Running head: This time will never be different- Justify This Time is Different Conclusion

This time will never be different- Justify This Time is

Different: Eight Centuries of Financial Folly's

Conclusion

By

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This time will never be different- Justify This Time is

Different: Eight Centuries of Financial Folly's Conclusion

APPROVED BY SUPERVISING COMMITTEE:

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Abstract

In *This Time is Different: Eight Centuries of Financial Folly*, Reinhart and Rogoff argue domestic debt plays an important role in countries' default and serial default is normal throughout history and around the globe. Analysis of 89 episodes of countries' external default data from 1827 to 2003 using model-based clustering method of unsupervised learning confirms Reinhart and Rogoff's argument.

Key Words: Unsupervised learning, domestic debt, serial default, model-based clustering, external default

Executive Summary

Reinhart and Rogoff argue that domestic debt plays a significant role in countries' default and that serial default is normal throughout history and around the globe.

Analysis of data provided by Reinhart and Rogoff of 89 episodes of countries' default on external debt from 1827 to 2003 (including external debt ratio and total debt ratio) validates their argument.

The analysis uses model-based clustering method to cluster defaulting countries in terms of similarity, producing two cluster groups based upon different timelines and regions. It separates countries that default from time to time without excluding any region. The analysis also produces the trend of domestic debt adjusted for inflation over 10 years in the aftermath of external default via visual display of the relationship between domestic debt and inflation. Model-based clustering method and visual display demonstrate that overlooked domestic debt is the missing link explaining (1) external default when countries have a very low level of external debt and (2) government choice of inflation as an economic tool in the aftermath of default.

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Table of Contents

Introduction	1
Problem Statement	1
Research Purpose	2
Identification and Definition of Variables	3
Research Question	4
Methodology	4
Analysis of Debt Structure at Default	4
Data and Source	4
Descriptive Analyses	4
Modeling Framework	12
Analysis of Government Strategy After Default	27
Data and Source	28
Descriptive Analyses	28
Modeling Framework	28
Findings	29
Results of Descriptive Analyses	29
Modeling Results	30
Summary and Conclusions	37
References	39
Appendix	42
Appendix A	42
Appendix B	42
Appendix C	43
Appendix D	43
Appendix E	44
Appendix F	44
Annendiy G	45

List of Tables

Table 1 Summary Statistics	5
Table 2 Pearson Correlation and Spearman Correlation among Variables	6
Table 3 Default countries from cluster 2	30
Table 4 Default countries from cluster 1	31
List of Figures	
Figure 1. Box plot for external, total, and domestic debt	5
Figure 2. External debt ratio distribution and total debt ratios distribution	6
Figure 3. Empirical Copula between external debt ratio and total debt ratio	7
Figure 4. Scatter plot of external debt ratio (< 1) and total debt ratio	8
Figure 5. Scatter plot of external debt ratio (>=1) and total debt ratio	9
Figure 6. Cullen and Frey Graph of external debt ratio	10
Figure 7. Goodness-of-fit plots to external debt ratio	11
Figure 8. Cullen and Frey graph of total debt ratio	12
Figure 9. Visualization of external debt ratio and total debt ratio on two dimensions	15
Figure 10. Random Uniformly Distributed Non-Clustering Dataset	16
Figure 11. Plots of BIC and classification uncertainty	17
Figure 12. Plots of classification and log density	
Figure 13 Histogram of external debt ratio and total debt ratio from cluster 1	
Figure 14. Empirical distribution check from cluster 1	
Figure 15. Scatter plot of external debt ratio and total debt ratio from cluster 1	21
Figure 16. Plot of empirical copula from cluster 1	21
Figure 17. Histogram of external debt ratio and total debt ratio from cluster 2 group	22
Figure 18. Empirical distribution check from cluster 2 group	23
Figure 19. Scatter plot of external debt ratio and total debt ratio from cluster 2	24
Figure 20. Plot of empirical copula from cluster 2	
Figure 21. Plot of empirical copula between external debt ratio and domestic debt ratio	О
from cluster 2	25
Figure 22. Plot of default countreis based on timeline	
Figure 23. Plot of the number of default countires within each region	
Figure 24. Adjustment of domestic debt over 10 year's period	29

Introduction

Learning from past mistakes is ordinarily assumed to be a helpful way to avoid future problems. In the case of national financial crisis, however, governments have often not taken cautionary steps in the aftermath of a financial crisis under the mistaken belief that the previous financial crisis was somehow "different" and that there is therefore little to learn that could forestall future calamity. Financial crises, therefore, continue to occur from time to time across the globe. Historical analyses of financial debacle (for example, Richard Portes (1998)) argue that governments have difficulty overcoming this line of thinking during boom times preceding crises.

This Time is Different: Eight Centuries of Financial Folly by Carmen M. Reinhart and Kenneth S. Rogoff (hereafter, RR) introduced the "this time is different syndrome." RR extensively analyze (based on a comprehensive dataset) the history of financial crises dating from England's seventeenth-century default to the 2008 US sub-prime mortgage debt crisis utilizing an extraordinary database of macroeconomic and financial series. RR arrive at a simple but powerful finding: while times change, locations change, and actors change, financial crises often exhibit more similarities than differences throughout history. Tools of data analysis offer us an opportunity to take a closer look at RR's data to determine the validity of this finding.

Problem Statement

RR argue that serial default occurs from time to time around the globe and that domestic debt plays a significant role in default even though external debt is at a very low

level. To make this argument, RR examine the role of domestic debt in external defaults and government management of domestic debt. RR compare the means of both external debt ratio (external debt to GNP) and total debt ratio (total debt to GNP) and argue that total debt ratio is greater than external debt ratio. RR use Kolmogorov-Smirnov (KS) test to determine that distributions of external debt ratio and total debt ratio differ significantly. RR use a comprehensive database that spans all regions in this analysis and include a number of important defaults and economic restructurings in Asian markets such as India and China.

RR's analysis, however, leaves room for additional data analysis. For instance, their calculation of a statistically significant difference between point estimates may be imprecise. Moreover, RR do not check for dependence between external debt ratio and total debt ratio, nor do they consider the possibility that these distributions could be a mixture model of two Gaussian distributions.

RR's conclusions, therefore, are not problem-free and call for further analysis to confirm their validity. The tools of data analytics and the availability of RR's massive dataset of macroeconomic and financial series offer an opportunity to examine the dependencies between external and total debt ratios and heterogeneity in the behavior of countries to validate (or refute) RR's conclusions.

