Dynamics of Central Government Debt in the European Union

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1. Introduction

This study aims to provide an in-depth understanding of the topic of central government debt in the European Union (EU). The first section, the Literature Review, is dedicated to an analysis of current knowledge. Here, we check previous studies, theoretical stances and empirical results to establish a basis for investigation.

The second part reveals the Theoretical Framework, providing the basis for our analysis. This part investigates the main theories and economic models relevant to public debt, prepares the analysisfor empirical exploration.

In the third part, the Methodology, we elucidate the research pattern, data sources and tools used to analyze the relationships and dynamics of central government debt in the EU. This section serves as a methodological basis that guides the study.

In the fourth part we analyze the Results obtained from the Fractional Component Models - Logit. Here, the knowledge obtained from the models offers the relationships between independent variables and central government debt over the period from 1997 to 2020.

The fifth part of the study presents the findings of the study. Here, we reflect on the results, discuss their significance for policymakers, and propose potential ways for future research.

2. Literature Review

The State's public debt is a relevant macroeconomic indicator and studies on it are often based on the composition of the indicator, the dynamics of expansion or decrease, the profile (maturity of short- or long-term securities) and mainly the exogenous effects that can influence this indicator.

Regarding the composition and explanation of the debt, it is possible to draw the equation as follows:

$$d_t - d_{t-1} = \frac{i_t - Y_t}{1 + Y_t} d_{t-1} + p_t + sfa_t$$

Therefore, the dynamic equation of public debt ($d_t - d_{t-1}$) is drawn as follows: the product of the lagged debt ratio and the differential between the effective rate (i_t) the nominal gross domestic product (Y_t), the primary deficit (p_t) and the cash flow residual (sfa_t). (Abbas et al. 2011).

Regarding the dynamics of expansion or contraction, it is possible to observe that the decrease in debt in developed economies has been correlated to economic growth and mainly to successive primary surpluses (Giannitsarou & Scott, 2008). Furthermore, inflationary periods have positive effects on reducing public debt. (Reinhart & Sbrancia, 2015)

Regarding to refinancing capacity, interest rate and other components of debt financing, it is possible to state that the remuneration paid for the long-term obligation contributes to increasing the debt/GDP ratio. Therefore, managing debt maturity in the current period becomes important to reduce debt in the long term (Equiza-Goñi, 2016).

3. Theoretical Framework

3.1 Theoretical Foundation

To design this study, the paper called “Determinants of sub-central European government debt” (Bellot et al., 2017) was used as a reference. This research's foremost objective is to analyze the determinants of European public debt in Europe (Italy, France, Austria, Germany, Belgium and

Spain), taking into account local administrations through panel data for the period from 1996 to 2010.

The model is designed as follows:

$$Direct\ debt\ var/GDP)ij\ =\ f(pij, demij, geoij, rij, fsij, ecoij\ budij\ lagij)$$

The dependent variable is direct debt variation in each region “i” studied for a period “j”. The independent variables are as follows: pij: political variables in region “i” in year “j”, demij: demographic variables and size in region “i” in year “j”, geoij: geographical variables in region “i” in year “ j”, rij: fiscal rules in region “i” in year “j”, fsij: financing system in region “i” in year “j”, ecoij: economic variables in region “i” in year “j”, budij: budgetary variables in region “i” in year “j”, lagij: lagged variables in region “i” in year “j”.

Political variables were introduced with the aim of understanding whether local governments that have the same political party administration can be decisive for the increase or not in public debt. Previous studies have indicated that equivalent central and regional government administrations contribute to debt decline.

Regarding demographic variables, the study seeks to understand whether factors such as population size, demographic density and population aging are decisive for the advancement or otherwise of debt rates. The core idea is to understand whether regions with high population density, namely large capitals, benefit from the characteristic of being too large to stop being financed by the central government.

The determinants of public debt expansion or contraction were estimated from panel data using fixed effects based on Haussman test results. Then, the Arellano-Bond estimator (Generalized Method of Moments) was used to estimate the dynamic model, understanding the lags of the dependent variable and its interactions with the independent variables.

$$y_{it} = \lambda y_{i,t-1} + x'_{it}\beta + f'_i\gamma + \varepsilon_{it}$$

$$\varepsilon_{it} = u_i + e_{it}$$

The outputs obtained match with the initial expectations, considering that the aging of the population contributed positively to the increase in public debt. Furthermore, for this same fraction of the population, tax increases are vetoed in local votes. In some countries in the sample

(Italy, France and Germany) the decentralized budget contributes to an increase in spending due to the lack of accountability of local authorities. Regarding population density, the Spanish example shows that there is a negative relationship between population growth and the stock of public debt.

