Bank Credit Risk Rating Process: Is There a Difference Between Agencies?

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Abstract

The purpose of this article is to compare the bank credit risk rating (BCRR) process between credit rating agency (CRA) after the 2012 revision of their methodologies using 76 banks from 23 EMENA countries rated simultaneously by S&P's, Moody's and FitchRatings. We made this comparison based on the CAMELS model with a proposed 'S' to BCRR. We use "ordered logit" regression for the rating classes and we complete our analysis by "linear multiple" regression for the rating grades. The results show that the BCRR processes are largely consistent between agencies but not aligned. Some differences appear in the important factors and relevant variables of the intrinsic credit quality component that manifest themselves in specific behaviors distinguishing one agency to another. The three agencies agree on the factors: Capital, Earnings, Liquidity and Supports and the most relevant support variable is the sovereign rating of the bank's country of establishment. The results also confirm a consistence between the BCRR's revealed and practiced methodologies revised by the CRA.

Keywords: bank credit risk rating, credit rating agencies, rating process, CAMELS Model, determinants, financial crisis

JEL Code: G21, G24, G32

1. Introduction

The upheaval in the world of finance caused by the events of the crises and bankruptcies of several companies over the last twenty years has not spared the functioning of the CRA. They urged them to publish several specific documents to answer questions about BCRR's methodologies and to undertake after the 2007-09 global crisis, as the IMF reported in the Global Financial Stability Report (2010), a review of the ratings issued as well as updates to their criteria and rating models. These reviews have attracted the attention of capital market players and restored their confidence in the CRA.

The revealed methodologies are the set of qualitative and quantitative criteria, grouped into factors and key analytical factors, developed by agencies in their publications (Gaillard, 2008). And the practiced methodologies are all these criteria integrated and applied in the rating process.

The studies of the evolution of BCRR revealed methodologies (Packer & Tarashev, 2011; Damak & Chichti, 2017) based on the specific publications of the three most world-renowned agencies: S&P's, Moody's (M) and FitchRatings (FR) (S&P's, 2011b; FitchRatings, 2011a, b; Moody's, 2012), clarified those points, among others. First, they have not been fundamentally upset since they are based on the same components (intrinsic credit quality or internal factors, environmental support or external factors), factors (qualitative, quantitative) and information (public, private). Then, the methodologies revealed have undergone modest but remarkable changes between the period before and after the subprime crisis, which have made it possible to take environmental support more explicitly into account. In addition, they have become refined and better formalized in such a way that they reduce the part of subjectivity in the attribution of the ratings. Moreover, with the revisions and restructuring done with a different level from one agency to another, they appear to be more harmonized from a structural point of view which allowed the reduction of the difference in their ratings. Finally, they have become more transparent but more complex. However, those works were limited to describing the evolution of the methodologies revealed before and after the subprime crisis without a thorough econometric study to detect the methodologies practiced.

A recent theoretical study was done by Damak (2018). The author adapted the famous CAMELS (Note 1) model by proposing an adjusted ‘S’ to the BCRR. And for the validation, he used a simple indicator based on quantifiable information available to the public from their financial statements. This adjusted model explicitly considers the two components of the BCRR. The intrinsic credit quality that generates 'Stand-alone' ratings and the environmental support that generates 'Support' ratings. Their combination gives the 'all-in' ratings (called also ‘issuer rating’ or ‘traditional rating’) on the universal scale of long-term ratings (S&P’s, 2011b; FitchRatings, 2011a, b; Moody’s, 2012). The adjusted model was empirically validated by using Moody’s BCRR but did not address the comparison between the CRA.

The scientific literature on the comparison between the CRA showed mixed results, on one hand, a consistence in the rating methodologies and in other hand, a partly difference in ratings, policies and behaviors but have not shown the difference in the rating process. In light of this finding, assuming that the BCRR are consistent with the micro and macro-economic theoretical foundations and that the CAMEL'S model with a proposed ‘S’ well explains the 'all-in' ratings, we try, in the context of this study, to answer the following question: Is there a difference between the BCRR process of the CRA?

Thus, our objective of this work is to complete the perspective of the comparison between the three agencies S&P's, Moody's and FitchRatings through the study of methodologies practiced by comparing their rating process from the publicly available information. Our contribution is manifested in the following two points: (i) the first point is to use the CAMEL'S' model with an adjusted 'S’ to compare the composites of rating processes. Indeed, previous research dealing with a comparison of CRA rating methodologies was limited to the use of certain variables without referring to a 'tailor-made' BCRR model. (ii) The second point is that this comparison is processed in 2012 after the completion of the revisions of their methodologies in response to the subprime crisis. Those revisions have considered some of the lessons learned from this global crisis (Packer & Tarashev, 2011).

Through this BCRR-adapted model, we will conduct an empirical study to detect any structural differences between agencies in the influence of each composite (components, factors, or variables) in ‘all-in’ ratings. The BCRR process after revision of each agency is of interest to the banks that ask for ratings. Indeed, they provide information on the specificity of each CRA and guide the choice of the agency and the period of the application for rating to benefit from the most favorable conditions in terms of credit risk. The results showed that a consistency exists, to a large extent, between rating processes of the three agencies, but with differences in the importance given to certain factors and the relevance of certain variables of the intrinsic credit quality component. The results also confirm a consistence between the BCRR's revealed and practiced methodologies revised by the CRA.

The rest of this paper is structured as follows: in the second section, we will present an overview of the review of the theoretical and empirical literature on comparisons between CRA. In the third section, we will present the conceptual framework and our research hypotheses. In the fourth section, we will outline the methodological aspects necessary to test the validity and robustness of our hypotheses. In the fifth section, we will analyze the results of the comparison between CRA. And in the sixth section, we will finish this work with a conclusion.

2. The Literature Review

The scientific literature that we are going to present focuses on the question of the comparison of the rating process between CRA. The agencies studied are mainly Moody's and S&P's. FitchRatings appears in comparative studies since 2007 (to our knowledge) with the study of Afonso, Gomes and Rother of sovereign rating followed by Hill, Brooks and Faff (2010) and Sehgal, Mathur, Arora and Gupta (2018); to name but a few. Other BCRR studies have compared the three major agencies (Packer & Tarashev, 2011; Bissoondoyal-Bheenick & Treepongkaruna, 2011; Salvador, Pastor, & De Guevara, 2014; Damak & Chichti, 2017). In addition, the U.S. agencies: Duff & Phelps Credit Rating Agency 'DCR' and 'A.M. Best', Japanese agencies ‘JCR, R&I' and the Chinese agency 'Dagong' appear in the comparative studies, respectively, of Cantor and Packer (1997) on the rating of companies, Pottier and Sommer (1999) on the rating of insurances and Zheng (2012) on the rating of sovereignty.