Research Purpose

The purpose of this research is to use data analytics tools to examine RR's conclusion given financial market conditions and associated government policies in particular time periods. While RR study different types of financial crisis (e.g., sovereign defaults,

which occur when a government fails to meet payments on its external or domestic debt obligations or both (Reinhart, 2009a); banking crises; exchange rate crises; and high inflation crises). This project focuses only on the evaluation of sovereign default (government default). Within that realm, this study (1) addresses a specific issue--the role of domestic debt in the history of countries' external default; (2) examines the relationship between such variables as external and domestic debt, external and total debt, and Gross National Product (GNP).

In particular, the research aims to achieve the following objectives:

- To examine the consistency of serial defaults throughout history;
- To examine RR's assertion that domestic debt plays a significant role in default by using more appropriate statistical methodology given the structure of the data;
 and
- To argue that domestic debt is overlooked.

Identification and Definition of Variables

Standard economic and financial variables are selected from RR's study, as indicated below:

- Domestic (Internal) and external debt: Domestic debt is the portion of total government debt that is owed to lenders within a country. Domestic debt's complement with respect to total debt is external debt.
- External debt ratio: External debt divided by revenue
- Total debt ratio: Total debt divided by total revenue

- Gross National Product (GNP): The market value of all products and services
 produced in one year by labor and property supplied by the citizens of a country.¹
 For RR, GNP equals revenue.
- Inflation: A general increase in prices and fall in the purchasing value of money.

Research Question

This research focuses on serial default from seventeenth-century default in England to the 2008 subprime crisis in the United States and aims to demonstrate that (1) serial default is a historical pattern and often displays more similarities than differences throughout history; and (2) domestic debt plays a significant role in default.

Methodology

Analysis of Debt Structure at Default

Data and Source

The database analyzed contains data points presented in tables, figures, and plots. A total of 89 observations were selected on external debt ratio, total debt ratio, and domestic debt ratio (derived from total debt ratio) for the research.

Descriptive Analyses

Standard statistical techniques were included such as 1) mean and standard deviation of the ratio of debt to revenue; (2) inspection of debt distribution; and (3) correlations between external debt ratio and total debt ratio.

¹ "Gross National Product." *Wikipedia*. Wikimedia Foundation, n.d. Web. 24 July 2016. https://en.wikipedia.org/wiki/Gross_national_product.

The initial analysis on these 89 observation revealed that all three variables have different means and outliers which are indicated in tables 1 and Figure 1. Total debt ratio has larger outliers.

Table 1
Summary Statistics

Variable Name	No of Obs	Min.	1st Qu.	Median	Mean	3rd Qu	Max.	Range	StDev
External Debt Ratio	89	0.00	1.12	1.95	2.47	3.44	17.79	17.79	2.33
Total Debt Ratio	89	0.94	2.40	3.92	4.37	5.14	19.61	18.67	3.26
Domestic Debt Ratio	89	0.09	1.01	1.29	1.90	2.30	10.88	10.79	1.81

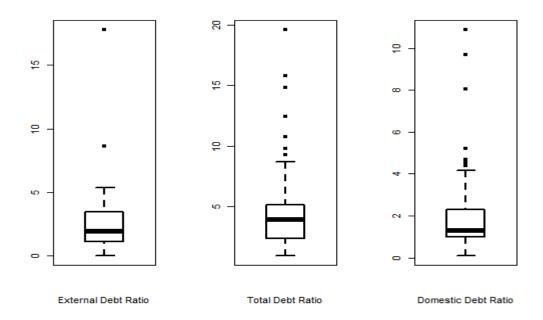


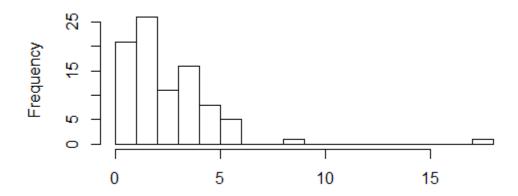
Figure 1. Box plot for external, total, and domestic debt ratio

Both Pearson and Spearman correlations demonstrate a very high positive relationship between external debt and total debt, as shown in Table 2.

Table 2 Pearson Correlation and Spearman Correlation among Variables

	Pearson	Spearman
External to Domestic Debt Ratio	0.2196669	0.2164136
External to Total Debt Ratio	0.8393286	0.8362263
Domestic to Total Debt Ratio	0.7147191	0.6574123

The distributions of variables in Figure 2 (top plot is external debt ratio, bottom plot is total debt ratio) show marked positive skewness rather than normal distribution.



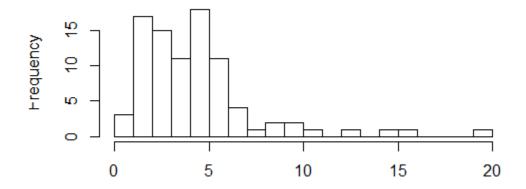


Figure 2. External debt ratio distribution and total debt ratios distribution

The right skewness, combined with high positive relation, signals the possibility of tail dependence between external and total debt ratio. To determine the dependency, empirical copula was conducted on these two variables in Figure 3.

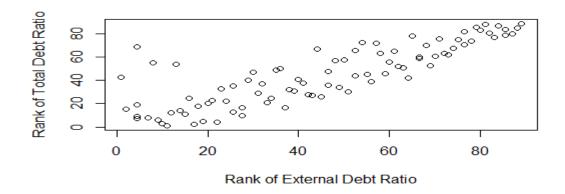


Figure 3. Empirical Copula between external debt ratio and total debt ratio

Clearly, the relationship between total and external debt ratio is not linear. Two patterns emerge from the graph: (1) strong upward positive relation and (2) outliers at the left top part. To check the nature of dependency on tail distribution, Copula (Copula is a display for analyzing dependency patterns) analysis was conducted using a value of external debt ratio less than 1 in Figure 4 and greater than or equal to 1 in Figure 5.

External debt ratio is less than 1

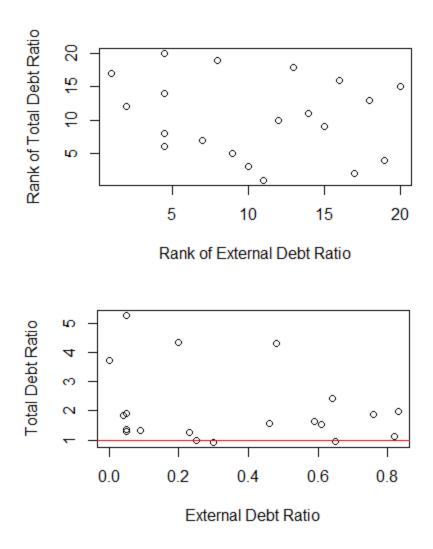


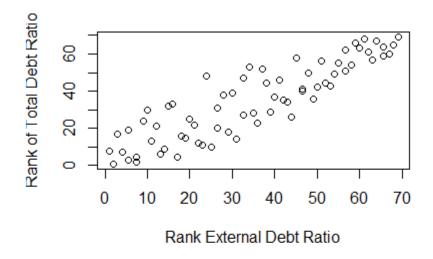
Figure 4. Scatter plot of external debt ratio (<1) and total debt ratio

The top plot of empirical copula in Figure 4 does not demonstrate strong dependence. Normal copula fit returns a negative estimated Rho= -0.29 and a non-significant p value = 0.35 (see Appendix A for copula section). At the bottom, a scatter plot between external debt ratio and total appears. Adding a horizontal line (abline =1, marked in red color on the graph) demonstrates that total debt ratio is 100 % or above while external debt ratio is close to 0 or below 100%. Interestingly, domestic debt occupies a large

portion of total debt; total debt would otherwise be close to or slightly larger than external debt.

