THE IMPACT OF BASEL III CAPITAL REGULATION ON PROFITABILITY: A HYBRID MODEL

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Abstract

This research examined the impact of Basel III capital regulation (BCR) on profitability (P) using a sample of 25 commercial banks in Lebanon over the period 2012–2017. BCR is measured using the capital adequacy ratio (CAR) and the common equity tier one ratio (CET1 ratio), P is measured using two ratios: ROAA and ROAE. To analyze the data, we constructed a hybrid model based on three statistical approaches. First, we modelled the dual impact of BCR and P using probabilistic inference in the framework of Bayesian Belief Network formalism (BBN). Second, to highlight more about the correlation between BCR and P, we used the Spearman correlation test as a nonparametric approach. Third, to study the simultaneous effect of the BCR ratio on Profitability we apply multivariate regression analysis. By analyzing the probabilistic inference for the first approach, we concluded that there is an effect from BCR on P. When we investigated more if this effect is significance using the Spearman correlation test and the multivariate regression analysis, we concluded that that the impact of BCR on P is only found between CAR and ROAA and this regression relationship is weak because only 24.3% of the changes in ROAA variance is explained by CAR.

Keywords: Basel III capital regulation (BCR); Profitability (P); Bayesian belief network (BBN); capital adequacy ratio (CAR); common equity tier 1 ratio (CET1 ratio)

The Impact of Basel III Capital Regulation on Profitability: A Hybrid Model

There are conflicting predictions concerning the impact of capital regulations on profitability in banks. While regulators seem to believe that higher capital requirements will have a positive impact on banking profitability, the results of the literature are ambiguous. Bitar, Pukthuanthong, and Walker (2018) explore a positive relationship between the capital ratio and profitability using a sample of 1992 banks from 39 OECD countries during the 1999–2013, however they mentioned that imposing higher capital ratios may have a negative effect on the efficiency and profitability of highly liquid banks. However, Tran, Lin, and Nguyen (2016) found that the relationship between regulatory capital and bank performance is not linear and depends on the level of capitalization. Regulatory capital is negatively related to bank profitability for higher capitalized banks but positively related to profitability for lower capitalized banks. They used a sample of unbalanced quarterly panel data of all U.S. banks from 1996 to 2013

In this article, we try to fill the gap by studying the impact of Basel III capital regulation (BCR) on profitability (P) using a sample of 25 commercial banks in Lebanon over the period 2012–2017. To analyze the data, we constructed a hybrid model based on three statistical approaches. First, we modelled the dual impact of BCR and P using probabilistic inference in the framework of Bayesian Belief Network formalism (BBN). Second, to highlight more about the correlation between BCR and P, we used the Spearman correlation test as a nonparametric approach. Third to study the simultaneous effect of CAR and CET1 ratio on P, we applied multivariate regression analysis.

The rest of this article is organized as follows: Section 1 presents the literature review that displays the impact of Basel capital regulation on profitability. Section 2 describes the data and variables of this study in addition to the hybrid model used to analyze them. Section 3 reveals the outcome of the statistical analysis. As for section 4, it examines the results and provides the conclusion.

Literature Review

In this section, our goal is to introduce how Basel Capital Regulation affects banking profitability based on academic researches related to this area. Firstly, we discussed the evolution of regulatory capital based on Basel accord (Basel I, Basel II & Basel III). Secondly, we presented a subset of literature based on two hypotheses in order to understand more how capital regulation affects profitability.

Basel capital regulation

Basel I. It was published by the Basel Committee on Banking Supervision (BCBS) in 1988. The main focus of this accord was the minimum regulatory capital, which is the bank's capital divided by the risk-weighted assets. Basel I provided an international platform on bank capital regulation, and was a quick answer to the internationalization of the banking sector.

Basel II. It is "introduced after the various financial crises of the 1990s (the Mexican Crisis of 1994, the Asian crisis, and the Brazilian and Argentinean crisis). Basel II did not modify the definition of capital introduced in the previous Accord and did not increase the minimum capital ratio (still at 8%). The critical innovation in Basel II is related to the computation of risk-weighted assets, which now included credit, market, and operational risk" (Motocu, 2013, par.1).

Basel III. It was published in 2011 resulting of the global financial crisis in 2008. Basel III amplified the quality and the level of capital by “admitting only the highest quality instruments in the core Tier, revising the components of Tier 1 and Tier 2 and eliminating Tier 3 from the regulatory capital within ten years” (Tanda, 2015, par.17). The capital ratio is now a combination of elements, and a percentage of the components of the total capital.

Based on the above, we can see that Basel Capital Regulation has progress from Basel I to Basel III. “In Basel III, banks have to strengthen the quality and level of capital by admitting the highest quality instruments in the core Tier 1 (Ibid, p.16).

In Figure one we showed the evolution in the quality, and the level of capital regulation requirements form (Basel I to Basel III) and how much changes are made in terms of capital regulation. “By 2019, the highest quality components of capital should represent at least 6% of RWA, of which at least 4.5% of RWA is held as common equity” (Ibid, par.16).

	Basel I	Basel II	Basel III						
			2013	2014	2015	2016	2017	2018	2019
Minimum common equity ratio			3.5%	4%	4.5%	4.5%	4.5%	4.5%	4.5%
Capital conservation buffer						0.625%	1.25%	1.875%	2.5%
Minimum common equity plus capital conservation buffer			3.5%	4%	4.5%	5.125%	5.75%	6.375%	7%
Phase-in of deductions from CET1				20%	40%	60%	80%	100%	100%
Minimum Tier 1 Capital	4%	4%	4.5%	5.5%	6%	6%	6%	6%	6%
Minimum Total Capital	8%	8%	8%	8%	8%	8%	8%	8%	8%
Minimum Total Capital plus conservation buffer	8%	8%	8%	8%	8%	8.625%	9.25%	9.875%	10.5%
Capital instruments that no longer qualify as non-core Tier 1 capital or Tier 2 capital			Phased out over 10-year horizon beginning 2013						

Figure 1. Evolution of minimum capital requirements from Basel I to Basel III [1]

The impact of capital regulation on profitability

The question of how capital regulation affects banking profitability is still far from being resolved. In this section, we develop two hypotheses to simplify and clarify these associations. 1-Higher capital adequacy ratios are associated with higher profitability 2- Higher capital adequacy ratios are associated with lower profitability.

Hypothesis 1: Higher capital adequacy ratios are associated with higher profitability. Bitar, Saad, and Benlemlih (2016) concluded that compliance with the Basel capital requirements enhances bank protection against risk, and improves profitability and efficiency using a sample of 168 banks in 17 Middle Eastern and North African countries from 1999–2013 period.

[1] https://www.bis.org/bcbs/index.htm?m=3%7C14%7C625 (last updated, 14/07/2019)

Lee and Hsieh (2013) studied the impacts of bank capital on profitability and risk using the generalized method of moments technique for dynamic panels for 42 Asian countries over the period 1994 to 2008. They found that in low-income countries, bank capital has a positive effect on profitability.

Tan and Floros (2013) studied the impacts of bank capital and the risk on profitability using data of 101 Chinese banks over the period 2003–2009. they found that the relationship between bank capital, risk, and profitability is significantly positive.

Finally, Awdeh, Moussawi, and Machrouh (2011) examined the impact of capital requirements on bank risk-taking and profitability using two simultaneous equations model in a sample of 41 Lebanese commercial banks between 1996 and 2008. The results showed that there is a positive correlation between bank profitability and an increase in capital.

Hypothesis 2: Higher capital adequacy ratios are associated with lower profitability. Goddard, Liu, Molyneux, and Wilson (2009) informed that Average profitability is higher for banks that are efficient and diversified, but lower for those that are more highly capitalized. They used a sample of eight European Union member countries, between 1992 and 2007.

Pasiouras (2008) illustrated that banks that are highly capitalized do not have necessary a better profit efficiency except if they are international banks and have expanded their operations abroad using data envelopment analysis (DEA) on a sample of Greek commercial banking industry over the period 2000–2004.

Finally, Altunbas, Carbo, Gardener, and Molyneux (2007) studied the relationship between capital, risk and profit efficiency for a large sample of European banks between 1992 and 2000. Empirical evidence shows that there are significant differences in the relationships between capital, risk, and efficiency for commercial and savings banks. In the case of co-operative banks, we do find that capital levels are inversely related to risks, and we find that efficient banks hold lower levels of capital.

Materials and Methods

Data and Variables

The aim of this section is to build the data and variables infrastructure. We described the Lebanese banking sector in terms of activity then we constructed our data. Next, we showed how we devised our timeline in the study into two timeline clusters based on BDL[2] circular. Finally, we defined our methodology while choosing the variables of interest: independent, dependent and explanatory variables.

