Fiscal rules compliance and social welfare

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Abstract

This paper considers Budget Balance Rules (BBR) compliance effects on social welfare in sixteen countries in the world between 2004 and 2015. Instead of fiscal rules strength or fiscal rules presence effectiveness, we focus on fiscal rules compliance to assess the impact of governments behavior on social area. The paper shows that governments go beyond the expected trade-off between BBR compliance and GDP Growth by operating a reallocation of their spending. Such choices in public expense lead to an increase in social inequalities. The analysis constitutes the first use of double/debiased machine learning for treatment recently developed by Chernozhukov et al. [2018] applied to fiscal discipline issues. Through this method we are able to highlight key determinants for BBR compliance and assess the compliance's effect on different macroeconomic and social indicators. We take care of Voter Preferences, computing a proxy with Latent Factor Analysis Approach, and show that they appear as a key variable for BBR compliance, giving an empirical proof that Wyplosz [2012]'s bias matters.

Keywords: Fiscal Rules compliance; Social Welfare; Fiscal Surveillance; Machine learning.

JEL Codes: E61, H11, H50, H61, H62.

1 Introduction

Attention paying to fiscal rules increased during the last two decades that expenrienced world shocks (2008-2009 and 2010-2013) due the financial crisis and recently the Covid-19 shock (2020). Fiscal rules were implemented to promote fiscal discipline since the common pool problem (Wyplosz [2012] or governments temporal inconsistency (Kydland and Prescott [1977] lead to important public discretionary behaviors[1]. Nowadays, fiscal rules are under debate since many suffer from a lack of compliance leading economist as Blanchard and al (2020) to argue in favor of replacing them by Fiscal Standards. Nevertheless, fiscal rules aim to support fiscal sustainability which is really stressed since de Sovereign debt crisis and the situation worsened with the Covid-19 health crisis. We are thus interested in economic counterpart of fiscal rules' compliance in order to bring light on the debate with empirical evidence.

We are in a several steps approach and the fiscal rules' compliance determinants identification constitute the first step. Determinants of fiscal rules were already studied in the literature (see Reuter [2019], Delgado-Téllez et al. [2017], Barbier-Gauchard et al. [2021]). In our analysis we focus on national fiscal rules and especially on Budget Balance Rules (BBR). We follow Barbier-Gauchard et al. [2021] approach by identifying the key determinants in fiscal rules compliance classification problem which is quite different from Reuter [2019] that used a logistic function reflecting a causal issue. The second step constitutes the Treatment Effect measurement. We expect that complied fiscal rules may have effects that non-complied fiscal rules couldn't have. We thus assess the influence of BBR compliance on economic environnement and social welfare indicators. This work is based on several simple hypotheses:

(1) to agree with evidence from the literature, we must verify that the complied BBR further reduce public deficits;

(2) The compliance effect is ambiguous. It could lead to an increase in government effectiveness as sugested by Larch and Santacroce [2020] but may also imply a trade-off beteween fiscal rules compliance and GDP growth objectives (Bohn and Inman [1996]);

(3) Regarding Musgravian functions [2], governments should promote allocation of public goods through public investments. We thus pay attention to fiscal rules compliance effect on government expenditure composition.

(4) Finally, since the government redistribution function is related to inequalities, we will assess fiscal rules compliance effect on inequalities measured by inequalities indicators including the well-known Gini Index.

The above hypotheses started from the mostly accepted until which ones are debated. Indeed, the link some studies found that fiscal rules are able to reduce inequalities in developing countries (Combes et al. [2019], others found that fiscal rules increase inequality based on disposable income measures in the European Union (Hartwig and Strum [2019]).

Social welfare is related to several key points of our analysis: (i) social welfare is related to the level of debt (Flodén [2001])[3]. The level of debt is linked to the redistributive government

[1] Such considerations are even more important in monetary union as European Monetary Union where externalities are really important (Dabrowski, 2015). Fiscal rules set the question of political constrain in monetary union (Grauwe [1975],Grauwe [2000]) and compliance is thus important to raise fiscal rules' credibility.

[2] Allocation ; Stabilization (Stabilization power of fiscal rules was already studied by Sacchi and Salotti [2015] or Guerguil et al. [2017] who highlight respectively that fiscal rules are able to stabilize GDP variations and public expenditures); Redistribution

[3] Aiyagari and McGrattan [1998] launches the debate by studying the question of the optimal amount of debt for social welfare in the US context.

function et could help people in smoothing their consumption. But it also lead to the common pool problem (Wyplosz [2012]) that is negative for future generations[4].

(ii) Social welfare is linked with gdp growth (Midgley [1999]). Improvements in GDP growth rate means that the country is in good health and governments effectiveness may increase. If BBR compliance have an impact on GDP growth and government effectiveness they finally could twice impact social welfare.

(iii), increasing (decreasing) public investments (inequalities) could increase social benefits and thus social welfare. Since studies on fiscal rules effect on inequalities don't find aligned results, we want to verify whether a social cost for compliance exists.

If we can interpret such a difference in the results by the disparity of the contexts studied, a major source comes from the method employed. Indeed methods to assess the effects of the rules are numerous including Instrumental Variable (IV) method, system-Generalized Method (sys-GMM) of Moments or propensity-score Matching. However Heinemann et al. [2018], pointed out that the majority of studies assessing the impact fiscal rules on fiscal discipline is highly biased because endogeneity is not controlled enough. IV and sys-GMM performance highly depends on instruments choice and quality[5] and propensity-scores is related to random assignment (conditional independence assumption must hold (Rosenbaum and Rubin [1983]). Even if several robustness checks are always implemented, there is no certainty that these studies can control for omission bias and in particular the importance of Voter Preferences discussed by Wyplosz [2012].

Our approach first extends traditional assessment of fiscal rules effectiveness to fiscal rules compliance performance. Second, we are able to measure the effectiveness of fiscal rules with regards to the ultimate objective set out in the rules. Our study excludes problems due to approaches using composite indices which are time invariant [6]. Nevertheless, variables related to composite indices as the strength of fiscal rule, are included in the present approach by testing if their are key predictors for compliance in our first step of the methodology. Third, our use of Double/debiased machine learning treatment (Chernozhukov et al. [2017], Chernozhukov et al. [2018]) for fiscal discipline assessment is unprecedent and excludes biases discussed previously. The algorithm based on Norman Orthogonality proposes strong asymptotic properties, providing a really powerfull estimator for causal inference and reduce the potential omission bias since we are able to test a hudge number of predictors. Fourth, we include a proxy measure for Voter Preferences to increase the robustness of our analysis.