The investigation of those researchs showed that the comparisons between the CRA were made according to two points of view. On the one hand, the comparison related to the revealed methodologies based on the specific publications of the three most world-renowned agencies. Packer and Tarashev (2011) and Damak and Chichti (2017) dealt with BCRR and Sehgal et al. (2018) with sovereign rating. They showed that many rating criteria are common to agencies under consideration and have drawn our attention to the existence of, what Van Laere, Vantieghem and Baesens (2012) called, a 'level of discretion' in the rating process that is different from one agency to another.

And in the other hand, the comparison between the CRA based on econometric studies related to theirs practiced methodologies, to the investigation of the rating determinants and/or the importance of some factors and variables in the rating process using ratings of corporate (Ederington, 1985), municipalities (Moon & Stotsky, 1993), insurances (Pottier & Sommer, 1999), BCRR (Bissoondoyal-Bheenick & Treepongkaruna, 2011; Van Laere & Baesens, 2011; Van Laere, Vantieghem, & Baesens, 2012; Salvador et al., 2014) and sovereignties (Cantor & Packer, 1996; Sehgal et al., 2018; Cuadros-Solas & Salvador, 2021), to name but a few. They showed total convergence in some studies and a partial divergence in others confirming the existence of some subjectivity in the rating attribution.

Those studies showed mixed results, on one hand, a consistence in the rating methodologies and in other hand, a partly difference in ratings and their policy but have not shown the difference in the rating process. Also, none of this work addressed the issue of comparing the BCRR rating process between the CRA after the completion of the methodology revision in response to subprime crises one of the most upsetting crises in the financial world. Table 1 summarizes a selection of these works with their main results.

3. Conceptual Framework and Research Hypothesis

3.1 CAMELS Model With a Proposed 'S' for the BCRR

As presented in the specific publications of the three CRA (S&P's, 2011b; FitchRatings, 2011a, b; Moody's, 2012) analyzed by Damak and Chichti (2017), the BCRR has two components. The first includes the internal factors for assessing the bank's intrinsic credit quality (stand-alone). The second component includes the external factors for assessing environmental support (supports). These two components are combined to give the 'all-in' ratings provided to the public by the three CRA on the long-term universal scale. The famous CAMELS model, in its composite and component form, is generally accepted as an important monitoring instrument and research topic for those interested in the behavior of banks for academic or applied purposes (Derviz & Podpiera, 2008). But since our goal is to compare

BCRR's rating processes between agencies, we are required to use a model that explains all-in ratings well. We chosean adaptation of this model with a specific 'S' for the BCRR proposed by Damak (2018). The use of this model allows for a complete and homogeneous comparison between the three agencies under consideration.

Table 1. Review of a selection of empirical studies on the rating process comparison between CRA

Authors/ Year	Subject/Sample/Period/Methods of analysis	Main results
Packer & Tarashev (2011)	Comparison of the revealed methodologies of the BCRR of S&P's, Moody's and FitchRatings and the ratings of 70 major banks in 10 countries for the period between mid-2007 and April 2011.	• With the onset of the subprime crisis, the differences in rating between the CRA have decreased. • Moody's acted more quickly at the beginning of this crisis by lowering bank ratings twice as much as the other two agencies.
Van Laere & Baesens (2011)	Comparison of the determinants of the 'all-in' ratings to LT from 2000 to 2009 of 2046 banks rated by S&P's and 680 banks rated by Moody's from 38 countries in North America and Western and Eastern Europe using the Ordered Probit model and regressions "Multi-level logistic" (stepwise)	• The BCRRs of Moody's and S&P's reflect different indicators and dimensions of a bank's financial health. • Moody's and S&P's set different standards for a particular rating grade. Moody's regressions have the highest explanatory powers. • Moody's ratings tend to be more sensitive to economic conditions.
Bissoondoyal-Bheenick & Treepong	Comparison of the determinants of the 'all-in' ratings to LT and CT of S&P's (foreign and local currencies), Moody's and FitchRatings from 2006 to 2009 of 69 commercial banks (20 Australians and 49 British) using the "ordered-response"	• The results of the determinants of the three agencies are similar when the study is done with the rating grades, but some differences exist in the results of the study with the rating classes. • Quantitative factors that reflect asset quality, liquidity risk, capital adequacy and operational performance are

karuna (2011)	model.	the main determinants of banks' ratings through rating agencies.
Van Laere & *al.* (2012)	Comparison of the determinants of the 'all-in' LT ratings of 505 banks rated by Moody's and 552 by S&P's from 40 countries from 2000 to 2011 using the "heteroscedastic-ordered probit" (stepwise-backward-forward) model.	• Moody's and S&P's agreed in only 22.97% of the ratings and for the 67.92% of cases, Moody's ratings were lower. • The level of discretion in the rating process is lower for large and profitable rated banks and is higher for Moody's. • Moody's and S&P's set different standards for a particular rating grade.
Salvador & *al.* (2014)	Comparison of the determinants of 'all-in' ratings to LT and 'stand-alone' Moody's and 'all-in' ratings to S&P's LT from 2000 to 2009 of 44 Spanish banks (2379 quarterly observations) using the variable effect ordered-probit model.	• The results of the three agencies are quite similar in regressions and forecasts. Moody's regressions have the highest explanatory powers. • There are some differences in the importance and meaning given to each factor that suggest that agencies adopt different rating policies.
Damak & Chichti (2017)	Comparison of the revealed methodologies of the BCRR of S&P's, Moody's and FitchRatings before the Asian crisis, between the two financial crises and after the subprime crisis.	• After the subprime crisis, S&P's is the agency that proposed the most important revisions to its methodology. With the restructuring and refinement carried out, Moody's and FitchRatings intervened to adjust the importance of the environmental support assessment and certain analytical elements. With these adjustments, their revealed methodologies appear more harmonized.
Sehgal & *al.* (2018)	Comparison of the revealed methodologies and the models of S&P's, Moody's and FitchRatings to identify the determinants of sovereign rating for 135 countries over the period 2008 to 2012 using «ordered Logit-Probit» regressions.	• Many criteria and determinants are common to all three agencies. They use similar measures ; however, they give different weighting to different factors.
Cuadros-Solas & Salvador (2021)	Examine whether sovereign ratings account for the potential spillovers from the banking sector to sovereign risk using a panel data sample of 447 sovereign ratings of Fitch, S&P's and Moody's for 30 European countries from 2002 to 2016 using the machine learning technique (random forest regression).	• With the outbreak of the crisis, the importance of these banking sector characteristics (namely, liquidity, concentration and volume of non-performing loans) for sovereign ratings increased substantially with a consistency for all the CRA inder concideration.

Source: This table is the author's construction from the collected studies.