Sampling and Period

Data source. Our source of information is token from the database provided by Bankdata[3] which is a consulting company established in Lebanon since 1986.

Sampling. According to the Association of Banks in Lebanon, there are 65 operational banks in Lebanon. In terms of activity, out of the total 65 operational banks, 12 are investment banks, and 53 are commercial banks, of

[2] Central Bank of Lebanon
[3] http://www.bankdata.com/AboutUs/Profile (last updated: 14/07/2019)

which 33 are Lebanese, and 20 are foreign and mixed. Islamic banks are excluded from the application of Basel III. As for investment and commercial banks, there is difference in the implementation of Basel III Minimum capital for banks as follow:

- "LBP 10 billion for the head office of a commercial bank and LBP 500 million for each additional branch.

- LBP 30 billion for establishing an investment/specialized bank" (Facts about the Lebanese Banking Sector,2020, par.1)

Every study of the impact of Basel III capital regulation (BCR) in Lebanon should take into consideration the difference in the implementation of Basel III between commercial, investment and Islamic banks.

Based on the mentioned above, we choose to study banks that are Lebanese and commercial. These banks implement Basel 3 capital regulation in the same protocol, and they represent the majority of the operational banks in Lebanon. (Commercial banks represent: 81.53 % of the operational banks in Lebanon and Lebanese banks represents 62.26 % of the commercial banks). Therefore, the sample selected for this study was 33. Then, we excluded banks, which are subsidiaries of other banking or insurance groups and banks for which a complete financial statement could not be found. Thus, this study ended up with a final sample of 25 banks. Appendix (A)

Sampling period. The sample period is from 2012 to 2017, covering the period after the development of Basel III accord. In this timeframe, the central bank of Lebanon has adopted the new capital according to 2 circulars: -Basic circular No 119[4] and intermediate Circular No 358[5]

In table 1, we showed the timeline set by these circulars for adopting Basel III capital regulation according to 2 measures: Capital Adequacy Ratio (CAR) and Common Equity Tier 1 Ratio (CET1 Ratio). The Basic Circular No 119 was published in 2008 and set a timetable for Lebanese banks to adjust their capital structure up to the year 2015, the intermediate Circular No 358 was published in March 2014 and set a timetable for Lebanese banks to adjust their capital up to the year 2018.

Table 1.

Basel III Timeline in Lebanon.

Basic circular no 119		**Intermediate circular no 358**	
2012	2015	2016	2018
CET1 ratio	**CET1 ratio**	**CET1 ratio**	**CET1 ratio**
4.50%	8%	8%	10.00%
CAR	**CAR**	**CAR**	**CAR**
8%	12%	12%	15%

4 http://www.bdl.gov.lb/circulars/index/5/33/0 (last updated): 14/07/2019)
5 http://www.bdl.gov.lb/circulars/intermediary/5/37/0/Intermediate-Circulars.html (last updated): 14/07/2019)

Based on the timeline set by circulars mentioned above, we will divide our study into 2 clusters of timelines: The First cluster is A (Contain the financial data of the sample between 2011-2015). The second cluster is B (Contain the financial data of the sample between 2016-2017). We excluded the year 2018 from cluster B because, in the time of the study, the financial data of the year 2018 was not completed.

Variables

Independent variable. Capital Adequacy Ratio (CAR) is a widely known ratio used by the Basel committee in evaluating the regulatory capital of a bank [6], also the central bank of Lebanon has determined CAR as a principal measure in adopting Basel III capital regulation according to Basic circular No 119 and intermediate Circular No 358.

CAR used in the literature also, for example: Awdeh, Moussawi, and Machrouh (2011), used CAR to study the impact of regulatory capital on bank risk-taking using a panel of Lebanese commercial banks over the period 1996–2008. Hogan, Meredith, and Pan (2017) used CAR to evaluate the effectiveness of risk-based capital (RBC) on US banks over the period between 2000-2015. Hogan (2015) used CAR to compares the RBC ratio to the standard capital ratio of equity over assets of US holding companies from 1999 through 2010. Hristov and Hülsewig (2017) used CAR to study the importance of the endogenous interaction between private debtors' default, aggregate loan losses and the bank capital regulation for the transmission of macroeconomic shocks using euro area data over the period 2000-2015.

In addition to CAR, The Common Equity Tier 1 Ratio (CET1 Ratio) is commonly used by European Banking Authority and by Basel Committee to measure the capital adequacy ratio for a bank[7]

For all these reasons we studied Basel III capital regulation (BCR) according to 2 measures **A-Capital Adequacy Ratio (CAR)** The capital adequacy ratio is calculated by dividing a bank's capital by its risk-weighted assets **B- Common Equity Tier 1 Ratio (CET1 Ratio)** "Tier 1 common capital ratio is a measurement of a bank's core equity capital, compared with its total risk-weighted assets, and signifies a bank's financial strength ." (Tier 1 Common Capital Ratio Definition,2019, par.1)

Dependent variable. We studied profitability according to 2 ratios: ROAA and ROAE.

"Return on average assets (ROAA) is an indicator used to assess the profitability of a firm's assets, and banks and other financial institutions must often use it as a means to gauge financial performance. The ratio shows how well a firm's assets are being used to generate profits. ROAA is calculated by taking net income and dividing it by average total assets. The final ratio is expressed as a percentage of total average assets. Return on average assets (ROAA) shows how efficiently a company is utilizing its assets and is also useful when assessing peer companies in the same industry." (Return on Average Assets – ROAA Definition,2019, par.1)

"Return on average equity (ROAE) is a financial ratio that measures the performance of a company based on its average shareholders' equity outstanding. Typically, ROAE refers to a company's performance over a fiscal

[6] https://www.consilium.europa.eu/en/policies/banking-union/single-rulebook/capital-requirements (last updated: 14/07/2019)

[7] https://www.consilium.europa.eu/en/policies/banking-union/single-rulebook/capital-requirements/ last updated: 14/07/2019)

year, so the ROAE numerator is net income, and the denominator is computed as the sum of the equity value at the beginning and end of the year, divided by 2. A high ROAE means a company is creating more income for each dollar of stockholders' equity. It also tells the analyst about which levers the company is pulling to achieve higher returns, whether it is profitability, asset turnover, or leverage. The product of these three measurements equals ROAE." (Return on Average Equity,2019, par.1)

In table 2, we show a summary of all variables in the study, including definition and formulas.

Table 2

Variables Description.

	Variables	Definition	Formulas
1.	**Capital adequacy ratio (CAR)**	Regulatory capital	(Tier 1 +Tier2)/risk weighted assets
2.	**CET1 ratio**	Regulatory capital	CET1 capital/risk-weighted asset
3.	**ROAA**	Profitability	Net Income /Average Total Assets
4.	**ROAE**	Profitability	Net Income /Average Equity

Methods and Empirical Model

This section aims to construct our hybrid model that analyzes the impact of Basel III capital regulation (BCR) on profitability (P) moving from cluster A to cluster B based on three statistical approaches. In the results section, we presented the outcome of those approaches. First, we modelled the dual impact of BCR on P using probabilistic inference in the framework of Bayesian Belief Network formalism (BBN). Second, to highlight more about the correlation between BCR and P, we used the Spearman correlation test as a nonparametric approach. Third, we applied multivariate regression analysis to study the simultaneous effect of CAR and CET1 ratio on P and to predict the shape of the relationship between those components.

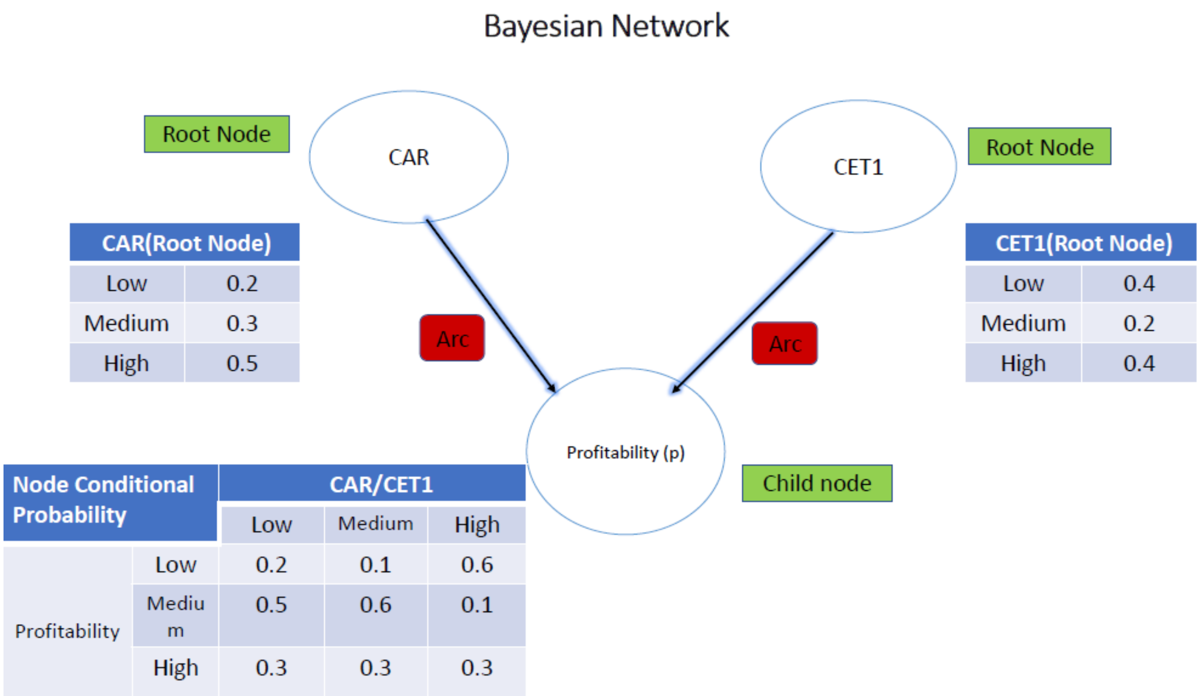
Bayesian Belief Network (BBN).

