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The Impact of Intellectual Capital Efficiency on Bank Risks: Empirical Evidence from the Saudi Banking Industry

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ABSTRACT

The main purpose of conducting this research is to investigate the impact of intellectual capital efficiency (ICE) and its components – human capital efficiency (HCE) and structural capital efficiency (SCE) - on bank credit and insolvency risks in the Saudi banking industry. To assess such a relationship, value added intellectual coefficient model (VAIC) along with a couple of panel data techniques were utilized by using quarterly observations spanning from the first quarter of 2009 to the fourth quarter of 2018. The carried out empirical results confirm the existence of a significant negative relationship between ICE, in particular HCE, and bank credit and insolvency risks.

Keywords: Intellectual Capital Efficiency, Human Capital, Structural Capital, Credit Risk, Insolvency Risk, Risk Management
JEL Classifications: O34, E24, J21, G32, C23, G21

1. INTRODUCTION

Since the late twentieth century, the attention devoted to Intellectual Capital (IC) has greatly increased. Arguably, this attention to intellectual capital is attributed to the weaknesses of the traditional accounting system in identifying the “hidden factors” (Lev, 2001) behind the significant gap between a firm’s market value and its book value, especially in the knowledge-based economy (Edvinsson and Malone, 1997). In fact, Lev (2001) pointed out that about 80% of the firm market value in the US economy cannot be explained by the traditional accounting system. Likewise, another study conducted by Ocean Tomo demonstrated that the share of intangible assets in the market value of the S&P 500 index increased from only 17% in 1975 to around 84% in 2015. Although the concept of IC has been used for several years up until now, there is still no clear cut for its definition nor its classification (Sharabati et al., 2013). A Swedish firm named Skandia came up with its first definition of IC in its 1994 annual IC report as “the possession of knowledge, applied experience, organizational technology, customer relationships, and professional skills” (Edvinsson, 1997). Even though there is no universal definition of IC, its definition still contains some common key words, such as accumulated knowledge, gained experience, intangible assets, maintaining good relationships, know-how, and innovation, which help firms gain more sustainable competitive advantages and enhance their market value (Edvinsson and Malone, 1997; Stewart and Ruckdeschel, 1998; and Clarke et al., 2011).

Given the increase in the necessity of IC in the service industry and knowledge-based economy, and its potential in creating competitive advantage, a large number of studies such as Salehi et al. (2014), Sehic et al. (2014), Ozkan et al. (2017), and Mondal and Ghosh (2012) have investigated and have had statistical evidence of strong impact of IC and its components on the bank financial performance measured by profitability and market value in Bosnia and Herzegovina, Turkey, Iran, and India. Nevertheless, to the best of our knowledge, very few studies such as Ghosh and Maji (2014) and Kaupelyte and Kairyte (2016) have come to investigate the impact of IC efficiency on bank risks. Risk-taking is an essential part of the core banking activities. In fact, one of the key roles of banks and the financial system is to intermediate funds efficiently and allocate them in a risk-informed manner towards effective and productive uses that best serve the economy (Huey and Li, 2016). Credit risk is considered to be one of the oldest risks associated with lending activities, which is the core business in the banking industry (Tang et al., 2009). In 1988, the Basel Committee constructed a framework for capital adequacy, known as Basel I standards, in order to establish a minimum level of capital for active international banks that helps to promote the soundness and stability of the international banking system. This framework was introduced in response to the collapse of two large international banks in 1974, Long Island's Franklin National Bank in the US and Bankhaus Herstatt in Germany (Stephanou and Mendaza, 2005; and Jablecki, 2009).

Due to the limitations of Basel I and in response to the banking crises that occurred in the 1990s, the Basel Committee introduced in 1999 more comprehensive capital adequacy requirements, known as the Basel II standards, which help address the market and operational risks along with promoting stronger risk management practices by the banking industry. Furthermore, after the great financial crisis of 2007 and 2008, the Basel Committee came up, in 2010, with additional guidelines in order to encourage a more flexible banking system, with emphasis on the four important banking parameters of capital adequacy, leverage, funding, and liquidity (Ghosh and Maji, 2014). It is essential to note that one of the most widely blamed factors behind the 2008 financial crisis was the excessive risk-taking by banks during the years ahead of the crisis (Bhattacharyya and Purnanandam, 2011). This recent financial crisis has raised more attention to the necessity of risk management in the banking industry, which makes it a vital function for banks to manage all types of risk in a proactive and efficient way in order to reduce the likelihood of becoming insolvent.

