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# Intellectual Capital and Bank Risk in Vietnam—A Quantile Regression Approach

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**Abstract:** This study empirically presents evidence of nonlinearity and heterogeneity relation between intellectual capital and risk-taking for the Vietnamese banking system. We used quantile regression methods on a data set of 30 Vietnamese banks from 2007 to 2019. The results showed that bank insolvency was positively affected by its value-added intellectual coefficient (VAIC) at the upper quantiles (i.e., 80th and 90th), while the opposite was true for credit risk (i.e., 10th and 20th quantiles). When observing the VAIC's components, risk-taking behaviors were also significantly affected by HCE (Human Capital Efficiency), CEE (Capital Employed Efficiency) and SCE (Structural Capital Efficiency) at the 90th quantile of instability distribution and the 10th quantile of credit risk distribution. Furthermore, the results also emphasized that there was an inverse U-shaped association between intellectual capital and bank risk-taking. Therefore, this study provides important implications for policymakers, regulators, bank managers and academics that encourage increasing investment in knowledge assets to minimize bank risks in the long run.



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**Keywords:** intellectual capital; bank risk-taking; Vietnam; quantile regression

## 1. Introduction

Since the late 20th century, Intellectual Capital (IC) has been received much attention from academics and practitioners because it is recognized as the hidden factors behind the significant gap between a firm's market value and its book value (Lev 2001). Even though the idea of IC has been used for several years, there is still no clear-cut for its definition nor its classification (Sharabati et al. 2013). Nahapiet and Ghoshal (1998) define intellectual capital as the knowledge and knowing the capability of a social collectivity, such as an organization, intellectual community or professional practice. Despite no universal concept of IC, its definition still contains some common keywords, 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 (Clarke et al. 2011).

There appear three main strands in the literature. Several studies have attempted to define IC from a theoretical perspective (Bontis 1998; Wu and Tsai 2005), while other have developed effective measures of IC-based performance (Pulic 2000) or explored the relationship between IC efficiency and some key characteristics of firms, industries and regions (El-Bannany 2008; Liang et al. 2011). The last common strand focuses on the effect of IC efficiency on financial performance, especially in the banking industry. Some studies confirm that banks should manage their IC as efficiently as possible because of its significant effects (Ozkan et al. 2017). Nevertheless, to the best of our knowledge, very few studies attempt to investigate the impact of IC on bank risk-taking.

Unfortunately, these studies provide mixed findings. One may argue that larger IC can help banks survive in financial distress (Curado et al. 2014; Kaupelytė and Kairyte 2016; Onumah and Duho 2019), while the other claims the negative effect of the IC's component on bank stability (Onumah and Duho 2019). On the other hand, Ghosh and Maji (2014) emphasize that IC can reduce credit risk but there is not enough evidence to confirm its impact on bank insolvency. With regard to a certain business case, Chatzkel (2003) mentions three core issues affecting the role of intellectual capital that has been highlighted by Enron's business failure. To be more specific, the effect of moving from a more traditional trading model to an intangible intensive trading model and the requirements for a viable intellectual capital are the main points. Because of the continuous disagreement, our study revisits this issue by examining the relationship in the Vietnamese banking system.

Vietnam's economy has witnessed remarkable changes since entering the World Trade Organization (WTO) in 2007. Indeed, Vietnam is considered to become the next Asian dragon with an annual economic growth of approximately 6.2% from 2007 to 2009, compared to 8.36%<sup>1</sup> of China over the same period. In which, the Vietnamese banking system is the backbone of the economy due to the fact that the capital market is still underdeveloped (Le 2019). In order to maintain healthy and sustainable stability, this requires the quality of management, shareholder's behavior, bank's competitive strategies, efficiency and risk management capacity. The recent banking reforms emphasize that IC is one of the increasingly important factors contributing to the success of banks; therefore, it is crucial to investigate whether IC has any effect on bank risk-taking in Vietnam.

This study contributes to the extant literature in several ways. Prior studies failed to indicate the turning point of the relationship between intellectual capital and bank performance given the non-linear relation between them due to the use of the conditional mean (Le and Nguyen 2020b). Therefore, our paper adds more evidence of the effects of IC on bank risk-taking in the context of Vietnam using a quantile regression approach. First, this approach allows us to report the full conditional distribution of bank risk-taking and to determine how IC affects banks on each quantile of the conditional distribution of risk-taking. Second, our study further determines where the turning point of the impact of IC on bank risk-taking is if the U-shaped relationship between them may exist. Last but not least, we also investigate the impact of IC's components on bank risk-taking. It is evident that in addition to human capital, structural capital as banking information systems, databases, patents and copyrights along with keeping a good relationship with others, all play an important role in the process of risk management and enhancing the bank system solvency (Bayraktaroglu et al. 2019; Ghosh and Maji 2014). Therefore, we empirically investigate the IC and its components on bank risk-taking.

The paper is organized as follows. Section 2 provides a brief review of the related literature and the hypotheses formulation of the study. Section 3 presents a research method and data. Section 4 reports empirical results while Section 5 concludes.

## 2. Literature Review

Although many studies have investigated whether IC significantly contributes to firms' value creation (Bontis 1998; El-Bannany 2008; Liang et al. 2011; Pulic 2000; Wu and Tsai 2005), the concepts of IC and its components are still a subject of ongoing debate (Obeidat et al. 2017). There are several different definitions of IC across enormous disciplines and perspectives as economics, strategy, finance, accounting, human resources, reporting and disclosure, marketing and communication (Abhayawansa and Guthrie 2010; Bayraktaroglu et al. 2019). Based on the various definitions and the availability of data, researchers and practitioners thus have developed different measures and used them in different industries (Bontis 2001; Chen et al. 2004; Tayles et al. 2007). In more detail, they are divided into 4 sets: (1) Direct Intellectual Capital Methods (DIC); (2) Market Capitalization Methods (MCM); (3) Return on Assets Methods (ROA); and (4) Scorecard Methods (SC)

<sup>1</sup> As reported by the National Bureau of Statistics of China.