2 Literature review in a nutchell

The number of national fiscal rules increased in OECD countries since 1990s but the biggest world shocks (2008-2009 and 2010-2013) and yhr Covid-19 crisis (2020) made fiscal rules impossible to comply. Such experiences highlighted the fiscal rules design trilemma Debrun et al. [2019] explaining that it is impossible for a rules to be enforceable, simple and flexible at the same time. Nevertheless all these crises highly increased debt unsustainability risk, leading to new reflections on fiscal rules. A large part of the literature has already proven that national fiscal rules can support the sustainability of public finances by strengthening fiscal discipline. Indeed,

[4]In this line, Evers [2012] proposed simple rules for federal fiscal transfers that assure stability against shock but also automatical redistribution among member states of a monetary union. Such approach pays attention to social welfare.

[5]see Fajeau [2021] for discussion on instruments use in GMM models for economics studies and Belloni et al. [2018] for a debiased GMM estimator that uses Machine Learning tools.

[6]This implies that they do not consider the current numerical target and do not take into account for macroeconomic country situation.

Debrun et al. [2008], Marneffe et al. [2010], Bergman et al. [2016] or Barbier-Gauchard et al. [2021] pointed out that fiscal rules have positive effect on fiscal discipline in EU contrries. Similar results were found by Tapsoba [2012] for developing countries or Combes et al. [2018] mixing countries.

However, all this work doesn't pay attention to fiscal rules compliance whereas it could impact fiscal rules effect in particular by introducing a trade-off between fiscal rules compliance and governements growth and/or social objectives. The seminal definiton of an Ideal fiscal rules proposed Kopits and Symansky [1998] introduced the concept of enforceability[7]. To make fiscal rules binding, sanctions can accompany the rules, as is the case in the SGP[8] and independant fiscal councils are in charge of monitoring[9]. Fiscal rules compliance is thus a major topics and the Literature mostly focused on fiscal rules compliance determinants. Delgado-Téllez et al. [2017] used a First Difference General Method of Moments to identify fiscal rules non-compliance determinants in Spain's regions taking into account that bailing out could be due to voluntary government behaviors (political motives as elections for example - see also L.Schuknecht [2004] for such consideration in EU context -) or unvoluntary government behaviors (cyclical events as economic shocks for example). Reuter [2019] used a logit model in a causal approach to identify the determinants of fiscal rules in European Union members between 1995 and 2015. In Reuter (2019) results we can find that the more strenght is the fiscal rule the more it is complied. Such rules could be too strict and thus not flexible (as expected by Kopits and Symansky [1998] definition) inducing social costs. A logit model is also used in Nandelenga and Ellyne [2020] that extend the study of fiscal rules' compliance in the conext of 20 sub-Saharian countries between 1997 and 2016.

In an other contribution, Reuter [2015] studied the dynamic of compliance showing that even if fiscal rules aren't comply, government implement efforts to move close to the limit. This work was extended to emerging and developping countries; including both national and supranational rules in Caselli et al. [2018]. [10]. Such studies point out the benchmark status that the fiscal rules seem to have.

Council [2013] gives attention to their budget balance rule compliance. They use a different approach by providing projection on the General Government Deficit, Primary Deicit and Structural Deficit to study the future fiscal rules compliance [11]. Baret et al. [2021] [12] highlighted the determinants that most accuratly forecast the SGP budget balance rule (the well-known 3% of public deficit) compliance. This last point sets a major difference from analyzes previously mentionned that studied the determinants of fical rules' compliance. Indeed, it is not a question of knowing which are all the elements that could influence fiscal rules' compliance but which weighs most strongly in the event of non-compliance. This suggests that some variables are more important than others in such assessment and the influence of a poorly correlated variable would not be enough to lead to a systematic rule violation. In our approach we are interested

[7] As defined by Kopits and Symansky [1998], the Ideal fiscal rule should be simple regarding the target, clear, enforceable, consistent in the time, accompagnied by an adequate fiscal framework

[8] The beginnings of European fiscal rules enforceability come from the Maastricht Treaty (1992) with the excessive deficit procedure. The supranational rule in the EMU has been formalized in the GSP. Indeed, in the event of a recession of at least 2% of GDP, the European Commission then considers the economy in an exceptional situation, lifting the obligations to comply fiscal rules included in SGP.

[9] see Beetsma et al. [2018] for an assessment of fiscal councils effect on governments commitment

[10] This latest result is similar the the magnet-effect described by Eyraud et al. [2018].

[11] they thus do not try to propose a measure of compliance and study its determinants

[12] Focusing on supranational fiscal rules, Baret and Papadimitriou (2020) analysed Stability and Growth Pact (SGP) compliance. Their results are twofold: i) they first highlight they key determinants in the issue of SGP compliance forecasting, ii) they propose a Support Vector Machine model as forecasting tool for SGP compliance with an accuracy between 90.4% and 98.1%.

in national budget rules' compliance and we also identify the most important variables for our study[13]. Nevertheless, our study is a causal approach and not forecasting model as in Baret et al. [2021], we will therefore identify the most important variables among present and past values[14].

3 Data and Stylized facts

3.1 Data

3.1.1 Fiscal Rules and Compliance

All Budget Balance Rules and their target definitions come from IMF Database (Schaechter et al. [2016]) and targeted values sources are developped in details in Appendix 1. But, despite this data availability, our dataset identification is driven by several constrains:

First, fiscal rules are defined as a numerical constrain set on public finance indicators (leading to budget balance rules (BBR), expenditure rules (ER), debt rules (DR) and revenue rules(RR)). Different type of rules imply different effects[15]. On that sense we have to study the compliance by type of rule. The selected rules must be comparable to obtain a reasonnable average effect and have thus to hold over the same period. We found countries who had a budget balance rules over the same period but wee were not able to identify enough countries which would have applied the same rule over such a period for the other types of rules. The study finally focuses on 16 countries[16] which had a BBR between 2004 and 2015.

Second, we had to precisely define each BBR including the possible presence of exclusion clauses. Because we adopt a simple definition of compliance - i.e. a country complied with (resp. did not comply with) the BBR if it presents an indicator above or equel to (resp. below) the target -, we must take into account the presence of escape clauses that allow countries to meet the limit if the economic situation is "exceptional"[17]. The presence of escape clauses can disrupt the distribution of compliance as they are a part of the fiscal rules' design. The escape clauses also set a hudge debate on the compliance definition that we try to consider by testing the influence of such escape clauses on our treatment effect.

