

# opción

Revista de Antropología, Ciencias de la Comunicación y de la Información, Filosofía,  
Linguística y Semiótica, Problemas del Desarrollo, la Ciencia y la Tecnología

Año 35, 2019, Especial N°

# 21

Revista de Ciencias Humanas y Sociales

ISSN 1012-1587/ ISSNe: 2477-9385

Depósito Legal pp 198402ZU45



Universidad del Zulia  
Facultad Experimental de Ciencias  
Departamento de Ciencias Humanas  
Maracaibo - Venezuela



# Intellectual capital efficiency and credit risk in sub-Saharan African banks

**Murtala Aliyu Ibrahim<sup>1\*</sup>**

<sup>1</sup>Tunku Puteri Intan Safinaz School of Accounting, College of Business, Univerisiti Utara Malaysia: Department of Accounting & Finance, Baze University Abuja, Nigeria  
[murtala.ibrahim@bazeuniversity.edu.ng](mailto:murtala.ibrahim@bazeuniversity.edu.ng)

**Mohd 'Atef Md Yusof<sup>2</sup>**

<sup>2</sup>Tunku Puteri Intan Safinaz School of Accounting, College of Business, Univerisiti Utara Malaysia  
[atef@uum.edu.my](mailto:atef@uum.edu.my)

## Abstract

The purpose of this paper is to study the relationship between intellectual capital (IC) and the credit risk of Sub-Saharan African (SSA) banks. The secondary objective is to test the modified models of Value Added Intellectual Coefficient (VAIC<sup>TM</sup>) method adopted from the study of Vishnu & Kumar Gupta, (2014). Data on 40 SSA banks were collected for empirical testing in this study. The results show no relationship between IC and credit risk. In conclusion, bank size was found to be with significant explanatory powers on credit risk of banks.

**Keywords:** Intellectual, capital, efficiency, credit, risk.

## Eficiencia del capital intelectual y riesgo de crédito en bancos del África subsahariana

### Resumen

El propósito de este documento es estudiar la relación entre el capital intelectual (IC) y el riesgo crediticio de los bancos del África subsahariana (SSA). El objetivo secundario es probar los modelos modificados del método del Coeficiente Intelectual de Valor Agregado

(VAICTM) adoptado del estudio de Vishnu & Kumar Gupta, (2014). En este estudio, se recopilaron datos de 40 bancos SSA para pruebas empíricas. Los resultados no muestran relación entre IC y riesgo de crédito. En conclusión, se encontró que el tamaño del banco tenía poderes explicativos significativos sobre el riesgo crediticio de los bancos.

**Palabras clave:** intelectual, capital, eficiencia, crédito, riesgo.

## 1. INTRODUCTION

The increasing credit risk and default on bank loans is something that requires urgent attention of researchers especially that of the developing economies of Sub-Saharan African Countries (SSAC). The data extracted from the World Bank website as at 17/02/2016 indicates that about 80% of the SSAC with available information on the credit risk indicators were showing a rising non-performing loan (NPLs) in the region (Non-Performing Loans accessed on 17/12/2016). Credit risk is in the offing when a debtor is unable to make good his obligation of paying back his loans. In this instance, banks being creditors perform the traditional role of collecting customers' deposits for safekeeping and on lending to those with viable investment ideas stand a risk of not being able to receive back in full the entire amount so disbursed as credit.

Kargi (2011) opined that credit creation is the primary revenue generating activity of banks that must be guarded professionally in an efficient manner so as to avoid unnecessary bankruptcies and liquidations in banking. Thus, banks survive mainly on the net interest margins after deducting the interest expense and other overheads to

arrive at their net income. That is the business of banks akin to what manufacturing companies do when they buy raw materials for further processing through value-adding activities. The result of which is raw-materials conversions into a semi or finish goods for onward sales with a markup. Thus, no bank is in doubt that 100% of its credit disbursements will ever return in full (Beck et al., 2010; Alhassan & Asare, 2016).

In fact, the standard practice under the prudential guidelines in banking requires that certain provisions be made by each bank against its total loan portfolio. This is usually based on standard parameters that are expected to take care of probable defaults when they eventually occur such that a devastating effect on the bank's earnings and capital stock can be minimized (Beck et al., 2010; Altwaijry, 2009).