Even though IC has received a considerable amount of attention in the knowledge-based economy lately, and its role has been addressed specifically in the service sector such as the banking industry, its role in the banking risk management has not yet been recognized by most of the monetary authorities. Human capital, being as an essential element of IC, has an important role in the process of credit risk management and in strengthening the solvency of a bank. The success of credit management relies mainly on the skill, knowledge, and creative and analytical mind of bankers, who utilize those abilities to address and identify any possible threats that might arrive from initiating and granting loans to borrowers. In addition to human capital, structural capital, including banking information systems, database, patents, and copyrights along with maintaining good relationship with others, all play an important role in the process of credit risk management and enhancing the bank system solvency. Because of this, banks can utilize both their human and structural resources to come up with new creative ideas, products, and services which enhance their sustainable competitive advantages and mitigate their risks (Ghosh and Maji, 2014).

Bearing this background in mind, this paper empirically investigates the effective impact of intellectual capital (IC) and its components (human capital and structural capital) on the credit and insolvency risks (measured by credit and solvency ratios) of listed banks in the Saudi stock market (Tadawul). In addition, the study addresses the influence of the capital adequacy ratio (CAR), as an important regulatory standard, on both types of bank risks under investigation. This study is very important and significantly contributes to the literature given the ultimate main goal of the Saudi Vision 2030 of shifting away from the dependence on oil as the main economic driver toward a knowledge-based economy. In addition, the banking sector is considered to be one of the most active and healthiest sectors in the Saudi economy, with combined commercial bank assets of 2.58 trillion Saudi riyals ($687 billion, as of November 2019), making it one of the largest banking industries in the region. Moreover, this study is the first in Saudi Arabia that investigates this kind of relationship between the IC and bank risk management.

This paper structure is organized as follows: second section provides a brief review of the related literature and the hypotheses formulation of the study, followed by, a brief discussion on the data. In the fourth section, the authors give a comprehensive summary of the adopted research methodology and the main findings of the study. Finally, the research conclusion is given in the fifth section.

2. EMPIRICAL LITERATURE REVIEW AND DEVELOPMENT OF HYPOTHESES

In the last few decades, the evaluation and management of IC have become a very vital topic for all types of organizations including banks. In fact, this topic is likely to receive more attention, since traditional accounting system is no longer suitable in explaining the developments in today's business environment (Sharabati et al., 2013). As reported by Ocean Tomo in 2015, about 84% of the S&P 500 firms' market value is driven by their intangible assets, which in other words is their IC. Most of the studies in the literature such as Gigante (2013), Ozkan et al. (2017), Onyekwelu et al. (2017) and Murugesan et al. (2018) address the impact of IC and its components on banks' financial performance. By applying the Value Added Intellectual Coefficient (VAIC) model as a measure of Intellectual Capital Efficiency, and Return On Equity (ROE) and Return On Asset (ROA) along with the bank market value as a measure of bank profitability, those studies concluded that IC and its components have a strong influence on the banks' financial performance in Europe, Turkey, Nigeria, and India. However, according to our best knowledge, only a few studies such as Ghosh and Maji (2014) and Kaupelyte and Kairyte (2016) have come to investigate the impact of IC and its components on bank risk management. Within this section, a brief summary of the related literature is provided.

Ghosh and Maji (2014) employed a fixed effect analysis on an annual panel data set of Indian commercial banks covering the period from 1998 to 2012, in order to investigate the impact of IC on bank credit risk and insolvency risk. By using the VAIC model developed by Pulic (1998), the results show that Intellectual Capital Efficiency (ICE) is reciprocally associated with bank credit risk; more specifically, Human Capital Efficiency (HCE) is found significant and negatively correlated with bank credit risk.

Moreover, Ghosh and Maji (2014) found that ICE and HCE have a greater influence on managing credit risk in public banks than in private banks, and in large banks than in small banks. However, Chosh and Maji (2014) failed to draw a definite conclusion about the influence of ICE on bank insolvency risk.

Following a similar methodology, Kaupelyte and Kairyte (2016) investigated the impact of IC and its components on three different levels – bank profitability, effectiveness, and risk management. The sample drawn in the study was based on an annual panel data set of 118 European listed banks, covering the period from 2005 to 2014. The main findings of the estimated fixed effect model show that the increase of Structural Capital Efficiency (SCE), as one of IC components, helps to increase the net interest margin in large banks. In addition, the study shows that an increase of Human Capital Efficiency (HCE) leads to stronger profitability ratios in small banks and better risk ratios in large banks.