(Sveiby 2010). In this study, we focus on the literature on the relationship between intellectual capital and bank risk-taking where IC is measured by the VAIC method, proposed by Pulic (2004). According to Sveiby (2010), this method is categorized into Return on Assets Methods.

Most of the studies concentrate on the impact of IC and its components on the bank performance (Buallay et al. 2019; El-Bannany 2008; Meles et al. 2016) by applying the Value-Added Intellectual Coefficient (VAIC) model and traditional accounting measures (i.e., bank profitability is proxied by Return on Asset (ROA) or Return on Equity (ROE), along with the bank market value). These studies figure out a significant influence of IC and its components on the banks' financial performance in both developed and developing markets. Recently, Nazir et al. (2020) point out that intellectual capital efficiency has a significant and positive impact on the profitability of financial institutions in China, Taiwan and Hong Kong, while human capital and structural capital are significantly related to the performance of financial institutions only in China. Similarly, when investigating the Ghanaian banking industry, Duho (2020) concludes that intellectual capital has a positive impact on the slack-based technical efficiency of banks, in which human capital is the main driver.

Regarding bank risk-taking, mixed findings have been found in several studies. Notably, Ghosh and Maji (2014) indicate the impact of IC and its components on bank credit and insolvency risks. Their results show that IC is reciprocally associated with bank credit risk. Among the components, Human Capital Efficiency (HCE) is significant and negatively correlated with bank credit risk. However, they fail to draw a definite conclusion about the impact of IC on banks' insolvency risk.

Nonetheless, Curado et al. (2014) state that banks with low IC score are likely to be failed in Portugal from 2005 to 2009. In the same vein, Onumah and Duho (2019) point out a positive relationship between IC and financial performance in Ghana from 2000 to 2015. Contrary to the study of Ghosh and Maji (2014), Onumah and Duho (2019) also figures out the positive and significant relationship between IC and financial stability. However, among the IC's components, Structural Capital Efficiency (SCE) has a negative impact on both financial performance and stability while Capital Employed Efficiency (CEE) increases financial performance but reduces financial stability.

Following a similar methodology of Ghosh and Maji (2014), Kaupelytė and Kairyte (2016) investigate the impact of IC and its components on three different levels as bank profitability, effectiveness and risk management. The sample drawn in the study is based on an annual panel dataset of 118 European listed banks, covering the period of 2005–2014. The main findings of the estimated effect model show that the increase of SCE helps to increase the net interest margin in large banks. Further, an increase of HCE leads to stronger profitability ratios in small banks and better solvency ratios in large banks.

The consistency on the topic of IC and bank risk-taking is still a matter of debate. Further, the fact that banks are more opaque than other industrial firms, which leads to greater opportunities for risk-taking behaviors (Ashraf et al. 2016). From these standpoints, this study aims to provide more comprehensive evidence of the influence of IC and its components on bank risk-taking; therefore, the first hypothesis is formed as:

**Hypothesis 1.** *There is no impact of IC measures on bank risk-taking.*

In addition, following Britto et al. (2014); Haris et al. (2019), this study is the first attempt to investigate whether a U-shaped relationship between IC measures (VAIC and its components) and bank risk-taking may exist. It is argued that when IC (and its components) goes beyond a certain threshold, it may have an inverse effect on bank risk-taking. Taken together, our second hypothesis is proposed as:

**Hypothesis 2.** *There is a non-existence of a non-linear relationship between IC measures and bank risk-taking.*

### 3. Methodology and Data

#### 3.1. Methodology

Following prior studies in banking such as [Le and Nguyen \(2020b\)](#), a quantile regression method as proposed by [Koenker and Bassett \(1978\)](#) is used. This approach is comprehensively discussed by [Jiang et al. \(2020\)](#) and [Le and Nguyen \(2020b\)](#). Also, we use the asymptotic normality of a two-step estimator as introduced by [Canay \(2011\)](#) to reduce intensive computation when utilizing Koenker's technique. Hence, our quantile model is determined as follows:

$$Q_{\tau}(RISK_{it}|X_{it}) = \alpha_i + \beta_{1\tau}VAIC_{it} + \beta_{2\tau}VAIC_{it}^2 + \gamma_{\tau}B_{it} + \theta_{\tau}M_t + \varepsilon_{\tau it}, \quad (1)$$

where  $Q_{\tau}(RISK_{it}|X_{it})$  is the  $\tau$ -th quantile-regression function.  $RISK_{it}$  is risk-taking behavior of a bank  $i$  during year  $t$  and is measured by either credit risk or bank stability. Following [Le et al. \(2019\)](#), [Le et al. \(2020\)](#), [Le \(2020\)](#), bank stability is measured as  $Z\text{-score}_{it} = \frac{ROA_{it} + CAR_{it}}{\sigma_{ROA_i}}$  where  $ROA_{it}$  is the return on assets,  $CAR_{it}$  is the ratio of total equity to total assets and  $\sigma_{ROA_i}$  is the standard deviation of return on assets over the examined period. A higher value of  $Z\text{-score}$  implies a greater bank stability. Moreover, credit risk is proxied by the growth rate of the ratio of non-performing loans to total loan ( $NPL$ ) ([Alihodžić and Ekšić 2018](#); [Le and Ngo 2020](#)). It is noticeable that, in our study, an inverse of  $Z\text{-score}$  is used as a proxy of bank insolvency, denoted by  $Z$ . Hence, a greater value of both  $NPL$  and  $Z$  implies a higher level of risk-taking or less bank stability.