According to Ghribi and Masmoudi (2013), a Bayesian Belief Network (BBN) is a graphical representation of a probabilistic model that encodes a set of conditional independence relationships. It has become a popular tool for decision-making systems in various fields such as biology: Hassen, Masmoudi, and Rebai (2008), computer science: Bouchaala, Masmoudi, Gargouri, and Rebai (2010) finance: Abid, Zaghdene, Masmoudi, and Ghorbel (2017) and in governmental trends Dbouk and Zaarour (2013).

Indeed, the BBN is one of the most comprehensive and consistent formalisms for the acquisition and modelling of complex systems outperforming the logistic regression in terms of diagnostic prediction Gevaert et al. (2006). We used Probabilistic Graphical Model software from ITS company in Lebanon to implement our BBN structure.

To Build a BBN, we should implement its components. It consists of two main components: (1) its structure involves nodes and arcs, the nodes represent variables, which can be discrete or continuous, the arcs represent relationships between variables. (2) The BBN parameters that consist of conditional probability tables (CPT), which is the probability of each node give it directs parents.

Figure.2 illustrates our implemented BBN that models the impact BCR on P. The nodes represent the variables of interest (CAR- CET1 Ratio and P) the arcs were selected from expert's view based on academic articles like Bitar, Saad, and Benlemlih (2016); Lee and Hsieh (2013) and others …. They all mention that the effect is from BCR to P and not vice versa.



CAR(Root Node)	
Low	0.2
Medium	0.3
High	0.5

CET1(Root Node)	
Low	0.4
Medium	0.2
High	0.4

Node Conditional Probability		CAR/CET1		
		Low	Medium	High
Profitability	Low	0.2	0.1	0.6
	Medium	0.5	0.6	0.1
	High	0.3	0.3	0.3

Figure 2. Bayesian network.

Probabilistic inference. Typically, implementing BBN components is the constructor of the Bayesian network; this construction should be from prior or domain knowledge, data, or a combination. After constructing BBN, we usually need to determine various probabilities of interest from the model of David Heckerman [8]. This latter consists of the primary outcome of BBN, which is its ability to respond to a probabilistic query. Probabilistic inference reflects a mechanism for calculating the distributions of variables given another evidence variable.

Saad et al. (2013) have indicated BBNs as powerful tools for knowledge representation and inference. Others, mentioned that most BBN are a well-known characteristic of statistical learning algorithms that have a high classification accuracy and a probabilistic inference Kirkos, Spathis, and Manolopoulos (2007); Zaarour et al. (2015).

[8] https://www.cis.upenn.edu/~mkearns/papers/barbados/heckerman.pdf

In our Inference, we used the Junction Tree algorithm to extract marginalization from data. "The basic premise of junction tree is to eliminate cycles by clustering them into single nodes. Multiple extensive classes of queries can be compiled at the same time into larger structures of data. There are different algorithms to meet specific needs and for what needs to be calculated. Inference algorithms gather new developments in the data and calculate it based on the new information provided." (Junction tree algorithm explained,2020, par.1) In our study, we used algorithms done by Spiegelhalter et al. (1993), Neapolitan (1990), and Jensen, Jensen, and Dittmer (1994).

For a little knowledge. http://ai.stanford.edu/~paskin/gm-short-course/lec3.pdf

In the results section, we presented the outcome of the BBN inference statistical analysis

Variables discretization. In order to use BBN in a proper way that maximizes its efficiency, we have to discretize our variables of interests. The process of "Discretization" is very crucial when using "conditional probability" as one of the most exciting features of BBN.

Based on the Consultancy with Mr. Shadi Riashi [9] member of The Banking Control Commission (BCCL). Variables are discretized in appendix (B).

Spearman correlation test. In the BBN section, we study the effect from BCR on P moving from cluster A to cluster B. To investigate more if this effect is a significance, we used statistical hypothesis testing called Spearman correlation test. Software SPSS version 25 is used to analyze the data using the spearman test. Finally, in the results section, we presented the outcome of the analysis.

The impact of CAR on ROAA. Let the null hypothesis H0: There is no relationship, statistically significant, between CAR and ROAA moving from cluster A to cluster B, assuming a significance level of 0.05.

Hence the alternative hypothesis Ha: There is a relationship, statistically significant, between CAR and ROAA moving from cluster A to cluster B assuming a significance level of 0.05.

Let CARa the CAR data mean taken for cluster A timeline.

Let CARb the CAR data mean taken for cluster B timeline.

Let ROAAa the ROAA data mean taken for cluster A timeline.

Let ROAAb the ROAA data mean taken for cluster B timeline.

Let CARdiff=CARb-CARa the difference CAR means values between the 2 clusters.

Let ROAAdiff=ROAAb-ROAAa the difference ROAA mean values between the 2 clusters.

CARdiff and ROAAdiff values are presented in Appendix (C).

In order to choose the adequate correlation test between the two-scale variables CARdiff and ROAAdiff, the normality test is applied to the sample size 25 (less than 50). Table 3 shows the results of the Shapiro-Wilk test of normality.

[9] http://www.bccl.gov.lb/ (last updated: 14/07/2019)

Table 3.

Shapiro-Wilk Test of Normality

	Statistic	df	Sig.
CARdiff	.565	25	.000
ROAAdiff	.943	25	.172

Results in Table 3 show that the CARdiff variable (Sig.=0.000 < 0.05) does not respect the normal distribution. Thus, we will use the non-parametric Spearman correlation test

The impact of CAR ratio on ROAE. Let the null hypothesis H0: There is no relationship, statistically significant, between CAR and ROAE moving from cluster A to cluster B, assuming a significance level of 0.05.

Hence the alternative hypothesis Ha: There is a relationship, statistically significant, between CAR and ROAE moving from cluster A to cluster B assuming a significance level of 0.05.

Let CARa the CAR data mean taken for cluster A timeline.

Let CARb the CAR data mean taken for cluster B timeline.

Let ROAEa the ROAE data mean taken for cluster A timeline.

Let ROAEb the ROAE data mean taken for cluster B timeline.

Let CARdiff=CARb-CARa the difference CAR means values between the 2 clusters.

Let ROAEdiff=ROAEb-ROAEa the difference ROAE mean values between the 2 clusters.

CARdiff and ROAEdiff values are presented in Appendix(D)

In order to choose the adequate correlation test between the two-scale variables CARdiff and ROAEdiff, the normality test is applied to the sample size 25 (less than 50). Table 4 shows the results of the Shapiro-Wilk test of normality.

Table 4

Shapiro-Wilk Test of Normality

	Statistic	df	Sig.
CARdiff	.565	25	.000
ROAEdiff	.799	25	.000

Results in Table 4 show that the CARdiff and ROAEdiff variables (Sig.=0.000 < 0.05) do not respect the normal distribution. Thus, we will use the non-parametric Spearman correlation test.

The impact of CET1 ratio on ROAA. Let the null hypothesis H0: There is no relationship, statistically significant, between CET1 and ROAA moving from cluster A to cluster B, assuming a significance level of 0.05.

Hence the alternative hypothesis Ha: There is a relationship, statistically significant, between CET1 and ROAA moving from cluster A to cluster B assuming a significance level of 0.05.

Let CET1a the CET1 data mean taken for cluster A timeline.

Let CET1b the CET1 data mean taken for cluster B timeline.

Let ROAAa the ROAA data mean taken for cluster A timeline.

Let ROAAb the ROAA data mean taken for cluster B timeline.