External debt ratio is great than or equal to 1

The same method was used for this case in Figure 5. A scatter plot appears at the bottom; the graph does not illustrate any strong relationship. However, the top empirical copula plot shows a clear pinch sigh at right top corner--a typical Gumbel copula (upper tail dependence).



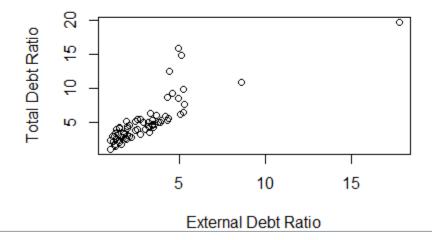


Figure 5. Scatter plot of external debt ratio (>=1) and total debt ratio

The Gumbel copula fit gives us a positive dependency at Rho = 3.02 (see Appendix B for Gumbel copula section). Both external debt ratio and total debt ratio are comotonic (positive dependence) and highly correlated.

To determine which distribution these two variables possibly follow, an empirical distribution was carried out using a Cullen & Frey graph (compare distributions in the skewness, kurtosis) with bootstrapping 1,000 times on both external debt ratio and total debt ratio.

Empirical external debt ratio distribution

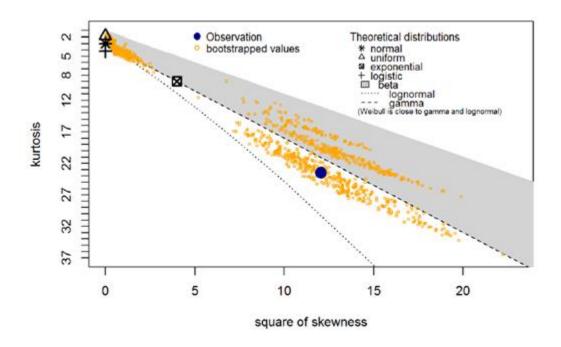


Figure 6. Cullen and Frey Graph of external debt ratio

The observation of external debt ratio is represented as a big blue dot on the graph.

Other distributions are represented with different icons. For example, star (*) represents

normal distribution. The distribution of external debt ratio could intuitively be seen log-normal, Weibull, gamma and exponential, as it is close to all of them. After applying KS test on the observations of external debt ratio, I obtained very significant p-values for Weibull, exponential, and Gamma distributions. To further check which distribution fits better, four Goodness-of-fit plots (Graphical comparison of multiple fitted distributions) to external debt ratio as provided by functions (denscomp, qqcomp, cdfcomp and ppcomp) are shown below in Figure 7.

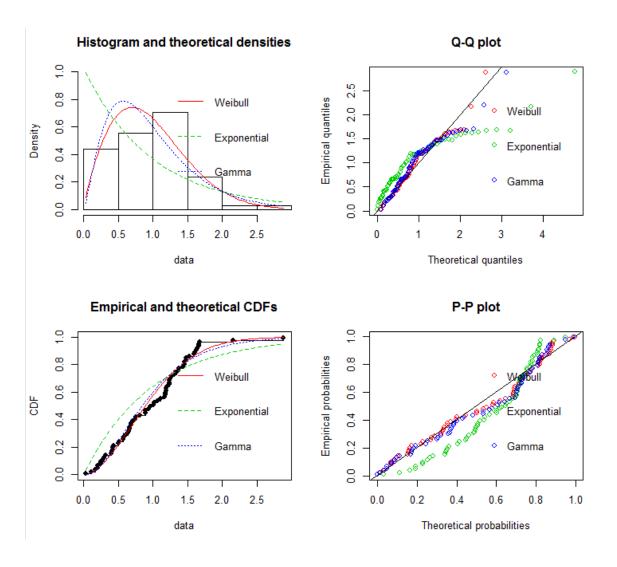


Figure 7. Goodness-of-fit plots to external debt ratio

Figure 7 demonstrates that none of them fit well; only Weibull and gamma seem to be better fit.

Empirical total debt ratio distribution

The same method was applied to total debt ratio, as shown in Figure 8. Here, total debt ratio follows a gamma distribution (the big dot lines on the graph) with p-value = 0.29 returned from KS test.

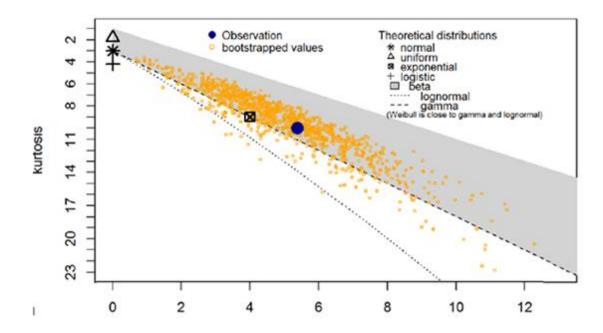


Figure 8. Cullen and Frey graph of total debt ratio

Modeling Framework

In this research, unsupervised learning was used to cluster on 89 observations of defaulting countries. During the implementation phase, different cluster methods were attempted, such as Mixmodel, K-means, Mclust, K-overlapping and Partitioning Around

Medoids (PAM). After taking log transformation on these two variables (external debt ratio and total debt ratio), model based method-Mclust emerges as a better candidate.

Therefore, the Mclust package of R software was specifically used for final implementation.

The Mclust is used for model-based clustering, classification, and density estimation based on finite normal mixture modeling. It provides functions for parameter estimation via the expectation—maximization (EM) algorithm for normal mixture models with a variety of covariance structures, as well as functions for simulation from these models. Mclust also includes functions that combine hierarchical clustering, EM, and the Bayesian Information Criterion (BIC) in a comprehensive clustering strategy. The optimal model is selected according to BIC for Mclust.