Third, some countries of our dataset need a special attention. (1) United Kingdom abandonned its golden rule in 2009 due to the Global Financial Crisis that led to an excessive deficit making impossible complying the Budget Balance Rule. They just reintroduced a budget balance rules in 2010. On that sense we could consider that United Kingdom voluntarily didn't comply the golden rule in 2009. In 2010, United kingdom adopted a multi-annual budget balance rule by targeting a balanced structural budget at the end of 5 years (2014). This new BBR is interpretated as an annual change targeted variables (Caselli et al. [2018], Reuter [2019]). We implement estimates based on these assumptions and then remove these years-corresponding-observations from our sample to verify that our interpretations do not lead to differences in the results. (2) Hungary had two fiscal rules between 2009 and 2011. Only the BBR that concerned General government is considered since all other countries are treated with only one BBR. Also, Hungary

[13]Such a condition is necessary in order to offer efficient machine learning estimators

[14]While in forecasting approaches only lagged variables could be used (see Baret et al. [2021])

[15]See for heterogeneities of fiscal rules effect Debrun et al. [2008] or Baret et al. [2021])

[16]Chile, Costa Rica, Denmark, Estonia, Finland, Germany, Hungary, Indonesia, Japan, Malaysia, New Zealand, Peru, Spain, Sweden, Switherland, United Kingdom. Israel is discarded due to the annual change in the targeted value of BBR.

[17]For example, the European Commission defines exceptionnal circunstances in the SGP escape clauses as a recession of 2% of GDP.

had no longer fiscal rules after 2011 in the IMF Database (Schaechter et al. [2016]). But Fiscal Compact (also known as The Treaty on Stability, Coordination and Governance (TSCG)) was transposed in their national law, on that sense we could consider that Structural deficit above 0.5% (because debt is higher that 60% as describes in TSCG). We also present results removing these observations based on our hypothesis, for the same reasons as above. (3) In Caselli et al. [2018] , Reuter [2019] Japan Golden rules isn't considered after 1993 since waiver looks as request. Since IMF Database includes it and Japan Government seems to still hold it, we follow IMF Databse and include it.

Appendix 2 summaries all BBR we retained and provided defintion details.

Figure 1 shows a high heterogeneity in government behavior regarding BBR compliance. Since some countries as Estonia, Indonesia or Malaysia take care of the rule compliance, other as Japan or Hungary highlight a poor compliance. These countries are historically, socialy and structurally different. On that sense, we expect that such differences between these countries will help in the identification of the budget rules compliance key determinants.

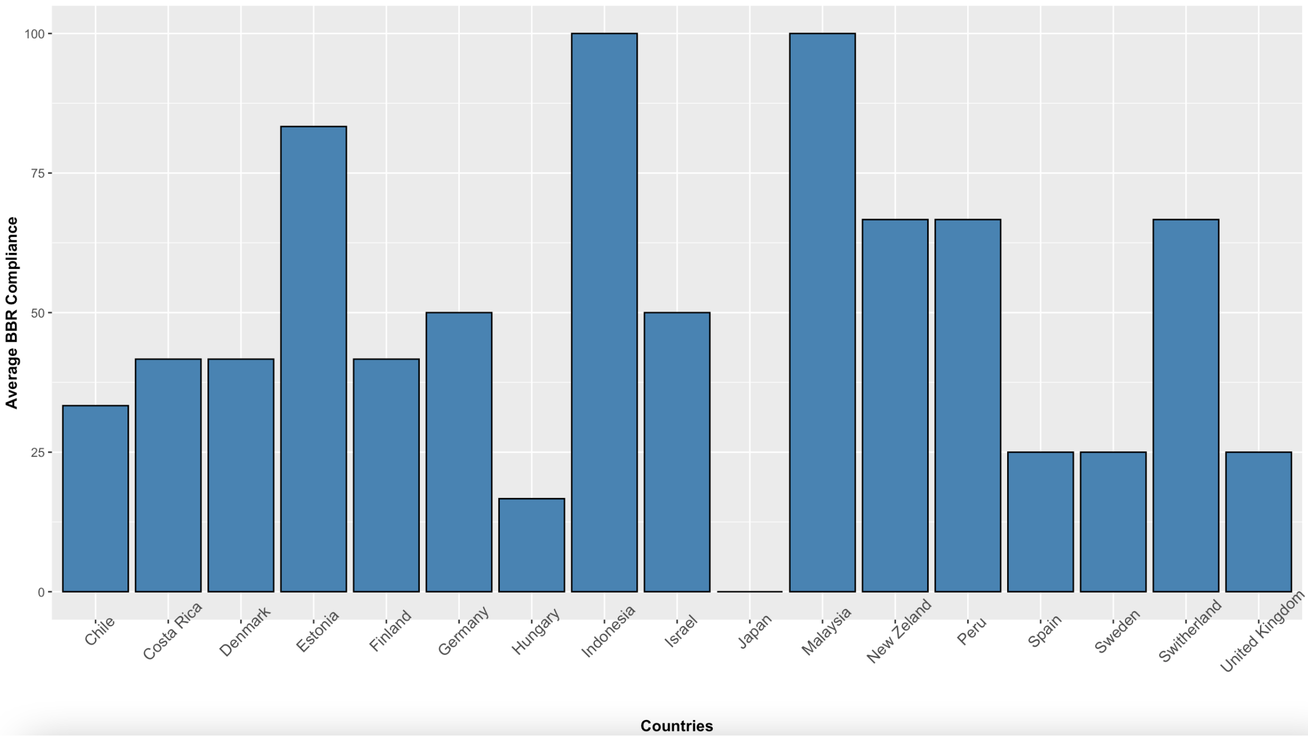

Figure 1: **Average Budget Balance Rules (BBR) compliance between 2004 and 2015**
Note: "0" means BBR non-compliance and "1" means BBR compliance.

In Figure 2, Government Effectiveness looks higher in countries that complied with their BBR, whereas the Gini index seems to be lower for BBR-compliers. Indeed the median of Government Effectiveness index was higher for complier countries than the median of non-compliers. During the GLobal Finacial Crisis (2007-2009) the differences were reduced but re-increased after 2009. During this period escape clauses were applied and/or compliance was really poor and countries didn't adopt really bevior regarding BBR compliance. On the contrary, the differences in Gini

Index highly increased since the Global Financial Crisis, suggesting that the social costs for compliance increased after 2008.