Let CET1diff=CET1b-CET1a the difference CET1 mean values between the 2 clusters...

Let ROAAdiff=ROAAb-ROAAa the difference ROAA mean values between the 2 clusters

CET1diff and ROAAdiff values are presented in Appendix (E).

In order to choose the adequate correlation test between the two-scale variables CET1diff and ROAAdiff, the normality test is applied to the sample size 25 (less than 50). Table 5 shows the results of the Shapiro-Wilk test of normality.

Table 5

Shapiro-Wilk Test of Normality

	Statistic	Df	Sig.
CET1diff	.455	25	.000
ROAAdiff	.943	25	.172

Results in Table 5 show that the CET1diff variable (Sig.=0.000 < 0.05) does not respect the normal distribution. Thus, we will use the non-parametric Spearman correlation test.

The impact of the CET1 ratio on ROAE. Let the null hypothesis H0: There is no relationship, statistically significant, between CET1 and ROAE moving from cluster A to cluster B, assuming a significance level of 0.05.

Hence the alternative hypothesis Ha: There is a relationship, statistically significant, between CET1 and ROAE moving from cluster A to cluster B assuming a significance level of 0.05.

Let CET1a the CET1 data mean taken for cluster A timeline.

Let CET1b the CET1 data mean taken for cluster B timeline.

Let ROAEa the ROAE data mean taken for cluster A timeline.

Let ROAEb the ROAE data mean taken for cluster B timeline.

Let CET1diff=CET1b-CET1a the difference CET1 mean values between the 2 clusters. Let ROAEdiff=ROAEb-ROAEa the difference ROAE mean values between the 2 clusters.

CET1diff and ROAEdiff values are presented in Appendix(F).

In order to choose the adequate correlation test between the two-scale variables CET1diff and ROAEdiff, the normality test is applied to the sample size 25 (less than 50). Table 12 shows the results of the Shapiro-Wilk test of normality.

Table 6

Shapiro-Wilk Test of Normality

	Statistic	Df	Sig.
CET1diff	.455	25	.000
ROAEdiff	.799	25	.000

Results in Table 6 show that the CET1diff and ROAEdiff variables (Sig.=0.000 < 0.05) do not respect the normal distribution. Thus, we will use the non-parametric Spearman correlation test.

Multivariate regression analysis

In the Spearman correlation test section, we study the effect of CAR on P and the effect of CET1 ratio on P independently. To investigate more about the simultaneous effect of CAR and CET1 ratio on P and to predict the shape of the relationship between those components, we used multivariate regression analysis. Software SPSS version 25 is used to analyze the data using multivariate regression analysis. Finally, in the results section, we presented the outcome of the analysis.

As presented in the correlation analysis, the Spearman non-linear correlation test was applied since the data is not normal, and independent/dependent variables linearity was not proven. Thus, a simple linear regression model cannot be applied in this context. Therefore, non-linear simple regression models (Inverse, Quadratic, Cubic, Inverse, Logarithmic, Power, etc.) should be checked.

In Table 7, we showed a summary of the non-linear regression models that we checked.

Table 7

Regression Model Summary

Model Summary and Parameter Estimates.

Dependent Variable: ROAAdiff

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.000	.000	1	23	.986	-.030	.000		
Inverse	.070	1.721	1	23	.202	.007	-.026		
Quadratic	.100	1.216	2	22	.316	-.101	.022	.001	
Cubic	.184	1.578	3	21	.224	-.171	.083	-.002	.000

The independent variable (CARdiff) contains non-positive values. The minimum value is (-27.09). The Logarithmic and Power models cannot be calculated. The dependent variable (ROAAdiff) contains non-positive values. The minimum value is (-.748). Log transform cannot be applied. The Compound, Power, S, Growth, Exponential, and Logistic models cannot be calculated for this variable.

As shown in the table 7 above, the Sig. values are all greater than 0.05. This means, that these models are not significant and do not represent the data accurately. More sophisticated/complex non-linear models should be investigated, which are out of the scope of this study. Another alternative to find a representative/significant regression model, is to check and eliminate first the outliers and extreme points. For this purpose, 6 points out of 25 points were eliminated. The new sample size becomes 19 points. The normality test is applied to the new sample size 19. Table 8 shows the results of the Shapiro-Wilk test of normality.

Table 8

Shapiro-Wilk Test of Normality

	Statistic	df	Sig.
CARdiff	.970	19	.785
ROAAdiff	.947	19	.351

Results in Table 9 show that the CARdiff and ROAAdiff variables (Sig. > 0.05) respect the normal distribution. Therefore, we will check the Linear Regression Model Conditions.

Checking Linear Regression Model Conditions:

1) Residual Normality

Figure 3 illustrates the normal p-p plot of the regression standardized residual. It can be noticed that the grey curve points are approximately close to the straight-line normal distribution. Hence, the error normality assumption for ROAAdiff is checked.

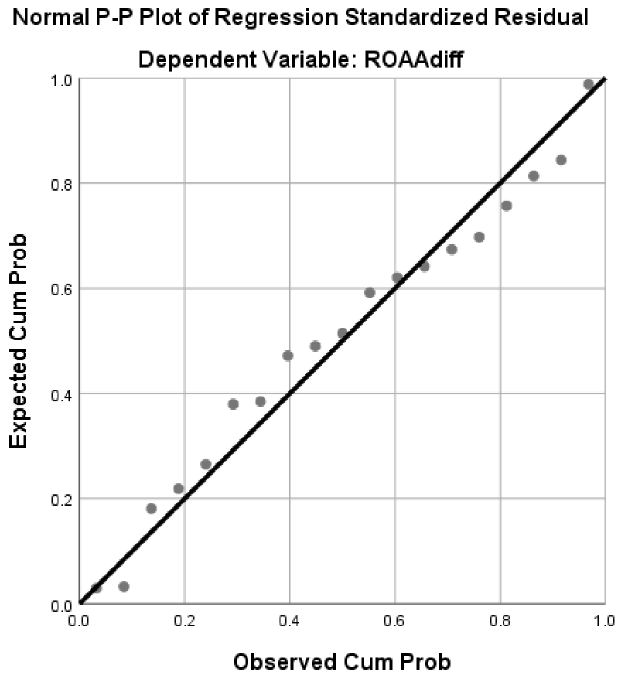


Figure 3. Residual normality.

2) Homoscedasticity

Figure 4 illustrates the Regression Standardized Residual vs Regression Standardized Predicted Value. The data does not have a distinct pattern, there are points equally distributed above and below zero on the X- axis, and to the left and right of zero on the Y-axis. Thus, the error of Homoscedasticity is checked.

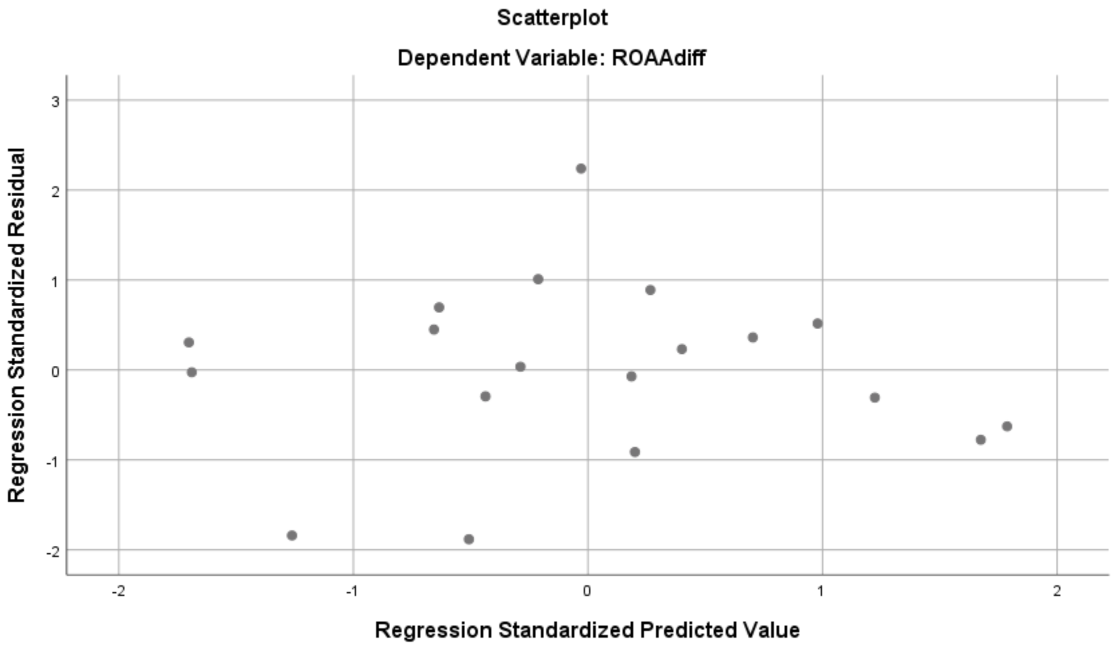


Figure 4. Homoscedasticity.