The size of the economy and the better conditions for income taxation in places with high GDP per capita contribute to greater indebtedness, considering that the debt financing capacity becomes better as the debt financing condition improves.

In summary, the paper demonstrates that the budgets of sub-sovereign governments are countercyclical, presenting economies of scale and adhering to the golden rule of public finances. Furthermore, higher debt levels are associated with population growth and lower per capita financing. Regions with high debt-to-GDP ratios tend to have lower future deficits.

3.2 Theoretical Model and Data

The research dependent variable is the Central Government Debt of the European Union (UE) between 1997 and 2020 years, offered by Eurostat. Besides, this research is composed of three-time series: between 1997-2006, 2007-2014, and 2015-2020. After that, we have classified the independent variables used in the panel into three categories: macroeconomic, institutional, and capital market variables.

The equation can be represented as follows:

$$DEBgov = N112G + GFCFtot + \ FDIind + \ IEFind$$

Table 1 - Descriptive Variables

Variables	Unit of Measure	Acronym	Source of Data
Dependent Variable			
Central Government Debt, Total	% of GDP	DEBgov	IMF
Independent Variables			
Gross Fixed Capital Formation - N112G Other buildings and structures	% of GDP	N112G	EuroStat
Gross Fixed Capital Formation, Total	% of GDP	GFCFtot	Eurostat
Financial Development Index	Index	FDIind	IMF
Index of Economic Freedom	Index	IEFind	Heritage Foundation

Source: Eurostat (2022)

Regarding macroeconomic variables bloc, they are three. The first one is the fraction of Gross Fixed Capital Formation corresponding to the infrastructure (N112G Other buildings and structures) of the European Union (UE). The main idea for using this index is to verify if exists a connection between the Central Government Debt in a given economy in specific infrastructure projects promotion (World Economic Outlook Database, 2022).

The second one is the global gross fixed capital formation index and the third one is the governmental fraction of the same index. The core idea for these variables is the same as N112G.

As for the institutional variables bloc, we have used the Economic Freedom Index, which translates into data the efficiency level of regulatory frameworks, the size of the State, the economy's overture, and the legal system efficiency of a given country (The Heritage Foundation, 2022).

Concerning capital market variables we have the Financial Development Index designed by the International Monetary Fund (IMF). The index aims to aggregate information on the countries' financial system access capacity, efficiency, and depth, evaluating the financial institutions and the capital market.

4. Methodology and Econometric Equations

Initially, the correlations between the variables will be presented according to the model below:

$$DEBGov = \beta 0 + \beta 1 N112G + \beta 2 GFCFtot + \beta 3 GFCFgov + \beta 4 FDIind + \beta 5 IEFind + \varepsilon$$

Next, the estimation methodology to be drawn up for this study is the Fractional Regression Model (FRM) in its four forms: Logit, Probit, Log-Log and Complementary Log-Log. The model in question is designed to assume the dependent variable between 0 and 1, being continuous and limited. For the independent variables, they are explained as a standard linear regression model, where x1 = 1...xn.

$$E(y|x) = \beta_{1+} \beta_2 \quad {}_{x^2} + \cdots \beta_k x_k \quad = x\beta$$

The robustness of the model is based on the use of quasi-maximum likelihood (QML) estimation (Papke & Wooldridge, 1996).

$$\mathrm{E}(\mathrm{y}|\mathrm{x}) = \mathrm{G}(\mathrm{x}\theta)$$

For the same work, the authors suggested cumulative distributions in the G function, where the effects become explicit in the equation below:

$$\frac{\partial E(y|\,x)}{\partial xj} = \theta j g(x\theta), \text{wherein } g(x\theta) = \frac{\partial G(x\theta)}{\partial x\theta}$$

There is also the possibility of considering numerous equal as one boundary values:

$$y_i = \begin{cases} 0 \; se \; y_i \;\; \in \; [0,1] \\ 1 \; se \; y_i \;\; = 1 \end{cases}$$

Next, it is important to present the second part of the model and its ratio of the conditional mean residual:

$$\mathrm{E}(y_i\,|x_i) = \mathrm{P}\,(y_i \; = 0|x_i)\mathrm{E}(y_i\,|x_i\,, y_i \; = \; 0) + \; \mathrm{P}\,(y_i \; = \; 1|x_i) = \; (1 - \; \mathrm{G}(x_i\,y))\;\mathrm{G}(x_i\,\beta) \; + \; \mathrm{G}(x_i\,y)$$

