Ten-Quarter Projection for Spanish Central Government Debt via WASD Neuronet

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Abstract. This paper makes a ten-quarter projection for Spanish central government debt (SCGD). Several Eurozone member states had been in debt crisis since 2008, including Spain. During the crisis, Spanish central government debt increased quickly. According to the data provided by the Bank of Spain, the SCGD reached to €969.5523 billion in December 2016, and debt-to-GDP ratio was more than 100% in 2016. It is important to conduct a projection for SCGD so that the government can make better fiscal policies and preparation for risks in future. In this paper, we use a 3-layer feed-forward neuronet to conduct a projection for SCGD. We use weights and structure determination (WASD) algorithm to build such a neuronet model and train the neuronet with Spanish central government debt data from December 1994 to December 2016. Finally, three different trends of SCGD are shown via experiments: quick increasing trend, increasing trend and decreasing trend.

Keywords: Central government debt · Debt crisis · Ten-quarter projection · WASD algorithm

1 Introduction

Government debt, also known as national debt and sovereign debt, is the debt owned by government. Central government debt, which is the most important part of general government debt, is the debt owned by central government.

Spain has a population of 46 million, which is the fourth largest economy in the Euro area (following Germany, France and Italy). Under the influence of the world financial crisis in 2007−2008, debt crisis broke out in several European countries including Spain [1–3]. That crisis had significant adverse economic effects and labour market effects, with unemployment rate in Spain reaching to 27% [4]. Spanish central government debt (SCGD) also increased quickly. Before the fourth quarter of 2007, SCGD was stable and increased very slowly. SCGD increased much quicker after the end of 2007. As the SCGD data provided by the Bank of Spain show, in the fourth quarter of 2007, SCGD was only €318.8691

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billion; but, in the fourth quarter of 2016, SCGD reached to €969.5523 billion, more than three times as many as that of nine years ago. Spain entered the crisis period with a relatively modest public debt of 36.2% of GDP; but, in 2014, the debt-to-GDP ratio was more than 100%.

Nowadays, government debt has become the most pressing and difficult policy challenge that western governments have to face. Many scholars have researched Spain or European sovereign debt crisis. Klaus and Lucio pointed out that sovereign debt crisis is a complex problem, and internal devaluation policies imposed in Greece, Ireland, Italy, Portugal and Spain are ineffective [5]. Mario and Carsten examined the European sovereign debt crisis focussing on Spain, and presented empirical evidence indicating that German and Spanish government bond yields are cointegrated [4]. Trabelsi analyzed the recent development in the Eurozone, mainly the PIIGS (Portugal, Ireland, Italy, Greece and Spain) countries' financial crisis (including debt crisis) and the threats the Eurozone risks, and proposed some solutions for the crisis [6].

With the rapid growth of central government debt in Spain, predicting the trend of SCGD becomes important for government's policies making. In this paper, we introduce the weights and structure determination (WASD) neuronet to project the Spanish central government debt (SCGD). We have used this kind of neuronet to project the United States public debt [7], and obtained satisfactory projection results. We get the quarterly SCGD data from December 1994 to December 2016 provided by the Bank of Spain. The neuronet is trained and validated with these data; then, we conduct a ten-quarter projection of SCGD using such neuronet models.

2 Structure and Training of WASD Neuronet

In this section, we build a 3-layer feed-forward neuronet; then, we use weights and structure determination (WASD) algorithm to determine the neuronet's connecting weights and structure.

2.1 Neuronet Structure

A 3-layer feed-forward neuronet is built for SCGD projection, which is shown in Fig. 1. The neuronet includes input layer, hidden layer and output layer. In the hidden layer, there are N neurons activated by a group of Chebyshev polynomials $\phi_j(\cdot)$ (with $j = 1, 2, \cdots, N$) [8,9]. The input layer or the output layer each has one neuron, which is activated by linear identity function. We set the connecting weights from the input layer to the hidden layer to be 1, and the connecting weights from the hidden layer to the output layer to be w_j (with $j = 1, 2, \cdots, N$) which should be adjusted. Furthermore, the thresholds of all neurons are set to be 0. These settings mentioned above considerably decrease the complexity of neuronet and computation.

