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Operational Risk, Bank Size and the Financial Performance of Commercial Banks in Kenya

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Abstract

Operational risk threatens banks financial viability and long-term sustainability. The purpose of this paper is to explore the effect of operational risk on financial performance of commercial banks in Kenya. The qualitative research design and ordered logistic model were employed. The data was analysed with the aid of STATA software. The conclusion of the study was that there exists an inverse relationship between operational risk and financial performance. The study also finds that bank size moderates the effect internal and external fraud on financial performance of commercial banks in Kenya by shrinking it. Bank size moderates the effect execution, delivery and process management on financial performance of commercial banks in Kenya by enhancing it. Commercial banks' management should adhere to the guidelines and procedures provided by the Central bank of Kenya on operational risk management.

Keywords: *Operational Risk, Bank size, Financial Performance, Commercial Banks.*

JEL Classification: G21, G32, O16, L25

Introduction

Operational risk threatens the financial stability and performance of financial sector. It is defined as all risks which would generate volatility in a bank's reserves, expenses and the value of its business (Basel Committee on Bank Supervision, 2006). It is the loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk which is the loss arise from events such as internal and external fraud, employment practices and workplace safety clients, products and business practices, damage to physical assets, business disruption and system failures, and execution, delivery and process management. It is based on the underlying causes of operational risk. If operational risk is not addressed systematically it can result into inconsistent performance and earnings for the stakeholders and impact a banks' revenues and net worth sometimes with disastrous systemic consequences as demonstrated by the Hess, 2011; Andersen et al., 2012; Cagan, 2009; Kirkpatrick, 2009; Robertson, 2011 and Rose, 2009 on the role played by operational risk in the 2007/08 financial crisis. Hence, the pricing and the consequent measurement of the operational risk capital charge has to be adequate to cover for these losses.

Literature Review

Extant literature on the measurement of operational risk point to a bias for quantitative measures. Moscadelli (2004), Embrechts *et al*., (2006) and Dutta and Perry (2007) have modelled Extreme Value Theory, while Schevchenko and Wuthrich (2006) apply Bayesian inference, Ramamurthy *et al.,* (2005) on the other hand adopts dynamic Bayesian networks and Bee, (2006) uses expectation maximization algorithms. These and a host of other quantitative approaches rely on what Hiwatashi and Ashida (2002) refer to as the quantitative layer of operational risk measurement mainly focusing on value at risk (VaR). The accuracy of the VaR estimate has however been argued to be is very dependent on the number of data points used as well on the particular model assumed. (Dahen, Dionne and Zajdenweber 2010). The VaR estimate has also been found to be very sensitive to the extreme losses observed, especially if data are sparse, which is frequently encountered when only internal data are used.

The qualitative layer, an equally important aspect of operation risk measurement, has received very little attention. In proposing the Standardized Measurement Approach (SMA) for operational risk, the Basel Committee on Bank Supervision (2016) point to the significance of descriptive information though it does not provide a direction on how such qualitative information may be integrated into the measurement framework. Additionally, in stressing the importance of qualitative information, Boller, Gregoire and Kawano (2015) argue that beyond pure quantitative data (e.g., costs, frequency), the capturing and understanding of qualitative information are critical. Qualitative information describes the causal drivers of operational risk and interdependencies with other risks and circumstances. It has been suggested that expert opinion is very important in operational risk management as it is more current forward looking than historical loss event data. As De Jongh *et al*, (2013) point out, the issue of scaling is a very important issue when incorporating external data and exactly how expert opinion should be incorporated remains a pertinent research issue. A thread of research towards this direction is that of Agostini, Talamo and Vecchione (2011) who propose an integration model that allows integrated parameter estimation through the use of historical loss events and expert opinion. Dahen and Dionne (2010) on the other hand propose scaling methods applied to both frequency and severity loss data and using credibility theory.

The paper employs a qualitative approach to identify how the causes of a loss event affects the returns of the shareholders. It includes the breakdown by four causes: people, processes, systems and external factors. Operational risk may materialize directly, for instance, in electronic fund transfer (transfer of funds to the wrong person) or could result indirectly as a credit or market loss. Since there is a close linkage of operational risk with other types of risks, it is very important for every institution to first have a clear understanding of the concept of operational risk before designing the appropriate operational risk measurement and management framework (Epetimehin and Obafemi, 2015).