Many scholars have developed different methods of measuring IC over time. Among the most common methods of measuring IC are; Direct Intellectual Capital Methods (DIC); Market Capitalization Methods (MCM); Return on Assets Methods (ROA); and Scorecard Methods (SC). In this study, one of the ROA methods (i.e. VAICTM method) will be adopted to investigate the relationship between the dependent and independent variables of the study. This study adopts VAICTM model due to its general acceptability by previous studies, especially in the banking industry. The model provides a means for measuring IC by using audited financial statements of banks which have been used to test the relationship between the efficiency of IC and

performance of banks in a number of studies. The model was developed by an Austrian professor for the measurement of IC by adding up human capital efficiency (HCE) to structural capital efficiency (SCE) to arrive at Intellectual Capital Efficiency (Chan, 2009).

Though the model faces some criticism for its key assumptions of measuring human capital with the total expenditures on the employees and not be able to measure the IC but rather the efficiency of IC Andriessen (2004) etc., the model still remains the most important tool in measurement of ICE in banking (Eilzaki & Jalalian, 2016).

## **2. LITERATURE REVIEW AND HYPOTHESES**

There are many studies on the concept of intellectual capital (IC) which have earned it several definitions. The concept was defined by many scholars in different forms i.e. intangible capital, intangible assets, intellectual capital, intangibles, and knowledge resource, etc. (Kaufmann and Schneider, 2004). This study adopts the definition of IC as the possession of knowledge, applied experience, organizational technology, customer relationships, and professional skills. This definition is apt and has clearly identified all the key elements of IC worthy of mention. Many scholars have categorized IC into different classes according to their understanding of the concept (Kaufmann and Schneider, 2004). To start with Edvinsson (1997), categories IC into

two broad areas; i.e. human and structural capital. But he proceeded to further break structural capital into two other elements; i.e. customer and organizational capital (Beattie & Smith, 2007).

In the same vein, Kaufmann and Schneider (2004), categorized IC into three component elements of internal structure, external structure and employee competence. Kaufmann and Schneider (2004) classified IC into three types; human, organizational and customer/relational capital. Thus, based on the above classifications, the European Commission sponsored a study in which three categorizations of IC was championed by Kaufmann and Schneider (2004) i.e. Human, Structural and Relational Capital. This classification appears most suitable to many researchers in this area of study. Human capital drivers, for example, worker aptitudes, instruction, capacities, training and development, commitment are considered valuable towards value creation of a firm (Beattie & Smith, 2010; Alexander et al., 2015).

After human capital, every other capital in an organization is structured. In effect, a human being can achieve virtually little without physical assets. Studies have highlighted the importance of structural capital in an organization towards the achievement of the overall goal. In the banking sector, relational/customer capital is very vital due to the homogeneity of banking products and services. Banks can quickly lose its customers to its rival competitor and with the customer not losing much from the uniformity of services in the banking industry. Therefore, banks are increasingly becoming concerned about the

relationship that exists with its customers so as to forestall the avoidable loss of customer's confidence. Thus, this study, therefore, examines the relationship between the components of intellectual capital and credit risk of banks through the test of the following hypothesis;

### **3. RESEARCH METHODOLOGY**

The study extracted its data largely from the Bankscope database limiting its search to only commercial banks in the SSA in countries that operate a functional stock market. This is for ease of data collection and standardized financial information disclosures. Additional financial information of the selected banks was also obtained from the individual banks' websites that met the first condition stated above. In all, forty-three banks (43) in twelve countries met the stated conditions (i.e. Botswana, Cape Verde, Gambia, Ghana, Kenya, Malawi, Namibia, Nigeria, South Africa, Tanzania, Uganda, and Zambia).

