3,2**	**-4,0**	**-3,6**
Greece	**-5,8**	**-4,1**	**-5,5**	**-6,0**	**-7,8**	**-8,8**
Ireland	3,5	4,8	0,9	-0,5	0,3	1,3
Italy	-1,8	-2,4	**-3,2**	-2,9	**-3,2**	**-3,5**
Luxembourg	3,1	5,5	5,7	2,0	0,3	-1,4
Netherland	0,3	1,2	-0,5	-2,1	**-3,1**	-1,8
Portugal	-3,0	**-3,2**	**-4,8**	**-3,3**	**-5,7**	**-6,2**
Danemark	0,9	1,9	1,1	0,0	-0,1	2,1
Sweden	0,6	3,2	1,4	-1,4	-1,2	0,4
United Kingdom	0,6	1,4	0,2	-1,9	**-3,1**	**-3,1**

Source: Eurostat ; Note: SGP compliance failed cases are in bold.

Several reforms (the reform of 2005, the Six Pack in 2011, the Two Pack in 2013) subsequently attempted to strengthen both the preventive arm (be able to have public finance at balance in the medium term) and the dissuasive arm (rules to respect and excessive deficit procedure yielding a financial sanction[21]) of the Stability and Growth Pact. The main idea is to foster public budget balance in the medium term. Indeed, such a procedure makes it possible to prevent non-compliance with the rule of 3% in the event of deterioration of the economic situation. Thus, country monitoring has been strengthened in recent years regarding public deficit structural and cyclical features. One of the key objective of the Macroeconomic Imbalances Procedure (MIP) scoreboard introduced with the Six Pack (2011) was to identify any risk of internal and external imbalances in the country that could destabilize public finance for a long time. This scoreboard covers primary and auxiliary indicators: i) external imbalances and competitiveness indicators: current account balance (3 year average), net external investment position (in % of GDP), real effective exchange rate (3 year % change), export market shares (5 year % change) and nominal unit labor cost (3 year % change); ii) internal imbalances indicators: house price index deflated (1 year % change), private sector credit flow consolidated (% of GDP), private sector debt consolidated (% of GDP), general government sector debt (% of GDP), unemployment rate (3 year average), total financial sector liabilities non-consolidated (1 year % change).

Unfortunately all these new measures seem insufficient to assess the risk for a country of exceeding the 3% threshold: many countries have continued to violate the rule as shown in Figure 1 and Table 2. We are interested in the preventive instrument, searching for the best indicators to forecast the 3% rule compliance. We are thus concerned by the reasons why the SGP is still not satisfied after all its reforms. In this paper, we focus our analysis on the 28 EU members over the period 2006-2018 which follows the first SGP reform and includes the two other reforms. Such choice allows us to look at the government efforts in response to SGP's reforms to have a complete dataset[22].

Figure 1 plots the SGP compliance of the 28 European countries between 2006 and 2018. It highlights high heterogeneities in government behavior regarding the SGP. As pointed out by

[21] ranging between 0.5% and 2% of the GDP if noncompliance is observed

[22] Many macroeconomic variables that we use are not complete until after 2005, and our algorithm is very sensitive to missing values.

the European Commission[23], the European Fiscal Framework and the SGP have become too complex. It appears difficult for a country to comply with all the SGP rules at the same time. The task of implementing a fiscal policy that takes care of all the MIP indicators and complies with the SGP goals simultaneously seems hardly possible. To make it worse, since the early 90's, national fiscal rules in the EU have substantially increased, adding one more layer of rules to comply with.

Note: "0" means SGP non-compliance and "1" means SGP compliance.

Figure 1: **SGP compliance in the 28 EU countries between 2006 and 2018**

Table 2 depicts an overview of public finance statistics and the SGP compliance. This heterogeneity of public finance reinforces what we found in Figure 1: it appears difficult for every Member States to behave identically towards the SGP. Countries as Luxembourg, Estonia or Sweden complied with the SGP during the period under study while France succeeded only 4

[23] See the European Commission website and communication on EU governance review

Table 2: **Public Finance Statistics in European Countries between 2004 and 2018**

Key indicator	Mean	Country with best value	Country with worst value
3 % limit compliance (in %)	63,70	Estonia, Luxembourg, Sweden (complied with the rule each year)	France (complied with the rule only 4 times)
Public Budget Balance (in % GDP)	-2,556	Finland in 2008: 5,129 (highest public balance over the period)	Ireland in 2011: -32,028 (highest public deficit over the period)
General government gross public debt (in % GDP)	58,69	Estonia in 2009: 3,664 (lowest public debt over the period)	Greece in 2017: 183,45 (highest public debt over the period)
Gross fixed capital formation (in % GDP)	21,96	Slovak Republic in 2009: 37,4 (highest GFCF over the period)	Hungary in 2015: 11,5 (lowest GFCF over the period)

times (in a third of the cases). As the Member States react differently to the same symmetrical shocks (Frenkel and Nickel [2002], Velickovski and Stojkov [2014], Bk and Maciejewski [2017]), they also react differently to a single and general fiscal rule. The European Commission is already applying the idea during the European Semester providing country-specific recommandations for public finance plans.

Even if the SGP failed in 36% of the cases[24], the sanctions were never applied to avoid the worsening of the economic situation of the Member State under scrutiny. Ireland highlighted a 32% of GDP public deficit during the Sovereign Debt Crisis and financial sanctions were never applied in the event of such difficulties. The major problem, if we let the deficit slip away, is that the debt can become too large. For example, the public debt of Greece was close to 200% in 2017, putting the EMU under the risk of a domino effect.

We can derive two conclusions from these findings: i) the low percentage of SGP success is a direct indication that the current form of the SGP monitoring should change, and ii) the tools of the dissuasive arm cannot be applied for fear of worsening the macroeconomic status of the EU member under control. A simple solution would be to improve the monitoring and revise the recommendations. We thus could improve the preventive arm of the SGP, focusing on the forecasting and monitoring process.

So, in our analysis we consider that i) a simpler rule would be more easily maintained by the Member States, ii) the focus should be placed on the preventive arm, iii) the key features that lead to the non-compliance should be identified. In these lines, we focus only on the initial and simpler "SGP 1.0" (as called in Debrun and Jonung [2019] which corresponds only to the 3% limit on public deficit) compliance. The proposed forecasting methodology has two steps : i) the identification of the key features for compliance using a feature selection procedure, ii) the training of a machine learning model that can accurately forecast the compliance with the rules one year in advance, giving the Member State enough time to change the outcome.

3.2 Fiscal rules compliance: potential predictors

We have tried to create a dataset containing all the potential features for forecasting the SGP compliance. Table 3 describes all the variables in our dataset. We used data for the 28 Euro-

[24]This finding about the SGP compliance is not surprising since similar findings exist for fiscal rules compliance in national level. Both show poor compliance. Despite the "Magnet-effect " of national fiscal rules, Eyraud et al. [2018] pointed out the "poor track record of compliance" with fiscal rules. Similarly, Reuter [2015] showed that governments make efforts to move closer to their national fiscal rules limit but in the end, in just 51% of the cases they successfully comply with the fiscal rules.

pean Union members for a period from 2006 to 2018. Our variables are divided into 3 groups namely Country Specific Variables, MIP scoreboard indicators, other Macroeconomic Variables. Basically, the MIP scoreboard is a good starting point since it contains variables intended to prevent external and internal imbalances[25] and offers many complete series of macroeconomic variables available for our study period. Nevertheless, the MIP scoreboard main objective is not to forecast the SGP compliance. We thus have collected more variables to complete our dataset.

We take into account the country characteristics using the following Country Specific Variables: a Dummy variable reflecting if the country was an Advanced[26] country in t-p and a Dummy variable reflecting if the country was an Emerging country in t-p; a Dummy variable reflecting if the country was a Resource-rich country in t-p, a Dummy variable indicating if the country was an EU Member in t-p, a Dummy variable reflecting if the country was a Federal Country in t-p (X1 to X5). With the Dummy variable reflecting if the country was a Eurozone member in t-p (X6) we check if the Eurozone members comply with the rule more often than non-Eurozone members. We also checked if the formal procedure provided by the SGP makes a difference (X7).

The MIP scoreboard primary and auxiliary indicators are included using variables X8 to X38 and the macroeconomic variables that are not monitored by the European Commission for internal imbalance are variables X39 to X47.

X39 is a binary dummy variable indicating the presence of an economic crisis. This is a simple but broad indicator that captures all potential changes in an economy. Then, we follow Wiese et al. [2018] who proposed a measure for governments fiscal volatility using the Bai-Perron structural break filter. We thus test for the presence of structural breaks identified by the Bai and Perron test in structural balance for each country (X46). Furthermore we use variables for Oil Prices, bonds yield, foreign currency and long-term sovereign debt ratings[27]. The fiscal space is simply measured as the difference between the public debt level of a country and the European Union median one (e.g. Cheng and Pitterle [2018] for an overview of fiscal space definitions). We have also introduced an indicator of the macroeconomic cycle (output gap is measured by the production function approach) which appears correlated with. In Reuter [2019] the output gap did not appear as an important determinant for national fiscal rule compliance while Larch and Santacroce [2020] highlighted a significant correlation between the output gap and SGP fiscal rules compliance. But the SGP provides escape clauses. We thus expect crises and cyclical fluctuations to have an impact on the forecasting of fiscal rules compliance.