Due to the lack of literature on this topic, especially in Saudi Arabia, and the fact that the Saudi economy is targeted to become more of a knowledge-based economy as an ultimate goal of the Saudi Vision 2030, this research is interested in finding out whether IC efficiency influences bank credit risk management and improves bank solvency. In theory, an increase in the efficiency of IC and its components will result in a decrease in the bank's credit and insolvency risks. Bontis et al. (2000) pointed out that structural capital, an IC component, includes all the non-human store of knowledge in an organization, which substantially supports the firm's human resources (the second component of IC), in turn, improving and enhancing the operational efficiency. With an enhancement in the operational efficiency, firms will be able to perform in a better way and reduce their operational risks (credit and insolvency risk in the case of banks). In this regard, the following are four hypotheses that are formulated and tested in this study:

- Hypothesis 1 (H_1^a): ICE is negatively associated with Saudi bank credit risks. Nevertheless, it is positively associated with Saudi bank solvency.
- Hypothesis 2 (H_1^b): HCE is negatively associated with Saudi bank credit risks. However, it is positively associated with Saudi bank solvency.
- Hypothesis 3 (H_1^c): SCE is negatively associated with Saudi bank credit risks. On the other hand, it is positively associated with Saudi bank solvency.
- Hypothesis 4 (H_1^d): CAR is negatively associated with Saudi bank credit risk. However, it is positively associated with bank solvency.

3. DATA

In order to measure the impact of IC efficiency on both banking credit risk and bank solvency, this paper utilizes a panel data set of all 11 listed banks in the Saudi stock market (Tadawul). All data in this paper are obtained from Bloomberg's database. The panel data cover quarterly observations over a 10-year period from the first quarter of 2009 to the fourth quarter of 2018, which is sufficient to come up with a coherent conclusion about the status of the risk management performance in Saudi banks. In this paper, there are two main dependent variables, which are the credit risk ratio (CR), as a measurement of bank credit risk, and the solvency ratio (SOL), as a measurement of bank insolvency risk (the higher the solvency ratio, the lower the insolvency risk is in the bank). For the independent variables, four variables are utilized – the intellectual capital efficiency (ICE), consisting of two components, human capital efficiency (HCE) and structural capital efficiency (SCE), and the capital adequacy ratio (CAR). In addition to these, this study uses the most popular two control variables in the literature, which are the bank size measured by taking the natural logarithm of total assets (lnTA), and the net interest margin (NIM), to mitigate the influence of some other variables that would illustrate the riskiness of Saudi banks.

3.1. Dependent Variables

3.1.1. Credit risk ratio (CR)

Credit risk is considered to be one of the oldest type of risks associated with banking activities, originating from non-performing loans. In this paper, the ratio of the provision for non-performing loans to total bank assets, which has been frequently used in the literature (Ozili, 2018, Laeven and Majnoni, 2003, Anwen and Bari, 2015), is employed as a measure of bank credit risk, and is defined as follows:

$$Credit\ Risk\ Ratio\ (CR) = \frac{Loan\ Provisions\ to\ NPL}{Bank\ Total\ Assets}$$

3.1.2. Insolvency risk

Insolvency is another type of risk that threats banks, which arises when a bank has difficulty meeting its obligations. In this paper, the bank solvency ratio (SOL) is used as a measure of a bank's insolvency risk in an inverse fashion – the higher the ratio, the lower is the insolvency risk. The bank solvency ratio is defined as follows:

$$Bank\ Solvency\ Ratio\ (SOL) = \frac{(NI + NCE)}{TL}$$

Where,
NI = Net Income,
NCE = Non-cash Expenses (Depreciation and Amortization),
TL = Total Liabilities.

3.2. Independent Variables

3.2.1. Intellectual capital efficiency (ICE)

Across all the literature, there is no universally accepted approach to measuring ICE. In this study, the value-added intellectual coefficient model (VAIC) developed by Pulic (1998) is utilized due to several reasons – it only uses publicly audited quantitative information (Chan, 2009) and it is able to measure the effectiveness of ICE rather than just calculating the ICE (Harsh and Tandon, 2015). More precisely, the ICE consists of the sum of Human Capital Efficiency (HCE) and Structural Capital Efficiency (SCE). Therefore, the ICE can be defined as follows:

$$ICE = HCE + SCE$$

There are several steps in measuring the VAIC. First, a firm's ability to generate value added to all of its shareholders is calculated; this is simply given by the difference between a firm's output (OUT) and its input (IN). OUT is the total amount of revenue generated by a firm in a specific year; IN is the sum of all of the operating expenses incurred by that firm in the process of earning revenue. Plus, Employee expenses, in which salaries and training costs are included, are treated as a value creating item for the firm (Tan et al., 2007; Clarke et al., 2011). Another way to define VA is the net value created by a firm across a specific year, and can be expressed as follows:

$$VA = OUT - IN = NI + T + I + D + A + EC$$

Where NI stands for the net income of the firm, T stands for the corporate tax, I stands for the company's interest expense, D is depreciation, A stands for amortization, and EC refers to the employee expenses.