Results

This section aims to present the outcome of our hybrid model mentioned earlier. First, in the descriptive statistics section, we presented a comparison between clusters A and B based on the Mean, Median and standard deviation of the variables of interest in the study. Second, in the empirical model section, we analyze our three statistical approaches.

In BBN inference section, we conclude that there is an effect (increase in P values) from BCR on P moving from cluster A to cluster B, however when we entered the control variable into the model it does not produce any significant changes in the effect of BCR on P. to investigate more if this effect is significant, we used statistical hypothesis testing: Spearman correlation test found that the sig value is statistically significant only between CAR and ROAA (Sig= 0.455). Therefore, we concluded that there is a weak relationship (Corr. Coeff. = 0.455 < 0.5) but statistically significant, between CAR and ROAA moving from cluster A to cluster B, assuming a significance level of 0.05. Finally, in the regression analysis section, we investigated more about the simultaneous effect of CAR on ROAA and predicted the shape of the relationship between those components., we concluded that the regression relationship is positive but weak because only 24.3% of the changes in ROAA variance can be explained by CAR.

Descriptive Statistics

This section aims to describe the basic features of the data in the study. First, we present the mean times series plot of the three variables of interest. Second, in order to compare the evolution of these variables over the years, we constructed a table contain the Mean, Median and standard deviation.

Mean times series plot over the years.

A- CAR Mean over years

Figure 5 presents the Bar chart of the CAR mean values over the years for the two clusters A and B. It shows that there are no significant changes over the years nor between the clusters.

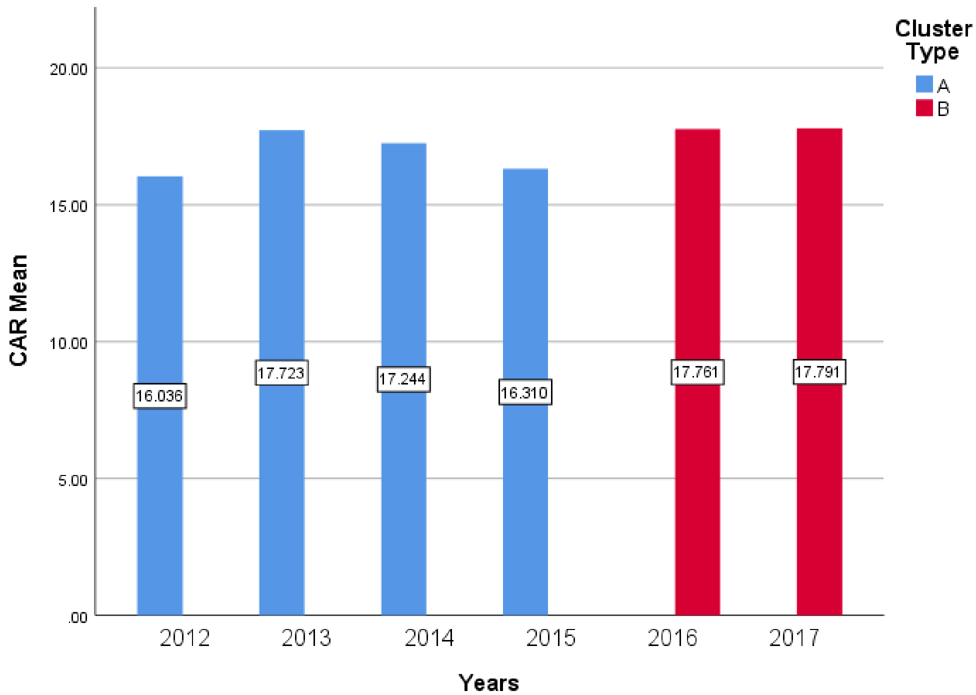


Figure 5. Clustered bar chart of the CAR mean values over the years.

B- CET1 ratio Mean over years

Figure 6 presents the Bar chart of the CET1 mean values over the years for the two clusters A and B. It shows clearly that there are no significant changes over the years nor between the clusters.

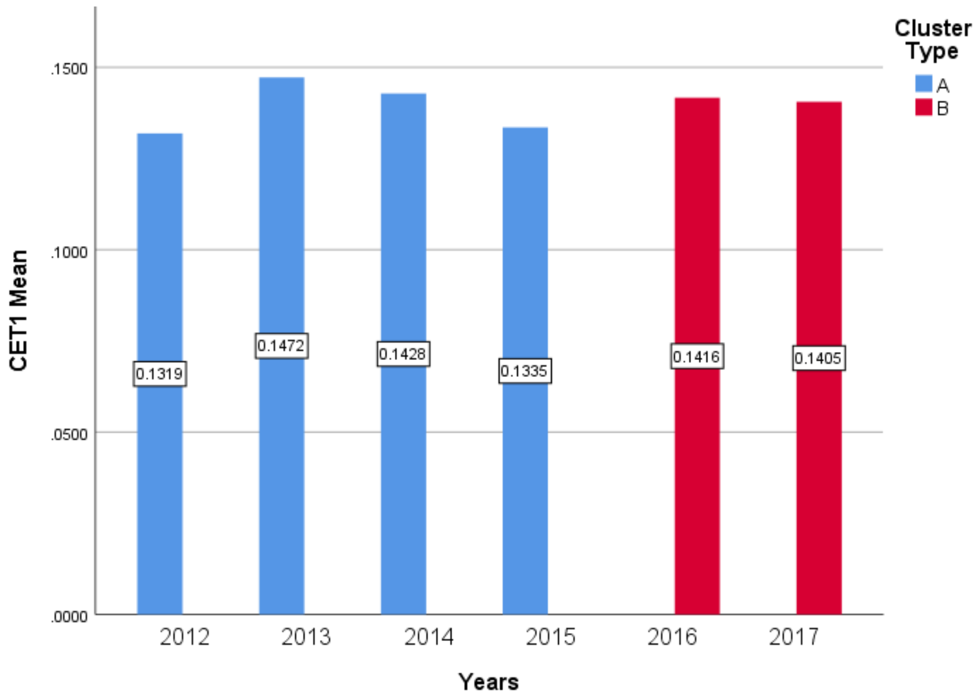


Figure 6. Clustered bar chart of the CET1 mean values over the years.

C- ROAA Mean over years

Figure 7 presents the clustered bar chart of the ROAA mean values over the years for the two clusters A and B. It shows that there are no significant changes over the years nor between the clusters.

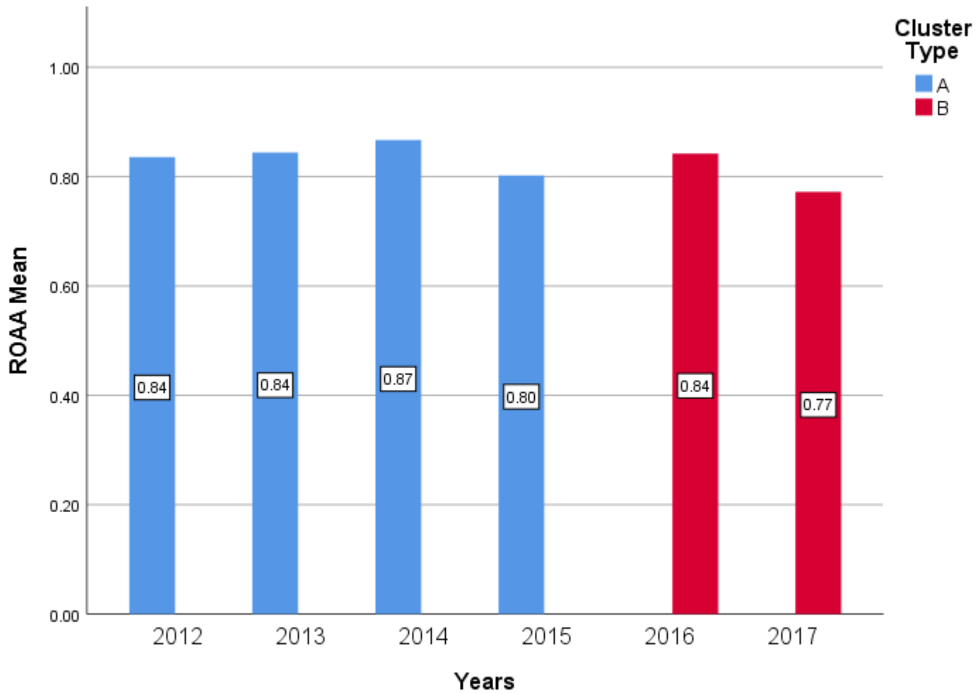


Figure 7. Clustered bar chart of the ROAA mean values over the years.