The European Commission and the IMF rate the fiscal rules rigor (the fiscal rules rigor reflects its theoretical coercitive power) by proposing the Fiscal Rules Indices. The European Commission's national Fiscal Rules Strength Index (FRSI) consider the main features of fiscal rules: legal basis (is the rule written as a law or is it a government commitment?), level of public finance coverage (does the rule applies to all public administrations or just central government?), enforcement procedure (does the rule imposes sanctions?), the presence of a monitoring institution (is there an independent fiscal "watch dog" in charge of fiscal rules good-conduct?), stabilization power (does the rule exclude public investment of cyclical components?). By applying a standardization procedure to these scores, the European Commission is able to provide the FRSI, a strength index for each national (and subnational) fiscal rule. In a nutshell, from a methodological point of view, the European Commission calculates the FRSI, which measures the strength index of each fiscal rule separately, whereas the FRI (used in our study) provides an aggregate version of the strength index of all fiscal rules at all levels of government in a given

[25]See Eurostat website's definition of MIP scoreboard

[26] IMF uses several criteria to elaborate countries classification. Among these, the three main ones are: per capita income level, export diversification and degree of integration into the global financial system.

[27]index from 1 to 21 coming from "A Cross-Country Database of Fiscal Space" of World Bank (2019)

country. We thus include the European Commission's FRI to test the hypothesis that countries implementing -in parallel- strong national fiscal rules are more likely to comply with the 3% rule of SGP. Following Annett [2000] and using the Database of Political Institutions from World-Bank, in variable X47 we calculate a measure of government fragmentation which reflects the dispersion of parties within the parliament[28]. We want to check if government fragmentation is related to the SGP compliance. Y is our binary dependent variable describing if a country complies with the SGP (3% limit) in year t. We are trying to forecast Y_t using lagged values of the 47 variables in our dataset $X_{i,j}, i = 1, ..., 47, j = t-1, t-2, t-3$.

[28] We used the Annett [2000] definition of society fractionalization applying to Government fractionalization : $Fractionalization = 1 - \sum_{i=1}^{M} \left(\frac{n_i}{N}\right)^2, \quad i = 1, ..., M$
with N the total number of seats in the country parliament, n_i is the number of seats belonging to the i-th party. Government fractionalization is thus defined as the probability that two randomly chosen deputies come from two different parties (that also corresponds to World bank definition of government fragmentation).

Table 3: **Variables Overview**

Variables	Correspondance Variables	Source/Database	
Y	Dummy variable =1 if 3% limit was complied in t	Authors' calculations	
X1	Dummy variable reflecting if the country was an advanced country in t-p	IMF Fiscal Rules Database	Country Specific Variables
X2	Dummy variable reflecting if the country was an Emerging country in t-p	IMF Fiscal Rules Database	
X3	Dummy variable reflecting if the country was a Ressource-rich country in t-p	IMF Fiscal Rules Database	
X4	Dummy variable reflecting if the country was an EU membership in t-p	IMF Fiscal Rules Database	
X5	Dummy variable reflecting if the country was a Federal Country in t-p	IMF Fiscal Rules Database	
X6	Dummy variable for Eurozone entrance in t-p	IMF Fiscal Rules Database	
X7	Dummy variable reflecting if the country was submitted to an enforcement procedure related to the supranational fiscal rules in t-p	IMF Fiscal Rules Database	
X8	Gross domestic product, deflator, in t-p	Eurostat	MIP Scoreboard Primary and Auxialiary indicators
X9	Total investment in t-p	Eurostat	
X10	Gross national savings in t-p	Eurostat	
X11	Inflation, average consumer prices, in t-p	Eurostat	
X12	Population in t-p	Eurostat	
X13	General government revenue in t-p	Eurostat	
X14	General government total expenditure in t-p	Eurostat	
X15	General government net lending/borrowing in t-p	Eurostat	
X16	General government gross debt in t-p	Eurostat	
X17	Net External Positions in t-p	Eurostat	
X18	Current account balance in t-p	Eurostat	
X19	Current account balance variations over 3 years in t-p	Eurostat	
X20	Real Effective Exchange Rate in t-p	Eurostat	
X21	Global export market share -% change over 5 years - in t-p	Eurostat	
X22	Nominal unit wage cost -% change over 3 years - in t-p	Eurostat	
X23	Debt of private sector in t-p, consolidated -% of GDP	Eurostat	
X24	Liabilities of the financial corporations sector, -% change over 1 year - in t-p	Eurostat	
X25	Unemployment rate - 3-year average - in t-p	Eurostat	
X26	Unemployment rate in t-p	Eurostat	
X27	Gross domestic product (real GDP) -% change over 1 year - in t-p	Eurostat	
X28	Gross fixed capital formation in t-p -% of GDP -	Eurostat	
X29	Gross domestic expenditure on R & D in t-p -% of GDP -	Eurostat	
X30	Direct investment in the reporting economy (flow) in t-p -% of GDP -	Eurostat	
X31	Direct investment in the reporting economy (stocks) -% of GDP	Eurostat	
X32	Net trade balance of energy products in t-p -% of GDP -	Eurostat	
X33	Real effective exchange rate, Euro area trading partners -% change over 3 years	Eurostat	
X34	Terms of trade (goods and services) -% change over 5 years - in t-p	Eurostat	
X35	Market share of world exports, volumes -% change over 1 year - in t-p	Eurostat	
X36	Labor productivity -% change over 1 year - in t-p	Eurostat	
X37	Residential construction in t-p -% of GDP -	Eurostat	
X38	Employment -% change over 1 year - in t-p	Eurostat	
X39	Dummy variable reflecting if there is a Crisis in t-p	Author's research	Other Macroeconomic Variables
X40	Output gap (production function approach) in t-p	AMECO Database	
X41	Oil Prices in t-p	FED	
X42	Bonds yield in t-p		
X43	Foreign currency long-term sovereign debt ratings, index from 1-21 , in t-p	*World Bank*[1]	
X44	Fiscal Space in t-p	Author's calculations	
X45	Fiscal Rules Index (by European Commission) in t-p	European Commission fiscal rules Database	
X46	Structural Breaks in t-p	Author's calculations (using Bai and Perron test)	
X47	Government fragmentation in t-p	*World Bank*[2]	

Note: [1]A Cross-Country Database of Fiscal Space, 2019.
[2]Database of Political Institutions.
Y is the Dependent variable. X are potential predictors tested in the feature selection step. All variables used as predictors are a p lagged variable. We test for $p = 1, 2, 3$ for each feature. 47 variables are included considering 3 lagged so 141 features are tested.

4 Empirical strategy

We conducted three sets of tests. In each set we used the best SVM model and compared it with the best logit model using the same dataset. First, we used just the main primary indicators of the MIP scoreboard as input variables. We wanted to check if these indicators, which are able to prevent internal (and external) imbalances could also be related with the SGP compliance. Then we tested our framework with the complete dataset of Table 3. If the second model outperforms the first one, it will be a direct indication that the MIP scoreboard is not enough to forecast SGP compliance. In the third set of tests we couple a well established feature selection method with our forecasting scheme, to identify just the necessary variables for our model.

4.1 Forecasting algorithms

4.1.1 The logistic function

In our analysis, we conducted tests using both a traditional econometric method (Logit) and an emerging methodology in Economics from the Machine Learning field (Support Vector Machine). Our goal is to create the most accurate forecasting model.

Our forecasting problem is transformed into a binary classification setup: we must forecast whether the countries in our dataset will comply with the rule (class 1) or not (class 0) $Y \in \{0; 1\}$. The goal of our system is to use the input variables to find the linear or non-linear separator that correctly classifies the cases.

The collected data are represented by $x_{i,j}, i = 1, \cdots, n$ and $j = 1, \cdots, m$, describing $n = 364$ datapoints with $m = 141$ features, arranged in vectors $\mathbf{x}_i = [x_{i,1}, \cdots, x_{i,141}]^T$. The logistic function constrains Y in a range of $(0, 1)$ and uses the sigmoid function :

$$p(y_i = 1) = \pi_i = \frac{exp^{\hat{\mathbf{x}}_i^T \boldsymbol{\beta}}}{1 + exp^{\hat{\mathbf{x}}_i^T \boldsymbol{\beta}}} \tag{1}$$

where $\hat{\boldsymbol{x}}_i = [1, \mathbf{x}_i^T]^T$ corresponds to a feature-column (the 1 corresponds to the intercept of the regression) and $\boldsymbol{\beta}$ is the column vector of the regression coefficients.

The classifier produces a probability score between 0 and 1. When the probability is lower than 0.5 the datapoint is put into class 0; when the probability is higher or equal to 0.5 the datapoint is put into class 1.