3.2.2. Human capital efficiency (HCE)

According to Edvinsson and Malone (1997), HC is the most critical component of ICE. In fact, HC refers to workers' knowledge, skills, competencies, training, education, experience, and know-how that an employee accumulates during his/her time at the organization. However, in the VAIC model, HC is defined as the wages and salaries of employees at a specific period of time (Pulic, 2000); as a matter of fact, it is considered as an investment of the company (Tan et al., 2007). Moreover, Clarke et al. (2011) calculated HCE as how much value added is generated by one monetary unit invested in human capital. Thereby, in this paper, the HCE can be formed as follows:

$$HCE = \frac{VA}{HC}$$

Thus, a higher HCE ratio results from a higher level of VA for a given level of wages and salaries (HC).

3.2.3. Structural capital efficiency (SCE)

Structural capital (SC) is considered the supportive non-physical infrastructure of an organization, that allows human capital to operate (Bollen et al., 2005). In the VAIC model, the structural capital is the difference between the VA and HC, i.e. SC=VA-HC. Thus, the SCE can be computed using the following formula:

$$SCE = \frac{SC}{VA}.$$

3.2.4. Capital adequacy ratio (CAR)

Capital adequacy ratio (CAR) is one of the Basel Committee banking supervision requirements, which requires all banks to maintain two types of capital (Tier 1 and Tier 2) in order to prevent depositors and shareholders from unexpected losses. This ratio is defined as follows:

$$CAR = \left[\frac{Tier\,1\,Capital + Tier\,2\,Capital}{Bank\ Risk - Weighted\ Assets}\right] \times 100$$

3.3. Control Variables

For the evaluation of intellectual capital (IC) and its influence on bank risks, two widely used control variables are taken into consideration in order to minimize the impact of other variables that may explain the riskiness of Saudi Banks. The two control variables are as follows:

3.3.1. Bank size

In this paper, the bank size is measured by the natural logarithm of bank total assets (lnTA), which is considered to be the most popular measure of bank size in the banking literatures (Rahman et al., 2009; Maji and Dey, 2012).

3.3.2. Net interest margin to total assets (NIM_TA)

The second control variable is the net interest margin (Interest Earned-Interest Expense) as a percentage of bank total assets. It is a proxy to measure bank efficiency. The higher the ratio, the higher the bank efficiency is, and the lower the bank risk exposure is.

4. RESEARCH METHODOLOGY AND EMPIRICAL RESULTS

Panel data techniques are utilized to measure the influence of the IC, and its components: human capital and structural capital, the capital adequacy ratio, and two control variables: natural log of total assets and net interest margin as a percentage of total assets, on bank credit risk and solvency in case of Saudi Arabia. Before proceeding with the panel data techniques, there are some steps that need to be taken in order to insure that the model is the suitable model and not spurious. Thus, our analysis starts with an examination of the time series data properties by applying a unit root test.

4.1. Unit Root Test

The Levin et al. (2002) test is utilized to examine the unit root among all of the variables under the study (2002).

From Table 1, one can realize that all variables are stationary at their levels except the net interest margin to total assets (NIM_TA), which became stationary after taking the first difference. Thus, the panel techniques are applied using the levels of all variables except the net interest margin as a percentage of total asset, which is taken using its first difference.

4.2. Models

In this paper, two models are implemented to examine the influence of the above-mentioned independent variables on Saudi bank credit risk (CR).

Table 1: Unit root tests

Variables	Test- level (Test statistic and P-V)	Test- first difference	Test- second difference
CAR	−3.18 P-V 0.00	-	-
CR	−5.65 P-V 0.00	-	-
SOL	−6.40 P-V 0.00	-	-
HCE	−2.77 P-V 0.00	-	-
SCE	−7.08 P-V 0.00	-	-
ICE	−2.93 P-V 0.00	-	-
lnTA	−4.41 P-V 0.00	-	-
NIM_TA	−0.67 P-V 0.25	−14.01 P-V 0.00	-

$$CR_{it} = a + \beta_1\, ICE_{it} + \beta_2\, CAR_{it} + \beta_2\, lnTA_3 + \beta_4\, \Delta \frac{NIM}{TA}_{it} + \varepsilon_{it} \quad (1)$$

The above model (1) does not segregate the IC components; thus, the ICE includes both human capital efficiency (HCE) and structural capital efficiency (SCE). However, to be more precise, this study will utilize another model in which there is a segregation between the IC components. Therefore, model (2) will illustrate the impact of the IC components.

$$CR_{it} = \alpha + \beta_1\, HCE_{it} + \beta_2\, SCE_{it} + \beta_3\, CAR_{it} + \beta_4\, lnTA_3 + \beta_5\, \Delta \frac{NIM}{TA}_{it} + \varepsilon_{it} \quad (2)$$

In addition, this paper examines the impact of the intellectual capital efficiency and its components coupled with other independent variables on the solvency of Saudi banks. First, the below model (3) does not separate the IC's components but examines the impact of IC as a whole with other explanatory variables on bank solvency (SOL). Thus, model (3) is as follows:

$$SOL_{it} = \alpha + \beta_1\, ICE_{it} + \beta_2\, CAR_{it} + \beta_2\, lnTA_3 + \beta_4\, \Delta \frac{NIM}{TA}_{it} + \varepsilon_{it} \quad (3)$$