The literature suggests several alternative approaches to measure IC ([Bayraktaroglu et al. 2019](#)). Due to the unavailability of data used to measure IC, we use the conventional VAIC methodology since it provides a standardized and consistent measure ([Shiu 2006](#)) and considered innovative both theoretically and methodologically ([Iazzolino and Laise 2013](#)). Following prior studies such as [Pulic \(2004\)](#), [Ozkan et al. \(2017\)](#), [Tran and Vo \(2018\)](#) and others, VAIC is calculated as  $VAIC_{it} = CEE_{it} + HCE_{it} + SCE_{it}$  where  $VAIC_{it}$  represents the value added intellectual coefficient;  $CEE_{it}$  is the capital employed efficiency;  $HCE_{it}$  is the human capital efficiency; and  $SCE_{it}$  represents the structural capital efficiency. To estimate the VAIC's components, it is necessary to calculate the total value added ( $VA$ ) as follows:  $VA_{it} = OP_{it} + PC_{it} + A_{it}$  where  $OP_{it}$  is operating profit of a bank;  $PC_{it}$  represents personnel expenses (salaries, wages and other benefits);  $A_{it}$  refers to the amortization and depreciation of the bank. Then, these components of VAIC are estimated as follows  $CEE_{it} = VA_{it}/CE_{it}$  where  $CE_{it}$  is capital employed by a bank and is measured as the book value of equity.  $HCE_{it} = VA_{it}/HC_{it}$  where  $HC_{it}$  refers to personnel expenses.  $SCE_{it} = SC_{it}/VA_{it}$  where  $SC_{it}$  represents structural capital and is measured as  $SC_{it} = VA_{it} - HC_{it}$ .

The literature proposes that increasing the efficiency of intellectual capital is the cheapest and safest way to ensure the sustainable operation of banks, thereby preventing banks from risk-taking. However, it can be difficult to use intangible resources efficiently. Also, higher investment in human and structural capital could reduce bank stability if management does not produce more efficiency. Therefore, we include the quadratic terms of VAIC ( $VAIC^2$ ) and its components ( $SCE^2$ ,  $HCE^2$  and  $CEE^2$ ) to investigate the existence of a U-shaped relationship between them and bank risk-taking.

$B_{it}$  is a set of bank-specific and market-specific variables. These variables chosen in the study are similar but not identical to those adopted in prior studies, so as to better reflect the Vietnamese institutional and regulatory framework. For instance,  $LERN$ , the Lerner index to measure bank market power by price (or marginal cost to price) ([Koetter et al. 2008](#)). The higher the market power a bank has, the fewer incentives for it to take risky projects.  $LOAN$ , the ratio of total loans to total assets, is used to control for the effect of lending specialization ([Le 2018](#)). Several studies show a positive impact of bank loans on bank profitability. [Ben Naceur and Goaid \(2008\)](#) and [Saona \(2016\)](#) suggest that risk-averse shareholders seek higher earnings to compensate for higher risk because loans have higher operational costs as they need to be originated, serviced and monitored. Bank inefficiency is measured by a cost-to-income ratio ( $CIR$ ) ([Le 2017](#)). More efficient banks may control

operating or monitor borrowers efficiently thus having lower risk. Alternatively, banks may skimp on operating costs by relaxing the procedure of credit monitoring and collateral valuation to accomplish short-run economic efficiency. These activities may in turn reduce loan quality, thus leading to higher risk [Ghosh and Maji \(2010\)](#).

For market-specific conditions, the Herfindahl-Hirschman concentration index (*HHI*) in terms of total assets is used to account for the effect of bank concentration ([García-Herrero et al. 2009](#)). *HHI* is estimated by the sum of squared of banks' market share in total assets. A greater value of *HHI* implies greater market concentration. An increase in bank profits and the franchise value is related to a highly concentrated market due to reduced competitive pressure and higher market power. Therefore, bank managers are less incentive to take more risky investments.

Finally, we also incorporate two variables annual economic growth rate (*GDP*) and annual inflation rate (*INF*), represented by  $M_t$  (a set of time-varying macroeconomic control variables), in the model to capture the possible effect of the business cycle on bank risk-taking.

### 3.2. Data

The data was manually gathered from the audited financial reports of individual banks from 2007 to 2019 on a consolidated basis according to Vietnamese Accounting Standards. It is worth noting that only 30 domestic commercial banks were considered in our study since 100% foreign-owned banks, joint-venture banks and foreign affiliates have faced some limitations on operating activities in the Vietnamese financial market. These banks together account for approximately 80% of total assets in the whole banking system. Due to several merger and acquisition activities in the examined period, an unbalanced panel data of 353 observations were obtained.<sup>2</sup> Furthermore, the data on macroeconomic conditions were collected from the World Bank database. Table 1 provides the descriptive statistics of the variables used in this study.

**Table 1.** The descriptive statistics of variables.

Variables	Obs.	Mean	SD	Min	Q (10)	Median	Q (90)	Max
Z	353	0.024	0.117	0.001	0.002	0.005	0.042	1.732
NPL	353	0.149	0.722	−0.550	−0.243	0.020	0.861	10.927
VAIC	353	4.783	2.278	−2.452	2.893	4.439	6.804	19.452
CEE	353	0.289	0.138	−0.045	0.145	0.276	0.488	0.826
HCE	353	3.775	2.147	−0.737	2.100	3.407	5.651	18.636
SCE	353	0.668	0.279	−2.767	0.533	0.706	0.823	2.356
LERN	353	0.105	0.033	0.069	0.071	0.101	0.158	0.169
LOAN	353	0.547	0.137	0.113	0.365	0.566	0.713	0.851
CIR	353	0.154	0.076	0.040	0.080	0.140	0.220	0.640
HHI	353	0.087	0.014	0.072	0.077	0.081	0.117	0.119
GDP	353	0.062	0.007	0.052	0.054	0.062	0.071	0.084
INF	353	0.076	0.062	0.006	0.026	0.065	0.186	0.231

The data shown in Table 1 indicate that among the three components of *VAIC*, *HCE* accounts for the highest proportion of *VAIC*. This is comparable with those of [Ozkan et al. \(2017\)](#) in Turkey and [Tran and Vo \(2018\)](#) in Thailand. Because there appear some negative *HCE* values, this arrives at some negative *VAIC* values due to negative *HCE* values. Negative *HCE* value is explained by the fact that banks make a loss while still paying salaries ([Le and Nguyen 2020a](#)). The same reasons are also used to explain the negative values of *CEE* and *SCE*.