The goal is to find the $\boldsymbol{\beta}$ according to $p(Y|X)$ that most accurately classifies correctly the observed data points. The problem is equivalent to maximizing the product of the likelihood probabilities:

$$\begin{aligned} l(\boldsymbol{\beta}) &= \sum_{i=1}^{n} [y_i log(\pi_i) + (1 - y_i) log(1 - \pi_i)] = \sum_{i=1}^{n} [\ y_i\ log(\frac{\pi_i}{1 - \pi_i}) + log(1 - \pi_i)] \\ &= \sum_{i=1}^{n} [y_i \hat{\boldsymbol{x}}_i \boldsymbol{\beta} - log(1 + exp^{\hat{\boldsymbol{x}}_i \boldsymbol{\beta}})] \end{aligned} \tag{2}$$

4.1.2 The Support Vector Machine (SVM)

a) The Support Vector Machine in linearly separable cases

SVM is a supervised machine learning method[29] for the binary classification of a set of data points. SVM aims at identifying a small subset of data points from the initial dataset, called Support Vectors, that define the position of the linear separator between the two classes.

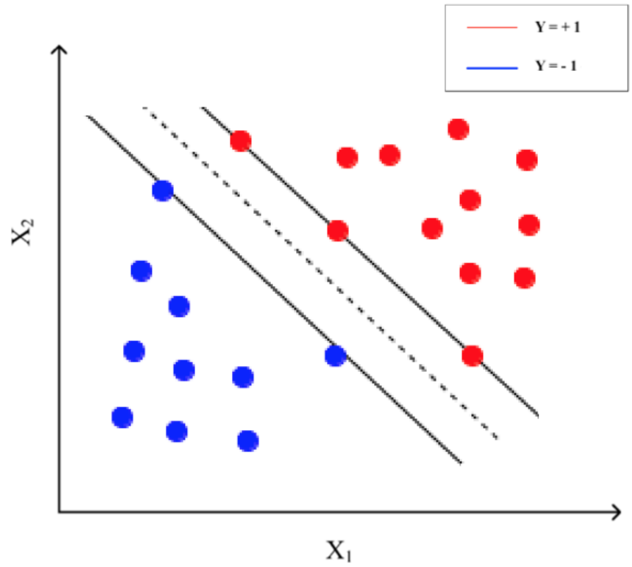


Figure 2: **Hyperplane and Support Vectors**

Consider y_i as the binary outcome taking the value of -1 or 1 (in the logistic model y_i takes the values 0 and 1). If the two classes are linearly separable, the separator is defined by:

$$f(\mathbf{x}_i) = \mathbf{w}^T \mathbf{x}_i - b = 0 \tag{3}$$

where $\mathbf{x}_i$ is the $i-th$ m-sized data point (for our tests the datapoints are $i = 1, \cdots, 364$ and the features are $m = 141$) ; $\mathbf{w}$ is the weight vector, b is the bias. In that sense all data satisfy:

$$\begin{aligned} &\mathbf{w}^T \mathbf{x}_i - b > 0 \quad if \quad y_i \in +1 \\ &\mathbf{w}^T \mathbf{x}_i - b < 0 \quad if \quad y_i \in -1, \qquad y_i f(\mathbf{x}_i) > 0 \end{aligned}$$

Ideally, the optimal separator is defined as the decision boundary that classifies each data point to the correct subspace and has the maximum distance from each class. This distance is often called "margin" and corresponds to the exact distance of the hyperplane with each class.

[29]Supervised learning is the concept where given a set of data and a set of observations, an algorithm creates a mapping function which describes the relationship from the data to the observations.

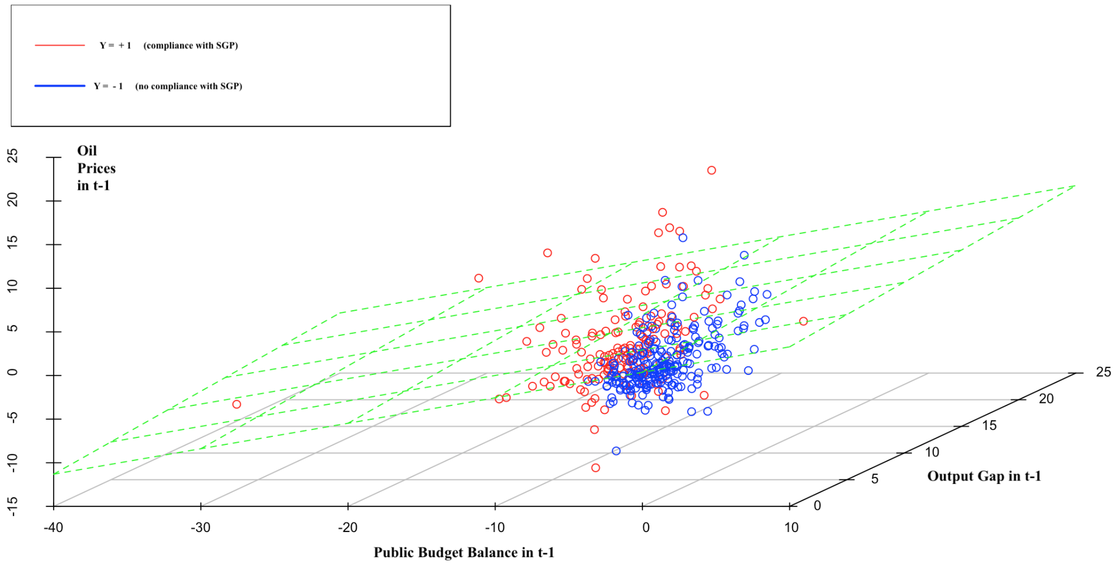


Figure 3: **Search for optimal linear separator hyperplane in the 3D data space of our dataset**

In Figure 2 and Figure 3 we provide a representation for the case of two and three dimensional systems[30]. The different colors of the data points correspond to the two classes of our dataset. In Figure 2 the linear separator corresponds to the dashed line, the margin lines corespond to the continuous lines, the Support Vectors are the point that lie in one of the margin lines.

The separating hyperplane is identified using the Lagrange relaxation of a quadratic problem:

$$\min_{\mathbf{w},b} \max_{\mathbf{a}} \left(\frac{1}{2} \|\mathbf{w}\|^2 - \sum_{i=1}^{N} a_i [y_i(\mathbf{w}^T \mathbf{x}_i - b) - 1] \right) \tag{4}$$

In Equation (5) $\mathbf{a} = [a_1, .., a_n]^T$ correspond to the non-negative Lagrange multipliers. (5) is never used to calculate the solution. Instead we use the simpler dual problem described by:

$$\max_{\mathbf{a}} \left\{ \sum_{i=1}^{N} a_i - \sum_{j=1}^{N} \sum_{k=1}^{N} a_j a_k y_j y_k \ \mathbf{x}_j^T \mathbf{x}_k \right\} \tag{5}$$

with $\sum_{i=1}^{N} a_i y_i = 0$ and $0 \leq a_i, \forall_i$. By solving (6) we obtain the location of the hyperplane given that:

$$\widehat{\mathbf{w}} = \sum_{i=1}^{N} a_i y_i \mathbf{x}_i \tag{6}$$

$$\widehat{b} = \widehat{\mathbf{w}}^T \mathbf{x}_i - y_i, i \in V, \tag{7}$$

where $V = \{i : 0 < a_i\}$ is the sert of support vector indices.

[30] In our case we have more than 3 variables/features so it is impossible to show the cloud of the datapoints in full. However the 3-d representation in Fig. 3 is created using three variables taken from our dataset.

To consider a system contaminated by the presence of noise and outliers in the dataset Cortes and Vapnik [1995] introduced non-negative slack variables $\xi_i \geq 0, \forall i$ that can tolerate the misclassification of some cases. In order to keep the misclassification set as small as possible, each misclassification yields an additional financial cost in the objective function that we try to minimize.

$$\min_{\mathbf{w}b\boldsymbol{\xi}} \max_{\boldsymbol{a\mu}} \left\{ \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^{N} \xi_i - \sum_{j=1}^{N} a_j [y_j(\mathbf{w}^T \mathbf{x}_j - b) - 1 + \xi_j] - \sum_{k=1}^{N} \mu_k^T \xi_k \right\} \tag{8}$$

where the non-negative slack ξ_i correspond to the distance of vector $\mathbf{x}_i$ from the hyperplane when classified erroneously. $\boldsymbol{\mu}_k = [\mu_1, ..., \mu_n]$ are Lagrange multipliers. The optimal hyperplane is finally given by:

$$\widehat{\mathbf{w}} = \sum_{i=1}^{N} a_i y_i \mathbf{x}_i \tag{9}$$

$$\widehat{b} = \widehat{\mathbf{w}}^T \mathbf{x}_i - y_i, i \in V, \tag{10}$$

where $V = \{i : 0 < a_i < C\}$ is the set of support vector indices. Parameter C is found using power of 2 grid search and $2^{-7} \leq C \leq 2^7$.