In Mclust, a Gaussian model represents each cluster, as shown below:

$$\phi_k(\mathbf{x} \mid \mu_k, \Sigma_k) = (2\pi)^{-\frac{p}{2}} |\Sigma_k|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(\mathbf{x}_i - \mu_k)^T \Sigma_k^{-1} (\mathbf{x}_i - \mu_k)\right\},$$

In this model, x represents the data, and k is an integer subscript specifying a particular cluster. Clusters are ellipsoidal, centered at the means μk . The co-variances Σk determine their other geometric features. Each co-variance matrix is parameterized by eigenvalue decomposition in the form of

$$\Sigma_k = \lambda_k D_k A_k D_k^T$$
,

where Dk is the orthogonal matrix of eigenvectors, Ak is a diagonal matrix whose elements are proportional to the eigenvalues of Σk , and λk is a scalar. The orientation of the principal components of Σk is determined by Dk, while Ak determines the shape of

the density contours; λk specifies the volume of the corresponding ellipsoid, which is proportional to λd k |Ak|, where d is the data dimension. Characteristics (orientation, volume and shape) of distributions are usually estimated from the data, and can be allowed to vary between clusters, or constrained to be the same for all clusters (Fraley and Raftery, 2002).

Log transformation

Figure 3 exhibits the nonlinear relationship. To get data ready, log transformation was applied to both external debt ratio and total debt ratio to normalize them.

Assess the Clustering Tendency and Data Visualization

A major issue in unsupervised machine learning is that clustering methods will return clusters even if the data does not contain any clusters. In other words, if a clustering analysis is applied blindly to a dataset, it will divide the data into clusters because that is what it is supposed to do. Before choosing a clustering approach, the analyst therefore has to decide whether the dataset contains meaningful clusters (i.e. nonrandom structures) or not. If it does, then how many clusters are there? This process is defined as "assessing clustering tendency" or "determining the feasibility of the clustering analysis." (Liang Wang, 2010)

Hopkins statistic is used to assess the clustering tendency of a dataset by measuring the probability that a given dataset is generated by a uniform data distribution (the dataset is uniformly distributed if the return value of H is about 0.5). Hopkins statistic was therefore used to identify possible patterns in the illustration of two-dimensional plots. If there is no pattern, the plot looks like uniform distributed points (Null hypothesis).

Existence of pattern shows up as either a clustering or regular pattern. The null and the alternative hypotheses are defined as:

- Null hypothesis: the dataset D is uniformly distributed (i.e., no meaningful clusters)
- Alternative hypothesis: the dataset D is not uniformly distributed (i.e., contains meaningful clusters)

The Hopkins test return H value = 0.23 on this dataset which is below the threshold 0.5 and indicates that the data are highly clusterable (see Appendix C for Hopkins test result).

To illustrate the dataset, this normalized external debt ratio and total debt ratio are plotted on two dimensions in Figure 9. Clearly, this dataset contains two clusters.

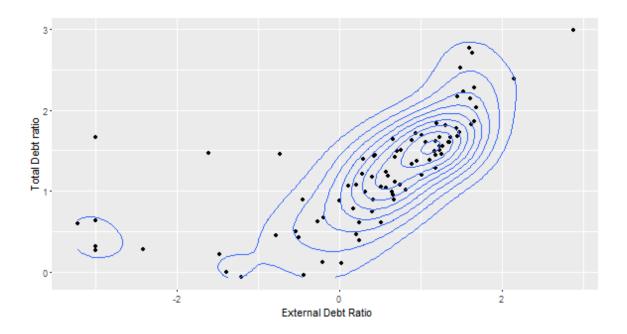


Figure 9. Visualization of external debt ratio and total debt ratio on two dimensions

As a contrast with non-clustering data, random uniformly distributed data was generated with the same dimension on the dataset, as illustrated in Figure 10, below:

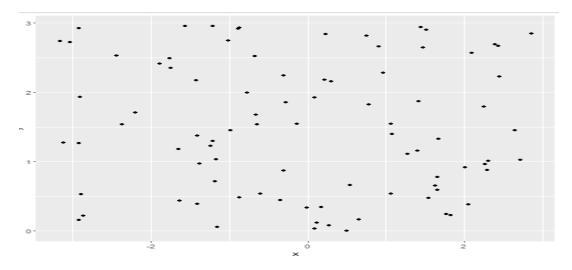


Figure 10. Random Uniformly Distributed Non-Clustering Dataset

The randomly generated data does not contain any meaningful clusters.

Model and Clustering

Mclust generated two clusters (indicated in left classification plot of Figure 12) from this dataset. The plot on model object produced from Mclust has four graphs in Figure 11 and Figure 12 respectively.

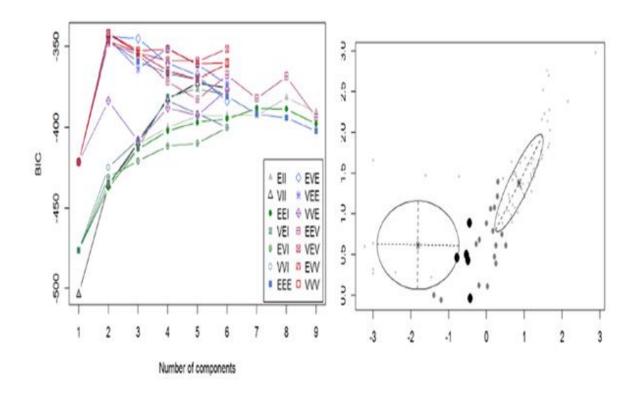


Figure 11. Plots of BIC and classification uncertainty

The left plot shows BIC for model-based methods applied to this dataset. Mclust uses an identifier for each possible parametrization of the co-variance matrix that has three letters: E for "equal," V for "variable," and I for "coordinate axes." The first identifier refers to volume, the second to shape, and the third to orientation. For example:

- EEE means that the clusters have the same volume, shape, and orientation in pdimensional space.
- VEI means variable volume, same shape, and orientation equal to coordinate axes.
- EIV means same volume, spherical shape, and variable orientation.

The first local (also global) maximum occurs for the unconstrained model with two clusters. The plot on the right depicts the uncertainty of the classification produced by the best model (unconstrained, two clusters) indicated by the BIC. Fraley and Raftery (F&R, 2002) analyze this type of plot. As they demonstrate in their work, large dots

show most uncertain classifying decisions. The symbols have the following meaning: large filled symbols are in the 95% quantile of that distribution which means higher uncertainty; smaller open symbols are in the 75–95% quantile of that distribution; small dots are in the first three quartiles of uncertainty (Fraley and Raftery, 2002)..