Then, we use WASD algorithm to determine the structure of neuronet. The weights and structure determination (WASD) algorithm can determine the connecting weights from the hidden layer to the output layer, and obtain the optimal

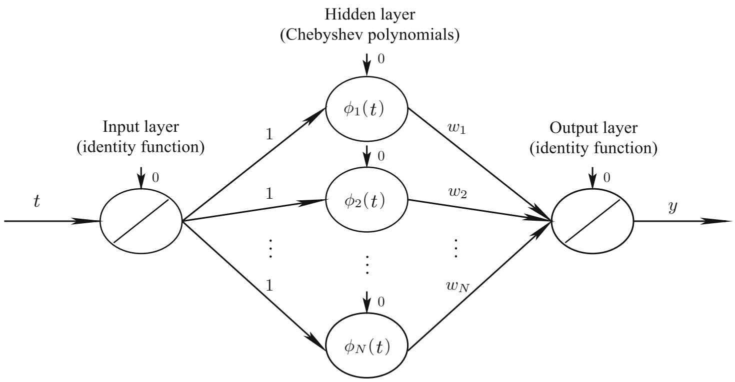


Fig. 1. Structure of 3-layer feed-forward WASD neuronet, which has input layer, hidden layer and output layer.

structure. For more details of the WASD algorithm, please refer to authors' previous works [10–14].

2.2 Normalization from [12/1994, 12/2016] to $[-1, \alpha]$

We get the SCGD data from the Bank of Spain, who officially provides the quarterly SCGD data from December 1994 to December 2016, so we can guarantee the accuracy of SCGD data. In this paper, originally and initially, the input of the neuronet is a date (e.g., 12/1994), the output is an SCGD datum in billion Euros (e.g., 209.3340). In order to make it convenient to normalize the input data, we change the format of date. We use the total number of months from 0 A.D. to the corresponding time as the input; for example, 23940 corresponds to 12/1994 because there are 23940 months from 0 A.D. to 12/1994, and 24204 corresponds to 12/2016. Therefore, the domain $[12/1994, 12/2016]$ is converted to $[23940, 24204]$. Because the neurons in the hidden layer are activated by Chebyshev polynomials of class 1, the input domain should be $[-1, 1]$. Therefore, we normalized $[23940, 24204]$ to $[-1, \alpha]$, with normalization factor $\alpha \in (-1, 0)$. Using the normalized data, we can train WASD neuronet.

2.3 WASD Neuronet Training and Validating

As mentioned in the previous subsection, the dates interval $[12/1994, 12/2016]$ is normalized to interval $[-1, \alpha]$. The performance of neuronet is related to the normalization factor $\alpha \in (-1, 0)$. With different values of α, we obtain different projection performances. Specifically, we use $\{(t_i, \gamma_i)|_{i=1}^{Q}\}$ as the training set of sample pairs, where $t_i \in \mathbb{R}$ denotes the ith input, $\gamma_i \in \mathbb{R}$ denotes the ith target output, and Q denotes the total number of sample pairs in the training set. In this paper, there are totally 86 sample pairs corresponding to 86 quarters from

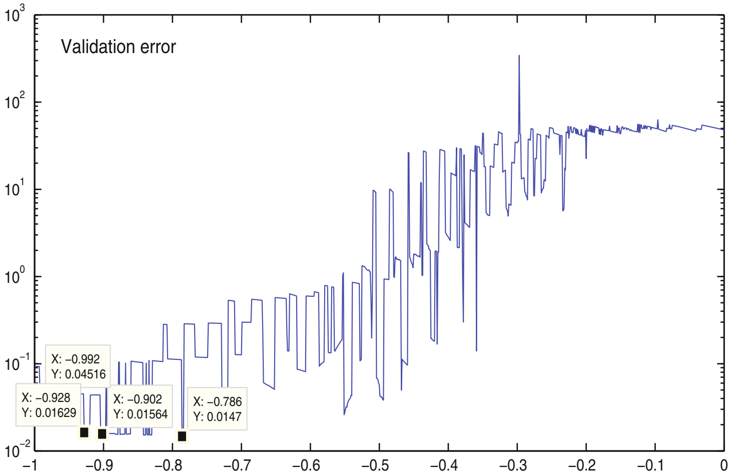


Fig. 2. Relationship between normalization factor α and validation error ϵ.

December 1994 to March 2016. We define the mean square error (MSE) [12] as follows:

$$E_N = \frac{1}{Q}\sum_{i=1}^{Q}\left(\gamma_i - \sum_{j=1}^{N} w_j\phi_j(t_i)\right)^2, \tag{1}$$

where E_N denotes the mean square error with the hidden layer's neurons number being N. By changing the number N of neurons in the hidden layer gradually, we obtain the relationship between N and MSE. As we know, the number of neurons in the hidden layer plays an important role in the neuronet's performance. Too many neurons in the hidden layer may cause over-fitting, while too few neurons cause under-fitting. Thus, we use the WASD algorithm to determine the optimal N by finding the corresponding N with the minimum MSE value. The optimal structure of neuronet can thus be determined.