b) The Support Vector Machine for the non linearly separable case

Real world phenomena are often nonlinear. Linear models like the SVM are unable to model these systems correctly. To overcome the problem of nonlinearity the SVM paradigm is coupled with the kernel trick. Kernels project the initial data space to a feature space of higher dimensionality. Instead of searching for the optimal separator in the data space, we look for it in the feature space and return the solution to the initial data space (see Figure 4). So when the kernel is nonlinear and although the separator in the feature space is linear (SVM yields only linear separators), the inverse projection of the separator in the data space is nonlinear. The kernel trick ensures low computational cost; the projection is performed in the inner product space [31], instead of projecting each point separately in the feature space. Introducing the kernel projection in the minimization of the objective function transform it to:

$$\max_{\mathbf{a}} = \sum_{i=1}^{N} a_i - \frac{1}{2} \sum_{j=1}^{N} \sum_{k=1}^{N} a_j a_k y_j y_k K(\mathbf{x}_j, \mathbf{x}_k). \tag{11}$$

with $\sum_{i=1}^{N} a_i yi = 0$ and $0 \leq a_i \leq C, \ \forall_i$. In our tests we investigated three kernels:

$$\textit{Linear} \qquad K_1(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j + r, \tag{12}$$

$$\textit{RBF} \qquad K_2(\mathbf{x}_i, \mathbf{x}_j) = e^{-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2}, \tag{13}$$

$$\textit{Polynomial} \qquad K_3(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i^T \mathbf{x}_j + r)^d, \tag{14}$$

Now, the rule for classifying a data point $\mathbf{x}$ is given by:

[31] kernel functions are called "generalized dot products'

$$f(\mathbf{x}) = sign\left\{\sum_{i=1}^{N} a_i y_i K(\mathbf{x}_i, \mathbf{x}) + b\right\} \tag{15}$$

Indeed, if $f(\mathbf{x}) > 0$ the point is classified as belonging to class $+1$; otherwise, it is in class -1.

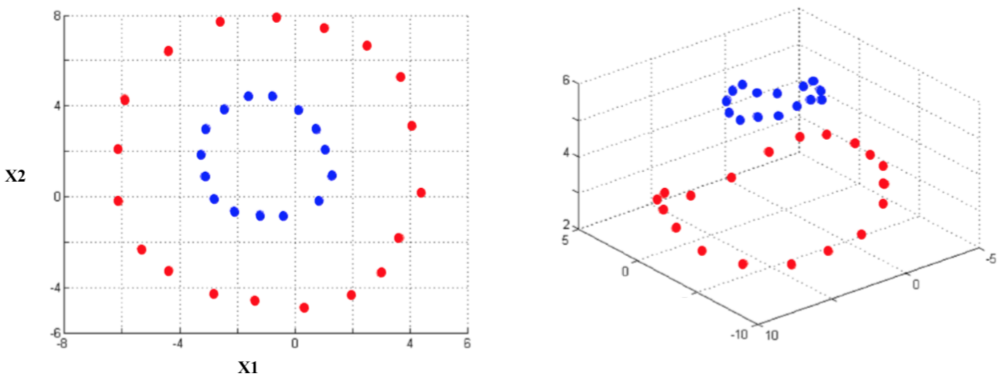


Figure 4: **Kernel projection to make the two classes linearly separable**

In Figure 4, the system in the left figure corresponds to a dataset of two non linearly separable classes. The system in the right is the projection of the same dataset in a 3D feature space that the two classes are linearly separable.

4.2 Feature Selection: The logistic LASSO

The goal of feature selection is the reduction of the feature set, by removing irrelevant or redundant features for our model. By reducing the feature set, we decrease the computational cost of training, and minimize the risk of model overfitting.

Friedman et al. [2009] proposed LASSO as a regularization alternative that overcomes the inability of ridge regression to reduce the number of predictors in the final model. LASSO applies a regularization process where the coefficients of some of the input variables are penalized and shrunk to zero. The main goal of the method is to minimize the prediction error, yielding as a by-product the feature selection of the variables.

The shrinkage operation identifies the key features from our dataset, avoiding the problem of transformation-based dimension reduction methodologies using Factor Anaysis, Principal Component Analysis or Independent Component Analysis, (to name but a few) which lead to factors that are uninterpretable.

Finally, the LASSO estimator applied in logistic regression is:

$$\hat{\beta}(\lambda) = \underset{\beta}{\operatorname{argmin}}(n^{-1}\sum_{i=1}^{n} \rho_{(\beta)}(X_i, Y_i) + \lambda||\beta||_1) \tag{16}$$

Parameter λ is found by grid search (view Appendix 1) and used the one-standard error rule. Finally we will choose the parsimonious model among the models of similar performance.

4.3 Measurement forecasting performance

The performance of our models is calculated using the forecasting accuracy defined as the ratio of the correctly forecasted observations over all the observations.

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{17}$$

where TP is the number of True Positive instances (correctly forecasted positive instances), TN is the number of True Negative instances (correctly forecasted negative instances), FP is the number of False Positive instances (incorrectly forecasted positive instances), FN is the number of False Negative instances (incorrectly forecasted negative instances). We remind that in our set-up a positive instance is a Member State that satisfied the rule in year t, while a negative instance describes the opposite case.

The forecasting accuracy is a simple and easy to use metric of the model's performance; nonetheless, it is a coarse and superficial measurement. Consider, for example, a dataset with 90 positive cases and 10 negative ones coupled with a naïve model yielding only positive forecasts. The accuracy of the model is 90%, which is quite misleading since it missed all the negative cases. The confusion matrix (Figure 5) is a deeper and richer representation of the model's performance, uncoupling the performance of the model in the two potential outcomes.

Indeed, a false positive case is damageable for the EU economy: if we incorrectly forecast that a country will comply with the SGP, no recommendations or measures will be prepared by the Commission since public finance are not expected to worsen. Too many false positive cases could jeopardize the sustainability of the entire currency area. So, it is important to create a forecasting model yielding the fewer possible false positives. This, however, should not produce the side effect of too many false negatives. The naïve example of the last paragraph describes such a trivial case. A false negative case, i.e., a country incorrectly forecasted to miss the rule, will force the Commission to recommend a set of unnecessary strict measures, that could harm the economy by reducing its fiscal capacity. So, it is important to assess the performance of the model in both the positive and the negative cases. Similar results are extracted using the Sensitivity and Specificity metrics of the model.

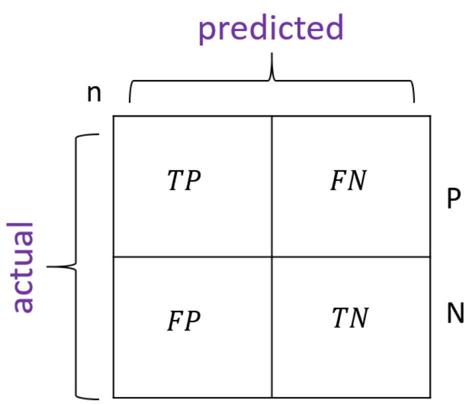


Figure 5: **The confusion matrix**

4.4 Robustness

Machine Learning methodologies are, in general, unaffected by the reverse causality bias, which is a common problem in classic econometrics. They suffer, though, from the curse of overfitting: a common error occurring when the model learns to describe the training data instead of the phenomenon at hand. Overfitting can be avoided using the Hold-Out Validation and the more powerful K-fold Cross Validation approach. In Hold-Out Validation the dataset is split into a 'training' set and 'test' set. The model is trained on the training set and the test set is used to evaluate the generalization performance of the model on unknown data. If the training accuracy is much higher than the testing accuracy, it is a strong indication that the model overfit the training dataset. Usually, we use around 80% of the data for the training and the rest for testing. K-fold Cross Validation repeats Hold-Out k times. Indeed, our data set is split up into k equally sized subsets and the training-testing steps are implemented k times. At each turn, a different subset is used as the 'test' set, whereas the rest of the k-1 subsets are grouped and constitute the 'training' set. The average performance from every fold is used to obtain the optimal model.

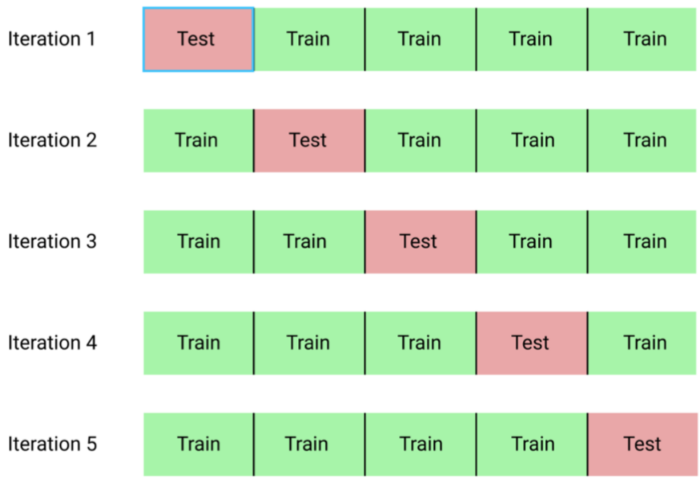


Figure 6: **5-fold cross validation example**

5 Results

5.1 Forecasting the SGP compliance

We tested every dataset using the SVM classification setup coupled with three kernels (the linear, the RBF and Polynomial one). We used the performance of the logistic regression on the same datasets as a benchmark for our ML models. In the first step of our study, we trained our models using the primary indicators of the MIP scoreboard. The goal was to evaluate the ability of the MIP scoreboard to forecast the compliance with the 3% rule. Then we performed the same training scheme using the whole 141 variables dataset. The results in the first two sets are reported in table 4.