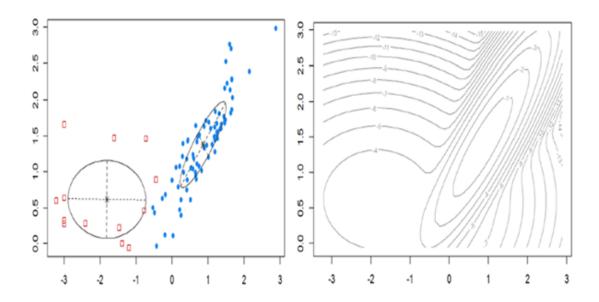


Figure 12. Plots of classification and log density

The plot on the left shows the classification of the dataset; there are two cluster groups. In the classification plot, points in different classes are indicated by different symbols. The ellipses superimposed on the classification and uncertainty plots correspond to the co-variance of the components. A logarithmic transformation was used for the density plot as a contour surface shown on the right.

Analysis of Clustering Output

The hypothesis is that the distribution will be normal after log transformation. To verify, the distribution from each cluster was checked.

Distribution from cluster 1 group

Density was plotted on data points from cluster 1 in Figure 13. Red represents external debt ratio, blue represents total debt ratio; the negative values on the X-axis are due to log transformation, as the original values are very small.

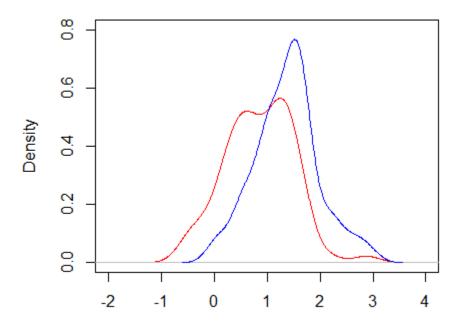


Figure 13. Density plot of external debt ratio and total debt ratio from cluster 1

To verify that these data points are indeed normally distributed, an empirical distribution check with bootstrap 1000 times (see Appendix D) was applied again. These two distributions (seen in Figure 14) are close to normal icon now (star * symbol on the

graph).

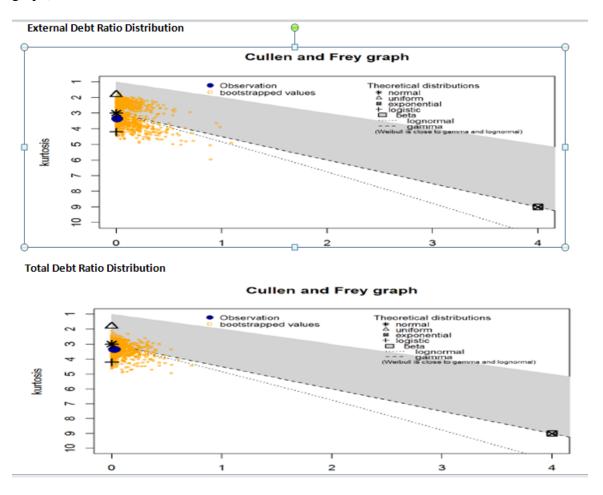


Figure 14. Empirical distribution check from cluster 1

It is interesting to see what the relationship between external debt ratio and total debt ratio looks like within cluster 1 in the scatter plot. We see that the plot in Figure 15 shows a strong positive relation with extreme outliers. This is an indication of possible tail dependency. Empirical copula analysis was again conducted and plotted (see Figure 16)

on these two variables.

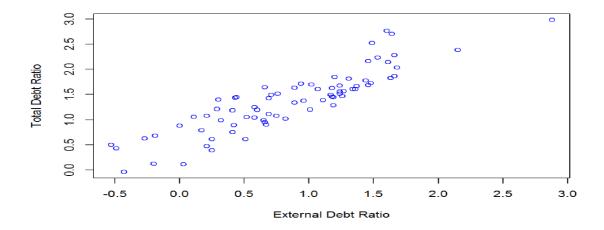


Figure 15. Scatter plot of external debt ratio and total debt ratio from cluster 1

A pinch at right corner is clearly visible. This is a typical Gumbel copula (see Appendix E). Gumbel copula shows tail dependency. This plot matches Figure 5, showing that external debt ratio and total debt ratio are highly correlated with comonotonic dependency (positive dependence between two variables).

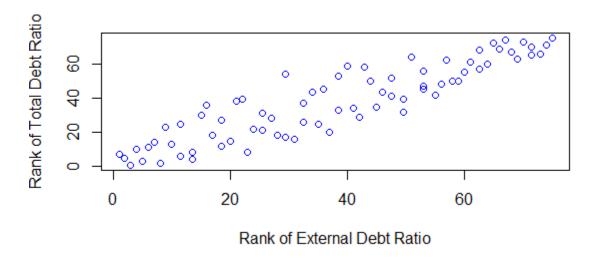


Figure 16. Plot of empirical copula from cluster 1

Distribution from cluster 2 group

The same steps were repeated with cluster 2. They do not show normal distribution in the density provided in Figure 17.

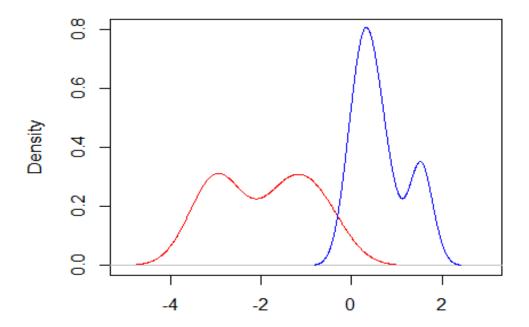


Figure 17. Density plot of external debt ratio and total debt ratio from cluster 2 group

The negative values are the log values of very low external debt ratio. Also, the Cullen and Frey graph in Figure 18 shows that the two distributions are close to either

uniform (triangle symbol on graph) or normal.

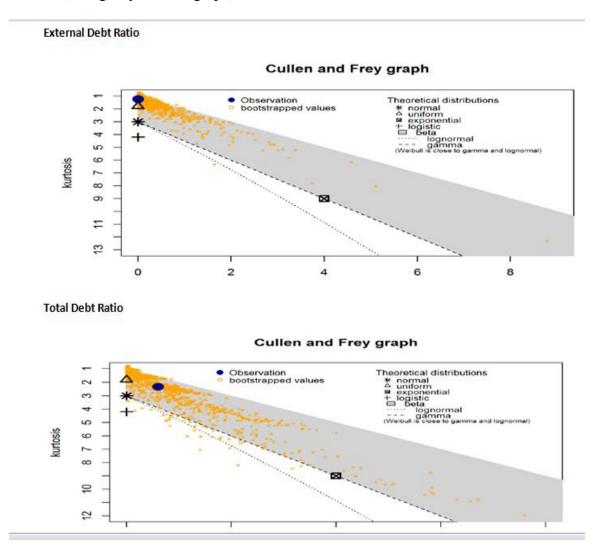


Figure 18. Empirical distribution check from cluster 2 group

Nevertheless, KS test's result on uniform distribution is significant with p values less than 0.05. KS test's result on normality with p value is greater than 0.05 (see Appendix F), which we fail to reject the normality.