Rating'all-in'=f (component 1, component 2)=f (Intrinsic credit quality, Environment supports)

Rating'all-in'=f(CAMEL, 'Supports')= f(CAMEL'S')=

f(Capital, Assets, Management, Earnings, Liquidity, 'Supports')=

f(Capital, Assets, Management, Earnings, Liquidity, Sovereign rating, Size, Origin of capital, Activity of the bank)

So, to achieve our goal and compare BCRR's rating process between agencies, we are required to use a model that explains and reconstructs 'all-in' ratings well. The use of this adjusted model for our study is motivated by the fact that it will allow us, also, to detect any structural differences between the CRA in the BCRR process, including the weight of components, the important factors and the relevant variables introduced in the analyze. This 'tailor-made' model allows for a complete and homogeneous comparison between the three agencies under consideration.

Given that our work is intended to test the importance of various composites in the rating process with a certain hierarchy [components [factors [variables]]], we use the term ‘weight’ for the components, ‘importance’ for factors and the term ‘relevance’ for variables.

3.2 Research Hypotheses

The investigation of studies focused on comparing the CRA rating processes with their behaviors, reactions, methodologies, and determinants in different sectors of activity shows consistency despite the existence of certain differences. This consistency, which has always existed, is justified by the fact that the rating methodologies of the three agencies come from, as Cantor and Packer said in 1994, the ‘same philosophy’. Ederington (1985), comparing the difference in ratings between Moody's and S&P's on a sample of bonds of corporate companies, did not find any significant differences in the determinants. But he offered three explanations for the differences in grades between the CRA. The first is that the agencies agree on the risk of default but apply different break points for their ratings. The second is that agencies include different factors in their rating models or apply different importance to these factors. And the third is that the differences simply reflect random variations in judgment. Hájek (2011) and Van Laere et al. (2012) add the discretion in the rating process as another explanation for the difference in ratings. On another side, Afonso *et al.* (2007) in studying sovereign ratings indicate that these differences all simply reflect the uncertainty that prevails in the extent of the risk of default. And Van Laere et al. (2012) confirm that the latest convergence of Moody's and S&P's following the change in their BCRR models in response to the subprime crisis does not necessarily imply that their rating processes are more aligned. From these arguments, our main hypothesis can be formulated as follows:

MH: “The rating processes of the CRA are largely consistent but not aligned.”

To test our main hypothesis, we are looking for any structural difference between the CRA in the influence that components or factors or variables have on the ‘all-in’ ratings using CAMELS model with ‘S' adjusted to BCRR. To become more pragmatic, our main hypothesis can be broken down into three sub-hypotheses and his confirmation need the cumulated confirmations of the three.

Packer and Tarashev (2011), in analyzing the behaviors of the three agencies S&P’s - Moody's - FitchRatings in the evaluation of banks, found evidence that with the onset of the subprime crisis, the differences in ratings between the CRA have declined. In the same context, the comparative study of their main analytical factors of the revealed BCRR methodologies, carried out based on their specific documentations by Damak and Chichti (2017), also showed some improvement in their consistency after the completion of their revisions in 2012. Thus, the last authors conclude that with the adjustment in the importance of the environmental support assessment and some analytical elements, the methodologies after revisions of the three agencies appear more harmonized in two points of view. The first is structural since they have the same components (intrinsic credit quality and environmental support). The second point of view is the relationship between the BCRR, the level of development of the country of the bank's establishment and its sovereign rating. Hence the following sub-hypothesis :

SH1: “The weights assigned to each component of the 'all-in' rating are similar for all agencies.”

The comparison between CRA, in more details, led Perry (1985) to state that the bond rating forecasting models should not be generalized because the two CRA Moody's and S&P's disagreed in 58% of cases. Bissoondoyal-Bheenick and Treepongkaruna (2011), in turn, found for the period 2006 to 2009 that the determinants of the 'all-in' ratings of the three agencies are similar when the study is done with the rating grades, but some differences result when the study is done with the rating classes of these grades. In this regard, Van Laere and Baesens (2011) state that Moody's and S&P's appear to have differences in the determinants of BCRR, sensitivity to economic conditions and behaviors when they are rating the same banks. Van Laere et al. (2012) also confirm that Moody's and S&P's set different standards even for a particular rating grade. Salvador et al. (2014), in studying the causes of the reduction in grades after the 2007-09 financial crisis, showed that the results of the three agencies are quite similar but there are some differences in the importance and meaning given to each BCRR factor. This suggests that agencies adopt different rating policies. They also add that the structural change detected, following the revision of the rating criteria, in the influence that each component or factor has on the ratings, does not occur equally for all agencies and all types of ratings considered despite the strong correlation between grades. Other studies on ratings other than of banks also showed some consistency in the rating criteria of the agencies, but with a difference in the importance of factors and the relevance of certain variables. From these arguments, our second and third hypotheses can be formulated as follows:

SH2: "The important factors of the ‘all-in’ rating differ party from one agency to another."

SH3: "The relevance of certain variables explaining the ‘all-in’ rating differs party from one agency to another."

4. Methodological Aspects

4.1 The Explanatory Variables

To test the validation of our hypotheses, you are going to take into consideration the same explanatory variables used by Damak (2018): 10 variables for CAMEL factors and 4 variables for ‘S’ factor. The explanatory variables selected to represent each factor of the two components of the 'all-in' rating model (intrinsic credit quality and environmental support) are presented in Table 2. All variables of CAMEL factors of intrinsic credit quality are three-year averages that precede the rating year (Note 2). This approach, called "Through-The-Cycle 'TTC" (as opposed to the 'Point-In-Time 'PIT') approach, neutralizes the impact of the business cycle on ratings, in order to obtain indicators less dependent on the characteristics of the business issuers' financial statements (Amato & Furfine, 2004; Alejandro & Analia, 2008). The source of our data is the "S&P Capital IQ" database in 2012 (Note 3).