Table 4: **"Compliance with 3% limit" forecasting accuracy: comparison of models (%)**

Model	MIP scoreboard Primary indicators included	All features included (141)	MIP scoreboard Primary indicators included	All features included (141)
Linear SVM model	64.6	83.5	85.1	87.0
Quadratic SVM model	69.5	83.0	79,6	88.9
RBF SVM	62.9	80.2	77,8	88.9
Logistic model	63.7	75.5	75.9	73.3
Validation method	k-Fold Cross Validation	K-fold Cross Validation	Hold-out	Hold-Out

Note: Hold-out splits up dataset into a 'trainset' (85%) and 'testset' (15%). Results are on testset. k-Fold Cross Validation is a 5-Fold Cross Validation and gives mean results. Parameter C in SVM is equal to 2^1 and obtained using power of 2 grid search.

Comparing the performance of the models trained on the two datasets, it is easy to verify that the full dataset models dominantly outperformed the MIP scoreboard primary indicators models in almost every case. In the MIP scoreboard dataset using the Hold-Out validation method the SVM coupled with the linear kernel achieved the top performance reaching 85.1% accuracy (the linear model fed with the full dataset using Hold-Out validation achieved 87%). In the full dataset the SVM models equipped with the non-linear kernels (the quadratic and the RBF kernel) using the Hold-Out validation both achieved 88.9% forecasting accuracy, which is the top performance achieved by any type of model using the Hold-Out validation. In the case of the strict Cross-Validation, the improvement of using the full dataset over the MIP scoreboard dataset is more impressive. The accuracy of the models using the MIP scoreboard on Cross-Validation ranges from 62.9% in the case of the RBF-SVM model, to 69.5% in the case of the Quadratic kernel-SVM model; the accuracy of the models using the full dataset on Cross-Validation ranges from 75.5% in the case of the logit model, to 83.5% in the case of the linear-SVM model (the top performance using the Cross-Validation). The hard evidence from the models' performance suggest that the full dataset has more forecasting power than the MIP scoreboard primary indicators. The next step of our study is to identify the variables of the full dataset that creates this advantage over the MIP scoreboard using the LASSO feature selection method.

LASSO Feature selection[32] highlithed a set of 12 key variables that are essential to forecast SGP compliance. Following Gogas et al. [2018] we used a second-step shrinking procedure. These selected variables were introduced into the SVM forecasting model and we implement a shrinking procedure. We compared the set that includes the LASSO selected variables with all the sets generated by removing one variable from this set. We kept the optimal one and continued the procedure until no improvement could be achieved. A set of eight features was identified from this procedure (table 5):

[32] Appendix 1 reports the LASSO procedure results. Following the one-standard error rule in LASSO, 12 features were identified as important.

Table 5: **Best predictors:**

General government fiscal balance in t-1
Liabilities of the financial corporations sector, % change over 1 year, in t-1
Dummy variable reflecting if there was a crisis in t-1 and t-2
output gap in t-1
Oil prices in t-1
Bond yield in t-1
Fiscal space in t-1

The feature set is composed by a) the General Government Fiscal Balance in $t-1$ (this was to be expected since a degraded fiscal balance in one year, will eventually have an impact in the next one), b) liabilities of the financial corporations' sector in $t-1$ (the global financial crisis highlighted the dependence between the solvency of financial institutions, the quality of their liabilities and the public finance sustainability[33], c) the dummy variable reflecting the occurrence of a crisis in $t-1$ and $t-2$, indeed, economic crises have a double impact on public deficits: they induce economic recessions and they create increased investment needs (in addition, the identification of these two features is a direct indication that the SGP escape clause should be adapted to crises duration and not only focus on the fall of the GDP during recessions), d) output gap in $t-1$ (the output gap is an indicator of the position in the economic cycle – the increased GDP volatility in times of poor economic conditions impacts the public deficit and thus the SGP compliance), e) the oil price in $t-1$(the level of the oil price has led to crises directly, as in the case of 1973 and 1979, or by proxy, as in 2008 - the "yellow vests" movement, triggered in 2018 by the oil prices in France, revealed once more the consequences on the public deficit that such situations can create), f) bond yield in t-1 and g) fiscal space in $t-1$ (both variables are related to the fiscal flexibility of a government, especially in periods of crises - this is in line with the Romer and Romer [2018] study that highlighted the importance of fiscal space during financial crises and normal recessions). In table 6, we report the performance of the feature set in every type of models and for both validation cases.

[33]For one, we note that commercial banks hold large quantities of treasure bills

Table 6: **"Compliance with 3% limit" forecasting accuracy with only Best Predictors(%)**

Model	Features selected by LASSO included	Features selected by LASSO included
Linear SVM model	90.4	98.1
Quadratic SVM model	84.6	87.0
RBF SVM ($\gamma = 12$)	86.5	88.9
Logistic model	78.5	76.3
Validation method	k-Fold Cross Validation	Hold-out

Note: Hold-out splits up dataset into a 'trainset' (85%) and 'testset' (15%). Results are on testset. k-Fold Cross Validation is a 5-Fold Cross Validation and gives mean results. Parameter C in SVM is equal to 2^1 and obtained using power of 2 grid search.

The models created using the selected features achieved the top performance in both types of validation (98.1% in the case of Hold Out Validation and 90.4% in the case of K-Fold Cross Validation) using the linear SVM model. We remind that the reported performance for Cross Validation is the mean testing accuracy of the 5 folds. Furthermore, we tested the top performing model in the whole dataset (all the observations) and achieved 91.7% forecasting accuracy. The confusion matrix of this case can be found in Figure 7.

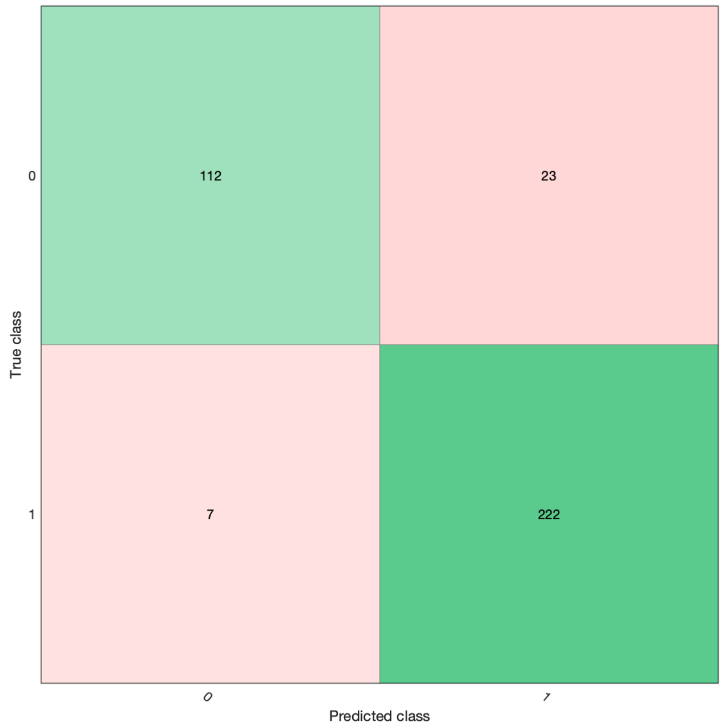


Figure 7: **Linear SVM confusion matrix (Hold-out Cross Validation)**

The confusion matrix revealed that the model forecasted correctly 112 of the 135 negative cases that a Member State did not comply with the 3% rule, while it kept the false alarms in relatively low levels: 7 false alarms in 229 positive cases (a false alarm happens when the model inaccurately forecasts the non-compliance with the 3% rule). So, the model displays high accuracy in identifying the non-compliance, while keeping in low levels the cases that a Member State will be given recommendations for unfounded reasons (false alarms).

It may be risky to make assessments on the testing sets using the presented scenarios (the models may be slightly suboptimal due to the use of grid search on the identification of the model hyperparameters), but there is a strong indication that the main MIP Scoreboard indicators dataset was the least successful: it does not appear as appropriate for monitoring internal imbalances compared to the LASSO feature set. Nevertheless, to be fair, the MIP Scoreboard indicators were not introduced, specifically, to monitor the SGP compliance.

Moreover, some of these indicators are defined over several years and thus increase the complexity for monitoring through them. In this sense, our advanced indicators used in the linear SVM model could provide a powerful tool to reinforce the European Fiscal framework surveillance with simple variables.