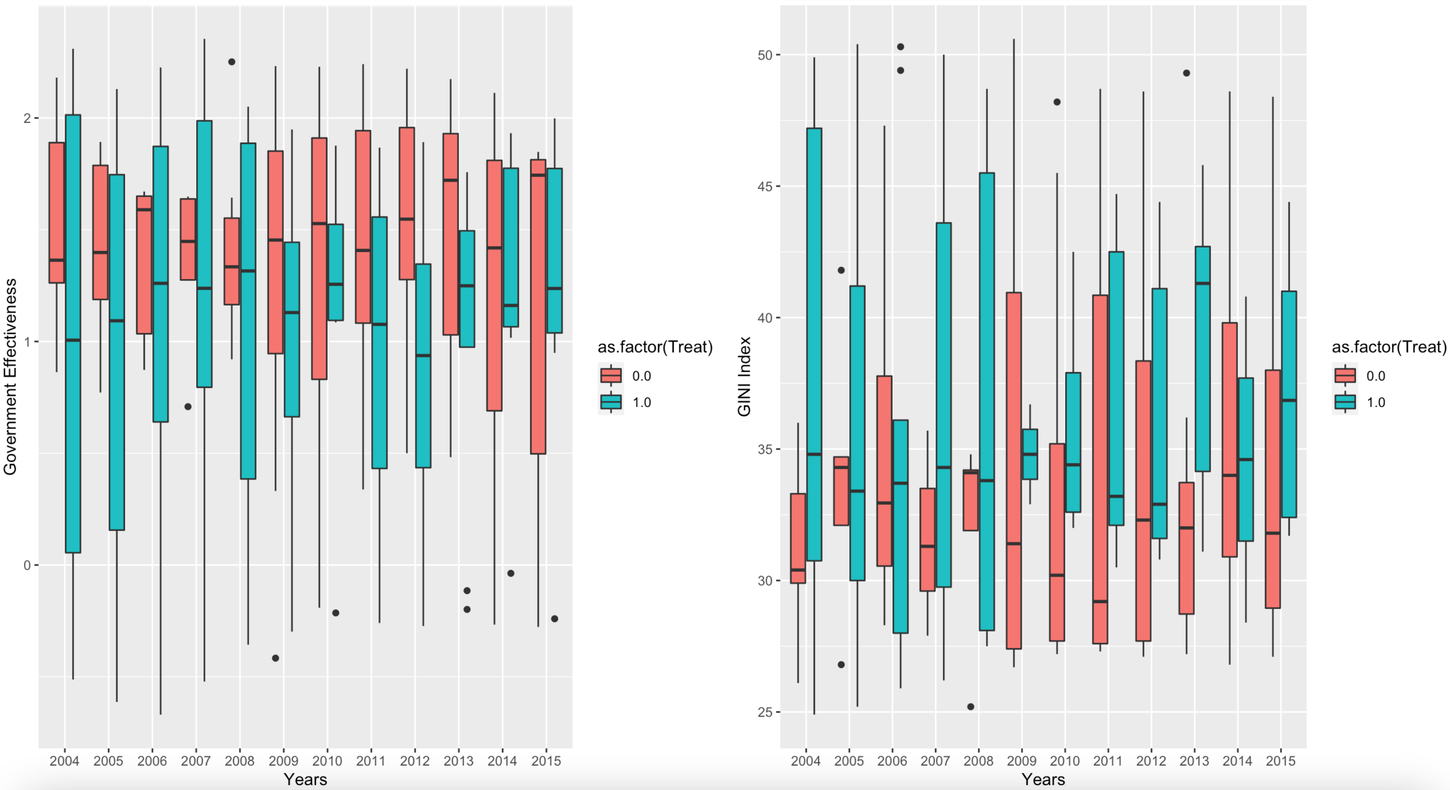

Figure 2: **Social Related Indicators and Budget Balance Rules Compliance**
Note: "0" means BBR non-compliance and "1" means BBR compliance.

3.1.2 The potential determinants

We expect that, in line with many results produced by studies looking at the determinants of compliance[18], compliance will be affected by many macroeconomic environment but also political variables (as the presence of election) or variables relative to the strenght of fiscal rules. However, we are interested in those which are recurrent from one country to another and which contain the most useful information for predicting compliance with the rules. The exhaustive list of potential predictors that are tested in our approach ais summary in table 1. We used well-known macroeconomic variables and inequalities indicators. Nevertheless, as Debrun and Kumar [2007], Wyplosz [2012] suggested that fiscal rules effect could suffer from reverse causality bias that is also support by recent findings in Heinemann et al. [2018]. Such bias still hold when assessing fiscal rules compliance effect. If compliance could imply differences in macro variables, these latters could also influence the government in their commitment (degraded public finances can strengthen the governments' willingness to comply fiscal rules in order to restore sound public finances). We will thus be really carefull in the used of lagged macro variables in the tested dataset for potential predictors. To increase the dataset we produce new measures. We provide

[18] Reuter [2019], Delgado-Téllez et al. [2017], Larch and Santacroce [2020] for example

a simple measure for GDP growth expactation based on the well-known moving-average approach (over 5 years). Indeed, we expect that governement will make some choices in their spending by expecting GDP growth results. Two other new measures require explanation here. The first one, is expected as to be a key determinant for BBR-compliance while the second will be used a dependent variable on which we want to assess the effect of BBR-compliance:

i) We follow Funk and Gathmann [2013] that used Latent Factor analysis to compute a measure of Voter Preferences for Swiss Canton. To do so, use five main variables that should reflect voter behavior namely Unemployment, Age dependency ratio (old in % of working-age poplation), the share of votes obtained by the largest government party, the vote share obtained by the first opposition party, the vote share obtained by independent parties. The Chi-test revealed (for varimax and promax rotation) that 2 factors are sufficient. We will thus use these two factors as control variables for Voter Preferences to test as potential predictors,[19].

ii) Following Afonso et al. [2006] and Afonso et al. [2019], we compute a measure for Government Efficiency. We aim at comparing the effect of BBR-compliance on Governement Effectiveness and Governement Efficiency. Since such indicator is computed over-year, we choose 3-over-years computation (instead of 5 as often found in the literature) to reduce the time-invariance of the indicator. In that sense we have three periods where the Governement Efficiency takes the same value: 2004-2007, 2008-2011, 2012-2015. We use mean-min function to aggregate the 3 sub-indicators that correspond to Musgravian functions: the proxy for distribution is Gini Index, the proxy for stabilization is the results of a sub-aggregation of the GDP per capita growth rate and Inflation (3 years average); and the proxy for Economic performance is the Unemployment.