Table 2. Variable definitions

Components ‘A-B’/’CAMEL, Supports‘ FACTORS/ Ratios and definitions			
EXPLANATORY (INDEPENDENT) VARIABLES			
A - The quantifiable explanatory variables in the intrinsic credit quality *(CAMEL)*			
	Expected sign		Expected sign
CAPITAL (C)		*EARNINGS (E)*	
CPAO/TAA= Common shareholders equity % Total adjusted assets	+	ROA= Net income % Total adjusted assets	+
RTier1= Tier 1 capital ratio	+	ROE= Net income % Equity ordinary tangible means	+
ASSETS (A)		*LIQUIDITY (L)*	
CON/PMC= Net ‘charge offs’ % Average customer loans	+	TPN/TAA= Total Net loans % Total adjusted assets	+/-
ANP/EC= Non-performing assets % Total credits	-	TD/TAA= Total deposits % Total adjusted assets	+/-
MANAGEMENT (M)			
CE/TAA= Operating expenses % Total adjusted assets	-		
PHI/PNB= Operating non-interest income % Operating income	+		
B - The quantifiable explanatory variables in the environment support (Supports)			
	Expected sign		Expected sign
RS Moy= the average[1] sovereign rating of the country of establishment of the bank on the date of rating respectively of: S&P’s, Moody’s, FitchRatings.	+	OC= Dummy variable for public banks or semi 1 and 0 for private banks	+
LnTAA= Total adjusted assets from last 12-31 preceding the year of rating (natural Log).	+	ACT= Dummy variable 1 for universal banks or having three activities and more, and 0 elsewhere	+
VARIABLES TO EXPLAIN			
	Correspondence between the LT ‘all-in’ rating scale and the numerical values assigned to each grade and class of rating		
VNG SP/M/FR= Numeric value of ‘all-in’ rating grade of S&P’s/Moody’s/FitchRatings in July 2012	Investment Grade : AAA=17, AA+=16, AA=15, …, BBB+=10, BBB=9, BBB-=8 ; Speculative Grade : BB+=7, BB=6, BB-=5, B+=4, B=3, B-=2 and CCC/CC/C=1		
VNC SP/M/FR 1-5= Numeric value of ‘all-in’ rating class of S&P’s/Moody’s/FitchRatings in July 2012	Investment Grade Classes : AAA/AA=5, A=4, BBB=3 ; Speculative Grade Classes : BB=2 and B/CCC/CC/C=1		

Source. This variable definition table is extract from Damak (2018) after a small adjustment by the author of the variables to explain and of control to adapt it to the needs of the study.

Notes. We use the average of the sovereign ratings of the three CRA. This choice is based on the rationale that we find persuasive from Cantor-and Pacher (1996), which states that the difference between agency ratings pushes investors to see the average rating.

4.2 The Variables to Explain

Our study focuses on the 'all-in' ratings of S&P's, Moody's and FR collected from their websites. To capture all the information on the 'all-in' rating process of each agency, we chose to conduct the study on grades and rating classes (Note 4) by making numerical conversions (see table 2). We retained the 'all-in' ratings of July 2012 of the completion of the rating adjustments of the three agencies. In fact, the agencies began revising their BCRR methodologies on the eve of the 2007-09 crisis and completed them by rating update between the end of 2011 and mid-2012 (Damak, 2018).

4.3 Sample Characteristics

We conduct our comparison on a sample of 76 banks rated simultaneously by the three agencies from 23 countries of Europe, Middle East, and North Africa (EMENA). We chose to limit our sample to those countries for three mainly reasons. First, the Europe region has the highest number of rated banks (Shen, Huang, & Hasan, 2012). Second, the movement of the adjustment of bank ratings, across the universe, based on revised methodologies in 2012 has led to many changes, mainly downgrades, in the ratings of banks in European countries (Packer & Tarashev, 2011). And finally, it is to avoid the effect of the region on the results and to be able to control and limited biases a result of the effect of the heterogeneity of the sample that may mask convincing evidence for the validation of our hypotheses. The final sample (Note 5) selected after the elimination of incomplete files (missing variables) is summarized in table 3.

4.4 Analytical Methods

After univariate (Note 6) and bivariate (Note 7) descriptive analyses, the first multivariate statistical method that we will use is ‘ordered logit ‘OLOGIT’’ regression (Scott & Freese, 2006) for the variable to explain the numerical value of the rating classes. It is used for estimating the probability and group membership of independent variable by making the logistic transformation of linear combination of the dependent variable. This choice is justified by the nature of the ordered scale with a reduced class number by which this variable is measured (class number less than or equal to 5). The use of this method takes into account the fact that the difference between the different levels of the credit risk scale is not constant. The difference in appreciation is all the greater the lower the range (Moody’s, 2001) (Note 8). To capture as many relevant variables as possible, we will complete our analysis by using a second multivariate statistical method the multiple linear regression (according to ordinary least square ‘OLS’) of the numerical value of the rating grades (decreasing scale of 17 to 1). Indeed, Menard (2002) specifies that when the number of categories in the ordinal variable to be explained exceeds 5, this variable can be treated as continuous.

Table 3. Sovereign rating, number of bank by country and by CRA

Country list	N ° of Banks rated simult. by the three CRA en 2012	Sovereign rating assigned in 2012			Country list	N ° of Banks rated simult. by the three CRA en 2012	Sovereign rating assigned in 2012		
		S&P’s	**Moody’s**	**FR**			**S&P’s**	**Moody’s**	**FR**
1 Belgium	4	AA	Aa3	AA	**13 Sweden**	3	AAA	Aaa	AAA
2 Denmark	2	AAA	Aaa	AAA	**14 G-Britain**	4	AAA	Aaa	AAA
3 Finland	1	AAA	Aaa	AAA	**15 R-Czech**	1	AA-	A1	A+
4 France	9	AA	Aaa	AAA	**16 Georgia**	1	BB-	Ba3	BB-
5 Germany	5	AAA	Aaa	AAA	**17 Poland**	3	A-	A2	A-
6 Greece	3	CCC/CC/C	Caa/Ca/C	CCC/CC/C	**18 Russia**	1	BBB	Baa1	BBB
7 Ireland	5	BBB+	Ba1	BBB+	**19 Slovenia**	1	A+	Baa2	A
8 Italy	10	BBB+	Baa2	A-	**20 Turkey**	4	BB	Ba1	BB+
9 Netherlands	4	AAA	Aaa	AAA	**21 Egypt**	2	B	B2	B+
10 Portugal	2	BB	Ba3	BB+	**22 Jordan**	1	BB	Ba2	BB
11 Spain	6	BBB+	Baa3	BBB	**23 Tunisia**	1	BB	Baa3	BBB-
12 Switzerland	3	AAA	Aaa	AAA	**N °banks**	**76**			

Source. This table is the author's construction from the collected data.

To test the validity of our four hypotheses, we will proceed in three steps. In the first one, we will, run the regressions of the following equations from (1) to (4) for each CRA.

$$Rating\text{'all-in'}_{it}=f(CAMEL'S')=f(A_{it-1} + B_{it}) + \varepsilon_{1it} \quad (1)$$

$$Rating\text{'all-in'}_{it}=f(CAMEL)=f(A_{it-1}) + \varepsilon_{2it} \quad (2)$$

$$Rating\text{'all-in'}_{it}=f(Supports)=f(B_{it}) + \varepsilon_{3it} \quad (3)$$

$$Rating\text{'all-in'}_{it}=f(Sovereign\ Rating)=f(RSMoy_{it}) + \varepsilon_{4it} \quad (4)$$

Where, Rating 'all-in'$_{it}$ is the vector of 'all-in' rating class or grade of the bank i in the period t (t =2012).

A_{it-1} is the matrix of 10 quantifiable variables of CAMEL factors (see Table 2) for the assessment of the intrinsic credit quality of the bank i. They are three-year averages preceding the period t (t=2012).