If we try to analyse the model performance in a national level, we encounter the following missed negative cases[34]: Belgium (2009 and 2011), Bulgaria (2014), Croatia (2006, 2013 and 2015), Czech Republic (2012), Denmark (2012), Finland (2014), France (2016), Germany (2009 and 2010), Ireland (2008), Italy (2006 and 2011), Lithuania (2008), Malta (2012), Poland (2014), Slovak Republic (2006), Romania (2007 and 2018), Slovenia (2013), Spain (2008). The 12 out of the 23 cases involve the two big crises namely the Global Financial Crisis 2007-2009 and the Sovereign Debt Crisis 2010-2012. It must be noted that during these periods, the Member States are more concerned in facing the direct implications of the crisis, than complying with the SGP rules. This change of macroeconomic aiming is usually unexpected and cannot be forecasted in the lagged instances of the feature variables. Let us remind that these crises led to the introduction of the escape clause in the Six-Pack in 2011.

5.2 Distance from separator hyperplane and policy implications

Findings of Section 5.1 lead to the optimum forecasting model which corresponds to a linear decision boundary (also called separator hyperplane) that separates the SGP compliant observations from the SGP non-compliers with 91.7% accuracy using 8 explanatory variables. The analytical form of the separator hyperplane is:

$$H : 3,546 \times x_1 - 0,285 \times x_2 - 0,338 \times x_3 - 0,458 \times x_4 - 1,014 \times x_5 - 0,416 \times x_6 - 0,581 \times x_7 - 0,175 \times x_8 + 0,793 = 0 \quad (18)$$

where x_1 corresponds to the General government fiscal balance in $t-1$, x_2 the Liabilities of the financial corporations sector (% change over 1 year) in $t-1$, x_3 Crisis dummy in $t-1$, x_4 Crisis dummy in $t-2$, x_5 the output gap in $t-1$, x_6 the Oil prices in $t-1$, x_7 the Bond yield in $t-1$ and x_8 the Fiscal space in $t-1$.

Through this identification we see several implications. First, we make the variables' impact interpretable. Indeed, the General government fiscal balance in $t-1$ is linked to a positive parameter. It is not surprising that an increase in the public balance affects positively the SGP compliance since the 3% rule is defined on the public budget balance. The parameter associated with the lagged value of Public Budget Balance is the largest one, reflecting that this

[34]Missed positive cases are the following: Bulgaria (2009), Croatia (2008), Hungary (2012), Italy (2014), Malta (2013), Slovak Republic (2013), United Kingdom (2016).

is the strongest factor with the highest influence on SGP compliance. On the other hand, crisis dummy in $t-1$ and $t-2$ has a negative influence for an observation to be in the compliance subspace. 1-year change in Financial Sector Liabiliaties (in $t-1$) is associate with a negative parameter. It is a MIP scoreboard auxiliary indicator with an indicative threshold of 16.5%. Thus, if a Member State highlights this indicator above the limit, we are in the presence of a potential imbalance. We can therefore suggest that a significant increase in this indicator favors the SGP non-compliance. We already mentionned that the Oil prices could be interpreted as an advance indicator for economic crisis as the economic history suggests. It is therefore not surprising that this variable is negatively related with the SGP non-compliance. All deviations from the economic trend reflected by change in the output gap also destabilize the public finance and decrease the SGP compliance. Bond Yields are also associated with a negative parameter. Indeed Bond Yield increases with the debt sovereign risk default (in the EU for example, Greece has the highest sovereign risk premium), it therefore seems possible that countries with high Bond Yields to run more deficit and thus less comply with the SGP. We also find a negative sign for the parameter relative to Fiscal Space suggesting that countries with more fiscal flexibility tend to increase public deficit and are less therefore expected to comply the SGP.

Second, we can use the analytical form of Equation 18 to calculate the distance between any point and the hyperplane. It is the distance that a country should be displaced to pass from the one subspace to the other. If a point is forecasted not to comply with the SGP, then the European Commission detailed recommendations should result in a displacement large enough to pass in other side. Obviously, between two “non-compliers” it is easier to change the “fate” of the country closer to the separation hyperplane, than of the one farther away. Similarly, we may use the distance in the case of a country forecasted to comply, to estimate a confidence parameter of the SGP compliance. A “complier” country close to the separator should be close monitored, since a small perturbation in the economic system or a public budget failure may displace it in the non-compliance subspace. The same alertness is not needed in the case of a country forecasted to comply with the SGP with a large distance between its point and the separator hyperplane.

If we consider one observation A with coordinates $(x_A,\ y_A,\ z_A,\ r_A,\ s_A,\ t_A,\ v_A,\ w_A)$, its distance from the separator hyperplane, is defined as follow:

$$d(A) = \frac{\mid 3,546x_A + -0,285y_A + -0,338z_A + -0,458r_A + -1,014s_A + -0,416t_A + -0,581v_A + -0,175w_A + 0,793 \mid}{\sqrt{3,546^2 + (-0,285)^2 + (-0,338)^2 + (-0,458)^2 + (-1,014)^2 + (-0,416)^2 + (-0,581)^2 + (-0,175)^2}} \tag{19}$$

Following this definition, SGP compliers distance from the decision boudary ranges from 0,00076 to 1,7305 whereas SGP non-compliers distance is between 0,0027 and 5,0717. We thus observe that some non-compliers are really far from the decision boundary as for example Ireland or Portugal in 2011, Greece from 2008 to 2013 or Slovenia in 2014. Such cases are really hard to help to run in compliance subspace, Greece is the better example that was under strict European Commsission monitoring for 10 years following the sovereign debt crisis.

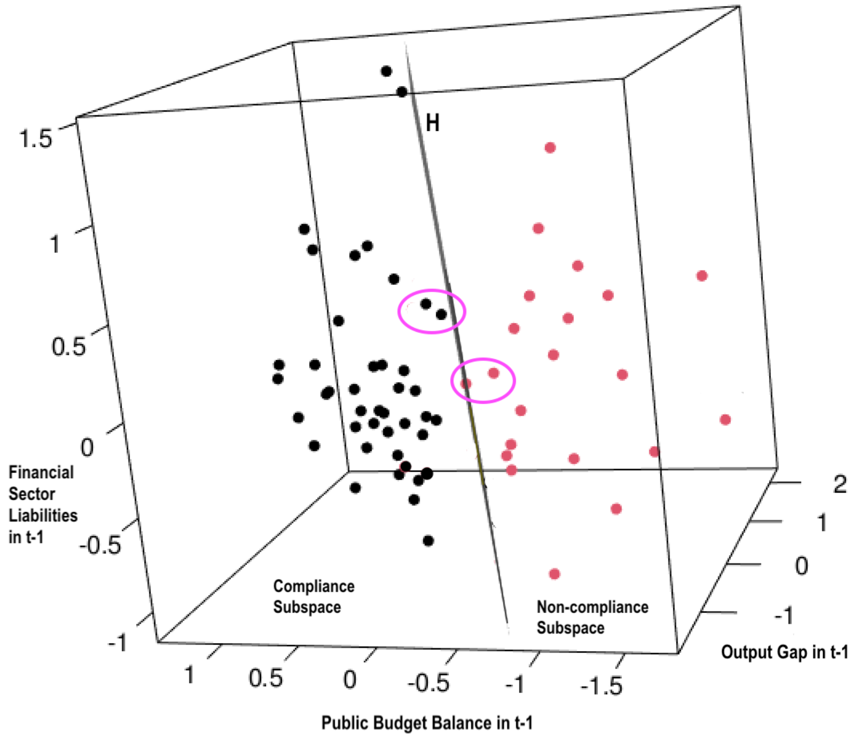


Figure 8: **Linear decision boundary in three Dimensions:**

Figure 8 shows $\frac{1}{5}$ of our dataset[35] and the linear separator hyperplane[36]. We can see that red dots circled in purple are the closest non-compliers from the Hyperplane. These observations could be easier influenced by policies to move in compliance area. These points could correspond to Belgium in 2014 or Croatia in 2012 that present low distance from hyperplane. Black dots circled in purple also require attention since they are not so "far away from the cliff" and European Commission could monitor them. Such case could correspond to the Slovak Republic in 2007 for example.

6 Conclusion

In this paper we proposed a new Machine Learning based forecasting model on the compliance with the SGP for the EU Member States. We focused our study on the public deficit rule, since a prompt forecasted breach of the 3% deficit limit can be fixed in a year. The same is not true for the public debt, which is in the heart of the third reform of the SGP. When the public debt is derailed, it needs multiannual recovery programs.

We identified a feature set of eight features from a dataset of 141 variables using the LASSO feature selection methodology. In our study, we used the Support Vector Machines model with

[35]These observations are randomly selected and we do not present all the observations to make the figure clearly legible.