The relationship between external debt ratio and total debt ratio in scatter plot Figure 19 is not obvious from this cluster group. The negative values on X-axis are the effect of log transformation on very low external debt ratio.

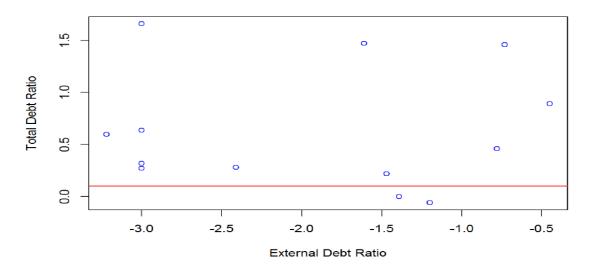


Figure 19. Scatter plot of external debt ratio and total debt ratio from cluster 2

With a horizontal line (abline at h=0.1 in red) added on the plot, we see that the total debt ratio is over zero % even though the external debt ratio is close to zero.

This result matches previous findings shown in Figure 4. Empirical copula was also conducted to see dependence between external debt ratio and total debt ratio from this

cluster group. This relationship is not obvious, as seen in Figure 20.

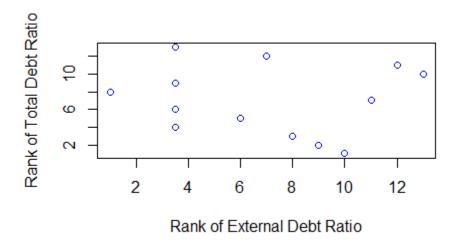


Figure 20. Plot of empirical copula from cluster 2

To further check, empirical copula was conducted on both external debt ratio and domestic debt ratio. The plot in figure 21 shows negative dependence (countermonotonic).

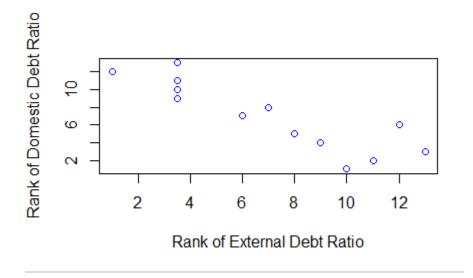


Figure 21. Plot of empirical copula between external debt ratio and domestic debt ratio from cluster 2

The negative dependency between external debt ratio and domestic debt ratio confirms the previous demonstration that external debt ratio is less than 1, as shown in Figure 4.

Clustering output based upon timeline

Figure 22 below depicts the output of clustering based upon timeline. The plot demonstrates that countries default from time to time and default happens in every region.

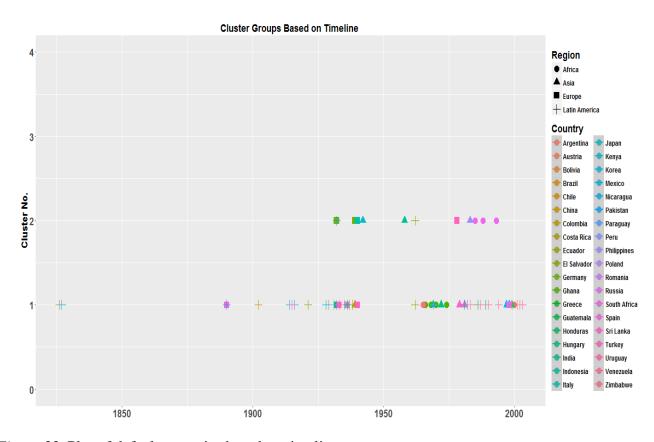


Figure 22. Plot of default countries based on timeline

Moreover, the frequency of default country from each region can be seen in each cluster, as shown in Figure 23.

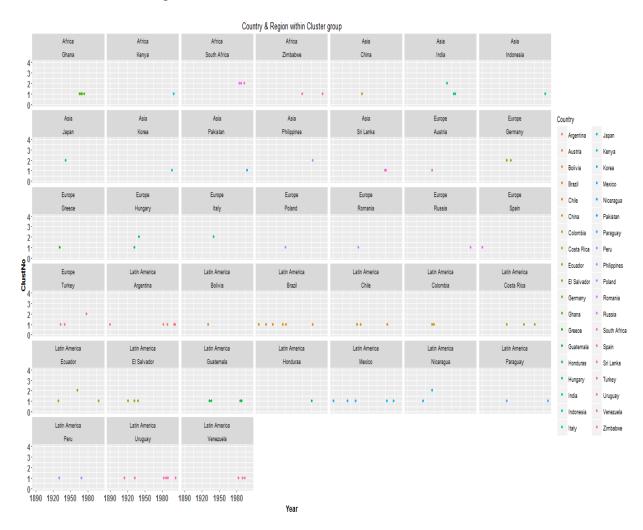


Figure 23. Plot of the number of default countries within each region

Analysis of Government Strategy After Default

Having examined external debt and total debt, it would now be interesting to assess the role domestic debt plays after countries default and the economic strategies governments select post-default.

Data and Source

Ten-year domestic debt data after government external default was selected to study the trend of domestic debt adjusted for inflation on each default country. Inflation data and some debt to GDP ratio data were obtained from RR's website and IMF's Historical Public Debt Database (HPDD).

Descriptive Analyses

How does domestic debt adjusted for inflation operate in each default country over time? To answer this, the value of domestic debt adjusted for inflation is calculated.

Default year is at time t.

Domestic debt adjusted for inflation = Debt at time t+1/(1+f)

where f is the rate of inflation during year t.

Modeling Framework

To study domestic debt adjusted for inflation over 10 years, the function xyplot() was chosen, which comes from the lattice package of R for statistical graphics. Figure 24 below shows how domestic debt adjusted for inflation increases in each default country.

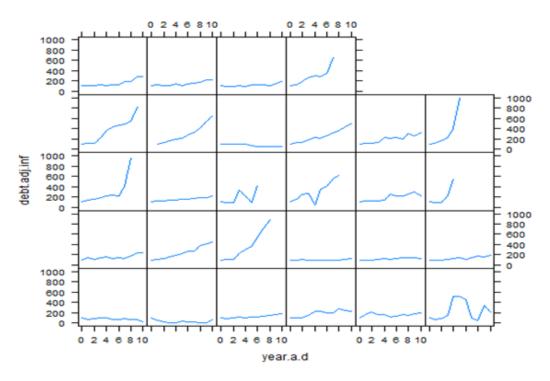


Figure 24. Adjustment of domestic debt over 10 year's period

Almost all trajectories are up in spite of inflation rate (note: extreme cases whose adjusted domestic debt for inflation is greater than 2,000 have been removed in order to see the trend clearly).