B_{it} is the matrix of 4 quantifiable variables (see table 2) for the evaluation of the environment supports of the bank i in the period t (t=2012).

$RSMoy_{it}$ is the vector of the average sovereign rating of the country of establishment of the bank i in the period t (t=2012).

ε_{pit} are the vectors of the residuals of the pth equation (p=1,2,3,4). The error term represents the part of the specification error and captures all of the private information that are formed by the confidential information held by the CRA about the bank i in the period t (t=2012) after revision and the interpretation of the expert group in charge of the folder.

In the second step, we will compare between the CRA the explanatory powers of OLS and OLOGIT regressions of the four equations to emphasize the weight of components and the most relevant variable.

In the third and last step, we will compare between the CRA the important factors, the relevant variables and the signification thresholds of some coefficients in the regression of the equation (1).

The explanatory powers of the OLS and OLOGIT regressions are measured respectively by 'adjusted R2' and 'Pseudo *R2*'. The explanatory powers of the equation (1) regressions provide information on the quality of the specification of CAMELS model with adjusted 'S'. High explanatory power indicates good specification. The weight of component 1 in the attribution of the 'all-in' rating can be measured by the importance of the explanatory power of the equation (2) regression and the difference between the explanatory powers of the regressions of equations (1) and (3). And the weight of component 2 can be measured by the importance of the explanatory power of the equation (3) regressions and the difference between the explanatory powers of the regressions of equations (1) and (2). A factor is qualified as important when at least one of the variables that measures it is relevant. A variable qualifies as relevant when its regression coefficient is significant at the thresholds of 1% or 5% or 10%. The relative relevance of the sovereign rating variable can be measured by the importance of the explanatory power of the equation (4) regression and the low difference between the explanatory powers of the regressions of equations (1) and (4).

For each regression, we will proceed to diagnose the multicollinearity with the «Variance Inflation Factor 'VIF'» (Note 9) and diagnose the model stability with «Bootstrap Inclusion Fractions 'BIF'» (Note 10) advocated by Nunez, Steyerberg and Nunez (2011). For checking the accuracy of the "proportional odds assumption" in 'all-in' rating regressions measured by classes, we use the likelihood-ratio test (Note 11) (Dolgun & Saracbasi, 2014). For diagnosing heteroskedasticity in 'all-in' rating regressions measured by grades, we use the «Breusch-Pagan» test (Note 12).

And given that the number of observations in our sample is not important for taking a sub-sample, we will test the robustness of our hypotheses by using the bootstrapping approach (Royston & Sauerbrei, 2009) with 1000 replications for regressions of the equation (1).

5. Analysis of Results

5.1 Univariate and Bivariate Descriptive Analyses

The comparison of the averages of the variables to explain, presented in table 4, shows that the average rating class of the three agencies for this sample of 76 banks is BBB/Baa3 (the corresponding numerical values by agency are 3.06 for Moody's, 3.17 for S&P's and 3.41 for FR) with average grades of Baa- on the Moody's scale, BBB on the S&P's and FR scales (the corresponding numerical values by agency are 8.92 for Moody's, 9.39 for S&P's and 10.30 for FR). Despite the small differences for the two measures of the 'all-in' rating (grades and classes), they are significant except for the difference between the middle classes of S&P's and Moody's. So, on the face of it, FitchRatings is, on average, the most generous CRA, since its average numerical values of classes and grades being the highest (3.41 and 10.30 respectively) and Moody's is, on average, the most severe.

Table 4. Average comparison tests

	S&P's	M	FR	S&P's/M	S&P's/FR	M/FR
Variables to explain	**Average**	**Average**	**Average**	**t-student**	**t-student**	**t-student**
VNC15	3,17	3,06	3,41	1,919	-3,395***	-4,787***
VNG	9,39	8,92	10,30	4,025***	-5,870***	-8,147***
N °of observation	76	76	76			

*** Significance at 1%, ** Significance at 5%, * Significance at 10%.

Source: Author' calculation.

The sample distributions of 76 banks rated simultaneously by the three agencies by distinguishing the five classes of the 2012 'all-in' rating are presented in table 5. We see that the percentage of banks with investment ratings is higher for FR (84.21%) relatively to S&P's and Moody's (71.05%). Also, the percentage of banks ranked in AAA/AA /Aaa/Aa is higher for S&P's (11.84%) relatively to Moody's and FR (7.89%).

Table 5. Descriptive statistics by variable, class of rating and CRA

Category of rating	**Investissement**			**Speculative**	
Class of rating	**AAA/AA / Aaa/Aa**	**A / A**	**BBB / Baa**	**BB / Ba**	**B/CCC/CC/C / B/Caa/Ca/C**
Numerical value assigned	**5**	**4**	**3**	**2**	**1**
Sample distributions by agency of 76 banks (observations) rated simultaneously by the three CRA in 2012					
S&P's (SP)					
Frequency	9	24	21	15	7
Frequency in %	11,84	31,58	27,63	19,74	9,21
Frequency cumulative in %	**11,84**	43,42	71,05	90,79	100
Freq. by category of rating in %	**71,05**			28,95	
Moody's (M)					
Frequency	6	25	23	12	10
Frequency in %	7,89	32,90	30,26	15,79	13,16
Frequency cumulative in %	**7,89**	40,79	71,05	86,84	100
Freq. by category of rating in %	**71,05**			28,95	
FitchRatings (FR)					
Frequency	6	36	22	7	5
Frequency in %	7,89	47,37	28,95	9,21	6,58
Frequency cumulative in %	**7,89**	55,26	84,21	93,42	100
Freq. by category of rating in %	**84,21**			15,79	

Source: This table is the author's construction

Table 6. Rating matrix of the 76 banks rated simultaneously by S&P's and Moody's in 2012

	Moody's	*Aaa/Aa*	*A*	*Baa*	*Ba*	*B/Caa/Ca/C*	
S&P's	***VNC***	***5***	***4***	***3***	***2***	***1***	
AAA/AA	***5***	**5**	4	0	0	0	**9**
A	***4***	1	**19**	4	0	0	**24**
BBB	***3***	0	2	**17**	2	0	**21**
BB	***2***	0	0	2	**10**	3	**15**
B/CCC/CC/C	***1***	0	0	0	0	**7**	**7**
		6	**25**	**23**	**12**	**10**	**76**

Source: Author' calculation

Table 7. Rating matrix of the 76 banks rated simultaneously by S&P's and FR in 2012

	FR	*AAA/AA*	*A*	*BBB*	*BB*	*B/CCC/CC/C*	
S&P's	***VNC***	***5***	***4***	***3***	***2***	***1***	
AAA/AA	***5***	**6**	3	0	0	0	**9**
A	***4***	0	**22**	2	0	0	**24**
BBB	***3***	0	10	**10**	1	0	**21**
BB	***2***	0	1	10	**4**	0	**15**
B/CCC/CC/C	***1***	0	0	0	2	**5**	**7**
		6	**36**	**22**	**7**	**5**	**76**

Source: Author' calculation.