[36]In Figure 8 the linear separator only integrates three dimensions of our separator hyperplane H which is in 8 dimensions, and and it is therefore summed up to $H : \alpha x + \beta y + \gamma z + b = 0$.

three kernels and used the Logit as benchmark. The top performing model, trained in a K-fold Cross Validation set-up, uses the linear kernel, and yields 91.7% forecasting accuracy in the whole dataset (forecasting accurately 112 out of the 135 cases of non-compliance and 222 out of the 229 cases of compliance).

Our findings may be examined under certain views:

First, we feed the discussion about "The Impact of Machine Learning on Economics" (Athey [2018]). Indeed, the Machine Learning models provide high forecasting power, and they should be considered in fiscal policy outcome forecasting and risk events prevention. In our case the Machine Learning models outperformed in every case (except one) their Econometrics counterpart. Our study may open the way to the use of this type of models in other macroeconomic studies.

Second, our paper could be interpreted as as a "risk-management approach" applied to fiscal surveillance and offers a solution to the need for fiscal framework simplification. Such simplification appears necessary for forecast endorsement by independent fiscal councils (Darvas et al. [2018], Debrun et al. [2019]). Our findings could lead to a first step in the European fiscal framework reform: i) MIP scoreboard indicators could be used in European Commission recommendations to help countries with their fiscal difficulties rather than for implementing excessive imbalance/deficit procedures; ii) simple advanced indicators should be implement to prevent SGP deviations and implement an alert-mechanism.

Third, we see several possibilities for future research: i) the analysis could be conducted on the Compliance Tracker Database (Larch and Santacroce [2020]) that includes data compliance with the other fiscal rules included in the SGP, such as the structural balance rule and the expenditure rule; ii) the model could also be transposed to national fiscal policy outcomes forecasting using available dataset at national level; iii) these models could also be extended to other macroeconomic outcomes in forecasting the way to achieve monitoring objectives (as in monetary policy issues and macro prudential policies).

References

A. Annett. Social Fractionalization, Political Instability, and the Size of Government. IMF Working Paper No. 00/82, 2000.

S. Athey. The Impact of Machine Learning on Economics. Chapter in NBER book The Economics of Artificial Intelligence: An Agenda, pages 507–547, 2018.

A. Barbier-Gauchard, K. Baret, and A. Minea. National Fiscal Rules Adoption and Fiscal Discipline in the European Union . Applied Economics, forthcoming, 2021.

M. Bergman, M.M. Hutchison, and S.E. Hougaard Jensen. Promoting sustainable public finances in the European Union: The role of fiscal rules and government efficiency. European Journal of Political Economy, 44:1–19, 2016.

H. Bk and S. Maciejewski. The symmetry of demand and supply shocks in the European Monetary Union. Bank i Kredyt, 2017.

O. Blanchard, A. Leandro, and J. Zettelmeyer. Redesigning the EU Fiscal Rules: From Rules to Standards. Mimeo, contribution presented to the 72nd Economic Policy Panel Meeting, 2020.

European Fiscal Board. Assessment of the fiscal stance appropriate for the euro area in 2021. Report, 2020.

F. Caselli, L. Eyraud, A. Hodge, F. Diaz Kalan, Y. Kim, V. Lledó, S. Mbaye, A. Popescu, W. H. Reuter, J. Reynaud, E. Ture, and P. Wingender. Second-Generation Fiscal Rules : Balancing Simplicity, Flexibility, and Enforceability - Technical Background Papers . Staff Discussion Notes No. 18/04, 2018.

H. W. J. Cheng and I. Pitterle. Towards a more comprehensive assessment of fiscal space. DESA Working Paper No. 153, United Nations, 2018.

European Commission. European Commission Fiscal Rules Database. 2017.

European Commission. Report on the application of the economic governance framework. Staff Working Document No 210, 2020.

T. Cordes, T. Kinda, P. Muthoora, and A. Weber. Expenditure Rules: Effective Tools for Sound Fiscal Policy? IMF Working Paper 15/29, 2015.

C. Cortes and V. Vapnik. Support Vector Network. Machine Learning, 20:273–297, 1995.

J. Creel. Ranking Fiscal Policy Rules: the Golden Rule of Public Finance vs. the Stability and Growth Pact. Documents de Travail de l'OFCE 2003-04, 2003.

T. Dabán. A Second-Generation of Fiscal Rules for Latin America. IMF Public Financial Management Blog, 2011.

Z. Darvas, P. Martin, and X. Ragot. European Fiscal Rules Require a Major Overhaul. Notes du conseil d'analyse économique, 47:1–12, 2018.

X. Debrun and L. Jonung. Under threat: Rules-based fiscal policy and how to preserve it. European Journal of Political Economy, 57:142–157, 2019.

X. Debrun, L. Moulin, A. Turrini, J. Ayuso i casals, and M. Kumar. Tied to the Mast? National Fiscal Rules in the European Union. Economic Policy, 23:297–362, 2008.

X. Debrun, M. Gerard, and J. Harris. Fiscal Watchdogs and Sound Fiscal Policy: Is the Barking Loud Enough to Tame Politicians? MPRA Paper No. 96683, 2019.

M. Delgado-Téllez, V. D. Lledó, and J. J. Pérez. On the Determinants of Fiscal Non-Compliance: An Empirical Analysis of Spain's Regions. IMF Working Paper 17/5, 2017.

L. Eyraud, X. Debrun, A. Hodge, V. Lledó, and C. A Pattillo. Second-Generation Fiscal Rules : Balancing Simplicity, Flexibility, and Enforceability. Staff Discussion Notes No. 18/04, 2018.

D. Foremny. Sub-national deficits in European Countries: The impact of fiscal rules and tax autonomy. European Journal of Political Economy, 34:86–110, 2014.

M. Frenkel and C. Nickel. How Symmetric Are the Shocks and the Shock Adjustment Dynamics Between the Euro Area and Central and Eastern European Countries? IMF Working Papers, 2002.

J. Friedman, T. Hastie, and R. Tibshirani. Regularization for Generalized Linear Models via Coordinate Descent. Department of Statistics Stanford University, 2009.

P. Gogas, T. Papadimitriou, and E. Chrysanthidou. Yield Curve Point Triplets in Recession Forecasting. International Finance, page 207–226, 2015.

P. Gogas, T. Papadimitriou, and A. Agrapetidou. Forecasting bank failures and stress testing: A machine learning approach. International Journal of Forecasting, 34:440–455, 2018.

M. Guerguil, P. Mandon, and R. Tapsoba. Flexible fiscal rules and countercyclical fiscal policy. Journal of Macroeconomics, 52:189–220, 2017.

S. Hauptmeier and C. Kamps. Debt rule design in theory and practice - the SGP's debt benchmark revisited. Presentation at ECFIN workshop "Fiscal rules in Europe", 2020.

Z. Huang, H. Chen, C-J. Hsu, and W-H. Chen ans S. Wuc. Credit rating analysis with support vector machines and neural networks: a market comparative study. Decision Support Systems, 37:543–558, 2004.

W. Härdle, Y-J. Lee, D. Schäfer, and Y-R. Yeh. Variable Selection and Oversampling in the use of Smooth Support Vector Machines for Predicting the Default Risk of Companies. Journal of Forecasting, 28:512–534, 2009.

IMF. Fiscal Rules—Anchoring Expectations for Sustainable Public Finances. Fiscal Affairs Department, IMF Policy Paper, 2009.

H. Ince and T. Trafalis. A Hybrid Model for Exchange Rate Prediction. Decision Support Systems, 42:1054–1052, 2006.

G. Kopits and S.A. Symansky. Fiscal Policy Rules . Occasional Paper No. 162, 1998.

M. Larch and S. Santacroce. Numerical compliance with EU fiscal rules: The compliance database of the Secretariat of the European Fiscal Board (Database). 2020.

M. Larch, E. Orseau, and W. van der Wielen. Do EU Fiscal Rules Support or Hinder Counter-Cyclical Fiscal Policy?). Journal of International Money and Finance, In Press, Journal Pre-proof, 2020.

M. Wafula Nandelenga and M. J. Ellyne. Fiscal Rules and the Compliance debate: Why do Countries adopt Rules and fail to comply. ERSA Working Paper No 815, 2020.

V. Plakandaras, T. Papadimitriou, and P. Gogas. Directional Forecasting in Financial Time Series using Support Vector Machines: The US/Euro Exchange Rate. Journal of Computational Optimization in Economics and Finance, 5:125–139, 2013.

W.H. Reuter. National numerical fiscal rules: not complied but still effective? European Journal of Economy, 39:67–81, 2015.

W.H. Reuter. When and why do countries break their national fiscal rules? European Journal of Political Economy, 57:125–141, 2019.

C. D. Romer and D. H. Romer. Phillips Lecture – Why Some Times Are Different: Macroeconomic Policy and the Aftermath of Financial Crises. Economica, 85:1–40, 2018.

A. Sacchi and S. Salotti. The impact of national fiscal rules on the stabilisation function of fiscal policy. European Journal of Political Economy, 37:1–20, 2015.