Findings

Results of Descriptive Analyses

The initial descriptive analysis in Figure 4 reveals that domestic debt constitutes a large portion of total debt. This finding is confirmed in Figure 19 of cluster 2 group in which the correlation coefficient from cluster 2 between external debt ratio and total debt ratio is very low at 0.033 whereas the correlation coefficient between domestic debt ratio and total is not low at 0.47 (see Appendix G). Basically, this is caused by hidden domestic debt. Recognizing the significance of domestic debt helps explain why many

countries default on (or restructure) their external debt at seemingly low external debt thresholds.

The high correlation in Figure 5 suggests that both external and total debt is high when countries default. This strong correlation is seen in Figure 16 with comonotonic dependency from cluster 1, a correlation coefficient between external debt ratio and total debt ratio was determined to be quite high at 0.90 (see Appendix G). This makes sense. In this case, a government has a higher external debt ratio and might be over borrowing. If domestic currency drops in value, then total debt ratio can become very high because external debt is denominated in foreign currency.

Modeling Results

Examine RR's point of view that domestic debt plays a significant role

The result from clustering 2 group shows that default countries have a very low level of external debt ratio whereas total debt ratio is high at 100%. Obviously, this is caused by domestic debt. This result confirms clearly that domestic debt plays a significant role in countries' default, but only for the countries in cluster 2.

Cluster 2 contains developing countries in recent time periods from the later 1980s to the early 1990s, as we see in Table 3.

Table 3

Default Countries from Cluster 2

Region	Country	Default Year	External.Debt. Ratio	Total. Debt. Ratio	Cluster.Num
Africa	South	1985	0.09	1.32	2

	Africa				
	South	1988	0.05	1.38	2
	Africa				
	South	1993	0.05	1.9	2
	Africa				
Asia	India	1958	0.2	4.35	2
	Japan	1942	0.04	1.83	2
	Philippine	1983	0.23	1.25	2
	S				
Europe	Germany	1939	0.05	1.31	2
	Hungary	1940	0.3	0.94	2
	Italy	1940	0.05	5.25	2
	Turkey	1978	0.25	1	2

In addition, this group includes developed European countries such as Germany, Italy, and Hungary. These European countries defaulted during the Great Depression of the 1930s. The negative effects of the Great Depression lasted until the beginning of World War II. And, during that time period, those European countries would be considered "developing" nations.

Examine the consistency of the serial defaults throughout history

We see that both external debt ratio and total debt ratio are highly correlated with comonotonic dependency from clustering 1 group in the previous section of analysis clustering output. Minimum external debt ratio in this group is around 60% and total debt ratio is quite high at 165% (above 100%). This clustering result corresponds to the

conventional wisdom: countries default when both external debt ratio and total debt ratio are high.

For example, consider Argentina in table 4, between 1980 and 2002. Argentina defaulted five times, three times on its domestic debt. Its two external debt defaults (in 1982 and 2001) did attract considerable international attention. The large scale 1989 default at external debt ratio 1,779% is scarcely known outside Argentina. This cluster1 group in table 4 includes emerging market countries and a number of now wealthy countries which were then emerging markets, such as Spain's default at external debt ratio 495% in year 1877, and Austria, Greece and Hungary's defaults in 1932.

Table 4

Default Countries from cluster 1

Region	Country	Year	External.Debt.Ratio	Total.Debt.Ratio	Cluster.Num
Africa	Ghana	1966	2.13	4.51	1
	Ghana	1968	1.99	4.13	1
	Ghana	1970	1.5	3.25	1
	Ghana	1974	1.12	2.9	1
	Kenya	2000	1.99	3.03	1
	Zimbabwe	1965	1	2.4	1
	Zimbabwe	2000	1.35	4.03	1
Asia	China	1939	5.14	14.84	1
	India	1969	1.94	5.14	1
	India	1972	1.53	4.17	1
	Indonesia	1999	2.77	5.42	1
	Korea	1997	1.95	2.45	1

	Pakistan	1998	3.32	6.28	1
	Sri Lanka	1979	1.23	2.95	1
	Sri Lanka	1981	2.03	4.45	1
Europe	Austria	1932	1.91	2.68	1
	Greece	1932	3.44	4.53	1
	Hungary	1932	1.29	1.48	1
	Poland	1936	1.51	2.12	1
	Romania	1933	4.3	5.35	1
	Russia	1998	3.9	4.95	1
	Spain	1877	4.95	15.83	1
	Turkey	1933	1.38	2.69	1
	Turkey	1940	0.61	1.53	1
Latin	Argentina	1890	4.42	12.46	1
America					
	Argentina	1982	1.79	3.44	1
	Argentina	1989	17.79	19.61	1
	Argentina	2001	1.68	2.86	1
	Argentina	2002	5.34	7.64	1
	Bolivia	1931	8.62	10.79	1
	Brazil	1826	4.4	5.56	1
	Brazil	1898	3.7	6.1	1
	Brazil	1902	3.45	5.3	1
	Brazil	1914	4.3	8.68	1
	Brazil	1931	4.99	8.51	1
	Brazil	1937	2.56	5.51	1
	Brazil	1983	0.83	1.98	1
	Chile	1931	3.51	4.29	1

Chile	1937	1.78	2.84	1
Chile	1983	1.23	1.6	1
Colombia	1932	1.83	3.28	1
Colombia	1935	2.44	3.79	1
Costa Rica	1932	3.23	4.44	1
Costa Rica	1962	0.59	1.65	1
Costa Rica	1981	1.19	2.2	1
Ecuador	1929	0.82	1.13	1
Ecuador	1999	5.09	6.2	1
El Salvador	1921	1.33	3.36	1
El Salvador	1932	1.93	2.58	1
El Salvador	1938	1.66	1.84	1
Guatemala	1933	1.52	2.43	1
Guatemala	1936	1.29	1.84	1
Guatemala	1986	4.22	5.87	1
Guatemala	1989	3.44	4.72	1
Honduras	1981	3.26	4.28	1
Mexico	1827	1.55	4.2	1
Mexico	1854	5.27	9.81	1
Mexico	1914	3.83	4.96	1
Mexico	1928	3.29	3.61	1
Mexico	1982	3.25	5.06	1
Mexico	1994	2.11	2.94	1
Nicaragua	1916	4.6	9.3	1
Paraguay	1932	0.76	1.87	1
Paraguay	2003	2.74	3.32	1
Peru	1931	3.95	5.24	1

Peru	1969	1.03	1.12	1
Urug	guay 1915	5.27	6.41	1
Urug	guay 1933	2.44	5.1	1
Urug	guay 1983	3.28	4.21	1
Urug	guay 1987	2.61	3.92	1
Urug	guay 1990	2.91	4.96	1
Urug	guay 2003	3.57	4.78	1
Vene	ezuela 1983	0.65	0.96	1
Vene	ezuela 1990	2.26	2.76	1
Vene	ezuela 1994	3.04	3.96	1

Clearly, the timeline is different for the above mentioned default countries. In particular, the same country defaulted multiple times over different time periods.