Then, model (3) is decomposed in terms of the IC to include HCE and SCE as shown in model (4). Thus, model (4) is structured as follows:

$$SOL_{it} = \alpha + \beta_1\, HCE_{it} + \beta_2\, SCE_{it} + \beta_3\, CAR_{it} + \beta_4\, lnTA_3 + \beta_5\, \Delta \frac{NIM}{TA}_{it} + \varepsilon_{it} \quad (4)$$

In this paper, panel econometric techniques are utilized, starting from the pooled model and going through random effect and fixed effect models.

4.2.1. Bank credit risk section

$$CR_{it} = a + \beta_1\, ICE_{it} + \beta_2\, CAR_{it} + \beta_2\, lnTA_3 + \beta_4\, \Delta \frac{NIM}{TA}_{it} + \varepsilon_{it} \quad (1)$$

4.2.1.1. Pooled model

A pooled model approach is utilized at first where we assume all banks have the same structure and environment – i.e. the presence of heterogeneity or individuality is ruled out and assumed that all banks are the same.

Table 2 shows that ICE has a significant negative relationship with bank credit risk so that if the ICE increases by one unit, the bank credit risk will decrease by 0.05% on average. In the same context, statistical evidence of a negative relationship between the CAR and the bank credit risk is observed in the above pooled model results so that if the CAR increases by one unit, the CR will decrease by 0.001 on average. However, in this kind of model, we assumed all the banks are the same, which is in fact not true. Thus, we need to have a better model that reflects the differences.

In order to accomplish this, we have two options – first, random effect and second, fixed effect models. We do not have the freedom to arbitrarily choose between the two models; however, there is a test to determine which is the right model to be used.

4.2.1.2. Random effect model

This model assumes all banks have a common mean value at the intercept point.

Table 3 shows the same results that were seen in the previous pooled model, but with different magnitudes. However, before we can accept these results, we have to test whether the random effect model is the right model to use, rather than the fixed effect model. Thus, the Hausman test is utilized at this point.

The Hausman test has a null hypothesis stating that the random effect model is an appropriate model to be used, while the alternative hypothesis states that fixed effect model is the appropriate one. Thus, from Table 4, since the $P < 5\%$, we determine that the fixed effect model is the right model among the three models to be used. Therefore, we shall proceed using the fixed effect model.

4.2.1.3. Fixed effect model

Table 5 shows statistical evidence of a negative relationship between ICE and CR such that if ICE increases by one unit, the CR will significantly decrease by 0.06 on average. Moreover, there is a negative relationship between CAR and CR so that if CAR increases by one unit, the CR will decrease by 0.001 on average.

Table 2: Pooled model results (IC Aggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	0.197473	0.099831	1.978083	0.0485
ICE	−0.047378	0.005145	−9.209449	0.0000
CAR	−0.000964	0.000214	−4.496609	0.0000
lnTA	0.015840	0.009632	1.644545	0.1007
d(NIM_TA)	−0.125757	0.100955	−1.245675	0.2135

Table 3: Random effect model results (IC aggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	0.531914	0.155170	3.427936	0.0007
ICE	−0.059998	0.005587	−10.73835	0.0000
CAR	−0.000983	0.000212	−4.634215	0.0000
lnTA	−0.007277	0.014127	−0.515100	0.6067
d(NIM_TA)	−0.074000	0.090335	−0.819177	0.4131

Table 4: Correlated random effect – Hausman test

Test cross-section random effects			
Test summary	**Chi-sq. statistic**	**Chi-sq. d.f.**	**Prob.**
Cross-section random	36.699759	4	0.0000

Table 5: Fixed effect model results (IC aggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	1.277562	0.225820	5.657436	0.0000
ICE	−0.063426	0.005938	−10.68128	0.0000
CAR	−0.001244	0.000225	−5.528861	0.0000
lnTA	−0.069051	0.020034	−3.446718	0.0006
d(NIM_TA)	−0.035181	0.090620	−0.388227	0.6980

Nevertheless, there is a negative relationship between the natural log of the total assets and the CR such that if the natural log of total assets increases by one unit, the CR will decrease by 0.07 on average. Thus, we can conclude that the statistical evidence implies that the intellectual capital efficiency will reduce the Saudi banks credit risk. This conclusion is compatible with the findings seen in India (Ghosh and Maji, 2014) and Europe (Kaupelyte and Kairyte, 2016).