Based on the well-trained neuronet models, we use additional 3 sample pairs to validate the neuronet models' projection performance. Note that sample pairs in interval $[12/1994, 03/2016]$ are used to train the neuronet (i.e., 86 sample pairs), while sample pairs in interval $[06/2016, 12/2016]$ are used to validate the performance (i.e., 3 sample pairs), which are also be normalized to the interval $[-1, \alpha]$. The validation error ϵ is defined as follows:

$$\epsilon = \frac{1}{M}\sum_{m=1}^{M}\left|\frac{y_m - \gamma_m}{\gamma_m}\right|, \tag{2}$$

where M denotes the number of validate sample pairs (i.e., $M = 3$ in this paper), y_m denotes the neuronet output with the mth sample input, and γ_m denotes the mth target output. We find again that different normalization factor α leads to different validation error ϵ. The relationship between them is shown in Fig. 2.

3 Projection Results

In the previous section, we train the neuronet successfully and validate the projection ability of the well-trained neuronet. We also obtain the relationship between the normalization factor and the validation error. As Fig. 2 shows, different values of α correspond to different validation errors. Smaller validation error means better projection result, or to say, more possible situation. We mark the global minimum point and several local minimum points in Fig. 2. Note that the global minimum point usually means the most possible situation, and the local minimum points also have relatively high possibilities. In this section, we choose the global minimum point and four local minimum points to analyze their projection results, and we list these points in Table 1.

Table 1. Validation errors of global minimum point and local minimum points

Value of α	-0.786	-0.839	-0.902	-0.928	-0.992
Validation error ϵ	0.0147	0.0153	0.0156	0.0163	0.0452

3.1 Projection Results via Global Minimum Point

Global minimum point here has normalization factor α corresponding to the minimum validation error in global range. As is shown in Fig. 2 and Table 1, $\alpha = -0.786$ corresponds to the global minimum point with the validation error $\epsilon = 0.0147$, which usually means the most possible situation. We conduct a ten-quarter projection from March 2017 to June 2019. The projection results with $\alpha = -0.786$ are shown in Fig. 3, and listed in Table 2. Specifically, in Fig. 3, the neuronet output data are very close to the real historical SCGD data before December 2016, which indicates the good performance of the neuronet. As the neuronet projects, SCGD has a quick increase in the ten quarters following the end of 2016, and the growth rate also increases. Moreover, Table 2 lists the detailed SCGD data in quarterly manner. In this table, we can see that SCGD exceeds €1000 billion for the first time in March 2017, and reach €3268.7426 billion in June 2019. The SCGD surges to a record high in June 2019, and triples within ten quarters.

We find that there was also a quick increase in the end of 2007. In 2012, Spain sank into debt crisis with a quick increase of SCGD. In December 2014, Spain's debt-to-GDP ratio exceeded 100%. Moreover, Spain's GDP has grown slowly in recent quarters, so this projection result shows an increase of SCGD and indicates that Spain may face a risk of debt crisis.

3.2 Projection Results via Local Minimum Points

Local minimum points have smaller validation errors than points around them. Similar to global minimum point, local minimum points are worth being discussed and analyzed. The validation errors of local minimum points may be a