Table 8. Rating matrix of the 76 banks rated simultaneously by Moody's and FR in 2012

	FR	*AAA/AA*	*A*	*BBB*	*BB*	*B/CCC/CC/C*	
Moody's	***VNC***	***5***	***4***	***3***	***2***	***1***	
Aaa/Aa	***5***	**4**	2	0	0	0	**6**
A	***4***	2	**23**	0	0	0	**25**
Baa	***3***	0	10	**12**	1	0	**23**
Ba	***2***	0	1	8	**3**	0	**12**
B/Caa/Ca/C	***1***	0	0	2	3	**5**	**10**
		6	**36**	**22**	**7**	**5**	**76**

Source: Author' calculation.

The descriptive statistics for the set of continuous and dummy variables (defined in Table 2) for the same sample show that as expected, the increase in ANP/EC for S&P's and Moody's and CE/TAA and OC for Moody's and the decrease in RSMoy for the three agencies are perfectly consistent with lower rating classes (qualified as bad risk). The influence of other variables in the 'all-in' rating is not clear.

Now, we're going to highlight the additional elements needed for a comparison between agencies and illustrate the distributions of the ratings of S&P's, Moody's and FitchRatings taken in pairs by the matrix from Tables 6 to 8. Compared with more precision, the matrix show that the same rating classes (see main diagonal) were given for 58/76 banks by S&P's and Moody's and for 47/76 banks by S&P's and FR and by Moody's and FR. The 51.31% (39/76) of the banks had the same rating classes by the three agencies. This percentage indicates strong correlations between the agencies' all-in ratings. Indeed, the Pearson coefficients of the numeric value of 'all-in' rating grades and classes of the agencies taken in pairs are more than 91.73% and 84.33%, respectively. For the remaining 37/76 banks, Moody's is also the most severe agency and FR the most generous. Indeed, FR assigned the highest rating (compared to other agencies) for 19 banks (S&P's for 4 banks and Moody's for one bank) and the worst rating for only 2 banks (S&P's for 4 banks and Moody's for 9 banks).

Summary, the results of the preliminary analysis provide a first evidence that there is some degree of consistency between the all-in ratings of the three agencies and that Moody's appears to be the most conservative. In the next section, we will compare the rating process of the three agencies using two multivariate statistical methods.

5.2 Multivariate Analysis

The results of the regressions of the equation (1) (Note 13) by OLS and OLOGIT with the sample of 76 banks rated simultaneously by the three agencies in 2012 for both measures (grades and classes) are presented respectively in Table 9. The explanatory powers of the four equations are summarized in Table 10.

The comparisons of the explanatory power regressions of the equations (2) and (3) and the regression explanatory power differences of equations (1) versus (3) then equations (1) versus (2) (table 10) shows very close results between the three agencies for the two measures of the 'all-in' rating. In fact, Adjusted R2 and Pseudo *R2* of the equation (2) range, respectively, from 36.05% to 38.99% and from 16.60% to 21.15%. And those in the equation (3) range, respectively, from 75.41% to 77.76% and from 44.58% to 47.86%. Also, the differences of Adjusted R2 and Pseudo *R2* of equations (1) versus (3) vary respectively from 0.0343 to 0.0489 and from 0.0798 to 0.1573 and those of equations (1) versus (2) vary respectively from 0.4011 to 0.4366 and from 0.3275 to 0.4244. Those results inform us about the similarity between the three agencies on the weights of the two components of 'all-in' rating (intrinsic credit quality, environment supports). These results are sufficient to confirm the first *SH1* sub-hypothesis which states that *"The weights assigned to each component of the 'all-in' rating are similar from one agency to another."*

Table 9. The results of equation (1) estimates

Agency	**S&P's**		**Moody's**		**FR**	
Results	**OLS**	**OLOGIT**	**OLS**	**OLOGIT**	**OLS**	**OLOGIT**
Variable to explain	**VNGSP**	**VNCSP15**	**VNGM**	**VNCM15**	**VNGFR**	**VNCFR15**
Column	**1**	**2**	**3**	**4**	**5**	**6**
	Coef. **(P-values)**	**Coef.** **(P-values)**	**Coef.** **(P-values)**	**Coef.** **(P-values)**	**Coef.** **(P-values)**	**Coef.** **(P-values)**
Constant	-6.1338** (0.026)		-5.8070** (0.022)		-0.2415 (0.920)	
A-Intrinsic credit quality (CAMEL)						
Capital						
CPAO/TAA	0.2296** (0.037)	0.3326** (0.032)	0.2560** (0.012)	0.4693** (0.022)	0.2516** (0.011)	0.4176** (0.011)
RTier1	-0.03319 (0.550)	-0.0846 (0.275)	-0.0503 (0.324)	-0.2284** (0.024)	-0.0248 (0.615)	0.0305 (0.706)
Assets						
CON/PMC	-0.0703 (0.888)	0.1408 (0.825)	-0.0919 (0.840)	-0.6911 (0.392)	-0.6124 (0.169)	-0.2660 (0.690)
ANP/EC	-0.1129*** (0.004)	-0.2218*** (0.003)	-0.1229*** (0.001)	-0.3240*** (0.008)	-0.0698** (0.044)	-0.0616 (0.227)
Management						
CE/TAA	-0.0202 (0.835)	0.0089 (0.945)	-0.0067 (0.940)	0.0748 (0.611)	-0.0973 (0.261)	-0.3005** (0.031)