Research and Methodology

The study employed a descriptive research design as the researcher intends to describe a situation or a condition as it is and offers the opportunity for a logical structure of the inquiry into the problem of study. Primary data was collected through the administration of expert opinion survey questionnaires to senior management employees of all 43 registered commercial banks in Kenya in the month of November 2015**.** The variables for operational risk included internal and external fraud (IEF), clients, products and business practices (CPBP), business disruption and system failure (BDSF) and execution, delivery and process management (EDPM).The reliability of the questionnaire was tested using the Cronbach's alpha correlation coefficient with the aid of Stata version 13.0 software.

Model specification and diagnostic tests

The objective sought to determine the effect of operational risk on the financial performance of commercial banks in Kenya. The dependent variable financial performance was measured using a five point Likert scale ranging from very low to very high performance with 1 indicating low and 5 very high performances. The dimensions of operation risk were four namely internal and external fraud (IEF), clients, products and business practices (CPBP), business disruption and system failure (BDSF) and execution, delivery and process management (EDPM). The influence of these dimensions was measured on a five point Likert scale ranging from no extent at all (1) to a very large extent (5).

The fact the dependent variable is ordinal implies that ordinary least squares cannot be used to analyze the data. OLS estimated relationship may predict values outside the acceptable range of 1 to 5. Further the data is discrete while OLS considers it as continuous. Thus the most appropriate model must provide for the discreteness of the data and predict values that lie within the range of 1 to 5. As such the model must be a discrete choice model. Discrete choice models provide for binary and multi-response dependent variables (Baltagi, 2005). In this paper the dependent variable had more than two categories leading to a multi-response specification. Specifically, the dependent variable was specified as;

$$y_i = \begin{cases} 1 & \textit{very low} \\ 2 & \textit{low} \\ 3 & \textit{moderate} \\ 4 & \textit{high} \\ 5 & \textit{very high} \end{cases} \tag{1}$$

Further, the multiple responses in (1) inherently elicited comparison of a bank with the industry in general.

Thus the dependent variable y_i is ordinal with 1 revealing poor financial performance and 5 revealing best performance relative to the industry performance. The multi-response and ordinal nature of the dependent variable required that the model be discrete but also ordinal. According to Verbeek (2004) the ordered logistic and probit models are appropriate for modelling ordered multiresponse dependent variables. The logistic model is preferred over the probit model for its simplicity. Considering the ordered logistic model the effect of operational risk on financial performance of banks in Kenya is specified as;

$$y_i = \Lambda\left(\beta_1 \mathrm{IEF} + \beta_2 \mathrm{CPBP} + \beta_3 \mathrm{BDSF} + \beta_4 EDPM + \varepsilon\right) = \frac{e^{\beta_o + \beta_1 \mathrm{IEF} + \beta_2 \mathrm{CPBP} + \beta_3 \mathrm{BDSF} + \beta_4 EDPM + \varepsilon}}{1 + \sum_{i=1}^{5} e^{\beta_o + \beta_1 \mathrm{IEF} + \beta_2 \mathrm{CPBP} + \beta_3 \mathrm{BDSF} + \beta_4 EDPM + \varepsilon}} \tag{2}$$

Where

IEF is internal and external fraud

CPBP is Clients, products and business practices

BDSF is business disruption and system failure

EDPM is execution, delivery and process management and

ε is the error term

The ordered logistic regression in model (2) is non-linear in parameters. β coefficients measure the natural logarithm of predicted probabilities odds ratio rendering β coefficient difficult to interpret (Verbeek, 2004). Therefore the β's cannot be interpreted as marginal effects of the dimensions. To get the marginal effects first the probability that the response is in category j is calculated as in equation (3).

$$P(\mathrm{Yi} = J \mid \mathrm{X}) = \Lambda\left(\alpha_{j-1} \le \beta_o + \beta_1 \mathrm{IEF} + \beta_2 \mathrm{CPBP} + \beta_3 \mathrm{BDSF} + \beta_4 EDPM + \varepsilon \le \alpha_j\right) \tag{3}$$

Where α_j is some perceived industry level of performance.