4.2.2. Decomposed IC into human capital and structural capital

$$CR_{it} = \alpha + \beta_1 HCE_{it} + \beta_2 SCE_{it} + \beta_3 CAR_{it} + \beta_4 lnTA_3 + \beta_5 \Delta \frac{NIM}{TA}_{it} + \varepsilon_{it} \quad (2)$$

4.2.2.1. Pooled model

As done previously, a pooled model is utilized to see whether the IC's components, along with other considerable variables, have significant influence on bank credit risk. In this model, the heterogeneity is denied so that all banks are the same.

Table 6 shows that there is a significant negative relationship between the human capital efficiency (HCE) and the banks credit risk (CR) such that if the HCE increases by one unit, the CR will decrease by 0.07 on average. In the same context, there is a significant negative relationship between the CAR and CR; for example, if the CAR increases by one unit, the CR will decline by 0.0004. However, the sign of the structural capital efficiency (SCE) is not compatible with the theory, which says that there is a negative relationship between the SCE and CR. Yet, one cannot consider this model as the right model, because not all banks have the same structure and their individuality cannot be denied and ignored. Thus, the random or fixed effect model must be utilized.

4.2.2.2. Random effect model

As mentioned before, in this model, all banks have a common mean value at the intercept point.

Table 7 shows the same results which have been provided in Table 6, but with different magnitudes. At this point, it is appropriate to utilize the Hausman test to choose the suitable model between a random effect or a fixed effect model, before we can proceed with an interpretation of these results.

Table 6: Pooled model results (IC decomposed)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	0.094277	0.090899	1.037161	0.3002
HCE	−0.066974	0.005038	−13.29440	0.0000
SCE	0.296162	0.034087	8.688285	0.0000
CAR	−0.000464	0.000200	−2.315392	0.0210
lnTA	0.009127	0.008741	1.044252	0.2969
d(NIM_TA)	−0.139437	0.091358	−1.526265	0.1276

Table 7: Random effect model results (IC decomposed)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	0.555940	0.148005	3.756230	0.0002
HCE	−0.078434	0.005269	−14.88520	0.0000
SCE	0.271205	0.030236	8.969531	0.0000
CAR	−0.000547	0.000195	−2.807951	0.0052
lnTA	−0.024387	0.013399	−1.820083	0.0694
d(NIM_TA)	−0.083067	0.080209	−1.035638	0.3009

From Table 8, since the P-value is considerably <5%, we can conclude that the fixed effect model is the right model to be used among the above three models. Thus, the fixed effect model is utilized and its results are shown in Table 9.

4.2.2.3. Fixed effect model

Table 9 shows that there is strong statistical evidence of a negative relationship between human capital efficiency and bank credit risk, such that if HCE increases by one unit, the bank credit risk will decrease by 0.08%. Moreover, Table 9 shows that if the CAR increases by one unit, the bank credit risk will go down by 0.001%. In the same context, the fixed effect model results show that the natural log of total assets has a negative relationship with the bank credit risk so that if the lnTA increases by one unit, the bank credit risk will decrease by 0.08 on average. However, the fixed effect model results show an opposite sign of what have been seen in the literature in terms of the structural capital efficiency.

4.2.3. Bank solvency section

Similar to the bank credit risk section, this section begins its investigation with the aggregate level of intellectual capital efficiency and uses a pooled model to measure the influence of ICE and other considerable explanatory variables on bank solvency.

$$SOL_{it} = \alpha + \beta_1 ICE_{it} + \beta_2 CAR_{it} + \beta_2 lnTA_3 + \beta_4 \Delta \frac{NIM}{TA}_{it} + \varepsilon_{it} \quad (3)$$

4.2.3.1. Pooled model

In this model, individuality and heterogeneity are ignored, so that all banks are assumed to have the same structure and business models.

Table 10 shows that there is a positive relationship between all variables and the bank solvency. ICE significantly has a positive

Table 8: Correlated random effect – Hausman test

Test cross-section random effects			
Test summary	Chi-sq. statistic	Chi-sq. d.f.	Prob.
Cross-section random	38.068539	5	0.0000

Table 9: Fixed effect model results (IC decomposed)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	1.229217	0.200423	6.133120	0.0000
HCE	−0.080402	0.005487	−14.65410	0.0000
SCE	0.268164	0.030349	8.835957	0.0000
CAR	−0.000788	0.000204	−3.866838	0.0001
lnTA	−0.080573	0.017807	−4.524817	0.0000
d(NIM_TA)	−0.050112	0.080420	−0.623126	0.5335

Table 10: Pooled model results (IC Aggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	−0.586893	0.254191	−2.308867	0.0214
ICE	0.138061	0.013099	10.53974	0.0000
CAR	0.014260	0.000546	26.11495	0.0000
lnTA	0.016945	0.024526	0.690925	0.4900
d(NIM_TA)	0.587884	0.257054	2.287009	0.0226

relationship with Saudi bank solvency such that if the ICE increases by one unit, the bank's solvency will increase by 0.14% on average. In addition, an increase of the CAR by one unit will result in an increase of the bank solvency by 0.014. Furthermore, the net interest margin has a positive relationship with bank solvency as well so that if there is an increase in the net interest margin by one unit, there will be an increase in bank solvency by 0.59 units. In short, these variables will have a positive impact on bank solvency. Two sides of the same coin, these variables will have a negative impact on bank insolvency risk. However, lnTA is not statistically significant. Yet, as was the case earlier, we cannot take this result as final because we have assumed that all banks have the same structure so that the individuality is ignored, which is in fact not always true. Therefore, we need to use either a fixed effect or a random effect model.