A. Schaechter, T. Kinda, and N. Budinaand A. Weber. Fiscal Rules in Response to the Crisis—Towards the 'Next-Generation' Rules. A New Dataset). IMF Fiscal Affairs Department, 2016.

A. Schick. Post-Crisis Fiscal Rules: Stabilising Public Finance while Responding to Economic Aftershocks. OECD Journal on Budgeting, 2010.

R. Tapsoba. Do National Numerical Fiscal Rules really shape fiscal behaviours in developing countries? A treatment effect evaluation. Economic Modelling, 29:1356–1369, 2012.

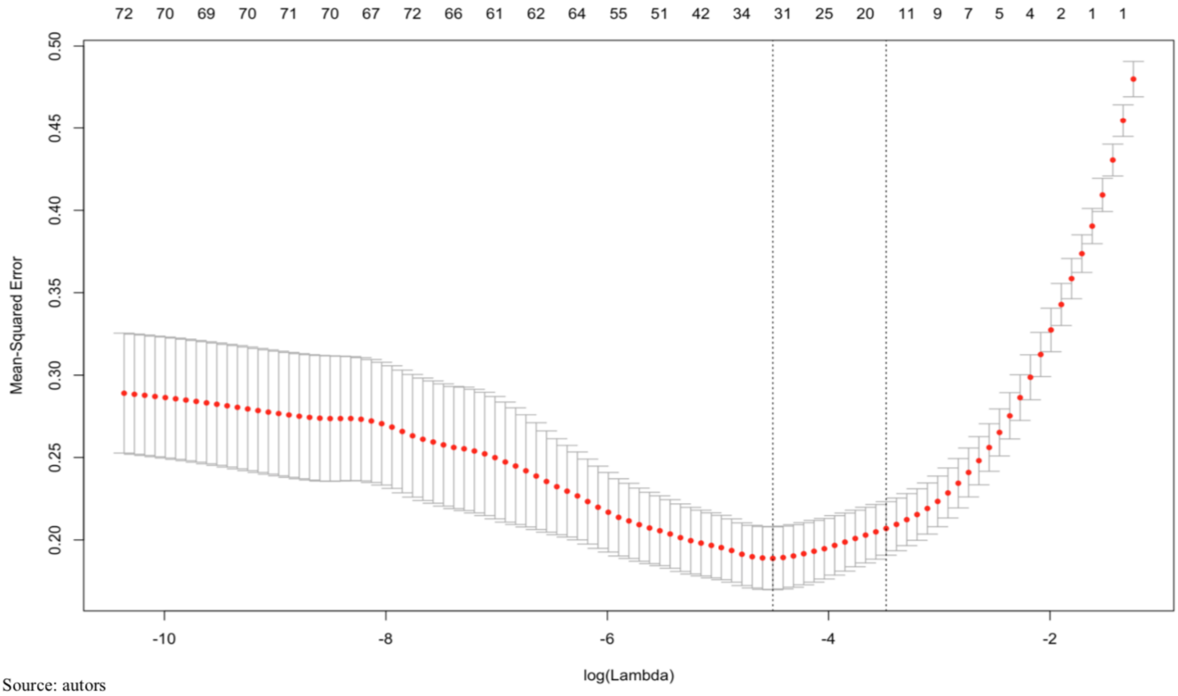
I. Velickovski and A. Stojkov. Is the European integration speeding up the economic convergence process of the Central and South-Eastern European countries? A shock perspective. Empirica, pages 287–321, 2014.

R. Wiese, R. Jong-A-Pin, and J. de Haan. Can successful fiscal adjustments only be achieved by spending cuts? Economic Policy, 54:145–166, 2018.

C. Wyplosz. Fiscal Rules: Theorical issues and historical experience. NBER Working Paper No. 17884, 2012.

Appendices

Appendix 1 : LASSO results



Source: autors

Appendix 2. Descriptive Statistics

Variables	Correspondance Variables	N	Mean	Min	Max	sd
Y	Dummy variable =1 if 3% limit was complied in t	364	0.629	0.00	1.00	0.483
X1	Dummy variable reflecting if the country was an advanced country in t-p	364	0.785	0.00	1.00	0.410
X2	Dummy variable reflecting if the country was an Emerging country in t-p	364	0.214	0.00	1.00	0.410
X3	Dummy variable reflecting if the country was a Resource-rich country in t-p	364	0.00	0.00	0.00	0.00
X4	Dummy variable reflecting if the country was an EU membership in t-p	364	0.967	0.00	1.00	0.178
X5	Dummy variable reflecting if the country was a Federal Country in t-p	364	0.107	0.00	1.00	0.309
X6	Dummy variable reflecting if the country was a Eurozone member in t-p	364	0.642	0.00	1.00	0.479
X7	Dummy variable reflecting if the country was submitted to an enforcement procedure related to the supranational fiscal rules in t-p	364	0.967	0.00	1.00	0.178
X8	Gross domestic product, deflator, in t-p	364	100.84	62.69	146.3	10.31
X9	Total investment in t-p	364	22.47	9.819	41.53	4.756
X10	Gross national savingss t-p	364	21.61	5.099	33.70	5.525
X11	Inflation, average consumer prices index, in t-p	364	98.10	67.04	169.8	14.89
X12	Population in t-p	364	17.92	0.403	82.66	22.63
X13	General government revenue in t-p	364	41.96	25.94	56.36	6.546
X14	General government total expenditure in t-p	364	42.63	-7.824	65.047	11.19
X15	General government net lending/borrowing in t-p	364	-2.601	-32.02	5.129	3.590
X16	General government gross debt in t-p	364	60.41	3.664	183.4	34.96
X17	Net External Positions in t-p	364	-37.31	-198.7	65.2	50.93
X18	Current account balance in t-p	364	-0.869	-23.90	13.80	6.021
X19	Current account balance variations over 3 years in t-p	364	-1.214	-21.00	11.00	5.722
X20	Real Effective Exchange Rate in t-p	364	0.770	-20.40	36.00	6.681
X21	Global export market share -% change over 5 years - in t-p	364	4.547	-31.68	95.57	23.88
X22	Nominal unit wage cost -% change over 3 years - in t-p	364	6.948	-21.00	78.30	10.35
X23	Debt of private sector in t-p, consolidated -% of GDP	364	144.9	39.10	379.4	70.46
X24	Liabilities of the financial corporations sector, -% change over 1 year - in t-p	364	8.145	-17.60	115.6	12.85
X25	Unemployment rate - 3-year average - in t-p	364	9.047	3.700	26.30	4.101
X26	Unemployment rate in t-p	364	8.976	2.900	27.50	4.324
X27	Gross domestic product (real GDP) -% change over 1 year - in t-p	364	1.966	-14.80	25.10	3.837
X28	Gross fixed capital formation in t-p -% of GDP -	364	21.93	11.50	37.40	4.196
X29	Gross domestic expenditure on R & D in t-p -% of GDP -	352	1.504	0.370	3.750	0.877
X30	Direct investment in the reporting economy (flow) in t-p -% of GDP -	364	25.01	-264.1	1336.6	118.6
X31	Direct investment in the reporting economy (stocks) -% of GDP	364	350.2	4.200	9479.1	1135.5
X32	Net trade balance of energy products in t-p -% of GDP -	364	-3.212	-14.90	2.300	2.062
X33	Real effective exchange rate, Euro area trading partners -% change over 3 years	364	1.487	-21.70	38.90	6.335
X34	Terms of trade (goods and services) -% change over 5 years - in t-p	364	1.102	-10.20	28.30	4.870
X35	Market share of world exports, volumes -% change over 1 year - in t-p	364	0.495	-10.30	36.40	4.816
X36	Labor productivity -% change over 1 year - in t-p	364	1.294	-7.700	20.90	2.784
X37	Residential construction in t-p -% of GDP -	350	4.347	0.600	13.50	2.121
X38	Employment -% change over 1 year - in t-p	364	0.658	-14.30	6.5	2.377
X39	Dummy variable reflecting if there is a Crisis in t-p	364	0.307	0.000	1.000	0.462
X40	Output gap (production function approach) in t-p	364	0.167	-12.89	20.29	4.345
X41	Oil Prices in t-p	364	73.76	43.29	99.67	19.84
X42	Bonds yield in t-p	351	3.849	0.090	22.50	2.460
X43	Foreign currency long-term sovereign debt ratings, index from 1-21 , in t-p	364	16.71	2.842	21.00	4.019
X44	Fiscal Space in t-p	364	3.966	-60.18	119.1	33.11
X45	Fiscal Rules Index (by European Commission) in t-p	364	0.542	-0.948	3.404	1.068
X46	Structural Breaks in t-p	364	0.225	0.000	1.000	0.418
X47	Government fragmentation in t-p	364	0.707	0.491	0.861	0.097

Note: Y is the Dependent variable. X are potential predictors tested in the feature selection step. All variables used as predictor are a p lagged of the variable. We report lag-1 in descriptive statistics to solve space and because lag-1 contains informations about lag-2 and lag-3 also tested in the paper. Fiscal Space is measured as the difference between country public debt and EU median debt for each year.