[19] If the feature selection setp reveals that one or both of the factors are a key determinants for fiscal rules' compliance we will conclude that studies on fiscal compliance need to control for Voter Preferences.

Table 1: **Variables Overview**

Variables	Correspondance Variables	Source/Database	
Dependant	Public Balance (in % of gdp)	World Bank	
Dependent	Interest payments (in % of expense)	World Bank	
Dependent	GG Gross Fixed Capital Formation (in % of gdp)	World Bank	
Dependent	GG Total Spending (in % of gdp)	World Bank	Social
Dependent	General Government Final Consumption (in % of gdp)	World Bank	Welfare
Dependent	GDP per capita expectations		Related
Dependent	GDP per capita (annual growth) in $t+1$		Indicators
Dependant	Government Effectiveness Index	World Bank	
Dependant	Government Efficiency Index	Author's calculation	
Dependent	Gini Index	World Bank	
Dependent	Poverty headcount ratio at $1,90\$$ a day (2011 PPP) (% of population)	World Bank	
Predictors	Control of corruption	WWGI	
Predictors	Political Stability	WWGI	
Predictors	Regulatory Quality	WWGI	
Predictors	Rule of law	WWGI	
Predictors	Voice and Accountability	WWGI	
Predictors	Dummy reflecting if the country is an Advanced country	IMF Fiscal rules' Database	
Predictors	Dummy reflecting if the country is a Ressource Rich country	IMF Fiscal rules' Database	
Predictors	Dummy reflecting if the country is an Emerging country	IMF Fiscal rules' Database	
Predictors	Dummy reflecting if the country is an Advanced country	IMF Fiscal rules' Database	Countries
Predictors	Dummy reflecting if the country is a EU member	IMF Fiscal rules' Database	Characteristic
Predictors	Dummy reflecting if the country is member of a currency union	IMF Fiscal rules' Database	indicators
Predictors	Political system	WWGI	
Predictors	Dummy reflecting if there was an legislative election in this year	WWGI	
Predictors	Dummy reflecting if there was an executive election in this year	WWGI	
Predictors	Executive Index of Electoral Competition	WWGI	
Predictors	The number of years the chief execute has been in place	WWGI	
Predictors	Time since formation of the largest government party	WWGI	
Predictors	Proxy 1 for Voter's preferences	Authors' calculations with LFA	
Predictors	Proxy 2 for Voter's preferences	Authors' calculations with LFA	
Predictors	Well specified escape clauses	IMF fiscal rules' Database	
Predictors	Monitoring of compliance outside government	IMF fiscal rules' Database	
Predictors	Formal enforcement procedure	IMF fiscal rules' Database	Fiscal
Predictors	Coverage level	IMF fiscal rules' Database	rule
Predictors	Dummy reflecting if an independent body sets budget assumptions	IMF fiscal rules' Database	Related
Predictors	Dummy reflecting of an independent body monitors implementation	IMF fiscal rules' Database	characteristics
Predictors	Dummy reflecting if the BBR is a golden rule	Authors' narrative approach and IMF fiscal rules Database	
Predictors	Dummy reflecting if the economy conjoncture is bad		
Predictors	Oils rents		
Predictors	Interest payments on debt in $t-1$		
Predictors	Gross Fixed Capital Formation (annual growth) in $t-1$		
Predictors	Gross Fixed Capital Formation (in % of gdp) in $t-1$		
Predictors	The Current account balance in $t-1$		
Predictors	The Unemployment rate in $t-1$		
Predictors	Trade (in % of gdp) in $t-1$		
Predictors	Inflation, consumer prices (annual %) in $t-1$		Macroeconomic
Predictors	Inflation, GDP deflator (annual %) in $t-1$		Environment
Predictors	Wage in $t-1$		Variables
Predictors	GDP per capita growth (annual %) in $t-1$		
Predictors	Labor Force in $t-1$		
Predictors	External Balance in $t-1$		
Predictors	General Government budget balance in $t-1$		
Predictors	General Government final consumption in $t-1$		
Predictors	Central government debt (in % of gdp) in $t-1$		
Predictors	Gross savings in $t-1$		
Predictors	Total expenses in $t-1$		

Note: GG = General Government; LFA = Latent Factor Analysis; GDP per capita expectation is computed using a moving-average approach based on GDP per capita data coming from the World Bank.

4 Methodology

4.1 Treatment Effect Estimation

Recently, some studies focused on the usefulness of machine learning (ML) for the causal inference that are in the applied econometric field (Varian [2014], Mullainathan and Spiess [2017] or Athey and Imbens [2017]).

Several techniques were developped to make to improve ML performance in order to highlight their advantages. Among these techniques we can find sample splitting (which uses different data partition to select models and parameters (see Athey et al. [2016] or Wager and Athey and Imbens [2017]) and orthogonalization (e.g. Chernozhukov et al. [2017]). Such approaches imply properties as asymptotic normality for these ML estimators (see Athey et al. [2017] for the general semiparametric case or Chernozhukov et al. [2018] for the average treatment effect case).

The main goal of our procedure is to estimate confidence intervals for a low-dimensional parameter β_0 with high-dimensional nuisance parameter η_0 and η_0 should be estimated with recent nonparametric statistical methods namely Machine Learning. Machine Learning methods highlight high level forecasting power (see Hardle (2009), Gogas and al (2019) or Baret et al. [2021]). However, this performance in forecasting issue does not imply inference performance about "causal" parameters. To solve such problem, Chernozhukov et al. [2017] developped "double/debiased" Machine Learning (also called orthogonalized Machine Learning), introducing sample splitting to propose strong estimator for causal parameters.

Our model is a partially linear model that could be written as follow:

$$Y = \beta_0 * D + \gamma_0(Z) + U, \qquad \mathbb{E}[U|Z, D] = 0, \tag{1}$$

with Y the outcome variable, D the treatment/policy variable, Z is a high-dimensial vector of controls/confounders, β is our paramter of interest.

Z corresponds to control variables because: $Treatment = b_0 + \theta_0(Z) + V$ with $\theta_0 \neq 0$

If conditionnal exogeneity (view Rosenbaum and Rubin [1983]) is complied, β_0 corresponds to the average treatment effect of the treatment. The Double/Debiased Machine Learning (DML) works in several steps:

1) In a first step we will use two machine learning approaches to predict Y and D on Z to obtain $\widehat{E[Y|Z]}$ and $\widehat{E[D|Z]}$. This step corresponds to the feature selection.