From then on, the marginal effects of the explanatory variables are derived by calculating the conditional mean E(y_i |x_i) at x_i as shown in the following equation:

$$\frac{\partial E\{y_i|x_i\}}{\partial x_i} = o <=> \frac{\partial p\{y_i|x_i\}}{\partial x_i j}\{1 - E|x_i y_i = 0\} + [1 - P[y_i = 1|x_i]\frac{\partial E(y_i|x_i y_i = o)}{\partial x_i j} = 0$$

In addition to the four models, some tests will be carried out to ensure the robustness of the estimates, such as: RESET, GOFF-I, GOFF-II and GGOFF (Ramalho et al., 2014).

4.1 Econometric Model Choice

Logit Fraction It produces large p-values every time, especially between 2007 and 2014 and between 2015 and 2020. This means that it will remain robust throughout time, which makes it a dependable option for the current analysis. The model's persistent statistical significance across several time periods highlights its capacity to explain and capture subtleties in the data. These findings provide assurance that Fractional Logit is a reliable instrument for the study.

Similar to the Fractional Logit, the Fractional Probit displays significant p-values, demonstrating similar statistical robustness. Given the similarities in significance levels, Fractional Probit seems like a good substitute for Fractional Logit. The steady achievement of p-values suggests that Fractional Probit, similar to its Logit equivalent, continues to function dependably over time. Taking into account the statistical strength and parallel significance, Fractional Probit is a viable alternative that could provide a more nuanced view or supplementary insights in comparison to

Fractional Logit. Because of this feature, Fractional Probit is a good substitute, offering selection flexibility for the models.

Fractional Loglog exhibits a strong statistical signal with persistent significant p-values for all eras. The observed importance over several timeframes indicates the robustness and dependability of the model in identifying significant links in the data. Good data is provided by Fractional Loglog, especially for the years 2015–2020. This particular time period, indicated by significant p-values, highlights how well the model explains changes in the observable phenomena across this time frame. The notion that Fractional Loglog could be a good option—particularly in the more recent years—highlights the possibility that it could offer insightful analysis and a thorough comprehension of the dynamics at work in the dataset.

Significant p-values were obtained using Fractional Cloglog, however the trend is not as stable. The particular qualities included in the dataset under consideration may influence the choice of Fractional Cloglog. The less consistent pattern when compared to Fractional Logit suggests that careful study is necessary, even though its significant p-values suggest that it can capture some useful information. Fractional Cloglog may still be a good option, providing a good strategy that is consistent with the dataset under analysis, depending on the properties.

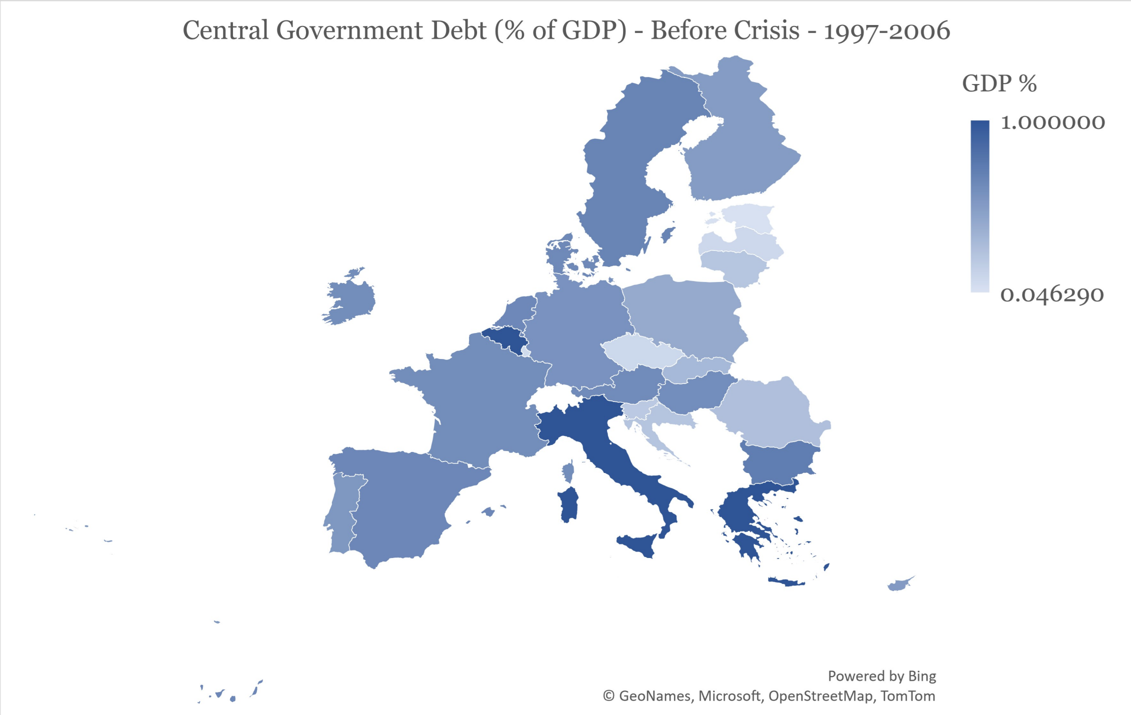
The statistical significance of the Fractional Component of the Two-Part Model - Logit model was maintained during the entire analysis period. This model was chosen because significant p-values were consistently seen during the investigation, suggesting statistical robustness over an extended period of time. The models' capacity to retain statistical significance across many temporal contexts implies that they are dependable and efficient instruments for comprehending the fundamental intricacies of the data being examined.