### **4. RESULTS AND DISCUSSIONS**

The Table below is a summary of Multicollinearity and Variance inflation factors (VIF) tests with respect to the variable of the study. These tests measure the extent to which variance in the estimated regression coefficients inflate as compared to when the

independent's variables are not linearly related. It is used to explain how much amount multicollinearity (correlation between predictors) exists in a regression analysis (Etcuban et al., 2019)

Table A: Collinearity & Variance Inflation Factors (VIF)  
Dependent Variable: NLA, LTA

Model	Coefficients <sup>a</sup>	Collinearity Statistics	
		Tolerance	VIF
1	HCE1	.996	1.004
	SCE1	.999	1.001
	RCE1	1.000	1.000
	CCE1	.997	1.003
2	HCE2	.871	1.148
	SCE2	.995	1.005
	RCE2	.999	1.001
	CCE2	.868	1.152
3	HCE3	.014	73.998
	SCE3	.020	50.720
	RCE3	.061	16.356
	CCE3	.986	1.014

From the table A above, and using the standard of VIF value of 10 and above to indicate multicollinearity, it can be concluded that, except for model three variables of HCE3, SCE3 and RCE3 there is no evidence of multicollinearity in the models (Chan, 2008; Barathi, 2007). This is supported by the rule of thumb that if  $VIF > 10$  then multicollinearity is high. However, at the on-set of the model formulation, the study foresaw the multicollinearity in model three because it was an inverse relationship of model two that was used to measure the intensity of the VAIC components in the study. The question of high VIF may not necessarily introduce threats unless

practically visible as supported by (Greene, 2003). The first hypothesis developed in this study which stated that IC is negatively associated with bank credit risk in the Sub-Saharan African banks was tested using regression, and the result is summarized in Table A below;

Table B: Regression result of IC and Credit Risk of Banks

Dependant Variables	Model	R2	F Value	p-value
NLA	1	0.001	0.28	0.6002
	2	0.001	0.26	0.6072
	3	0.004	0.85	0.3565
LTA	4	0.000	0.10	0.7487
	5	0.000	0.09	0.7606
	6	0.006	1.50	0.2212

n = 240, \*p < 0.05

From the above table, we can interpret statistically that all the three models in each of the dependent variables (NLA and LTA) do not show any significant relationship between ICE and credit risk in banks. The coefficient of determination (R2) which is an absolute determinant of a relationship in a regression model is less than 0.01 in all of the 6 cases. The closer the coefficient of determination is to one (1) the better the relationship between the independent and dependent variables. The F-Value outcome is also supportive of the same position. Except for model no 3 in LTA dependent variable, all F-values in the remaining five (5) models are less than one (1).

Table B, on the other hand, is the summary of regression results. The result comes in 12 different equations, six with the introduction of control variables of the study and the remaining six without them. For each of the equations, only those variables that have shown some level of significance were captured in the result table.

**Table C: Regression result of IC Components and Credit Risk of Banks**

Dependant Variables	Model	Control in the Model	Significant Variables	Coefficient	p-value
NLA	1	(a) Yes	Talg	-0.0118	0.000
		(b) No	HCE1	-0.0026	0.009*
	2	(a) Yes	Talg	-0.0104	0.000
		(b) No	HCE2	-0.0006	0.000
	3	(a) Yes	Talg	-0.0124	0.000
		(b) No	Constant	0.0431	0.000
LTA	4	(a) Yes	Talg	-0.0052	0.000
		(b) No	Constant	0.0250	0.000
	5	(a) Yes	Talg	-0.0047	0.000
		(b) No	HCE2	-0.0002	0.002*
	6	(a) Yes	Talg	-0.0555	0.000
		(b) No	Constant	0.0217	0.000

n = 240, \*p < 0.05

In all, among the six models that control variable was not introduced, model 2(b) seems to have the highest significance indicator. The coefficient of determination (R<sup>2</sup>), though very low (i.e. 6.85%), is greater than in all of the five other models. It has a corresponding F-Value of 5.78 and a p-value of 0.001 (at  $\alpha = 5\%$ ). Another interesting thing about this model is that HCE2 is found to be

statistically significant with a coefficient of -0.00063 and at-value of 0.000. This implies that among all the components of IC, HCE is the only component that has some explanatory powers on credit risk of banks. HCE has been consistent in model 1 & 2 in NLA dependent variable while in LTA dependent variable HCE only show some level of significance in model 2. With the introduction of control variables of bank size (proxied by the log of total assets) and GDP growth rate, the result improved in all cases. The impact of bank size was found to be very significant on credit risk in commercial banks.