4.2.3.2. Random effect model in bank solvency

In this model, we assume that all banks have a common mean value at the intercept point.

Table 11 shows the same results as shown in Table 10, in which the pooled model is utilized but with different magnitudes of the coefficients. However, before we go ahead and start interpreting these model results, we need to make sure it is the right model to use. Therefore, the Hausman test is again utilized to draw a coherent conclusion about which model, random effect or fixed effect should be used.

From the Hausman test in Table 12, the P-value is again considerably <5%; thus, the fixed effect model is the right one to be used in this case.

4.2.3.3. Fixed effect model

This model allows for heterogeneity among all of the banks under the study so that each bank has its own intercept.

Table 13 shows the same results that were seen in both the pooled and random models but with different magnitude of the coefficients.

Table 11: Random effect model results (IC aggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	−0.105148	0.371564	−0.282987	0.7773
ICE	0.203578	0.013744	14.81169	0.0000
CAR	0.014938	0.000523	28.54592	0.0000
lnTA	−0.053628	0.033941	−1.580013	0.1148
d(NIM_TA)	0.664971	0.223928	2.969578	0.0031

Table 12: Correlated random effect – Hausman test

Test cross-section random effects			
Test summary	**Chi-sq. statistic**	**Chi-sq. d.f.**	**Prob.**
Cross-section random	38.449056	4	0.0000

Table 13: Fixed effect model results (IC aggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	0.111004	0.559916	0.198251	0.8429
ICE	0.233258	0.014723	15.84286	0.0000
CAR	0.015188	0.000558	27.21392	0.0000
lnTA	−0.085317	0.049674	−1.717543	0.0866
d(NIM_TA)	0.687394	0.224689	3.059309	0.0024

Thus, the fixed effect model results provide statistical evidence of a positive relationship between all variables, except the lnTA, and bank solvency. In other words, a negative relationship between all variables, except the lnTA, and bank insolvency risk, two sides of the same coin. Statistically, if the IC increases by one unit, the bank solvency will increase by 0.23%. In addition, if there is an increase in CAR by one unit, there will be an increase in bank solvency by 0.015. Moreover, if there is an increase in the NIM_TA by one unit, there will be an increase in bank solvency by 0.69. We should not be too concerned about the negative sign on the coefficient for bank size (lnTA), since it is not statistically significant and might be due to collinearity between this variable and others in the equation.

4.2.4. Decomposed IC into human capital and structural capital

In this section, we extend model 3 to model 4 so that it includes each of the IC components. Thus, the ICE can be decomposed into human capital efficiency (HCE) and structural capital efficiency.

$$SOL_{it} = \alpha + \beta_1\, HCE_{it} + \beta_2\, SCE_{it} + \beta_3\, CAR_{it} + \beta_4\, lnTA_3 + \beta_5\, \Delta \frac{NIM}{TA}_{it} + \varepsilon_{it} \quad (4)$$

4.2.4.1. Pooled model

In this model, banks are treaded as the same in terms of the human capital and structural capital efficiency so that their individuality is ignored.

Table 14 shows that there is a statistically significant positive relationship between the IC components, CAR, and net interest margin as a percentage of TA and Saudi bank solvency; the opposite sign is true for the bank insolvency risk. However, the natural log of TA is not significant. Statistically, there is a positive relationship between human capital efficiency (as one of the intellectual capital components) and Saudi bank solvency, so that if there is an increase in the HCE by one unit, there will be an increase in the bank solvency by 0.13 on average. Moreover, if there is an increase in the structural capital efficiency, there will be an increase in the bank solvency by 0.35 on average. In addition, if there is an increase in CAR by one unit, there will be an increase in the bank solvency by 0.015 on average. Finally, if there is an increase in the net interest margin as percentage of total assets by one unit, there will be an increase in the bank solvency by 0.58 on average. However, lnTA is not found to be statistically significant. In fact, we cannot take these results as final, since we assumed that all banks have the same human capital efficiency and structural capital efficiency, which is not always the case. Therefore, we need to examine the influence of the IC components, along with other explanatory variables, using either a random effect or a fixed effect model.