D- ROAE Mean over the years and between clusters

Figure 8 presents the clustered bar chart of the ROAE mean values over the years for the two clusters A and B. It shows that there are no significant changes over the years nor between the clusters.

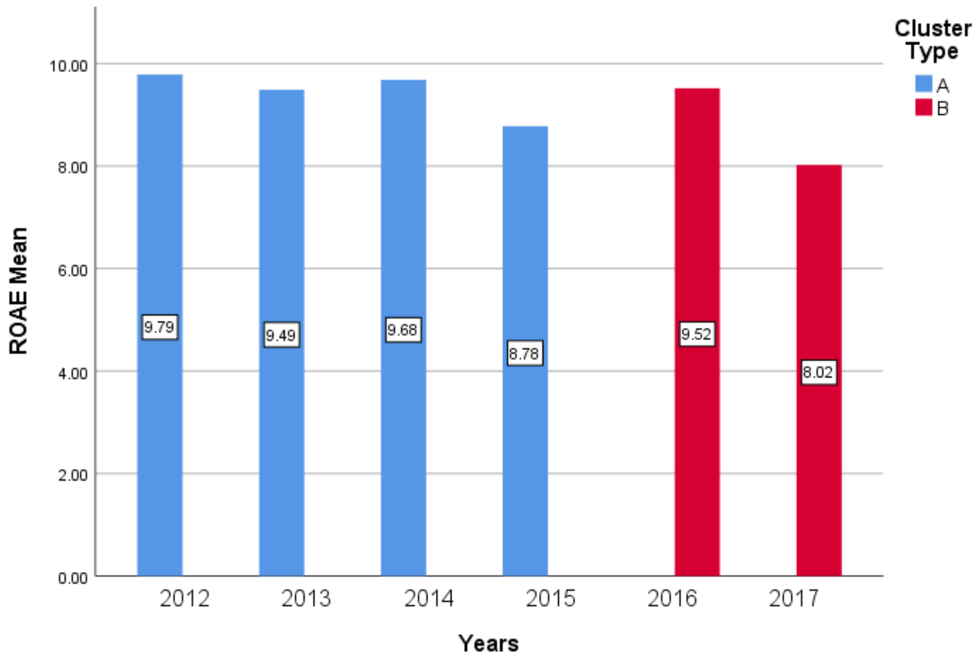


Figure 8. Clustered bar chart of the ROAE mean values over the years and between clusters.

Comparisons between CAR, CET1 ratio and P over clusters.

Table 9.

Comparisons Between CAR, CET1, and P Over Clusters

	Cluster A					Cluster B				
Variables	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
CAR	16.82	13.80	9.95	8.69	77.66	17.77	16.51	5.02	11.36	36.23
CET1	0.1388	0.1093	0.1083	0.0520	0.7749	0.1410	0.1223	0.0578	0.0877	0.3622
ROAA	0.84	0.8850	0.341	0.01	1.68	0.807	0.795	0.5637	-1.52	2.08
ROAE	9.43	10.2	4.53	0.04	21.06	8.77	8.63	6.099	-7.16	27.48

Table 9 presents the descriptive statistics of CAR, CET1, ROAA, and ROAE over clusters. It shows that the mean and median values for the independent variables CAR and CET1 for cluster B are slightly higher than the values in cluster A (ex: Mean CARB = 17.77 > Mean CAR A = 16.82). However, Table 5 shows that the mean and median values for the dependent variables ROAA and ROAE for cluster B are slightly lower than the values in cluster A (ex: Mean ROAE B = 8.77 < Mean ROAE A = 9.43). Moreover, the Std. Dev. Values show the same pattern. Values for the independent variables CAR and CET1 in cluster B are less than the values in cluster A (ex: Std. Dev. CARB = 5.02 < Std. Dev. CAR A = 9.95). This means that the CAR and CET1 values across years in cluster B are less deviated and therefore closer to the mean values in comparison with cluster A

Empirical Model

Inferential statistics using BBN. In this section, we presented BBN inferential statistics for two clusters of timelines: the first cluster (A) contains the financial data of the sample between 2011 and 2015. The second cluster (B) contains the financial data of the sample between 2016 and 2017. The sample size is the same, 25 banks, for the two clusters A and B. Also, a brief descriptive comparison between the two clusters is presented.

Cluster A. Table 10 shows the CAR, CET1, ROAA and ROAE probability values for different levels LOW, MEDIUM and HIGH. P(CAR=LOW) =0.01, P (CAR= MEDIUM) =0.17 and P (CAR= HIGH) = 0.82. Thus, the probability of the Capital Adequacy Ratio increases with the increase of the CAR level. The same can be applied for the Common Equity Tier 1 Ratio. On the other hand, the probability values of ROAA and ROAE increase going from LOW to MEDIUM levels. However, these values decrease for HIGH levels. For example: P (ROAA = LOW) = 0.19 increasing to P (ROAA = MEDIUM) = 0.51 and then decreasing to P(ROAA = HIGH) = 0.3.

Table 10

CAR, CET1, ROAA and ROAE Probability Values for Cluster A

	Variables Probability		
	LOW	MEDIUM	HIGH
CAR	0.01	0.17	0.82
CET1	0.02	0.13	0.85
ROAA	0.19	0.51	0.3
ROAE	0.3	0.55	0.15

Table 11 presents the effect of the CAR and CET1 independent variables, separately, on the conditional probabilities of the dependent variables ROAA and ROAE. For example, the conditional probability of ROAA having a LOW level, given that the CAR level is LOW is equal to 0.25. P(ROAA=LOW|CAR=LOW) =0.25. The results show almost the same pattern for ROAA and ROAE. Comparing ROAA to ROAE for CAR and CET1 LOW levels, the results in terms of probability values are the same. Regarding other levels, the probability values of ROAA and ROAE increase going from LOW to MEDIUM levels. However, these values decrease for HIGH levels.

Table 11

Effect of CAR and CET1, Separately, on ROAA and ROAE Probabilities for Cluster A

		ROAA Probability			ROAE Probability		
		LOW	MEDIUM	HIGH	LOW	MEDIUM	HIGH
CAR	LOW	0.25	0.5	0.25	0.25	0.5	0.25
	MEDIUM	0.05	0.58	0.37	0.11	0.58	0.32
	HIGH	0.2	0.52	0.28	0.38	0.56	0.06
CET1	LOW	0.25	0.25	0.5	0.25	0.25	0.5
	MEDIUM	0.07	0.47	0.47	0.07	0.8	0.13
	HIGH	0.19	0.56	0.26	0.38	0.53	0.09

Table 12 presents the effect of the CAR and CET1 independent variables, jointly, on the conditional probabilities of the dependent variables ROAA and ROAE. For example, the conditional probability of ROAA having a LOW level given that the CET1 level is MEDIUM, and the CAR level is LOW is equal to 0.25. P(ROAA=LOW|CET1=MEDIUM,CAR= LOW)=0.25. Also, the probability values of ROAA and ROAE are the same for the two cases (CET1=MEDIUM, CAR=LOW) and (CET1=LOW, CAR=MEDIUM). Moreover, almost all the probability values of ROAA and ROAE increase going from LOW to MEDIUM levels. However, these values decrease for HIGH levels.

Table 12

Effect of CAR and CET1, Jointly, on ROAA and ROAE Probabilities for Cluster A

		ROAA Probability			ROAE Probability		
CET1	**CAR**	LOW	MEDIUM	HIGH	LOW	MEDIUM	HIGH
LOW	LOW	-	-	-	-	-	-
LOW	MEDIUM	0.25	0.25	0.5	0.25	0.25	0.5
LOW	HIGH	-	-	-	-	-	-
MEDIUM	LOW	0.25	0.5	0.25	0.25	0.5	0.25
MEDIUM	MEDIUM	0.11	0.56	0.33	0.11	0.67	0.22
MEDIUM	HIGH	0.13	0.25	0.63	0.13	0.75	0.13
HIGH	LOW	-	-	-	-	-	-
HIGH	MEDIUM	0.08	0.58	0.33	0.17	0.5	0.33
HIGH	HIGH	0.21	0.54	0.25	0.41	0.53	0.06

Cluster B. Table 13 shows the CAR, CET1, ROAA and ROAE probability values for different levels LOW, MEDIUM and HIGH. P(CAR=LOW) =0.02, P (CAR= MEDIUM) =0.30 and P(CAR= HIGH)= 0.68. Thus, the probability of the Capital Adequacy Ratio increases with the increase of the CAR level. The same can be applied for the Common Equity Tier 1 Ratio. On the other hand, the probability value of ROAA increases going from LOW to MEDIUM levels. However, it decreases for the HIGH level. For example: P (ROAA = LOW) = 0.16 increasing to P (ROAA = MEDIUM) = 0.53 and then decreasing to P (ROAA = HIGH) = 0.31. Regarding ROAE, the probability decreases with the increase of the ROAE level.