From (3) the change in the probability of an individual i choosing alternative j (ΔP_{ij}) is given by;

$$\frac{dP_{ij}}{dx} = P_{ij}(\beta_j - \overline{\beta}) \qquad (4)$$

Where β_j is the coefficient of dimension j and $\overline{\beta}$ is the mean of the β_j's

The calculation of the average marginal effects as in equation (4) is preferred over those at the mean, $\left(\frac{dP_{ij}}{dx} = \beta_j(1 - P_{ij})\right)$ since they are more representative (Wooldridge, 2003). The calculation of average marginal effects implies that unlike in the binary choice models where marginal effects have the same sign as the coefficient in multi-response models such as ordered logit model the marginal effects may have different signs to that of the coefficient (Verbeek, 2004). Additionally, the marginal effects will be such that there are positive for low performance when they are negative for high performance and vice versa (Wooldridge, 2003). Therefore, it follows that marginal effects across performance levels will always sum to zero (Wooldridge, 2003)

Test for Moderation

To test for moderation effect of size equation (2) was extended to accommodate the Keppel and Zedeck procedure. First, size was introduced as an explanatory variable as shown in model (5)

$$y_i = \Lambda(.) = \frac{e^{\beta_o + \beta_1 \mathrm{IEF} + \beta_2 \mathrm{CPBP} + \beta_3 \mathrm{BDSF} + \beta_4 EDPM + \beta_5 Size + \varepsilon}}{1 + \sum_{i=1}^{5} e^{\beta_o + \beta_1 \mathrm{IEF} + \beta_2 \mathrm{CPBP} + \beta_3 \mathrm{BDSF} + \beta_4 EDPM + \beta_5 Size + \varepsilon}} \qquad (5)$$

Secondly, the interaction terms between the domains and size were introduced in 1.5 to establish whether size was a moderator as shown in equation (6)

$$y_i = \Lambda(.) = \frac{e^{\beta_1 \mathrm{IEF} + \beta_2 \mathrm{CPBP} + \beta_3 \mathrm{BDSF} + \beta_4 EDPM + \beta_5 Size + \sum_{i=1}^{4} \beta_{i+5} size*x + \varepsilon}}{1 + \sum_{i=1}^{5} e^{\beta_1 \mathrm{IEF} + \beta_2 \mathrm{CPBP} + \beta_3 \mathrm{BDSF} + \beta_4 EDPM + \beta_5 Size + \sum_{i=1}^{4} \beta_{i+5} size*x + \varepsilon}} \qquad (6)$$

The decision making criteria was that if β_5 in (5) was insignificant but $\beta_5 - \beta_9$ significant in model (6), then size is a moderator whose direction and effect is given by the signage of the $\beta's$

Parallel odd assumption

This assumption is also known as the proportionality assumption that the distance between each category is equivalent (proportional odds assumption). Violation of this assumption implies that coefficients change across performance groups. This assumption is often violated in practice (Verbeek, 2004). If violated the heterogeneous ordered logit model should be estimated. The assumption is tested using a likelihood ratio test. The hypothesis is that there is no difference in the coefficients between models; that is the parallel odd assumption holds.

Specification and Goodness of fit

To assess reliability of the ordered logit model the log-likelihood ratio was used to evaluate goodness of fit and link test was estimated to assess whether the model was correctly specified.

Results and Discussion

Response Rate

Structured questionnaires were used to collect the primary data from 43 banks in Kenya. The successful response was 26 out of the expected 43 responses. The unsuccessful response consisted of unreturned questionnaires and unfilled questionnaires. In percentage form the successful response rate was 60 per cent. This response rate is considered satisfactory to make conclusions for the study. Mugenda and Mugenda (2003) observed that a 50 per cent response rate is adequate, 60 per cent and above is good, while 70 per cent rated very well. This implies that based on this assertion, the response rate in this case of 60.5 per cent is therefore good. Therefore, the findings obtained from the analysis of the primary data set was generalized for the entire population. Further most of the respondents were from big and medium banks that control a high percentage of the market share in the sector.

Reliability and validity of Constructs

Reliability shows the degree to which scores are free from random errors. The study tested the internal reliability of the research instrument by computing Cronbach's Alpha coefficient for all items in the structured questionnaire. The Cronbach's alpha coefficients range between 0 and 1 with higher alpha coefficient values being more reliable. A Cronbach Alpha coefficient value of 0.7 and above was to be acceptable and reliable as recommended (Sekaran, 2003).