Table 1 also shows that the 10th and 90th quantiles of *Z* are approximately 0.0% and 4.2%, while these figures of *NPL* are −55% and 86.1%, respectively. This indicates risk-

<sup>2</sup> For further discussion on merger and acquisition activities in the Vietnamese banking system, please see [Le \(2017\)](#).

taking, measured by bank insolvency, varies a lot from lower quantile to higher quantile. Moreover, the histogram of *Z* and *NPL* (presented in Figure 1) illustrates the skewed and heavily right-tail distribution. Such fact further reinforces the necessity of a quantile approach. Though the standard conditional mean method can be appropriate to model average risk, it cannot provide an accurate description of risk spread (Le and Nguyen 2020b; Pires et al. 2015). Additionally, we also examine whether multicollinearity among independent variables may exist. Tables 2 and 3 present the results of the correlation matrix and variance inflation factor (VIF) values, respectively. Although there is a relatively high correlation between *LERN* and *INF*, their *VIF* values are less than 10, suggesting that there is no multicollinearity among them.<sup>3</sup> Furthermore, we run the same model when including *LERN* and *INF* separately and then the same results are obtained.<sup>4</sup>

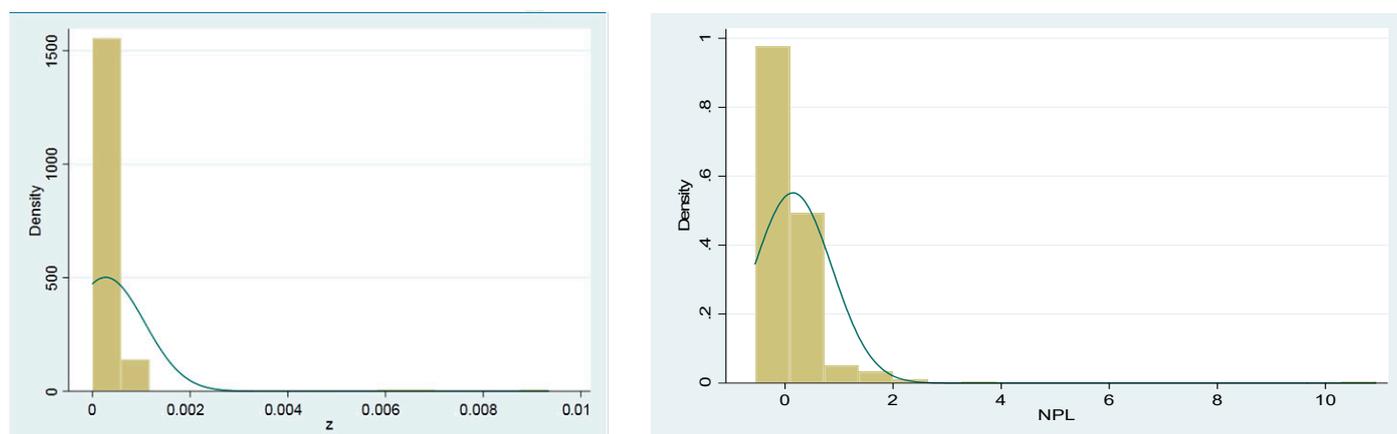


Figure 1. Histogram for *Z* and *NPL*.

Table 2. Correlation matrix.

	Z	NPL	VAIC	CEE	HCE	SCE	LOAN	LERN	CIR	HHI	GDP	INF
Z	1.000											
NPL	−0.040	1.000										
VAIC	0.089	0.105	1.000									
CEE	0.279	−0.101	0.207	1.000								
HCE	0.067	0.115	0.320	0.130	1.000							
SCE	0.070	0.047	0.586	0.176	0.507	1.000						
LOAN	0.043	−0.169	−0.129	0.326	−0.149	−0.124	1.000					
LERN	0.104	0.132	0.305	−0.059	0.308	0.220	−0.367	1.000				
CIR	−0.006	−0.058	−0.171	−0.002	−0.157	−0.240	0.038	−0.288	1.000			
HHI	0.026	−0.069	−0.007	0.417	−0.039	0.004	0.391	0.018	0.158	1.000		
GDP	−0.106	−0.149	−0.094	0.188	−0.107	−0.068	0.264	−0.469	0.082	−0.046	1.000	
INF	0.084	0.127	0.298	−0.013	0.296	0.224	−0.335	0.959	−0.280	0.014	−0.361	1.000

Table 3. Variance Inflation Factor (VIF) results.

Variable	VIF (Z)	VIF (NPL)	VIF (Z)	VIF (NPL)
VAIC	1.11	1.14	-	-
CEE	-	-	1.40	1.42
HCE	-	-	1.42	1.39
SCE	-	-	1.43	1.41
LOAN	1.48	1.41	1.53	1.45

<sup>3</sup> Any VIF exceeding 10 indicates a problem of multicollinearity (Hair et al. 2010).

<sup>4</sup> The table of results cannot be presented here due to the length restriction. However, they are available upon request.

Table 3. Cont.

Variable	VIF (Z)	VIF (NPL)	VIF (Z)	VIF (NPL)
LERN	8.03	5.46	7.06	5.50
CIR	1.16	1.22	1.20	1.32
HHI	1.30	1.32	1.50	1.58
GDP	1.99	1.49	2.03	1.51
INF	6.57	4.16	5.60	4.18
Mean VIF	3.09	2.31	2.57	2.20

## 4. Results

### 4.1. Quantile Regression Analysis

Early studies suggest that the ordinary least squares (OLS) regression might have seriously under or overestimate effects in heterogeneous distributions (Cade and Noon 2003; Le and Nguyen 2020b). Therefore, the results of pooled OLS and panel OLS with fixed effects are not presented here due to the length restriction.

As the previous traditional regressions have not strongly explained the impacts of IC on bank insolvency though they can provide a good estimation of the bank credit risk. Moreover, neither of them can capture the whole distribution of conditional bank stability. Hence, we employ quantile regression to address the heterogeneity effects among variables along with the quantile distribution. For ease of exposition, we only focus on interpreting our main interest variables.