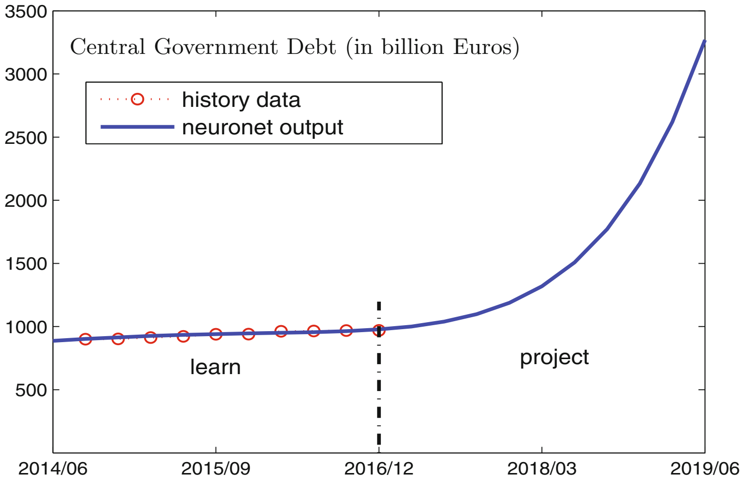


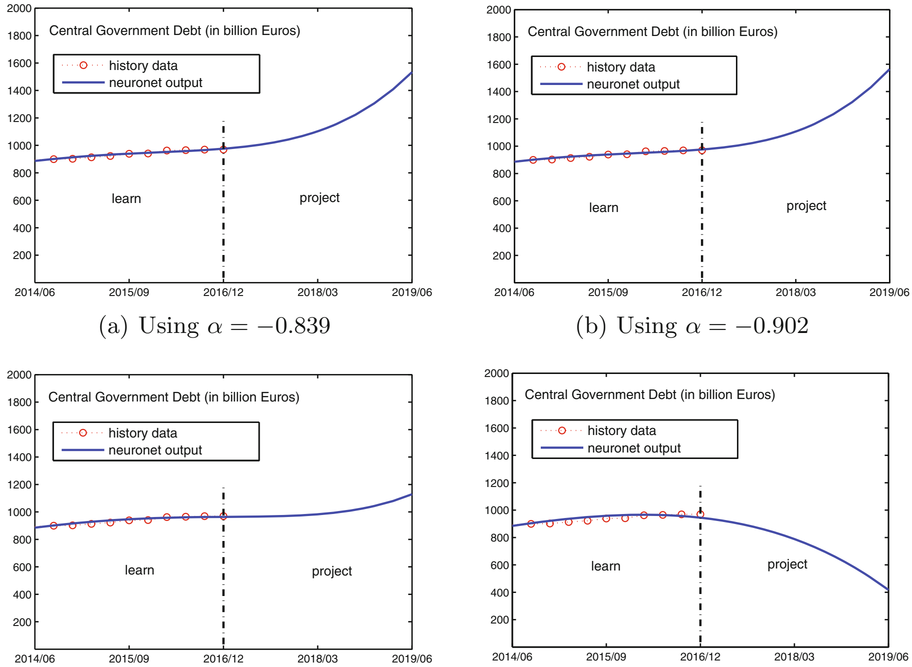
Fig. 3. Projection result of SCGD via WASD neuronet with global minimum point $\alpha = -0.786$.

Table 2. Projected data of SCGD corresponding to Fig. 3

Date (month/year)	03/2017	06/2017	09/2017	12/2017	03/2018
SCGD (billion Euros)	1000.9648	1038.8157	1098.1584	1187.9370	1319.6588
Date (month/year)	06/2018	09/2018	12/2018	03/2019	06/2019
SCGD (billion Euros)	1507.9560	1771.2369	2132.4639	2620.0196	3268.7426

little larger than that of global minimum point, which means that the situations of local minimum points also have high probabilities. So, we use four local minimum points $\alpha = -0.839$, -0.902, -0.928 and -0.992 to analyze their projection results. The projection results are shown in Fig. 4.

As Fig. 4(a) shows, SCGD increases in the next ten quarters, which is similar to global minimum point, but the growth rate corresponding to $\alpha = -0.839$ is smaller. After ten quarters, in June 2019, SCGD reaches to €1533.5036 billion. Besides, there is an increasing trend in Fig. 4(b) as well with $\alpha = -0.902$. In June 2019, SCGD reaches to €1563.7275 billion. This situation is quite similar to the situation in Fig. 4(a). Their growth rates are almost the same, and their SCGD data are very close. As for Fig. 4(c), there is also an increasing trend, but, compared with the previous situations, SCGD grows very slowly in Fig. 4(c). SCGD remains at a steady level in the first five quarters, and then increases to €1128.8017 billion in June 2019. However, the trend in Fig. 4(d) with $\alpha = -0.992$ is quite different from other trends. The SCGD decreases in the next ten quarters, and finally reaches to €417.2324 billion in June 2019.



(a) Using $\alpha = -0.839$ (b) Using $\alpha = -0.902$

(c) Using $\alpha = -0.928$ (d) Using $\alpha = -0.992$

Fig. 4. Different projection results of SCGD via WASD neuronet using different local minimum point values of α.

3.3 Projection Results Analysis

We choose five normalization factor points including one global minimum point and four local minimum points, which have smaller validation error values than others. Noticeably, most of results except Fig. 4(d) project that the SCGD increases, and the trend of global minimum point increases quicker than other increasing trends, so we can divide all the five situations into three trends: quick increasing trend (with $\alpha = -0.786$), increasing trend (with $\alpha = -0.839$, -0.902 or -0.928) and decreasing trend (with $\alpha = -0.992$).