Table 13

CAR, CET1, ROAA and ROAE Probability Values for Cluster B

	Variables Probability		
	LOW	MEDIUM	HIGH
CAR	0.02	0.30	0.68
CET1	0.02	0.21	0.77
ROAA	0.16	0.53	0.31
ROAE	0.43	0.37	0.2

Table 14 presents the effect of the CAR and CET1 independent variables, separately, on the conditional probabilities of the dependent variables ROAA and ROAE. For example, the conditional probability of ROAA having a LOW level given that the CAR level is HIGH is equal to 0.16. P(ROAA=LOW|CAR=HIGH) =0.16.

Table 14

Effect of CAR and CET1, Separately, on ROAA and ROAE Probabilities for Cluster B.

		ROAA Probability			ROAE Probability		
		LOW	MEDIUM	HIGH	LOW	MEDIUM	HIGH
	LOW	-	-	-	-	-	-
CAR	MEDIUM	0.11	0.61	0.28	0.39	0.5	0.11
	HIGH	0.16	0.55	0.29	0.55	0.29	0.16
	LOW	-	-	-	-	-	-
CET1	MEDIUM	-	-	-	-	-	-
	HIGH	0.13	0.58	0.28	0.51	0.36	0.13

Comparison between cluster A and cluster B without control variable. Table 15 presents a comparison between the two clusters A and B in terms of the conditional probability of the dependent variable ROAA, taking into consideration the effect of the independent variables CAR and CET1 jointly. Results show that there is a difference between the conditional probability values between the two clusters. For example, going from LOW to the MEDIUM level regarding ROAA variable, the probability increases from 0.08 to 0.58 in cluster A taking CAR and CET1 HIGH and MEDIUM levels respectively (P(ROAA=LOW|CET1=MEDIUM, CAR=HIGH)=0.08 increases to P(ROAA=MEDIUM |CET1=MEDIUM,CAR= HIGH)=0.58). These probabilities increase slightly for cluster B, where the values become 0.11 and 0.61, respectively.

Table 15

Comparison Between the Two Clusters A and B in Terms of the ROAA Conditional Probability Taking Into Consideration CAR and CET1 Jointly.

		ROAA Probability, Cluster A			ROAA Probability, Cluster B		
CAR	**CET1**	LOW	MEDIUM	HIGH	LOW	MEDIUM	HIGH
LOW	LOW	-	-	-	-	-	-
LOW	MEDIUM	0.25	0.25	0.5	-	-	-
LOW	HIGH	-	-	-	-	-	-
MEDIUM	LOW	0.25	0.5	0.25	-	-	-
MEDIUM	MEDIUM	0.11	0.56	0.33	-	-	-
MEDIUM	HIGH	0.13	0.25	0.63	-	-	-
HIGH	LOW	-	-	-	-	-	-
HIGH	MEDIUM	0.08	0.58	0.33	0.11	0.61	0.28
HIGH	HIGH	0.21	0.54	0.25	0.16	0.55	0.29

Table 16 presents a comparison between the two clusters A and B in terms of the conditional probability of the dependent variable ROAE, taking into consideration the effect of the independent variables CAR and CET1 jointly. Results show that there is a difference between the conditional probability values between the two clusters. For example, going from LOW to the MEDIUM level regarding ROAA variable, the probability increases from 0.17 to 0.5 in cluster A taking CAR and CET1 HIGH and MEDIUM levels respectively (P(ROAA=LOW|CET1=MEDIUM, CAR=HIGH)=0.17 increases to P(ROAA=MEDIUM |CET1=MEDIUM,CAR= HIGH)=0.5). The first probability increases significantly for cluster B where the value becomes 0.39. Meanwhile, the second probability remains at the value of 0.5.

Table 16

Comparison Between the Two Clusters A and B in Terms of the ROAE Conditional Probability Taking Into Consideration CAR and CET1 Jointly.

		ROAE Probability, Cluster A			ROAE Probability, Cluster B		
CAR	**CET1**	LOW	MEDIUM	HIGH	LOW	MEDIUM	HIGH
LOW	LOW	-	-	-	-	-	-
LOW	MEDIUM	0.25	0.25	0.5	-	-	-
LOW	HIGH	-	-	-	-	-	-
MEDIUM	LOW	0.25	0.5	0.25	-	-	-
MEDIUM	MEDIUM	0.11	0.67	0.22	-	-	-
MEDIUM	HIGH	0.13	0.75	0.13	-	-	-
HIGH	LOW	-	-	-	-	-	-
HIGH	MEDIUM	0.17	0.5	0.33	0.39	0.5	0.11
HIGH	HIGH	0.41	0.53	0.06	0.55	0.29	0.16

Comparison between cluster A and cluster B with control variable. Table 17 presents a comparison between the two clusters A and B in terms of the conditional probability of the dependent variable ROAA, taking into consideration the effect of the independent variables CAR and CET1 jointly and the control variable Bank Size. Results show that there is a difference between the conditional probability values between the two clusters.

For a fair comparison, the CAR and CET1 levels are fixed to HIGH levels. The analysis is based on different control variable Bank Size levels. Going from the lowest level Delta up to the highest-level Alpha for cluster A and LOW ROAA level, the ROAA probability is decreasing (from 0.82 down to 0.03). On the other hand, taking the case of MEDIUM ROAA level, the results show an increase in ROAA probability going from Delta to Alpha Bank Size (from 0.09 up to 0.68)

Table 17

Comparison Between the Two Clusters A and B in Terms of the ROAA Conditional Probability Taking Into Consideration CAR and CET1 Jointly.

			ROAA Probability, Cluster A			ROAA Probability, Cluster B		
Bank Size	**CAR**	**CET1**	LOW	MEDIUM	HIGH	LOW	MEDIUM	HIGH
Alpha	LOW	MEDIUM	0.25	0.5	0.25	-	-	-
Alpha	MEDIUM	LOW	0.25	0.25	0.5	-	-	-
Alpha	MEDIUM	MEDIUM	0.11	0.56	0.33	-	-	-
Alpha	MEDIUM	HIGH	0.11	0.44	0.44	0.08	0.62	0.31

Alpha	HIGH	MEDIUM	0.13	0.25	0.63	-	-	-
Alpha	**HIGH**	**HIGH**	0.03	0.68	0.3	0.05	0.52	0.43
Beta	MEDIUM	HIGH	0.17	0.67	0.17	0.25	0.5	0.25
Beta	**HIGH**	**HIGH**	0.21	0.57	0.21	0.08	0.75	0.17
Gamma	**HIGH**	**HIGH**	0.36	0.27	0.36	0.29	0.43	0.29
Delta	**HIGH**	**HIGH**	0.82	0.09	0.09	0.71	0.14	0.14

Table 18 presents a comparison between the two clusters A and B in terms of the conditional probability of the dependent variable ROAE, taking into consideration the effect of the independent variables CAR and CET1 jointly and the control variable Bank Size. Results show that there is a difference between the conditional probability values between the two clusters.

For a fair comparison, the CAR and CET1 levels are fixed to HIGH levels. The analysis is based on different control variable Bank Size levels. Going from the lowest level Delta up to the highest-level Alpha for cluster A and LOW ROAE level, the ROAE probability is decreasing (from 0.82 down to 0.03). On the other hand, taking the case of the MEDIUM ROAE level, the results show an increase in ROAE probability going from Delta to Alpha Bank Size (from 0.09 up to 0.88).

Table 18

Comparison Between the Two Clusters A and B in Terms of the ROAE Conditional Probability Taking Into Consideration CAR and CET1 Jointly.

			ROAE Probability, Cluster A			ROAE Probability, Cluster B		
Bank Size	**CAR**	**CET1**	LOW	MEDIUM	HIGH	LOW	MEDIUM	HIGH
Alpha	LOW	MEDIUM	0.25	0.5	0.25	-	-	-
Alpha	MEDIUM	LOW	0.25	0.25	0.5	-	-	-
Alpha	MEDIUM	MEDIUM	0.11	0.67	0.22	-	-	-
Alpha	MEDIUM	HIGH	0.11	0.44	0.44	0.23	0.69	0.08
Alpha	HIGH	MEDIUM	0.13	0.75	0.13	-	-	-
Alpha	**HIGH**	**HIGH**	0.03	0.88	0.1	0.29	0.48	0.24
Beta	MEDIUM	HIGH	0.33	0.5	0.17	0.63	0.13	0.25
Beta	**HIGH**	**HIGH**	0.61	0.32	0.07	0.67	0.17	0.17
Gamma	**HIGH**	**HIGH**	0.82	0.09	0.09	0.71	0.14	0.14

Delta	**HIGH**	**HIGH**	0.82	0.09	0.09	0.71	0.14	0.14

Spearman correlation test. In BBN inference section, we concluded that there is an effect (increase in P values) of BCR on P moving from cluster A to cluster B. When we entered the control variable into the model it does not produce any major changes in the effect of BCR on P. To investigate more if this effect is significant, we used the statistical hypothesis testing; Spearman correlation test. We found that the sig value is statistically significant only between CAR and ROAA (Sig= 0.455). Therefore, we rejected the null hypothesis H0, and we concluded that there is a weak relationship (Corr. Coeff. = 0.455 < 0.5) but statistically significant, between CAR and ROAA moving from cluster A to cluster B assuming a significance level of 0.05.