Model 2 (a) got a better explanatory power of 15.15% coefficient of determination and a corresponding 8.36 F-value. All the six models under this group have shown some level of significance due to the impact of the dominant control variable in the equation (i.e. bank size). Bank size was found to be the only significant variable in all the six models displacing even the HCE that was found to be significant in the previous section of the study. The newly introduced variable, RCE has not shown any level of significance in any of the 12 models of this study thereby leading us to conclude statistically that the variable does not have any impact on the dependent variable of the study. Thus, we can conclude that except for HCE which have shown some level of significance in three (3) of the six models without the control variables, all other components of IC are not statistically related to credit risk in commercial banks (Yazdekhasti et al, 2015).

**Table D: Comparison between Extended and Traditional VAIC™ Models**

Dependant Variables	Model	R2	F Value	p-value	Singnificant Variables	Coofficient	t-value
NLA	1(a)	3.13%	1.90	0.1111	Constant	0.0505	0.000
					HCE1	-0.0026	0.010*
	2(a)	7.60%	4.83	0.0009	Constant	0.0683	0.000
					HCE2	-0.0006	0.001*
	3(a)	1.49%	0.89	0.4697	Constant	0.0406	0.000
	VAIC (a)	3.30%	2.46	0.0632	Constant	0.0504	0.000
HCE1					-0.0026	0.010*	
LTA	1(b)	3.17%	1.92	0.1008	Constant	0.0251	0.000
					HCE1	-0.0012	0.014*
	2(b)	4.29%	2.63	0.0351	Constant	0.0303	0.000
					HCE2	-0.0002	0.008*
	3(b)	2.50%	1.51	0.2004	Constant	0.1818	0.000
	VAIC (b)	3.31%	2.54	0.0569	Constant	0.0251	0.000
HCE1					-0.0012	0.014*	

n = 240, \*p < 0.05

Table D above compares the regression results of the extended and traditional model of the VAICTM models in this study. The difference between the models is the introduction of the RC in the extended model for its perceived relevance in the banking sector which was hitherto not recognized by the traditional model developed by Ante Public. Out of the 6 Models in the study, only 2(a) and 2(b) extended models show the greater coefficient of determination of 7.6% and 4.29% than the corresponding traditional VAICTM model result of 3.30% and 3.31% respectively.

In Table D, the results of the third hypothesis, i.e. comparative performance of the three proposed models vis-a-vis the VAIC model, has been shown. For NLA as the measure of

credit Risk, the VAIC model has the highest R2 value of 3.3 percent out of  $\frac{2}{3}$  of the models while  $\frac{1}{3}$  suggest that the extended modified model is better-off by recording an R2 of 7.6%. When the LTA was used as the dependent variable, the VAIC model has remained with the highest R2 value of 3.31 percent still in  $\frac{2}{3}$  of the models while  $\frac{1}{3}$  suggests that the extended modified model is better-off by recording an R2 of 4.29%.

## **5. CONCLUSION**

This research work is an attempt to study the impact of IC on credit risk of commercial banks in the Sub-Saharan African countries. The study adopted VAICTM model as a tool for measuring IC in the banking sector with little modification as proposed by (Chan, 2008). Due to shortcomings of the original VAICTM model of not incorporating RC and especially due to the perceived importance of relationship management in banking, this study adopted the proposed model to test the relationship between IC and credit risk of banks. Financial information was sourced from 12 countries in the region based on the established criteria and out of it 45 banks were obtained and further pruning on the availability of data reduced their numbers to 40 which gave the study 240 number of observations. The two measurements of the dependent variable were NLA & LTA while the ICE components were made

up of HCE, SCE, and RCE. The VAICTM, on the other hand, include CCE as an additional variable.

In the academic field, the study has opened another page in the area of finance by using secondary financial information data to manage IC. The findings will encourage future studies to test the veracity of the extended r-VAICTM model as an alternative IC model in banking studies. This research work has a few limitations. Just like prior studies that adopted VAICTM, there is an inherent challenge of overstating the value added in the model as discussed by several findings of the previous studies.

Thus, the VAIC model itself has faced stiff opposition from a number of researchers regarding its assumptions of value addition. It is therefore important for future researches to develop a more realistic measurement model that will give a better result in the future. Besides, this study faced some challenges in the data collection exercise as some data was not readily available. This was why the study decided to take the residue after deducting HC and RC from value added to represent SC instead of the proxies like research and development expenses (a proposed proxy for SC) to value added.