5. Results

N112G Gross Fixed Capital Formation - N112G Other buildings and structures

An inverse relationship between N112G and the Central Government Debt is implied by the negative coefficient for N112G (Gross Fixed Capital Formation - N112G Other buildings and structures), meaning that a rise in N112G is linked to a fall in the debt level. This is a persistent negative association for all three investigated periods (2007-2014, 2015-2020, and 1997-2006). The adverse link may have diminished with time, as seen by the effect's diminishing amplitude, but it is still statistically significant throughout all time periods, with p-values less than 0.01.

This finding implies that variations in Gross Fixed Capital Formation, namely within the N112G category The Central Government Debt is significantly influenced by the index. The negative coefficient suggests that lower levels of public debt are linked to times when there were greater investments in certain fixed capital formation types. This may be explained by a rise in economic activity and development, which could result in better revenue generation or resource allocation efficiency. The relationship's stability and statistical significance highlight how important is the index for comprehending and forecasting changes in Central Government Debt during the time periods under investigation.

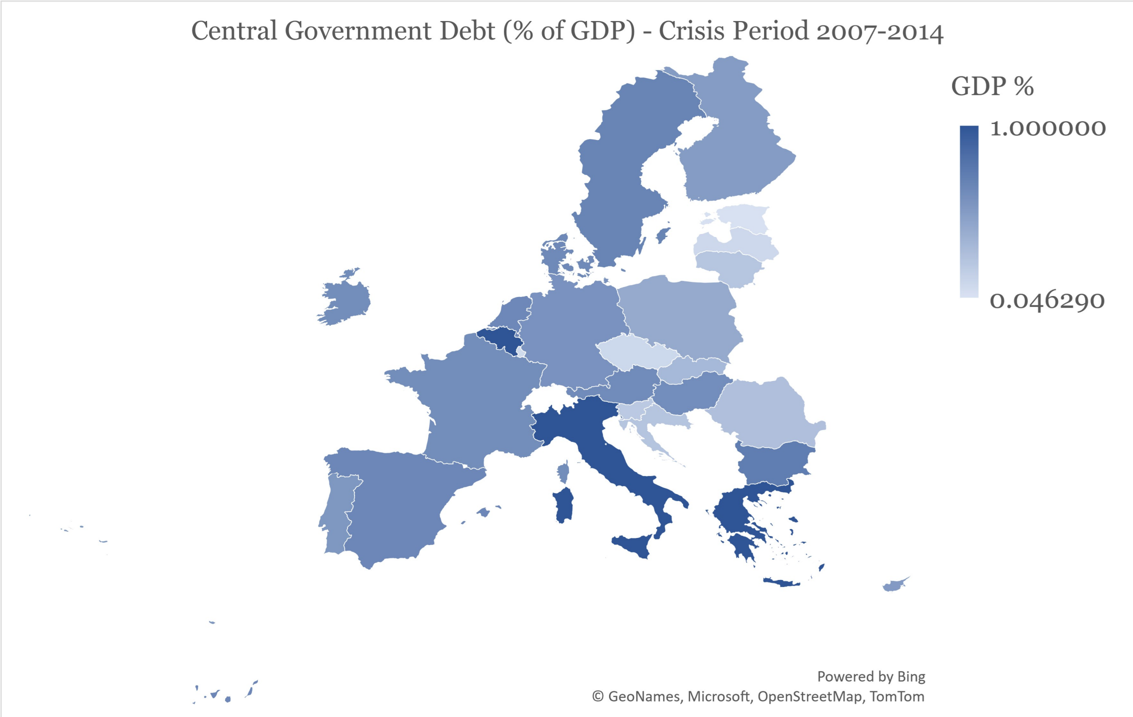


GFCFtot - Gross Fixed Capital Formation

The coefficient GFCFtot (Gross Fixed Capital Formation, Total) shows a positive correlation between total gross fixed capital formation and central government debt throughout the first period, which runs from 1997 to 2006. This implies that a growth in government debt during this period was associated to greater levels of total fixed capital formation.

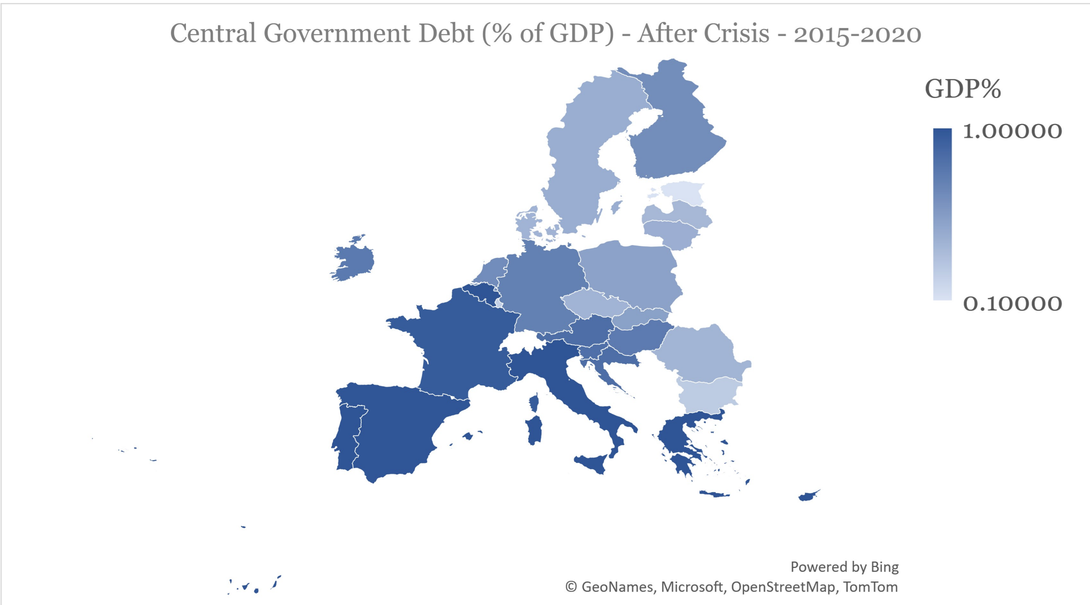