2) We then extract residuals $\widehat{W} = Y - \widehat{E[Y|Z]}$ and $\widehat{V} = D - \widehat{E[D|Z]}$. This step is an extraction of the residuals.

3) Following Frish-Waugh-Lovell procedure (1930) we regress $\widehat{W}$ on $\widehat{V}$ that allow us to obtain $\widehat{\beta_0}$. This step is the orthogonalization procedure.

All these steps are done with cross-validation procedure. More precisely, we use k-fold cross validation. We thus split our dataset in k subsets; $k-1$ subsets are used as training set while the k^{th} constitues the testing set. We will use 5-fold validation in all the paper. As discussed in Athey and Imbens [2019], each nuisance parameter could converge at rate close to $N^{-1/4}$ which corresponds to a magnitude order slower than ATE estimate. The use of orthogalization precisely allows the good working of the approach because errors in estimating nuisance parameters are orthogonal to the sample average errors in ATE (see) Chernozhukov et al. [2018]for theorical details or Athey et al. [2017] for applications estimating heterogeneous effects with unconfoundedness).

4.2 Feature Selection Estimators

Following Chernozhukov et al. [2017] and Chernozhukov et al. [2018], we will use different feature selection procedures to compare the results. More than a robustness test, it allows us to make our results generalisable. As techniques, we propose: Least Absolute Shrinkage and Selection operator that received an increased use in the literature, the l2-boosting. In all the following technical part, we should keep in mind that the dependant variable of interest are continous while the treatment effect (BBR compliance) is a binary variable. On that sense, the following algorithms will be adapt of each case (continuous or binary). Because our main dependent variable (The Overall Public Balance, the Interest payments, the Total public spending, the Governement final consumption, the GDP per capita expectation, the GDP per capita in $t + 1$, the Governement effectiveness, the Musgravian Index, the Gini Index and the poverty headcount ratio) are continuous, Root-Mean-Squared-Errors of each feature selection model are reported in tables of results.

4.2.1 LEAST ABSOLUTE SHRINKAGE and SELECTION OPERATOR (LASSO)

Friedman et al. [2009] proposed LASSO as a regularization that operate a shrinkage procedure. It thus presents major advantage face to the ridge regression that couldn't the number of features (Pereira et al. [2016]. The LASSO implements a feature selection that corresponds to the reduction of the feature set, by removing irrelevant ones for our model. It corresponds to a regularization process where the coefficients of redundant predictors are penalized and set to zero. Such approach also reduce both the risk overfitting and the prediction error.

As Baret et al. [2021], we retain LASSO rather than methodologies that implies transformation-based dimension as Principal Component Analysis (PCA) that provide factors that have no direct economic interpretability.

Finally, the LASSO estimator is:

$$\hat{\beta}(\lambda) = \underset{\beta}{\operatorname{argmin}}(n^{-1}\sum_{i=1}^{n}\rho_{(\beta)}(X_i, Y_i) + \lambda||\beta||_1) \tag{2}$$

where λ is the shrinkage parameter provided through grid search and used the one-standard error rule (see Baret et al. [2021]).

4.2.2 L2-BOOSTING

The so-called Gradient boosting is a machine learning application of boosting. It is based on the combination of the best possible next model with previous models, minimozes the total model prediction error. The Boosting with l2 loss function follows the functionnal gradient descent procedure, including a l2-penalty term. Such procedures needs an initialization step, by seting target outcomes for the first next model (with the goal the miniminze the error). This first step includes the regularization parameter. The second step consists in tje projection of gradien descent to learner. It leads to the negative gradient which corresponds to the residual vector of boosting procedure. Third step is the line search the use iteration to repeat the procedure until miniziming the overoll error.

This algorithm is equivalent to functionnal gradient descent technique. The main goal is to estimate the function

$F : \mathbb{R}^d \longmapsto \mathbb{R}$, minimizing an expected cost

$$\mathbb{E}[C(Y, F(X))], C(.,.) : \mathbb{R} \times \mathbb{R} \longmapsto \mathbb{R}^+ \quad (1)$$

where Y_i is our dependant variable and X_i the potential predictors for observations $i = 1, ...n$. Alternatively, Y is continious and the problem is solved through regression, or Y is discrete and we are in a classication issue. Cost function C(.,.) verifies important properties to make sure that gradient approach well works: it is smooth and convex in the second argument.

L2-Boost cost function is: $C(y, f) = \frac{|y-f|^2}{2}$ with $y \in \mathbb{R}$ or $y \in \{0, 1\}$, $f \in \mathbb{R}$.

Following Friedman et al. [2000], the population minimizers to Estimate (1) is:

$$F(x) = \mathbb{E}[Y|X = x]$$

. The application of functional gradien descend to the dataset lead to minimize the empirical risk and estimate $F(.)$ given by:

$$n^{-1} \sum_{i=1}^{n} C(Y_i, F(X_i))$$

.

We thus apply this algorithm in a binary/classification issue when the dependent variable is the treatment (BBR (non-)compliance) and in a linear approach four our main variables of interests (GDP growth, Government Spending and social indicators) that are continuous. For further details on Generic functional gradient descend and L2 boosting with linear/classification learners, see Bühlmann and Yu [2003].

5 Results

Table 2 reports the key common determinants for BBR-compliance retained by our two feature selection algorithms. They seem to select the same predictors. Dummy for Crisis has a negative on BBR-compliance since, obviously, it appears difficult for governments to comply with fiscal rules during big shocks. The presence of escape clauses also leads to governements to temptation og non-compliance. Escape clauses must operates during the worst economic circunstances. Nevertheless they seem to highly affect governements behavior all over our period, suggesting that their presence lead governements to count on them to relax. On the contrary, the presence of Formal enforcement procedure as sanctions for non-compliance affects positively BBR-compliance. We can find such procedure in the STability and Growth Pact and this could explains the positive effect of being a member of a currency on the BBR-compliance. The lagged value of interest payments on debt increase the compliance in the next year, suggesting that governments try to implement effort to comply while their non-productive expense increase to send a positive signal to financial market. Without surprise, the lagged value of public balance affects positively the BBR-compliance since it is easier to comply your fiscal rule when public finance are in good health. Finally, the first latent factor we computed as prowy for voter preferences appears as significant. This suggests that we have to take into account for voter preferences when we assess fiscal rules effects. Indeed the voter preferences seem to icnrease the BBR-compliance, reflecting an average preference of the voters for disciplined governements. The number of years of a chief executive has been in place is positively linked with BBR-compliance. If voters indeed prefer complier-government, a disciplined chief executive will stay longer and increase BBR-compliance.