In addition, the clustering 2 group also showed that countries default from time to time even when external default is at a very low level. Figure 22 (clustering output based upon timeline) not only confirms this point, but also shows three spike episodes of default in countries across each region over long time period.

- Later portion of 1920 1940: The majority of default countries are from Europe and Latin America. The Great Depression (early 1930s) plays a dominant role in defaulting countries during this period.
- Middle portion of 1960 1970: The majority of default countries are from Africa and Asia.
- 1980 to 2000: The majority of default countries are from Latin America and Asia in emerging markets.

Domestic debt is overlooked

Another interesting finding as visually displayed in Figure 24 is that governments keep borrowing after their countries default. Almost all trajectories are up in spite of inflation rate in Figure 24. The trajectories should be downward if it was nominal domestic debt (have not been adjusted for factors like inflation. It refers to the current value of the debt). Clearly, domestic debt is overlooked.

Governments do not have access to international capital anymore after default on external debt, nor do they collect taxes. To simply survive in a poor economy and rid themselves of growing domestic debt, governments use inflation as a tool to reduce domestic debt since they cannot do it with external debt. Those countries are "debt intolerant" (referring to the inability of emerging markets to manage levels of external debt that, under the same circumstances, would be manageable for developed countries). Debt intolerant countries tend to have weak fiscal structures and weak financial systems. Default often exacerbates these problems, making these same countries more prone to future default (Reinhart, 2004).

Overall, research output shows that domestic debt occupies large portion of total debt when country defaults. We see this result clearly in cluster 2. This finding makes the authors' point that domestic debt plays a significant role in default more clear when countries default at very low level of external debt. Basically, this is the effect of hidden domestic debt which solves the puzzle of countries defaulting even though the external debt is very low.

The cluster output based upon timeline shows that countries default from time to time without limitation of region in the long historic period. Finally, we see that domestic debt is indeed overlooked. The forgotten domestic debt explains the link between external debt and inflation. Governments keep borrowing domestically when they have no access to international capital markets even in the aftermath of external default and inflation.

Summary and Conclusions

This study confirms RR's conclusion that domestic debt plays a significant role in default based upon result of cluster 2. Defaults explored (including some serial defaults, such as Brazil, which defaulted seven times between 1826 -1983, see table 3 in cluster 1 and South Africa, which defaulted three times between 1985-1993, see table 4 in cluster 2) are common throughout history around the globe as we have seen in both cluster 1 and 2. It is important to realize that overlooked domestic debt explains the strategy many governments chose in the aftermath of default.

Is "this time really different"? Default occurs from time to time without excluding any region. Policy makers should pay more attention to the warning that "the current boom, unlike the many booms that preceded catastrophic collapses in the past (even in our country) is built on sound fundamentals…"². Governments should pay far more attention to domestic debt and balance risk and debt opportunities. More specifically,

² Reinhart, Carmen M.; Rogoff, KennethS.2009d. This Time Is Different: Eight Centuries of Financial Folly (Kindle Locations 2235-2237). Princeton University Press. Kindle Edition.

37

governments with a history of serial default or "debt intolerance" should shy away from borrowing, even when market conditions seem attractive.

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Appendix

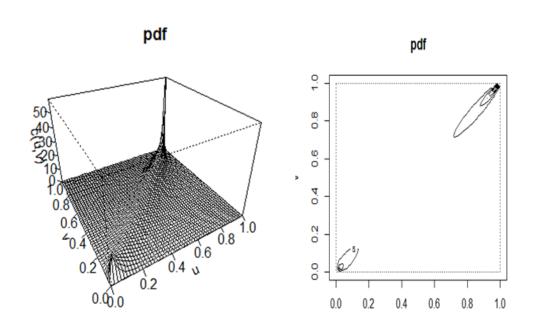
[1] 48.62274

```
Appendix A
Copula Section
fitCopula(n.obj, pobs(z))
fitCopula() estimation based on 'maximum pseudo-likelihood'
and a sample of size 20.
   Estimate Std. Error z value Pr(>|z|)
The maximized loglikelihood is 0.4761
Optimization converged
Number of loglikelihood evaluations:
function gradient
   29
          6
Appendix B
Gumbel copula
library(copula)
obj = gumbelCopula(param=5,dim=2)
g.copula = fitCopula(obj, pobs(w))
summary(g.copula)
summary(g.copula)
$method
[1] "maximum pseudo-likelihood"
$loglik
```

```
$convergence
[1] 0
$coefficients
   Estimate Std. Error z value Pr(>|z|)
param 3.016087 0.5430329 5.554151 2.78964e-08
Randomly generate data
This is on 2 dimensions with the same dataset
n <- nrow(f.t.df)
random_df <- data.frame(</pre>
 x = runif(nrow(f.t.df), min(f.t.df\$F.Debt.Ratio), max(f.t.df\$F.Debt.Ratio)),
 y = runif(nrow(f.t.df), min(f.t.df$T.Debt.Ratio), max(f.t.df$T.Debt.Ratio)))
# Plot the data
ggplot(random_df, aes(x, y)) + geom_point()
Appendix C
Hopkins test
set.seed(123)
hopkins(f.t.df, n = nrow(f.t.df)-1)
$H
[1] 0.2270414
Appendix D
#Check on external Debt ratio of cluster 1
descdist(F.Debt.Ratio[1:75], discrete = FALSE, boot=1000)descdist ()
```

Appendix E

Gumbel Coupla (upper tail dependency)



Appendix F

KS test on cluster 2 group

Uniform test

D = 0.78808, p-value = 1.942e-07

D = 0.47, p-value = 0.003727

Normality test

D P.Value ## 0.2434586 0.4240991

D P.Value ## 0.1861779 0.6923478

Appendix G

```
Correlation coefficient for cluster1

cor(x1,y1, method="spearman")

[1] 0.9040228

Correlation coefficient for cluster 2

External debt ratio and total debt ratio

cor(x2,y2)

[1] 0.0330602

cor(x2,y2, method="spearman")

[1] -0.06685885

Domestic debt ratio and total

cor(z2, y2)

[1] 0.4664926
```