Tables 4–7 present baseline results using panel quantile regression methods when bank risk-taking is proxied by both Z and NPL, respectively. Estimated coefficients are reported for the 10th, 20th, 25th, 50th, 75th, 80th and 90th percentiles of the conditional distribution of bank risk-taking. From these tables, some interesting findings can be drawn as the following.

Table 4. Baseline results for Z and VAIC: Quantile regression.

Quantiles	0.10	0.20	0.25	0.50	0.75	0.80	0.90
VAIC	0.000 (0.000)	0.000 (0.002)	0.005 (0.005)	0.014 (0.012)	0.021 (0.018)	0.028 ** (0.022)	0.032 ** (0.025)
VAIC <sup>2</sup>	−0.000 (0.000)	−0.000 (0.001)	−0.001 (0.000)	−0.008 (0.004)	−0.013 (0.006)	−0.019 ** (0.010)	−0.024 ** (0.016)
LERN	0.000 (0.000)	0.000 (0.000)	0.000 (0.011)	0.155 (0.169)	0.292 (0.250)	0.475 (0.333)	0.281 (0.482)
LOAN	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	0.021 * (0.012)	0.059 *** (0.180)	0.054 ** (0.022)	0.021 * (0.034)
CIR	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.001)	0.011 (0.020)	0.009 (0.029)	−0.007 (0.037)	0.045 (0.056)
HHI	0.000 (0.000)	−0.000 (0.001)	−0.000 (0.017)	0.123 (0.248)	−0.716 ** (0.417)	−0.939 ** (0.457)	−1.090 (0.691)
GDP	0.000 (0.000)	−0.000 (0.001)	−0.000 (0.015)	−0.059 (0.255)	−0.515 (0.387)	−0.578 (0.425)	−0.653 (0.642)
INF	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.002)	−0.047 (0.034)	−0.036 (0.056)	−0.010 (0.061)	−0.067 (0.093)
Constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	−0.025 (0.025)	−0.026 (0.037)	0.004 (0.032)	−0.028 (0.072)
No. Obs	320	320	320	320	320	320	320
Pseudo R <sup>2</sup>	0.000	0.000	0.000	0.065	0.071	0.082	0.102

Note: This table presents pooled quantile regression for the 10th, 20th, 25th, 50th, 75th, 80th and 90th quantiles. The dependent variable is Z. Standard errors are in parentheses. \*, \*\* and \*\*\* denote statistical significance at 10%, 5% and 1%, respectively.

**Table 5.** Baseline results for *NPL* and *VAIC*: Quantile regression.

Quantiles	0.10	0.20	0.25	0.50	0.75	0.80	0.90
VAIC	0.001 ** (0.005)	0.002 * (0.007)	0.004 (0.005)	−0.002 (0.007)	−0.008 (0.011)	−0.001 (0.001)	−0.003 (0.002)
VAIC <sup>2</sup>	−0.001 *** (0.000)	−0.001 * (0.000)	−0.003 ** (0.005)	0.001 (0.003)	0.007 (0.000)	0.005 (0.000)	0.006 (0.000)
LERN	0.000 (0.000)	0.000 (0.000)	0.000 (0.011)	0.143 (0.169)	0.281 (0.250)	0.475 (0.333)	0.281 (0.482)
LOAN	0.000 (0.000)	0.000 * (0.000)	0.000 (0.001)	0.021 * (0.012)	0.046 (0.180)	0.034 (0.022)	0.021 ** (0.034)
CIR	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.001)	0.011 (0.020)	0.009 (0.029)	−0.007 (0.037)	0.045 (0.056)
HHI	0.000 (0.000)	−0.000 (0.001)	−0.000 (0.017)	0.123 (0.248)	−0.716 (0.417)	−0.939 (0.457)	−1.090 * (0.691)
GDP	0.000 (0.000)	−0.000 (0.001)	−0.000 (0.015)	−0.059 (0.255)	−0.515 (0.387)	−0.578 (0.425)	−0.653 (0.642)
INF	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.002)	−0.047 (0.034)	−0.036 (0.056)	−0.010 (0.061)	−0.067 (0.093)
Constant	0.033 (0.009)	0.034 (0.007)	0.028 (0.008)	0.044 (0.011)	0.065 (0.016)	0.089 (0.020)	0.131 (0.035)
No. Obs.	367	367	367	367	367	367	367
Pseudo R <sup>2</sup>	0.125	0.105	0.126	0.178	0.253	0.277	0.346

Note: This table presents pooled quantile regression for the 10th, 20th, 25th, 50th, 75th, 80th and 90th quantiles. The dependent variable is *NPL*. Standard errors are in parentheses. \*, \*\* and \*\*\* denote statistical significance at 10%, 5% and 1%, respectively.

Regarding the insolvency of the bank (*Z*), the coefficient of *VAIC* in Table 4 is generally positive and significant at the 80th and 90th quantiles. However, the sign of *VAIC*<sup>2</sup> becomes negative, which verifies the nonlinearity U-shaped character of the impact of *VAIC*. The signs of *VAIC* imply that increasing investment in intellectual capital is likely to increase bank instability; however, this effect is reversed when *VAIC* investment reaches a certain threshold. These findings are consistent with [Onumah and Duho \(2019\)](#). Further, the same results are also found in credit risk (*NPL*), at the 10th and 20th quantiles.

When observing *VAIC*'s components (*CEE*, *HCE*, *SCE*), Table 6 shows the significant impact of *HCE* and *SCE* on *Z* at the 90th quantiles, while that of *CEE* is at 75th and 90th quantiles. A positive relationship between *HCE* and *Z* is in the line with the results of [Ghosh and Maji \(2014\)](#), demonstrating that investment entering *HCE* will increase bank insolvency because banks are too confident in participating in risky projects in short-term periods. However, we find an inverse U-shaped relationship between these variables, demonstrating a higher investment in human capital can enhance bank stability in the long run. On the other hand, the negative relationship between *SCE* and *Z* indicates that a bank, with well-controlled databases of policies and procedures, is less risky and more stable. This finding is consistent with the study of [Ghosh and Maji \(2014\)](#) but is in contrast to [Onumah and Duho \(2019\)](#). Nevertheless, too many investments in *SCE* may inversely impact bank risk-taking. Moreover, Table 7 also shows the significant relationship between *NPL* and *HCE* at the 10th quantile, while other components, unfortunately, show insignificant coefficients. Again, the results of *HCE* and *NPL* are the same as those of *Z*.