The next period (2007-2014) sees a change, with the coefficient going negative and indicating an inverse link between total fixed capital formation and government debt. A reduction in the Central Government Debt is correlated with higher investments in gross fixed capital formation during this time.

The coefficient returns to a positive value in the most recent period (2015–2020), suggesting that total fixed capital formation and government debt have a positive association that is still present. This positive link is statistically significant ($p<0.01$), indicating that between 2015 and 2020, there may be a correlation between rising levels of total gross fixed capital formation and rising levels of government debt.



FDlind - Financial Development Index

Over the three study periods (1997-2006, 2007-2014 and 2015-2020), there appears to be a consistent and positive correlation between the Financial Development Index and Central Government Debt, as indicated by the consistently positive coefficient for the index. This suggests that the Central Government Debt tends to climb along with the financial development index, which rises with higher levels of financial development in the EU countries.



This association is supported by the statistical significance of the positive relationship in all year, as shown by p-values less than 0.01. This finding suggests that there may be a correlation between higher levels of government debt and variables that promote improved financial growth, such as easier access to financial services, a healthy financial market, or upgraded financial infrastructure.

IEFind - Index of Economic Freedom

Throughout all three of the study period years (1997-2006, 2007-2014, and 2015-2020), there is a strong negative correlation between the Index of Economic Freedom and Central Government Debt, as indicated by the constantly negative coefficient for the index. This implies that central government debt tends to decline as economic freedom rises.