Table 2: **Compliance determinants:**

LASSO - L2BOOSTING common determinants
Dummy crisis (-)
Dummy Well-specified escape clause (-)
Dummy Formal enforcement procedure (+)
Voice and Accountability (-)
Dummy for Federal country (+)
Dummy for member of a currency union (+)
Years chief executive (+)
The First proxy for Voter Preferences (+)
$lag-1$ interest payments (in % of expense) (+)
$lag-1$ of Public Balance (in % of GDP) (+)

Note : Years chief executive reflects the number of years the chief executive was in office . Election system takes value 2 for parliamentary system, 1 for Assembly-elected President and 0 for Presidential system (see Database of Political Institutions 2015 (2016) for further details). Only the ten common indicators are reported. Lasso retained 15; l2-Boosting retained 10. The signs (+) and (-) reflects the impact sign of the variable on BBR-compliance.

Table 3 presents the ATE of BBR-compliance on our variables of interest. We decompose our results in a first part that summarizes the Average Treatment Effect (ATE) on the Macroeconomic Variables while the second part reveals the ATE on Social related indicators. All our results are stable accross feature selections approaches used in the first step of our DML algorithm. Nevertheless, the RMSE for the dependant variables provided by L2-Boosting is lowest in every cases, showing that it is the best model.

The Table 3 -part 1- highlights that, according to literature linking fiscal rules and fiscal discipline, the BBR compliance increases the Overall public balance (column 1). Nevertheless, BBR-compliers seem to not pay less interest on debt (column 2), suggesting that they finally do not benefit from better interest from the market. The Total spending decrease for BBR-compliers while General Government Investment (Gross Fixed Capital Formation (GFCF)) increases. On that sense, we are interested to see how these governement succeed in compliance. Without any surprise, they operate a cut in Government final consumption. By this increase in GFCF, compliers seem to expect growth benefit (they indeed present a GDP growth expectation significantly higher in average as suggested by colomun 6). However, in practice, their spending re-allocation do not provide higher gdp growth in the newt year as suggested by column 7 where BBR-compliance has no impact on the newt year GDP per capita growth. Table 3 -part 2- reports results in accordance with this last finding since neither Governement Effectiveness nor Governement Efficiency are affected by compliance. The principal result is found in column 3 of Table 3 part 2 that shows an increase in Gini Index. By forcing compliance, accompagnied by a volontee to increase simultaneously GFCF, government try to go beyond the trade-off between BBR-compliance and growth objectives. This practice is done including a price for social spending included in the Goverment Final consumption expenditure. As a result, inequalities increase. As suggested by the last column Table 3 part 2, the poorest are affected by the spending re-allocation.

Table 4 shows robustness check by removing observations for the UK and HUngary on which we wet hypotheses in 3.1.1. Our results still hold with the two methods, and L2-boosting still being the best model regarding the RMSE measure.

Table 3: **ATE of Budget Balance Compliance with 5-fold cross-validation**

Part 1: ATE on Macroeconomic indicators

DML Estimator \ Dependant Variable	GG Public Balance	Interest payments (% of expense)	GG GFCF (in % of GDP)	Total spending (in % of GDP)	GG final consumption (in % of GDP)	GDP per cap. expectation	GDP per cap. Growth in $t+1$
LASSO	0.534***	0.058	0.263***	-0.125***	-0.107***	0.601***	0.140
	(0.100)	(0.049)	(0.077)	(0.034)	(0.028)	(0.170)	(0.098)
RMSE y	0.532	0.338	0.370	0.172	0.202	0.402	0.557
BOOSTING	0.481***	0.108	0.266***	-0.095***	-0.141***	0.526***	0.077
	(0.087)	(0.030)	(0.068)	(0.023)	(0.029)	(0.151)	(0.109)
RMSE y	0.392	0.234	0.283	0.125	0.136	0.341	0.403

Note: GG = General Government, GFCF = Gross Fixed Capital Formation. The median standard error across the splits are reported in brackets.

Part 2: ATE on Social indicators

DML Estimator \ Dependant Variable	Government Effectiveness	Musgravian Index	Gini Index	Poverty headcount ratio at 1, 90$ a day (2011 PPP) (% of population)
LASSO	-0.014	0.128	0.087*	0.079**
	(0.033)	(0.140)	(0.072)	(0.035)
RMSE y	0.147	0.635	0.344	0.216
BOOSTING	-0.019	0.099	0.032*	0.049**
	(0.031)	(0.133)	(0.065)	(0.036)
RMSE y	0.118	0.284	0.274	0.192

Note: GG = General Government. The median standard error across the splits are reported in brackets.

Table 4: **Robustness ATE of Budget Balance Compliance with 5-fold cross-validation: without observations related to hypotheses set by authors in 3.1.1**

Part 1: ATE on Macroeconomic indicators

DML Estimator \ Dependant Variable	GG Public Balance	Interest payments (% of expense)	GG GFCF (in % of GDP)	Total spending (in % of GDP)	GG final consumption (in % of GDP)	GDP per cap. expectation	GDP per cap. Growth in $t+1$
LASSO	0.530***	0.040	0.232***	-0.120***	-0.100***	0.541***	0.120
	(0.100)	(0.047)	(0.070)	(0.033)	(0.028)	(0.175)	(0.097)
RMSE y	0.530	0.388	0.360	0.152	0.172	0.383	0.521
BOOSTING	0.432***	0.107	0.250***	-0.093***	-0.158***	0.534***	0.058
	(0.086)	(0.041)	(0.066)	(0.029)	(0.028)	(0.147)	(0.111)
RMSE y	0.383	0.224	0.266	0.120	0.128	0.340	0.380

Note: GG = General Government, GFCF = Gross Fixed Capital Formation. The median standard error across the splits are reported in brackets.

Part 2: ATE on Social indicators

DML Estimator \ Dependant Variable	Government Effectiveness	Musgravian Index	Gini Index	Poverty headcount ratio at $1,90\$$ a day (2011 PPP) (% of population)
LASSO	-0.014	0.127	0.082**	0.087**
	(0.030)	(0.132)	(0.070)	(0.036)
RMSE y	0.137	0.602	0.343	0.220
BOOSTING	-0.021	0.092	0.031*	0.037**
	(0.043)	(0.124)	(0.066)	(0.036)
RMSE y	0.110	0.287	0.255	0.185

Note: GG = General Government. The median standard error across the splits are reported in brackets.