Additionally, the results from these tables also figure out several interesting points. First, we find that the coefficients of *VAIC* (and *VAIC*<sup>2</sup>) are statistically significant in higher quantiles (i.e., 80th and 90th) of *Z*, while the opposite is true for *NPL* (i.e., 10th and 20th). Second, the absolute values of estimated coefficients are different for each quantile. The magnitude is increasing from lower to higher quantiles in the distribution. Such variation validates our concerns of heterogeneity among coefficients. For the case of bank stability, Table 4 shows the estimated coefficient of *VAIC* at the 90th quantile is 0.032, higher than

that of the 80th quantile (0.028). Similarly, the estimated coefficient of  $VAIC^2$  at the 90th quantile is  $-0.024$ , while that of the 80th quantile is  $-0.019$ . Similar findings are also found in Table 5 in regard to the relationship between  $VAIC$  and  $NPL$ .

In order to provide further insights into the non-linear relationship between IC measures and bank risk-taking, we need to estimate the turning points. It should be noted that evidence would support the inverted U-shaped relationship at the  $\tau$  quantile if  $\beta_{1\tau} > 0$  and  $\beta_{2\tau} < 0$  where  $\beta_{1\tau}$  and  $\beta_{2\tau}$  denote the coefficients of linear and quadratic terms of  $VAIC$  at  $\tau$  quantile, respectively. The turning point level of  $VAIC$  is calculated as  $VAIC_{\tau}^* = -\frac{\beta_{1\tau}}{2\beta_{2\tau}}$ .

More specifically, the value of turning points of the U-shaped relationship tends to be relatively small at lower quantiles and then start to increase at higher quantiles. For instance, when conditional bank insolvency is high at the 80th quantile, the turning point is 73.6%. This argues that the effect of investment in intellectual capital on bank instability will turn from positive to negative when  $VAIC$  exceeds about 73.6%. This critical level will reduce to 66.6% at the 90th quantile, implying that investments in IC may initially induce higher risk but then will gradually stabilize banks. For the  $VAIC$ 's components, the turning point of  $HCE$  is 69.0% and  $SCE$  is 26.4% at the 90th quantile.

**Table 6.** Baseline results for Z and  $VAIC$ 's components: Quantile regression.

Quantiles	0.10	0.20	0.25	0.50	0.75	0.80	0.90
CEE	0.000 (0.000)	-0.000 (0.005)	-0.000 (1.180)	0.029 (0.044)	0.103 * (0.057)	0.067 (0.082)	0.202 * (0.108)
CEE <sup>2</sup>	-0.000 (0.000)	0.000 (0.007)	0.000 (1.510)	0.038 (0.058)	-0.021 (0.075)	0.007 (0.108)	-0.168 (0.141)
HCE	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.062)	0.006 (0.002)	0.015 (0.008)	0.024 (0.015)	0.029 * (0.020)
HCE <sup>2</sup>	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.003)	-0.003 (0.002)	-0.009 (0.008)	-0.015 (0.012)	-0.021 * (0.015)
SCE	0.000 (0.000)	-0.000 (0.002)	-0.000 (0.422)	-0.003 (0.017)	-0.005 (0.021)	-0.006 (0.031)	-0.070 * (0.040)
SCE <sup>2</sup>	0.000 (0.000)	0.000 (0.001)	0.000 (0.220)	0.003 (0.009)	0.009 (0.011)	0.009 (0.016)	0.037 * (0.021)
LERN	0.000 (0.000)	0.000 (0.000)	0.000 (0.040)	0.200 (0.169)	0.502 ** (0.220)	0.553 * (0.315)	0.395 (0.413)
LOAN	0.000 ** (0.000)	0.000 (0.001)	0.000 (0.516)	0.012 (0.012)	0.036 ** (0.016)	0.050 ** (0.023)	0.046 (0.030)
CIR	-0.000 * (0.000)	-0.000 (0.002)	-0.000 (0.503)	-0.007 (0.020)	0.032 (0.026)	0.052 (0.037)	0.103 (0.049)
HHI	-0.000 (0.000)	-0.000 (0.035)	-0.000 (6.607)	-0.205 (0.265)	-1.080 *** (0.344)	-1.221 ** (0.493)	-1.725 *** (0.647)
GDP	-0.000 *** (0.000)	-0.000 *** (0.031)	-0.000 (5.903)	-0.215 (0.258)	-0.302 (0.335)	-0.203 (0.480)	-1.044 * (0.629)
INF	-0.000 (0.000)	-0.000 (0.004)	-0.000 (0.832)	-0.117 (0.106)	-0.312 ** (0.138)	-0.305 (0.198)	-0.171 (0.259)
Constant	0.000 (0.000)	0.000 (0.002)	0.000 (0.557)	-0.009 (0.025)	-0.046 (0.033)	-0.062 (0.047)	-0.003 (0.062)
No. Obs	320	320	320	320	320	320	320
Pseudo R <sup>2</sup>	0.000	0.000	0.000	0.118	0.152	0.158	0.189

Note: This table presents pooled quantile regression for the 10th, 20th, 25th, 50th, 75th, 80th and 90th quantiles. The dependent variable is Z. Standard errors are in parentheses. \*, \*\* and \*\*\* denote statistical significance at 10%, 5% and 1%, respectively.