The observed association is reinforced by the statistical significance of this negative relationship, with p-values lower than 0.01 in all periods. According to the negative coefficient, nations with more economic freedom generally have lower levels of public debt.

In this way, the study suggest that economic freedom may contribute to fiscal responsibility and lower government debt. The statistically significant negative coefficient reveals that economic freedom as a factor influencing Central Government Debt dynamics.

6. Econometric Estimations: Modeling Economic Relationships

Table 2 - Correlation Matrix - 1997-2006

	DEBgov	N112G	GFCFtot	FDIind	IEFind
DEBgov	1				
N112G	-0.681***	1			
GFCFtot	-0.488***	0.696***	1		
FDIind	0.434***	-0.522***	-0.238***	1	
IEFind	-0.205***	-0.023	0.169***	0.482***	1

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3 - Correlation Matrix - 2007-2014

	DEBgov	N112G	GFCFtot	FDIind	IEFind
DEBgov	1				
N112G	-0.485***	1			
GFCFtot	-0.388***	0.675***	1		
FDIind	0.364***	-0.665***	-0.331***	1	
IEFind	-0.148**	-0.192***	0.018	0.206***	1

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4 - Correlation Matrix - 2015-2020

	DEBgov	N112G	GFCFtot	FDIind	IEFind

DEBgov	1				
N112G	-0.529***	1			
GFCFtot	-0.239***	0.240***	1		
FDIind	0.461***	-0.643***	0.004	1	
IEFind	-0.634***	0.187**	0.478***	0.015	1

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 - Fractional logit regression model

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.288***	-0.199***	-0.174***
	(0.0375)	(0.0685)	(0.0575)
GFCFtot	0.00415	-0.0222	0.0308**
	(0.0180)	(0.0332)	(0.0152)
FDIind	2.167***	0.738*	2.663***
	(0.290)	(0.445)	(0.662)
IEFind	-0.0726***	-0.0593***	-0.183***
	(0.00781)	(0.0201)	(0.0171)
Constant	5.484***	6.050***	12.38***
	(0.558)	(1.835)	(1.178)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6 - Fractional probit regression model

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.171***	-0.117***	-0.106***
	(0.0224)	(0.0396)	(0.0341)
GFCFtot	0.00266	-0.0121	0.0160*
	(0.0107)	(0.0199)	(0.00944)
FDIind	1.284***	0.473*	1.578***
	(0.176)	(0.278)	(0.373)
IEFind	-0.0430***	-0.0353***	-0.107***
	(0.00453)	(0.0115)	(0.00932)
Constant	3.250***	3.572***	7.357***
	(0.325)	(1.025)	(0.654)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7 - Fractional loglog regression model

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.173***	-0.112**	-0.126***
	(0.0231)	(0.0463)	(0.0465)
GFCFtot	0.00510	-0.00711	0.0133
	(0.0101)	(0.0250)	(0.0119)
FDIind	1.311***	0.634	1.466***
	(0.199)	(0.400)	(0.504)
IEFind	-0.0443***	-0.0300**	-0.124***
	(0.00482)	(0.0134)	(0.0122)
Constant	3.678***	3.401***	9.308***
	(0.359)	(1.123)	(0.989)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8 - Fractional cloglog regression model

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.207***	-0.160***	-0.130***
	(0.0289)	(0.0427)	(0.0350)
GFCFtot	0.000401	-0.0211	0.0211**
	(0.0156)	(0.0191)	(0.00899)
FDIind	1.526***	0.522**	1.873***
	(0.216)	(0.260)	(0.345)
IEFind	-0.0491***	-0.0500***	-0.113***
	(0.00556)	(0.0118)	(0.00883)
Constant	3.405***	4.693***	7.259***
	(0.402)	(1.053)	(0.601)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9 - Fractional component of two-part model - logit specification

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.249***	-0.268***	-0.102**
	(0.0329)	(0.0433)	(0.0520)
GFCFtot	0.0284*	-0.0379**	0.0423***
	(0.0146)	(0.0187)	(0.0146)
FDIind	1.832***	0.823***	2.402***
	(0.242)	(0.297)	(0.580)
IEFind	-0.0584***	-0.0923***	-0.148***

	(0.00615)	(0.0115)	(0.0150)
Constant	3.710***	8.810***	9.178***
	(0.372)	(0.927)	(1.054)
Observations	235	166	129