PHI/PNB	0.0006	-0.0001	0.0014	0.0057***	0.0001	-0.0025
	(0.640)	(0.978)	(0.240)	(0.008)	(0.992)	(0.325)
Earnings (Profitability)						
ROA	-0.5845	-0.9525*	-0.8071**	-1.5435**	-0.7738**	-0.85748
	(0.142)	(0.086)	(0.028)	(0.021)	(0.030)	(0.132)
ROE	-0.0003	-0.0100*	-0.0002	-0.0193*	-0.0004*	-0.0005
	(0.286)	(0.098)	(0.435)	(0.084)	(0.079)	(0.849)
Liquidity						
TPN/TAA	0.0003	0.0044	0.0026	-0.0011	0.0014	-0.0047
	(0.982)	(0.810)	(0.824)	(0.960)	(0.902)	(0.809)
TD/TAA	0.0239*	0.0162	0.0265**	0.0530**	0.0154	0.0407*
	(0.086)	(0.400)	(0.039)	(0.038)	(0.210)	(0.055)
B-Environment Supports ('S')						
RS Moy	0.4938***	0.6028***	0.5306***	1.03756***	0.4559***	0.7828***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LnTAA	0.7424***	0.9655***	0.6331***	1.1712***	0.4001**	0.6065**
	(0.000)	(0.001)	(0.001)	(0.002)	(0.025)	(0.039)
OC	-0.4006	-0.3013	-0.3345	0.0619	-0.46389	-1.1404
	(0.466)	(0.686)	(0.506)	(0.943)	(0.342)	(0.170)
ACT	0.3379	1.2613*	0.4138	0.9055	0.5106	1.1296
	(0.474)	(0.056)	(0.339)	(0.245)	(0.225)	(0.105)
N°of observation	76	76	76	76	76	76
Diagnostics of the explanatory power						
R2	0.8284		0.8589		0.8294	
R2 Adj	0.7890		0.8265		0.7902	
Prob> chi2		0.0000		0,0000		0.0000
Pseudo *R2*		0.5256		0.6359		0.5441
Diagnostics of multicolinearity[1]						
VIF Moyen	2.00	2.00	2.00	2.00	2.00	2.00
VIF Max	4.07	4.07	4.07	4.07	4.07	4.07
Diagnostics of model stability[2]						
% BIF min (Vi) 1000	44.80%	35.10%	44.10%	47.90%	40.10%	51.10%
rép.	(TD/TAA)	(ROA)	(ROA)	(ROE)	(ROA)	(TD/TAA)
% BIF max (Vi) 1000	99.80%	100.00%	100.00%	100.00%	100.00%	99.80%
rép.	(RS Moy)	(RS Moy)	(RS Moy)	(RS Moy)	(RS Moy)	(RS Moy)
Diagnosis of proportional odds[3]						
Likelihood-ratio test						
chi2		71.19		82.38		53.22
Prob > chi2		0.0033		0.0002		0.1148

***Diagnostics of heteroskedasticity*[4]**			
Breusch-Pagan			
chi2	0.19	0.02	0.73
Prob > chi2	0.6647	0.8919	0.3920
***** Significance at 1%, ** Significance at 5%, * Significance at 10%.**			

Source: Author' calculation.

Notes. 1-By calculating the Variance Inflation Factor (VIF). 2-By using the "Bootstrap Inclusion Fractions 'BIF'" test with 1000 replications. The model is even more stable that the BIF minimum is high. The % BIF min. (Vi) 1000 rep. is the percentage of minimum 'BIF' of the significant variable (vi) with 1000 replications. The % BIF max (Vi) 1000 rep. is the percentage of maximum 'BIF' of the significant variable (vi) with 1000 replications. 3-High Chi2 and low "p-value" indicate the presence of proportional odds approach. 4-High Chi2 and low "p-value" indicate the presence of heteroskedasticity. Variable definitions. See Table 2.

Table 10. The regression explanatory power summary of the equations from (1) to (4)

Results	**OLS**			**OLOGIT**		
Variable to explain	**VNGSP**			**VNCSP15**		
Explanatory power	**R2 Adj**			**Pseudo *R2***		
Agency	**S&P's**	**Moody's**	**FR**	**S&P's**	**Moody's**	**FR**
Column	**1**	**2**	**3**	**4**	**5**	**6**
Equation (1)	0.7890	0.8265	0.7902	0.5256	0.6359	0.5441
Equation (2)	0.3605	0.3899	0.3891	0.1981	0.2115	0.1660
Equation (3)	0.7541	0.7776	0.7559	0.4458	0.4786	0.4527
Equation (4)	0.7257	0.7607	0.7470	0.3887	0.4391	0.4209
Explanatory power comparaisons						
Eq. (1) – Eq. (2)	0.4285	0.4366	0.4011	0.3275	0.4244	0.3781
Eq. (1) – Eq. (3)	0.0349	0.0489	0.0343	0.0798	0.1573	0.0914
Eq. (1) – Eq. (4)	0.0633	0.0658	0.0432	0.1369	0.1968	0.1232
Equation (1): Rating 'all-in' = f(CAMEL, Supports)				*Equation (2): Rating 'all-in' = f(CAMEL)*		
Equation (3): Rating 'all-in' = f(Supports) = f(RS, LnTAA, OC, ACT)				*Equation (4): Rating 'all-in' = f(Rating Souverain (RS))*		

Source: Author' calculation.

Despite the strong correlation between the ratings of the three agencies and the similarity of the weights assigned to each component of the 'all-in' rating, the comparison of the regressions carried out between the CRA show some disparity that we will expose in the following.

The equation (1) regressions (Table 9) made with the 'all-in' ratings of S&P's (columns 1&2), Moody's (columns 3&4) and FR (columns 5&6) shows that the explanatory powers of regressions measured by adjusted R2 and Pseudo *R2* exceed 78.90% and 52.56% respectively, and in general, the estimated coefficients have the expected signs. The three agencies are consistent on four factors (Capital, Earnings, Liquidity and Supports) and on the most relevant support variable "sovereign rating". Moody's and FR also both give importance to the Management factor. S&P's and Moody's give importance to the quality of assets. Only S&P's gives importance to the activity of banks. Moody's in equation (1) regression of rating classes (column 4) seems to have the spectra of factors (6 factors) and variables which represent them (9 variables) the broadest. Overall, these results suggest that the important factors and the relevant variables for the three agencies are not the same.

We will comment for each agency the two regressions of the equation (1) by exposing important factors measured by one or more relevant variable. Specifically, for S&P's, three factors (Capital, Assets and Supports) are important in these two regressions. The factor Liquidity is important only in the grade regression (column 1). And the factor Earnings is important only in the class regression (column 2). The grade regression shows positive effects of Capital (measured by CPAO/TAA), liquidity (measured by TD/TAA) and supports (measured by RS Moy and LnTAA) and negative effects of the quality of assets (measured by ANP/EC) on the variation in rating grades. The class regression shows on the one hand the negative effects of profitability (measured by ROA and ROE) contrary to what is expected and on the other hand the positive effects of supports (measured by RS Moy, LnTAA and ACT) on the probability of being well classed.

For Moody's, five factors (Capital, Assets, Earnings, Liquidity and Supports) are important in these two regressions. The grade regression (column 3) shows a positive effects of capital adequacy (measured by CPAO/TAA), Liquidity (measured by TD/TAA) and supports (measured by RS Moy and LnTAA) on the change in rating grades. And it shows a negative effects of poor asset quality (measured by ANP/EC) and of profitability (measured by ROA) contrary to what is expected. The class regression (column 4) also shows, on the one hand, a positive effect of good management (measured by PHI/PNB) and on the other hand, a negative (not anticipated) effects of capital adequacy (measured by RTier1) and profitability (measured by ROE).