**Table 7.** Baseline results for *NPL* and *VAIC*'s components: Quantile regression.

Quantiles	0.10	0.20	0.25	0.50	0.75	0.80	0.90
CEE	0.050 (0.015)	0.044 (0.015)	0.045 (0.017)	0.035 (0.020)	−0.045 (0.035)	−0.067 (0.040)	−0.168 (0.068)
CEE <sup>2</sup>	−0.050 ** (0.020)	−0.045 (0.020)	−0.044 (0.023)	−0.041 (0.027)	0.045 (0.048)	0.063 (0.054)	0.172 (0.092)
HCE	0.001 ** (0.000)	0.005 (0.000)	0.004 (0.000)	−0.005 (0.000)	−0.003 (0.001)	−0.003 (0.001)	−0.001 (0.003)
HCE <sup>2</sup>	−0.001 ** (0.000)	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
SCE	−0.003 (0.002)	0.009 (0.002)	0.009 (0.002)	0.015 (0.002)	0.017 (0.005)	0.016 (0.00)	0.012 (0.010)
SCE <sup>2</sup>	0.002 (0.001)	0.003 (0.001)	0.003 (0.001)	0.004 (0.001)	0.003 (0.002)	0.002 (0.003)	−0.001 (0.004)
LERN	0.000 (0.000)	0.000 (0.000)	0.000 (0.040)	0.200 (0.169)	0.502 (0.220)	0.553 * (0.315)	0.395 (0.413)
LOAN	0.000 ** (0.000)	0.000 (0.001)	0.000 (0.516)	0.012 (0.012)	0.036 (0.016)	0.050 ** (0.023)	0.046 (0.030)
CIR	−0.000 * (0.000)	−0.000 (0.002)	−0.000 (0.503)	−0.007 (0.020)	0.032 (0.026)	0.052 (0.037)	0.103 (0.049)
HHI	−0.000 (0.000)	−0.000 (0.035)	−0.000 (6.607)	−0.205 (0.265)	−1.080 (0.344)	−1.221 ** (0.493)	−1.725 * (0.647)
GDP	−0.000 * (0.000)	−0.000 ** (0.031)	−0.000 (5.903)	−0.215 (0.258)	−0.302 (0.335)	−0.203 (0.480)	−1.044 * (0.629)
INF	−0.000 (0.000)	−0.000 (0.004)	−0.000 (0.832)	−0.117 (0.106)	−0.312 ** (0.138)	−0.305 (0.198)	−0.171 (0.259)
Constant	0.004 (0.003)	0.009 (0.003)	0.006 (0.003)	0.006 (0.004)	0.020 (0.007)	0.026 (0.008)	0.131 (0.035)
No. Obs.	367	367	367	367	367	367	367
Pseudo R <sup>2</sup>	0.101	0.062	0.059	0.072	0.099	0.118	0.139

Note: This table presents pooled quantile regression for the 10th, 20th, 25th, 50th, 75th, 80th and 90th quantiles. The dependent variable is *NPL*. Standard errors are in parentheses. \* and \*\* denote statistical significance at 10% and 5%, respectively.

For the 10th quantile of the credit risk (*NPL*), the turning point of *VAIC* is 50%, suggesting that the impact of investment in intellectual capital on a bank's risk appetite will turn from negative to positive when *VAIC* exceeds about 50%. For banks in the 20th quantile of *NPL* conditional distribution, the number is up to about 100%. When breaking down, the turning point of *HCE* is also 50% at the 10th quantile.

#### 4.2. Inter-Quantile Difference

Our findings specify that the impact of *VAIC* and its components on bank risk-taking is heterogeneous across the distributions of *Z* and *NPL*. To test whether or not these differences are statistically significant, following [Koenker and Bassett \(1978\)](#), the inter-quantile regressions are utilized to check for slope equality throughout the quantiles. The estimated coefficients of inter-quantile regressions are exactly the difference in coefficients of two quantiles regressions estimated separately and the estimated variance-covariance matrixes are obtained using bootstrapping methods with 200 bootstrap replications. We only present statistically significant results between upper quantiles (the 90th, 80th and 75th quantiles) and the lower quantiles (the 10th, 20th and 25th quantiles).

Table 8 indicates that heterogeneity among coefficients does exist even when controlling bank-specific and macro factors. Regarding bank insolvency, banks in upper quantiles generally have greater estimated coefficients in absolute of *VAIC* and *VAIC*<sup>2</sup>. For example,

the difference between the upper quantile and the lower quantile  $Q(90/10)$  for  $VAIC$  and  $VAIC^2$  are 0.009 and  $-0.001$ , respectively, which are statistically significant at the 1% level. Table 9, on the other hand, shows only the differences in  $Q(90/10)$  for  $HCE$  and  $HCE^2$ , at 0.017 and  $-0.009$ .

In terms of credit risk, in  $Q(90/10)$  for  $VAIC$  and  $VAIC^2$ , the figures are 0.004 and  $-0.001$  and are statistically significant at 5% and 10%, respectively. Meanwhile, the difference in  $Q(90/10)$  for  $HCE$  is 0.001. Unfortunately, the coefficients of  $HCE^2$  and other components are not statistically significant.

Overall, our empirical results indicate that the influence of intellectual capital on bank risk-taking is not only U-shape but also heterogeneous across the risk-taking distribution.

Regarding the other variables, we only concentrate on interpreting those with their significant coefficients in inter-quantile regression. Accordingly,  $CIR$  is only positively and significantly associated with  $Z$  at the higher quantiles, thus the skimp costs hypothesis may hold. Accordingly, banks may skip on operating costs through a lax approach to credit monitoring and collateral valuation to achieve short-run economic efficiency, which, in turn, reduces loan quality and thus leading to higher insolvency (Le 2018). Besides, a positive relationship between  $HHI$  and bank risk-taking points out that a more competitive banking system is related to lower bank risk-taking. This confirms the early view of Le et al. (2020); Mirzaei et al. (2013). Finally, a negative impact of  $GDP$  on  $Z$  supports the traditional opinion that there appears an increasing demand for banks' services and products during the cyclical upswings of the economy, which results in higher bank profitability.