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10 - Binary component of two-part model - probit specification

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.279**	-0.109	-0.401**
	(0.129)	(0.0720)	(0.179)
GFCFtot	-0.130*	-0.0124	-0.131*
	(0.0665)	(0.0318)	(0.0695)
FDIind	2.474**	-0.0771	2.063*
	(1.097)	(0.735)	(1.090)
IEFind	-0.0682***	-0.0368**	-0.131***
	(0.0264)	(0.0183)	(0.0362)
Constant	6.209***	2.771*	11.55***
	(1.723)	(1.420)	(2.635)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11 - Binary component of two-part model - loglog specification

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.286**	-0.0675	-0.407**
	(0.120)	(0.0592)	(0.164)
GFCFtot	-0.158**	-0.00552	-0.104*
	(0.0678)	(0.0266)	(0.0626)
FDIind	2.440**	-0.0612	2.427**
	(0.972)	(0.629)	(1.055)
IEFind	-0.0781***	-0.0226	-0.138***
	(0.0251)	(0.0158)	(0.0343)
Constant	7.922***	1.721	11.74***
	(1.978)	(1.243)	(2.663)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12 - Binary component of two-part model - cloglog specification

	(1997-2006)	(2007-2014)	(2015-2020)

N112G	-0.418**	-0.294**	-0.493*
	(0.207)	(0.121)	(0.259)
GFCFtot	-0.0998	-0.0374	-0.254**
	(0.0940)	(0.0515)	(0.105)
FDIind	3.387*	-0.00785	2.456
	(1.762)	(1.177)	(1.534)
IEFind	-0.0794*	-0.0913***	-0.172***
	(0.0409)	(0.0278)	(0.0567)
Constant	5.640***	7.527***	16.25***
	(2.170)	(2.012)	(4.176)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13 - Fractional component of two-part model - logit specification

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.249***	-0.268***	-0.102**
	(0.0329)	(0.0433)	(0.0520)
GFCFtot	0.0284*	-0.0379**	0.0423***
	(0.0146)	(0.0187)	(0.0146)
FDIind	1.832***	0.823***	2.402***
	(0.242)	(0.297)	(0.580)
IEFind	-0.0584***	-0.0923***	-0.148***
	(0.00615)	(0.0115)	(0.0150)
Constant	3.710***	8.810***	9.178***
	(0.372)	(0.927)	(1.054)
Observations	235	166	129

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14 - Fractional component of two-part model - probit specification

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.150***	-0.158***	-0.0635**
	(0.0198)	(0.0258)	(0.0316)
GFCFtot	0.0168*	-0.0236**	0.0243***
	(0.00871)	(0.0116)	(0.00889)
FDIind	1.105***	0.525***	1.445***
	(0.149)	(0.184)	(0.340)
IEFind	-0.0353***	-0.0559***	-0.0892***
	(0.00365)	(0.00689)	(0.00859)
Constant	2.243***	5.307***	5.586***

	(0.222)	(0.551)	(0.617)
Observations	235	166	129

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15 - Fractional component of two-part model - loglog specification

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.149***	-0.154***	-0.0739*
	(0.0202)	(0.0290)	(0.0410)
GFCFtot	0.0161*	-0.0245*	0.0221*
	(0.00846)	(0.0139)	(0.0115)
FDIind	1.134***	0.603***	1.395***
	(0.164)	(0.221)	(0.434)
IEFind	-0.0362***	-0.0575***	-0.0984***
	(0.00379)	(0.00791)	(0.0109)
Constant	2.675***	5.765***	6.818***
	(0.247)	(0.628)	(0.846)
Observations	235	166	129

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16 - Fractional component of two-part model - cloglog specification

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.189***	-0.196***	-0.0804**
	(0.0260)	(0.0288)	(0.0331)
GFCFtot	0.0222*	-0.0309**	0.0304***
	(0.0118)	(0.0130)	(0.00841)
FDIind	1.342***	0.646***	1.750***
	(0.184)	(0.205)	(0.324)
IEFind	-0.0422***	-0.0682***	-0.100***
	(0.00457)	(0.00783)	(0.00802)
Constant	2.296***	6.139***	5.792***
	(0.258)	(0.625)	(0.597)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 17 - Quantile Regression

	(1997-2006)	(2007-2014)	(2015-2020)