The impact of CAR on ROAA. Let the null hypothesis H0: There is no relationship, statistically significant, between CAR and ROAA moving from cluster A to cluster B, assuming a significance level of 0.05.

Hence the alternative hypothesis Ha: There is a relationship, statistically significant, between CAR and ROAA moving from cluster A to cluster B assuming a significance level of 0.05.

Table 19 shows the correlation value with the corresponding significance value Sig. It indicates that the Sig. Value is equal to 0.022, which is less than 0.05. Therefore, we will reject the null hypothesis H0, and we can conclude that there is a weak relationship (Corr. Coeff. = 0.455 < 0.5), statistically significant, between CAR and ROAA moving from cluster A to cluster B assuming a significance level of 0.05.

Table 19

Spearman Correlation Analysis.

			ROAAdiff
Spearman's rho	CARdiff	Corr. Coeff.	.455*
		Sig. (2-tailed)	.022
		N	25

The impact of CAR ratio on ROAE. Let the null hypothesis H0: There is no relationship, statistically significant, between CAR and ROAE moving from cluster A to cluster B, assuming a significance level of 0.05.

Hence the alternative hypothesis Ha: There is a relationship, statistically significant, between CAR and ROAE moving from cluster A to cluster B assuming a significance level of 0.05.

Table 20 indicates that Sig Value is equal to 0.121, which is higher than 0.05. Therefore, we will accept the null hypothesis H0, and we can conclude that there is no relationship statistically significant, between CAR and ROAE moving from cluster A to cluster B assuming a significance level of 0.05.

Table 20

Spearman Correlation Analysis.

			ROAEdiff
Spearman's rho	CARdiff	Corr. Coeff.	.318
		Sig. (2-tailed)	.121
		N	25

The impact of CET1 ratio on ROAA. Let the null hypothesis H0: There is no relationship, statistically significant, between CET1 and ROAA moving from cluster A to cluster B, assuming a significance level of 0.05.

Hence the alternative hypothesis Ha: There is a relationship, statistically significant, between CET1 and ROAA moving from cluster A to cluster B assuming a significance level of 0.05.

Table 21 indicates that Sig Value is equal to 0.253, which is higher than 0.05. Therefore, we will accept the null hypothesis H0, and we can conclude that there is no relationship, statistically significant, between the CET1 and ROAA moving from cluster A to cluster B, assuming a significance level of 0.05.

Table 21

Spearman Correlation Analysis.

			ROAAdiff
Spearman's rho	CET1diff	Corr. Coeff.	.238
		Sig. (2-tailed)	.253
		N	25

The impact of CET1 ratio on ROAE. Let the null hypothesis H0: There is no relationship, statistically significant, between CET1 and ROAE moving from cluster A to cluster B, assuming a significance level of 0.05.

Hence the alternative hypothesis Ha: There is a relationship, statistically significant, between CET1 and ROAE moving from cluster A to cluster B assuming a significance level of 0.05.

Table 22 indicates that the Sig Value is equal to 0.47, which is higher than 0.05. Therefore, we will accept the null hypothesis H0, and we can conclude that there is no relationship statistically significant, between CET1 and ROAE moving from cluster A to cluster B assuming a significance level of 0.05.

Table 22

Spearman correlation analysis.

			ROAEdiff
Spearman's rho	CET1diff	Corr. Coeff.	.152
		Sig. (2-tailed)	.47
		N	25

Multivariate regression analysis. In the Spearman correlation test section, we study the effect of CAR on P and the effect of CET1 ratio on P independently. The result was there is a weak relationship between CAR and ROAA (Corr. Coeff. = 0.455 < 0.5) moving from cluster A to cluster B, assuming a significance level of 0.05. To investigate more about the simultaneous effect of CAR on ROAA and to predict the shape of the relationship between those components., we used multivariate regression analysis.

The control variable Bank Size cannot be added to the model since in BBN section (3.2.1) we concluded that when we entered the control variable into the model, it does not produce any major changes in the effect of BCR on P. Tables (23 and 24) presented the linear regression model summary between CAR and ROAA. They show that the significant (Sig. F change=0.032) Coefficient of Determination R Square is equal to 0.243, indicating that 24.3% of the changes in ROAAdiff variance can be explained by CARdiff. CARdiff has a significant (Sig.= 0.032) positive influence on ROAAdiff at the 5% level. The regression formula between CAR and ROAA is: **ROAAdiff = 0.140 * CARdiff- 0.34**

Table 23

Regression Analysis Between CAR and ROAA.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.493[a]	.243	.198	.26114	.243	5.451	1	17	.032

a. Predictors: (Constant), CARdiff

b. Dependent Variable: ROAAdiff

Table 24

Regression Analysis Between CAR and ROAA.

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.340	.124		-2.734	.014
	CARdiff	.140	.060	.493	2.335	.032

a. Dependent Variable: ROAAdiff

Based on all mentioned above, we can finally say that the impact of BCR on P moving from cluster A to cluster B is only founded between CAR and ROAA and this regression relationship is positive but weak because only 24.3% of the changes in ROAA variance can be explained by CAR.

Discussion

This article examined the impact of Basel III capital regulation (BCR) on profitability (P) in Lebanese banks using a sample of 25 commercial banks in Lebanon over the period from 2012 to 2017. We asked our critical question: how can we study the impact of BCR on P?

To answer this question, we considered a timeline for the study from 2012 to 2017, covering the period after the development of the Basel III accord. In this timeframe, the central bank of Lebanon has adopted the new capital adequacy ratio according to 2 circulars: -Basic circular No 119 and intermediate Circular No 358. Then Based on the timeline set by circulars mentioned above, we divided our study into 2 clusters of timelines: The First cluster is A (contains the financial data of the sample between 2012-2015). The second cluster is B (includes the financial data of the sample between 2016-2017). By studying the effect of BCR on P moving from cluster A to cluster B, we can answer our research question.

We studied BCR according to two measures: A-Capital Adequacy Ratio (CAR) B- Common Equity Tier 1 Ratio (CET1 Ratio) and we studied P using 2 ratios: ROAA and ROAE.

We constructed a hybrid model that analyzed the impact of BCR on P moving from cluster A to cluster B based on three statistical approaches. First, we modeled the dual impact of BCR and P using probabilistic inference in the framework of Bayesian Belief Network formalism (BBN). Second, to highlight more the correlation between BCR and P, we used the Spearman correlation test as a nonparametric approach. Third, we applied multivariate regression analysis to study the simultaneous effect of CAR and CET1 ratio on P and to predict the shape of the relationship between those components.

For the first approach, we conclude that there is an effect (increase in P values) from BCR on P moving from cluster A to cluster B, but when we entered the control variable into the model, it does not produce any significant changes in the effect of BCR on P.

To investigate more if this effect is significant, we used the second approach to study the effect of CAR on P and the effect of the CET1 ratio on P separately. The null hypothesis H0 in the study was: there is no effect statistically significant of BCR on P moving from cluster A to cluster B assuming a significance level of 0.05. Hence the alternative hypothesis Ha: there is an effect statistically significant of BCR on P moving from cluster A to cluster B.

We found that the sig value is statistically significant only between CAR and ROAA (Sig= 0.455). Therefore, we rejected the null hypothesis H0, and we concluded that there is a weak relationship (Corr. Coeff. = 0.455 < 0.5), but statistically significant, between CAR and ROAA moving from cluster A to cluster B assuming a significance level of 0.05.

To analyze the simultaneous effect of CAR on ROAA, we used the third approach. we concluded that the regression relationship is positive but weak because only 24.3% of the changes in ROAA variance can be explained by CAR.

Based on all mentioned above, we can finally say that the impact of BCR on P moving from cluster A to cluster B is only founded between CAR and ROAA and this regression relationship is weak because only 24.3% of the changes in ROAA variance can be explained by CAR.

This result is aligned with Lee and Hsieh (2013) and Liu, Molyneux, and Wilson (2009) findings that emphasized that the impact of bank capital on profitability is positive but relatively weak.

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Declarations of interest

None.

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