For FitchRatings, only two factors (Capital and Supports) are important in these two regressions with a positive effects on the variation in rating grades and the probability of being well classed. The grade regression (column 5) shows negative effects of profitability (measured by ROA and ROE) and poor asset quality (measured by ANP/EC). The class regression (column 6) shows, on the one hand, the positive effects of capital adequacy (measured by CPAO/TAA), liquidity (measured by TD/TAA) and supports (measured by RS Moy and LnTAA), and a negative effect of mishandled expenses (measured by CE/TAA).

With these results, our sub-hypothesis *SH2* which states that *"The important factors of the ‘all-in’ rating differ party from one agency to another"* can be confirmed.

The unwanted negative effects of ROA and ROE for the three agencies can be explained by the marginal effect of profitability on the ranking of banks from a credit risk perspective in 2012 a period characterized by the depth of the European debt crisis one of the consequences of the subprime crisis. And those of RTier1 for Moody's can be explained by the decrease in the importance of this Bale I ratio in prudential regulation.

To highlight other disparities in the relevant variables and/or in their degree of relevance, we are going to present some examples from table 9. The Management factor (measured by PHI/PNB) is important only for Moody’s to class banks. For the Capital factor, the variable with significant coefficients is CPAO/TAA in the two regressions for the three CRA, but with different coefficients that vary between 0.2296 and 0.2560 in the grade regressions and between 0.3326 and 0.4693 in the class regressions. For the RTier1 Capital variable, the coefficient is significant only for Moody's. For the Support factor, the coefficients of LnTAA variable are significant in the two regressions for the three agencies, but with different thresholds of significance and with coefficients that vary between 0.4001 and 0.7424 in the grade regressions and between 0.6065 and 1.1712 in the class regressions. These examples are sufficient to confirm our sub-hypothesis *SH3*, which states that *"The relevance of certain variables explaining the ‘all-in’ rating differ party from one agency to another."*

Additional details in our results have caught our attention about a specific behavior distinguishing Moody’s from the other agencies. The superiority of the explanatory powers of Moody's (Table 10, columns 2&5) compared to those of other agencies in the different equations for the two measures of the 'all-in' rating.

So the 'all-in' ratings of the three agencies are strongly correlated with a weighted similarly components, but with a disparity in important factors and relevant variables that manifest themselves in distinct characteristics from one agency to another in the rating process. With the cumulation of the three sub-hypotheses, we can confirm with great ease our main hypothesis *MH* which states that *“The rating processes of the CRA are largely consistent but not aligned.”*

5.3 Robustness Check

The results (Note 14) will be commented versus table 9. Given the loss of the overall meaning of nearly the whole class regressions, we will comment only grade regressions. They show that the Support variables and CPAO/TAA Capital variable in the three regressions of grades (columns 1, 3&5) don’t lose their relevancies with this approach. Also, the coefficients of ANP/EC Asset variable and the ROA Earnings variable remained significant in respectively Moody’s (column 3) and FR (column 5) grade regressions. This result further confirms the main hypothesis *MH* and better validity for the grade regressions for the three CRA.

6. Conclusion

The comparison of the 'all-in' rating processes showed a large consistency between the three agencies with a similarity in the weights assigned to each component of this rating, but with differences in the importance given to certain factors and the degree of relevance of certain explanatory variables. The difference between agencies lies mainly in the first component of the 'all-in' rating, so called, the ‘intrinsic credit quality’ factors. These differences manifest themselves in some specific behaviors distinguishing one agency to another. Moody's is the most severe and has the broadest spectra of important factors and relevent variables and the superior explanatory powers of the different equations compared to other agencies.

The three agencies are agreed on the factors: Capital, Earnings (Profitability), Liquidity and Supports and the most relevant support variable is the ‘sovereign rating’. These results that reflect the practiced methodologies are consistent with those of previous studies and findings made in light of the investigation of the specific documents of CRA. The latters showed that after revisions made to varying degrees from one agency to another, in response to the 2007-09 financial crisis, the revealed methodologies by the three agencies appear to be more harmonized structurally and relationally between BCRR and its sovereign rating, despite differences in their methodologies.

At the end of this work, we can say that although we have tried to contribute to the existing literature, this research work cannot hide the existence of certain limits. Indeed, we used the famous CAMELS model with an adjusted ‘S’ to consider the peculiarities of the BCRR with a sample of banks of EMENA in the period of 2012. The use of other models with samples from other regions in another period could be the subject of later comparative studies.

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Notes

Note 1. CAMELS is the acronyms of Capital, Assets, Management, Earnings, Liquidity and Sensitivity to market risk.

Note 2. The averages of the financial ratios of N-3, N-2 and N-1 are used as independent variables to explain the N-year ratings.

Note 3. S&P's (2011a) states that it makes analytical adjustments to the amounts reported in the financial statements and regulatory filings of the rated entities. These adjustments, under the S&P's terms, are made to generate measures that are more meaningful reflections of the economic reality of financial risks and to level the ratio differences. They will facilitate comparisons between institutions and periods, which improves the analytical relevance and consistency of the financial ratios used in the credit analysis.

Note 4. Bissoondoyal-Bheenick and Treepongkaruna (2011) found that the studies on grades and classes gives different results in the comparison between agencies.

Note 5. We collected initially 231, 128 and 107 banks rated in 2012 by respectively S&P's, Moody's and FitchRatings and held back only the 76 banks rated simultaneously by the three agencies.

Note 6. We calculated the means, standard deviations, minimums, and maximums of the variables by year of rating. But we have not carried over the corresponding table. We used the stata 12 for all our data treatments.

Note 7. We calculated the correlations between the variables using the Pearson coefficient for CAMEL variables (Pearson coefficients less than 77.21 %), Khi-2 test for dummy variables (OC and ACT) and analysis of variance (ANOVA) for mixed variables. We also compared the means or proportions of the variables by year of rating using Student's test. But we have not carried over the corresponding tables.

Note 8. We used the likelihood-ratio test of proportionality of odds across response categories. High Chi2 and low "p-value" indicate the presence of proportional odds approach.

Note 9. The VIF measure the multicollinearity between the explanatory variables. VIF=1/(1-R2i) with R2i is the coefficient of determination of the regression of the variable i with the other explanatory variables. A VIF superior to five indicates a strong multicollinearity.

Note 10. The BIF is a way of assessing the degree of stability of the model. The instability of the model occurs when the selected predictors are sensitive to a small change in data (Royston and Sauerbrei, 2009). The BIF is the frequency of the variables used in each sample and could be interpreted as a criterion of the importance of a variable. A variable, which is weakly correlated with others and significant in the complete model must be selected in half of the bootstrap (BIF greater than or equal to 50%) samples. With the 'p-values' lower, the BIF increases to 100%.

Note 11. High Chi2 and low "p-value" indicate the presence of proportional odds approach.

Note 12. High Chi2 and low "p-value" indicate the presence of heteroskedasticity.

Note 13. For the equations from (2) to (4), we reported only the explanatory powers of regressions.

Note 14. We don't report the table of Bootstrapping regressions.

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