In the quick increasing trend, the SCGD data increases from €1000.9648 billion in March 2017 to €3268.7426 billion in June 2019. According to the historical SCGD data, we know that SCGD tripled in seven years and six months (from €315.4733 billion in March 2008 to €938.7676 billion in September 2015) mainly because of Spain's housing bubble, banking crisis and local government debt problem. Note that, in Fig. 5, we show the historical SCGD data from December 2003 to September 2010, which include the period of debt crisis (starting from December 2007) in 2008 and 2009. As shown in the figure, before the debt crisis broke out, there was a marked decrease in SCGD, and then there was a rapid increase. Compared with that situation, the quick increasing trend

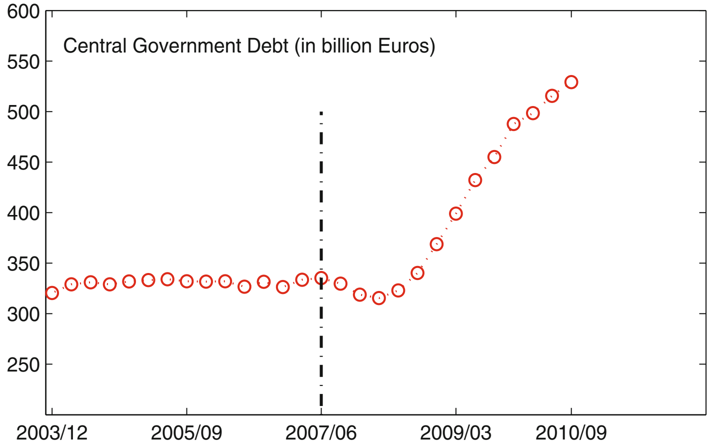


Fig. 5. Historical SCGD data from December 2003 to September 2010 including period of debt crisis (starting from December 2007) in 2008 and 2009.

predicted from now on does not have a decrease before the increase, which follows from the dissimilarity that the possibility of debt crisis is minor. Besides, in the increasing trend, the growth rate of SCGD is slower than the situation of quick increasing trend, especially in Fig. 4(c) with $\alpha = -0.928$. In Fig. 4(a) and Fig. 4(b), the growth rates of SCGD are similar to the recent years' (from March 2008 to December 2015) growth rate. As for trend in Fig. 4(c), we notice that, since March 2016, SCGD has increased more slower than before: SCGD was €962.0809 billion in March 2016, and €969.5523 billion in December 2016.

According to our analysis above, we could conclude that the increasing trend fits the current situation, which indicates that the SCGD will be increasing but under control. Finally, consider again the decreasing trend. From historical SCGD data, we find that SCGD decreased for many times; for example, SCGD decreased from €331.6199 billion in September 2006 to €326.3689 billion in December 2006; and, from June 2007 to March 2008, SCGD had a decrease for four consecutive quarters. Ten consecutive quarters' decrease has never happened in the mentioned history, and the trend may appear possibly because of polynomial characteristics, or indicating some emergencies ahead. In summary, more projection results show that SCGD follows the increasing trend. Besides, according to Spain's current economic situation and economic aid from the European Union, we incline to the increasing trend; or to say, we believe that SCGD may increase in the next ten quarters, but may not increase quickly. The other two trends also have possibilities: SCGD may increase quickly or decrease in next ten quarters. Spanish government should also prepare for these potential trends.

4 Conclusion

In this paper, we have conducted a ten-quarter projection for Spanish central government debt via a 3-layer feed-forward neuronet, with the WASD algorithm used for determining the connecting weights and structure of the neuronet. We have trained the neuronet with history SCGD data from December 1994 to March 2016. The projection results have been divided into three trends: quick increasing trend, increasing trend and decreasing trend. Projection results of the global minimum point have shown that the SCGD may increase quickly in the next ten quarters; results of three local minimum points have shown that the SCGD may increase gently; and results of one local minimum point have shown that the SCGD may decrease. Besides, according to our further analysis of the projection results, we may conclude from the dissimilarity that Spain would not have a debt crisis for the coming nearly 10 quarters. However, kindly note that all theories and models may be essentially approximate, erroneous, and even wrong. In addition to the above, based on this paper, we (including interested readers) may carry out more and further work such as comparing WASD method with other methods in SCGD projection and making accurate projection on the dates of future potential debt crisis.

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