6 Conclusion

The paper provides an assessment of Budget Balance Rules compliance effect on macroeconomic and social welfare related indicators. It uses Double Debiased Machine Learning methodology through two feature selection algorithm as comparison for the results. All the results do not depend on the shrinking algorithm. The paper shows that Voter preferences need to be taking into account in fiscal rules analysis since voter prefences are retained as a key determinant for fiscal rules compliance. Governements with national Budget Balance Rules seem to try to go beyond the trade-off between BBR compliance and Growth objectives leading to a re-allocation of spending. Governement favor Gross Fixed Capital Formation but decrease Governement Final Consumption that include social spending. As a consequence the Inequalities are a cost for compliance and even more for the poorest classes since the poverty head account is increased by compliance. The discussion behind the results should not be to stop complying fiscal rules but better design them. Flexible fiscal rules have been largely discussed in the literature (see Eyraud et al. [2018], Caselli et al. [2018]) and they look as a solution to solve the issue pointed out by our results. Debrun and Jonung [2019] proposed a fiscal-Taylor, following an over-cycle expenditure benchmark, while others as Creel et al. [2014] argue in favor of a well-known Golden Rule. Both seem to work against the loose in public social spending but the fiscal rules should be precisely defined, including a social area objective. Nevertheless, an expenditure benchmark or a golden rule requiere a harmonisation of governments accounting, especially for the members of a common currency union as the Euro Area. This leads to a higher debate on what should be considered as a productive expenditure and how to compute Governement Capital Fixed consumption (see Schreyer [2003] for discussion on productive capital and countries computional hypotheses). Our results also lauch the debate on the use on Machine learning in the econometric field Athey [2018]. Indeed, our paper provides both traditionnal results as the disciplined effect of BBR compliance but extend them to new findings with models that help us to reduce the dimension of predictors and highlight the most important. Such work is a really helpfull tool foor public decision maker.

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Appendices—For *online publication only*

Appendix 1: Origin of Budget Balance Rules' targeted values

Country	Years	Database origin for Budget Balance Rule's Target
Chile	2004-2015	IMF World Economic Outlook Database 2018
Costa-Rica	2004-2015	Fiscal balance comes from World Bank*(except in 2015, Fiscal Balance comes from Banco Central de Costa Rica(BCCR) and Gross Fixed Capital Formation comes from IMF Investment and Capital Stock dataset 1960-2015
Denmark	2004-2015	IMF World Economic Outlook Database 2018
Estonia	2004-2015	IMF World Economic Outlook Database 2018
Finland	2004-2015	Eurostat
Germany	2004-2010	Eurostat
Germany	2011-2015	IMF World Economic Outlook Database 2018
Hungary	2004-2015	IMF World Economic Outlook Database 2018
Indonesia	2004-2015	IMF World Economic Outlook Database 2018
Israel	2004-2015	IMF World Economic Outlook Database 2018
Japan	2004-2015	IMF World Economic Outlook Database 2018
Malaysia	2004-2015	IMF World Economic Outlook Database 2018 and Gross Fixed Capital Formation comes from IMF Investment and Capital Stock dataset 1960-2015
New Zealand	2004-2015	New Zeland Treasury "Fiscal Time Series Historical Indicators 1972 - 2018"
Peru	2004-2015	IMF (Peru: Selected Issues Paper, IMF, 2012, number 12-27) and Banco Central de Reserva del Perú (BCRP)
Spain	2004-2015	IMF World Economic Outlook Database 2018
Sweden	2004-2015	IMF World Economic Outlook Database 2018
Switherland	2004-2015	IMF World Economic Outlook Database 2018
United Kingdom	2004-2009	Eurostat
United Kingdom	2010-2015	IMF World Economic Outlook Database 2018

Country	Constrained variable	Target Value	Period	Comments	Level of Government constrained
Chile	Structural Balance	1	2001-2007		Central
	Structural Balance	[0.5; -2]	2008-2015	Rule defined in a range	Central
Costa Rica	Budget Balance excluding gross investment	0	2001-2015	Golden Rule	Central
Denmark	Structural Balance	0.5	2001-2011		General
	Structural Balance	-0.5	2014 2015		General
Estonia	Structural Balance	0	1993 2011		General
	Structural Balance	0	2012		General
Finland	Structural Balance	[0;1]	1999-2013	1% between 2007 and 2011	Central
	Budget Balance (Total)	[-2.75; -2.5]	1999-2008	-2.75% between 1999 and 2002	Central
	Budget Balance (Total)	-1	2011		Central
Germany	Budget Balance excluding net investment	0	1969-2010		Central
	Structural Balance	-0.35	2011		Central
Hungary	Primary Balance	0	2004 2009		General
	Annual changes of Primary Balance	0	2010 and 2011		General
	Primary Balance	0	2009 2011	Not included in our analysis	Central
	Structural deficit above 0.5% (because debt is higher that 60% as described in TSCG)	-0.5	2012-2015	Transpose in national law from TSCG, interpreted as national BBR by hypothesis here	General
Indonesia	Budget Balance (Total)	-3	1967-2015		General
Israel				Not included due to annual change in the targeted value. Not a numerical rule.	
Japan	Budget Balance excluding net investment	0	1990--2015	Golden Rule	Central
Malaysia	Budget Balance excluding net investment	0	1959-2015	Golden Rule	Central
New Zealand	Budget Balance excluding net investment	0	1994-2015	Golden Rule	General
Peru	Budget Balance	[-1; 2]	2000 2013		Central
	Structural Balance	-1	2014		General
Spain	Budget Balance (Total)	[-2;0]	2003 2011	Limit related to GDP growth	General
Sweden	Budget Balance	[1;2]	2000	Only 1% since 2007	General
Switzerland	Structural Balance	0	2003		Central
United Kingdom	Budget Balance excluding net investment	0	1997 2008	Golden Rule	General
	Annual changes in Budget Balance (Total)	0	2010		General

Note: BBR = Budget Balance Rule. We stop all reported periods in 2015 because IMF Fiscal Rules Database only report fiscal rules until 2015. It does not mean that fiscal rules are no more in force after 2015.
Source: Caselli and al (2018), Reuter (2017), Eyraud and al (2018), - The table assumes some differences for Hungary, Israel, Japan and United Kingdom developed in section 3.1 .

Appendix 2. Fiscal rules included in our analysis -Only 2004-2015 period is considered for this paper-