**Table 8.** The results of inter-quantile regression VAIC.

Inter-Quantile	Z			NPL
	(90–10)	(80–20)	(75–25)	(90–10)
VAIC	0.009 *** (0.004)	0.019 *** (0.002)	0.028 *** (0.002)	0.004 ** (0.004)
VAIC <sup>2</sup>	-0.001 *** (0.000)	-0.012 *** (0.000)	-0.015 ** (0.000)	-0.001 * (0.000)
LERN	0.003 (0.004)	0.476 (0.323)	0.292 (0.309)	0.001 (0.003)
LOAN	0.059 (0.052)	0.053 (0.030)	0.059 *** (0.013)	0.021 (0.032)
CIR	0.081 (0.105)	-0.001 * (0.049)	0.009 (0.031)	0.031 (0.027)
HHI	-0.167 (0.716)	-0.744 *** (0.259)	-0.863 *** (0.238)	-0.005 ** (0.012)
GDP	-0.213 (0.602)	-0.380 (0.409)	-0.466 (0.381)	0.032 (0.235)
INF	-0.125 (0.346)	-0.249 (0.202)	-0.138 (0.188)	0.013 (0.032)
Constant	-0.034 (0.108)	-0.037 (0.041)	-0.027 (0.037)	0.097 (0.037)
No. Obs	320	320	320	367

Notes: This table shows the difference in quantile regression estimates for an inter-quantile regression:  $Q(75/25) = Q_{0.75}(y) - Q_{0.25}(y)$ ,  $Q(80/20) = Q_{0.80}(y) - Q_{0.20}(y)$  and  $Q(90/10) = Q_{0.90}(y) - Q_{0.10}(y)$ . The bootstrapped cluster standard errors (in parentheses) are obtained with 200 bootstrap replications. \*, \*\* and \*\*\* denote statistical significance at 10%, 5% and 1%, respectively.

**Table 9.** The results of inter-quantile regression VAIC's components.

Inter Quantile	Z	NPL
	(90–10)	(90–10)
CEE	0.202 (0.083)	0.216 (0.083)
CEE <sup>2</sup>	−0.168 (0.113)	−0.242 (0.122)
HCE	0.017 ** (0.022)	0.001 * (0.004)
HCE <sup>2</sup>	−0.009 * (0.002)	−0.000 (0.000)
SCE	−0.070 (0.062)	−0.014 (0.044)
SCE <sup>2</sup>	0.037 (0.083)	0.002 ** (0.001)
LERN	0.395 (0.362)	0.247 (0.432)
LOAN	0.103 * (0.055)	0.012 (0.028)
CIR	−1.725 * (0.311)	0.023 (0.012)
HHI	−1.044 *** (0.564)	−0.143 * (0.023)
GDP	−0.171 * (0.233)	−0.176 (0.132)
INF	−0.003 (0.053)	−0.005 (0.032)
Constant	0.202 (0.083)	0.082 (0.030)
No. Obs	320	367

Notes: This table shows the difference in quantile regression estimates for an inter-quantile regression:  $Q(90/10) = Q_{0.90}(y) - Q_{0.10}(y)$ . The bootstrapped cluster standard errors (in parentheses) are obtained with 200 bootstrap replications. \*, \*\* and \*\*\* denote statistical significance at 10%, 5% and 1%, respectively.

#### 4.3. Robustness Checks

It may be concerned that our study on the relationship between IC measures (VAIC and its components) and bank risk-taking may be affected by latency and indigenoussness. More specifically, omitted variables and reverse causality are the most important and common problems that can lead to biased inconsistent parameter estimates. Therefore, we re-estimate the model under the two-step system General Moment Method (GMM) and the explanatory variables change with time delay in one year to avoid concurrency. For the sake of brevity, we only report our main interest variables. The results, as shown in Table 10, again confirm our above findings.

**Table 10.** VAIC, VAIC's components and Z, using system GMM.

	Z		NPL	
	VAIC	VAIC's Components	VAIC	VAIC's Components
$\pi_{t-1}$	0.170 *** (0.005)	0.069 ** (0.028)	0.076 *** (0.020)	0.075 *** (0.017)
VAIC	0.135 *** (0.026)		0.133 *** (0.045)	
CEE		4.248 *** (0.641)		−0.363 (0.820)
HCE		0.053 ** (0.024)		0.092 ** (0.044)
SCE		−1.725 *** (0.454)		−0.331 (0.204)
Constant	2.053 (0.223)	3.773 (0.629)	−2.112 (0.478)	−1.546 (0.294)
No. Obs.	291	291	309	309
No. of Groups	30	30	30	30
AR1 ( <i>p</i> -value)	0.056	0.064	0.001	0.002
AR2 ( <i>p</i> -value)	0.377	0.336	0.558	0.348
Hansen test ( <i>p</i> -value)	0.883	0.956	0.239	0.837

Notes: The table contains the results estimated using the system GMM estimator. Variables in italics are instrumented through the GMM procedure following [Arellano and Bover \(1995\)](#). Robust standard errors are in parentheses. \*\* and \*\*\*Significant at 5 and 1 per cent levels, respectively.

## 5. Conclusions

This study investigated the impact of VAIC and its components on the risk-taking behaviors of the Vietnamese banking system from 2007 to 2019 using the quantile regression method. Our study contributes to the literature by uncovering a non-linear U-shaped feature of intellectual capital (and its components) that is previously unidentified. Our main results also highlight the heterogeneity of sensitivity to intellectual capital across banks with different risk-taking levels. These results pass a robustness test of potential endogeneity, hence, provide strong evidence for our claim that there exists pronounced nonlinear heterogeneous intellectual capital impact among Vietnamese banks.

This study provides several directions for policymakers and bank managers to target at preventing banks from taking the disproportional risk. First, intellectual capital may hamper bank stability in the short term, however, investments in intellectual capital would increase stability at a certain threshold. Second, among three components of intellectual capital, structural capital (i.e., a well-controlled database of policies and procedures), however, should be moderately invested because they may threaten the bank stability if they are excessively financed.

The study has some limitations. The alternative measures of intellectual capital and risk-taking may be used to confirm our main findings. Furthermore, our study covers one emerging market and a limited period of study, suggesting that the need for future research in other emerging nations that have similar banking structure for the robustness of the results.

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