Table 14: Pooled model results (IC disaggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	−0.649757	0.254720	−2.550868	0.0111
HCE	0.126124	0.014117	8.934163	0.0000
SCE	0.347338	0.095521	3.636246	0.0003
CAR	0.014565	0.000561	25.96314	0.0000
lnTA	0.012856	0.024493	0.524876	0.5999
d(NIM_TA)	0.579550	0.256008	2.263798	0.0240

4.2.4.2. Random effect model for banks' solvency (IC's components)

This model allows all banks to have a common mean value at the intercept point.

From Table 15, there is statistical evidence of a positive (negative) relationship between all variables, except lnTA which again is not significant, and the Saudi bank solvency (the Saudi bank insolvency risk). However, as was the case previously, we cannot consider these outcomes as final because we need to test which model is the most suitable to measure the influence of the IC components along with others variables on bank solvency. Thus, once again, the Hausman test is implemented so that we can have a coherent conclusion regarding the right model that should be used for this job.

From the Hausman test in Table 16, we reject the null hypothesis which says that the random effect model is the right model to be used, and we accept the alternative hypothesis which says the fixed effect model is a proper model for this task. Thus, the next step is to calculate a fixed effect model.

4.2.4.3. Fixed effect model for banks' solvency (IC's components)

In this model, we allow for individuality or heterogeneity among all banks under investigation.

Table 17 shows that there is statistical evidence of a positive (negative) relationship between the IC components and other variables, except lnTA, which was again found not significant, and the bank solvency (the bank insolvency risk). Thus, we can conclude that if the HCE increases by one unit, the bank solvency will increase by 0.22% on average. In addition, if there is an increase in the SCE by one unit, there will be an increase in the bank solvency by 0.51% on average. Moreover, if there is an increase in CAR by one unit, there will be an increase in the bank solvency by 0.016% on average. Nevertheless, if there is an increase in the net interest margin as percentage of total assets by one unit, there will be an increase in the bank solvency by 0.68% on average.

Table 15: Random effect model results (IC disaggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	−0.321004	0.304247	−1.055076	0.2919
HCE	0.169749	0.013646	12.43924	0.0000
SCE	0.424758	0.083108	5.110938	0.0000
CAR	0.015092	0.000516	29.26904	0.0000
lnTA	−0.037099	0.028340	−1.309096	0.1912
d(NIM_TA)	0.634862	0.221245	2.869504	0.0043

Table 16: Correlated random effect – Hausman test

Test cross-section random effects			
Test summary	Chi-sq. statistic	Chi-sq. d.f.	Prob.
Cross-section random	38.449056	4	0.0000

Table 17: Fixed effect model results (IC disaggregated)

Variables	Coefficient	Std. error	t-statistic	Prob.
C	0.071201	0.554002	0.128521	0.8978
HCE	0.219281	0.015166	14.45875	0.0000
SCE	0.506254	0.083890	6.034728	0.0000
CAR	0.015563	0.000564	27.61230	0.0000
lnTA	−0.094802	0.049221	−1.926045	0.0547
d(NIM_TA)	0.675101	0.222295	3.036963	0.0025

5. CONCLUSION

The main purpose of this study is to apply an empirical approach of investigation of the bank risk management in Saudi Arabia. More specifically, we examine how the intellectual capital (IC) and its components (human capital and structural capital) influence both of bank credit and insolvency risks. An adequate number of empirical analyses have confirmed that intellectual capital (IC) is the main driving force for the success of any organization operating in the service sector such as banks, especially in a knowledge based economy. However, most of those conducted studies only investigated the impact of intellectual capital (IC) and its components on the financial performance of a firm (profitability), and very few studies tried to investigate the IC impact on the firm risk management. Given the importance of such a topic in the banking industry, and the Saudi ultimate goal of shifting toward a knowledge-based economy, this paper examines the impact of IC on the risk management of banks operating in Saudi Arabia.

By utilizing the VAIC model developed by Pulic (1998) to obtain the effectiveness of IC and its components, and implementing several panel data techniques, the findings of this study conclude that there is a negative relationship between the intellectual capital efficiency and Saudi bank credit risk. Moreover, the magnitude of the intellectual capital coefficient toward bank risk management is greater than capital adequacy ratio (CAR), which is a very interesting finding. In context, a fixed effect model shows that there is only a negative relationship between the human capital efficiency, as one of the intellectual capital efficiency factors, and Saudi bank credit risk. The other intellectual capital efficiency factor, structural capital, is shown to have a positive sign of the coefficient, which is not compatible with the theory and the literatures. However, when it comes to bank solvency, this study has shown that the right model to be used is the fixed effect model. In this respect, the model has shown that there is a positive relationship between intellectual capital efficiency and the Saudi bank solvency, which indicates a negative impact on bank insolvency risk. This is because both bank solvency and bank insolvency risk are two sides of the same coin.

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