**REFERENCES**

- ALEXANDER, G., BAPTISTA, A., & YAN, S. 2015. **On Regulatory Responses to the Recent Crisis: An Assessment of the Basel Market Risk Framework and the Volcker Rule.** Financial Markets, Institutions & Instruments. Vol. 24, N° 2–3: 87–125. USA.
- ALHASSAN, A., & ASARE, N. 2016. **Intellectual capital and bank productivity in emerging markets: evidence from Ghana.** Management Decision. Vol. 54, N° 3: 589–609. UK.
- ALTWAIJRY, A. 2009. **Intangible assets and future growth: evidence from Japan.** Asian Review of Accounting. Vol. 17, N° 1: 23–39. UK.
- ANDRIESSEN, D. 2004. **IC valuation and measurement: classifying the state of the art.** Journal of Intellectual Capital. Vol. 5, N° 2: 230–242. UK.
- BARATHI, G. 2007. **The intellectual capital performance of the Indian banking sector.** Journal of Intellectual Capital. Vol. 8, N° 1: 96–123. UK.
- BEATTIE, V., & SMITH, S. J. 2010. **Human capital, value creation and disclosure.** Journal of Human Resource Costing & Accounting. Vol. 14, N° 4: 262–285. UK.
- BEATTIE, V., & THOMSON, S. 2007. **Lifting the lid on the use of content analysis to investigate intellectual capital disclosures.** In Accounting Forum. Vol. 31, pp. 129–163. Elsevier. Netherlands.

- BECK, T., CULL, R., FUCHS, M., GETENGA, J., GATERE, P., RANDA, J., & TRANDAFIR, M. 2010. **Banking sector stability, efficiency, and outreach in Kenya**. World Bank Policy Research Working Paper Series. Vol. 1. USA.
- CHAN, K. 2009. **Impact of intellectual capital on organizational performance: An empirical study of companies in the Hang Seng Index (Part 1)**. The Learning Organization. Vol. 16, N° 1. UK.
- CHAN, S. 2008. **Bank Efficiency in Selected Developing Countries**. Universiti Utara Malaysia. Malaysia.
- EDVINSSON, L. 1997. **Developing intellectual capital at Skandia**. Long Range Planning. Vol. 30, N° 3: 320–373. Netherlands.
- GREENE, W. 1993. **Econometrics Analysis**. 2nd edition. Macmillan. Germany.
- KARGI, H. 2011. **Credit risk and the performance of Nigerian banks**. Ahmadu Bello University, Zaria. Nigeria.
- KAUFMANN, L., & SCHNEIDER, Y. 2004. **Intangibles: a synthesis of current research**. Journal of Intellectual Capital. Vol. 5, N° 3: 366–388. UK.
- YAZDEKHASTI, A., ERFAN, N., & NAZARI, N. (2015). **Investigating the Relationship between Spiritual Intelligence and Social Adaptation among Girl High School Students in Shahreza City**. UCT Journal of Social Sciences and Humanities Research, 3(1), 20-23.
- ETCUBAN, J. O., CAMPANILLA, B. S., & HORTEZA, A. D. (2019). The Use of Mathcad in the Achievement of

Education Students in Teaching College Algebra in a University. *International Electronic Journal of Mathematics Education*, 14(2), 341-351.  
<https://doi.org/10.29333/iejme/5718>.

EILZAKI, A., & JALALIAN, A. (2016). The impact of satellite programs on the family based on the international law and human rights. *UCT Journal of Management and Accounting Studies*, 4(1), 1-6.





**UNIVERSIDAD  
DEL ZULIA**

---

# **opción**

Revista de Ciencias Humanas y Sociales  
Año 35, Especial N° 21, (2019)

Esta revista fue editada en formato digital por el personal de la Oficina de Publicaciones Científicas de la Facultad Experimental de Ciencias, Universidad del Zulia.  
Maracaibo - Venezuela

[www.luz.edu.ve](http://www.luz.edu.ve)

[www.serbi.luz.edu.ve](http://www.serbi.luz.edu.ve)

[produccioncientifica.luz.edu.ve](http://produccioncientifica.luz.edu.ve)