N112G	-0.0446***	-0.0403***	-0.0284***
	(0.00750)	(0.00784)	(0.0101)
GFCFtot	0.000153	-0.0161***	0.00436
	(0.00347)	(0.00365)	(0.00264)
FDIind	0.408***	0.331***	0.575***
	(0.0745)	(0.0871)	(0.0923)
IEFind	-0.0129***	-0.0185***	-0.0283***
	(0.00180)	(0.00248)	(0.00274)
Constant	1.402***	2.307***	2.370***
	(0.109)	(0.188)	(0.178)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 18 - Quantile Regression - Bootstrap

	(1997-2006)	(2007-2014)	(2015-2020)
N112G	-0.0446***	-0.0403***	-0.0284**
	(0.0127)	(0.0106)	(0.0139)
GFCFtot	0.000153	-0.0161***	0.00436
	(0.00543)	(0.00536)	(0.00629)
FDIind	0.408***	0.331***	0.575***
	(0.0689)	(0.100)	(0.101)
IEFind	-0.0129***	-0.0185***	-0.0283***
	(0.00223)	(0.00315)	(0.00318)
Constant	1.402***	2.307***	2.370***
	(0.165)	(0.221)	(0.170)
Observations	260	208	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 19 - Quantile Regression - 25, 50, 75, 90

	(1997-2006)	(1997-2006)	(1997-2006)	(1997-2006)	(2007-2014)	(2007-2014)	(2007-2014)	(2015-2020)	(2015-2020)	(2015-2020)	(2015-2020)
	Q25	Q50	Q75	Q90	Q25	Q75	Q90	Q25	Q50	Q75	Q90
N112G	-0.0576***	-0.0446***	-0.0514***	-0.0716***	-0.0539***	-0.0515***	0	-0.0187	-0.0284**	-0.0381*	-0.0438***
	(0.00916)	(0.0110)	(0.0130)	(0.0154)	(0.0178)	(0.0184)	(0.0201)	(0.0144)	(0.0132)	(0.0201)	(0.0161)
GFCFtot	0.00531	0.000153	-0.00183	-0.00476	-0.00799	-0.00656	0	0.0118*	0.00436	0.00308	-0.00293
	(0.00407)	(0.00509)	(0.00619)	(0.00712)	(0.00729)	(0.0105)	(0.0102)	(0.00641)	(0.00540)	(0.00578)	(0.00654)
FDIind	0.373***	0.408***	0.487***	0.309	0.165	0.306*	0	0.623***	0.575***	0.481***	0.507**

	(0.0733)	(0.0778)	(0.130)	(0.219)	(0.114)	(0.171)	(0.238)	(0.162)	(0.109)	(0.180)	(0.205)
IEFind	-0.0111***	-0.0129***	-0.0137***	-0.0165***	-0.0207***	-0.0112*	0	-0.0383***	-0.0283***	-0.0237***	-0.0271***
	(0.00176)	(0.00212)	(0.00321)	(0.00333)	(0.00348)	(0.00587)	(0.00498)	(0.00395)	(0.00307)	(0.00522)	(0.00648)
Constant	1.187***	1.402***	1.654***	2.306***	2.363***	1.854***	1***	2.695***	2.370***	2.300***	2.798***
	(0.102)	(0.157)	(0.314)	(0.293)	(0.228)	(0.424)	(0.360)	(0.251)	(0.187)	(0.444)	(0.490)
Observations	260	260	260	260	208	208	208	156	156	156	156

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6. Conclusion

Summarizing, the examination of the Fractional Component of Two-Part Model - Logit models has provided significant insights on the factors influencing Central Government Debt over three different periods (1997-2006, 2007-2014, and 2015-2020). The independent variables had different effects. Government debt and investment in gross fixed capital formation (N112G) showed a inverse connection, suggesting that lower levels of government debt are linked to periods with more investments

With a significant positive relationship in the first period, a negative relationship in the second, and yet another significant positive association in the third, Total Gross Fixed Capital Formation showed an different dynamic. This variability highlights how important was divided the series in pre crisis, crisis and after crisis panel.

Government debt and the Financial Development Index have a positive association with the independent variable, indicating that higher levels of financial development are linked to higher levels of government indebtedness. A negative correlation was found between government debt and the Index of Economic Freedom (IEFind), suggesting that nations with higher levels of economic freedom also tend to have lower levels of public debt.

These results highlight how financial and economic issues interact to shape the dynamics of government debt. This understanding is important for policymakers, providing significant insights for strategic decision-making to generate sustainability and economic balance in the region

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