Table 1: Reliability Test of the data

Variable	No of Items	Reliability Coefficient	Conclusion
Financial Performance	3	0.9307	Reliable
Operational Risk	4	0.9062	Reliable

Table 1 shows that financial performance had a reliability coefficient of 0.9307 while operational risk had a reliability coefficient of 0.9062. Therefore, the constructs used by the survey questionnaire were internally reliable.

Table 2: Summary Statistics

Variables	N	Mean	Standard Deviation	Min	Max
Performance	26	4.080	0.909	2	5
IEF	26	3.885	1.107	1	5
CPBP	26	4.038	1.038	1	5
BDSF	26	3.808	1.059	1	5
EDPM	26	3.800	1.000	1	5
SIZE	26	2.769	0.430	2	3

Table 2 shows that the mean score for performance, internal and external fraud, clients, products and business practices, business disruption and system failure as well as execution, delivery and process management is 4.080, 3.885, 4.038, 3.808 and 3.800 respectively. These scores approximate to a value of 4 on five point Likert scale adopted by the study. Therefore, on average the respondents agreed that their banks financial performance was to a great extent. The fact that the mean score of the components of operational risk is 4 implies that the respondents agreed that internal and external fraud, clients, products and business practices, business disruption and system failure as well as execution, delivery and process management affected commercial banks financial performance to a great extent.

The mean score of size is 2.8. This approximates to a value of three on the 3 point categorization adopted by the study. Therefore, on average the respondents agreed that commercial banks in Kenya have total assets more than 40 billion Kenya shillings. This is consistent with the population of banks under study. Large and medium sized banks are the majority in the sector and have assets of more than 40 billion Kenya shillings.

Results and discussion

The objective sought to determine the effect of operational risk on financial performance of commercial banks in Kenya. Primary data was analysed using an ordered logistic model. Table 3 shows reports the findings on the effect of operational risk on financial performance of commercial banks in Kenya.

Table 3: Effect of operational risk on financial performance of commercial banks in Kenya

VARIABLES	Ordered Logit Coefficients
IEF	-1.580*
	(0.958)
CPBP	-2.080**
	(1.010)
BDSF	-2.772**
	(1.126)
EDPM	-1.689*
	(0.968)
Constant cut1	-21.41***
	(7.673)
Constant cut2	-16.46***
	(6.310)
Constant cut3	-9.669**
	(4.846)
LR chi2(4)	31.78***
Pseudo R2	0.5206
Parallel odds assumption test chi statistic	2.86

KEY: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
IEF represents internal and external fraud clients, CPBP represents products and business practices, BDSF represents business disruption and system failure and EDPM represents execution, delivery and process management

Table 3 shows the ordered logit coefficients of model (2) and the corresponding diagnostics tests. The log likelihood test that all the coefficients are jointly equal to zero has a chi statistic of 31.78 and a corresponding p-value less than 0.01. Thus the calculated chi statistic is greater than its critical value at one per cent level of significance. Hence the hypothesis that the coefficients are jointly equal to zero is rejected at one per cent level of significance. Therefore, the dimensions of operational risk are jointly significant in explaining variations in financial performance of commercial banks in Kenya.

Additionally, results show that the likelihood ratio test of Parallel odds assumption has a test statistic (chi) of 2.86 with a corresponding p-value greater than 0.05. Thus the calculated chi statistic is less than the critical at one per cent level of significance. Thus the hypothesis that the parallel odds assumption holds is not rejected at one per cent level of significance. Therefore, the coefficients for the various categories of the dependent variable are similar.

With respect to the coefficients of the various domain Table 3 shows that the coefficient of IEF, CPBP, BDSF and EDPM are significantly different from zero at 10, five, five and 10 per cent levels of significance respectively. As observed earlier these coefficients should not be interpreted rather the marginal effects of each of the domain should. Table 4 shows the marginal effects.

Table 4: Base model and average marginal effects for each domain

Explanatory Variable	Base model coefficient	Explanation of category	Average Marginal effects: dE(y/x)/dx
IEF dy/dx from 1 to 5	-1.580*	Low	0.189**
		Moderate	-0.080*
		High	-0.102*
		Very High	-0.007
CPBP dy/dx from 1 to 5	-2.080**	Low	0.247**
		Moderate	-0.105**
		High	-0.134**
		Very High	-0.009
BDSF dy/dx from 1 to 5	-2.772**	Low	0.329***
		Moderate	-0.139**
		High	-0.179***
		Very High	-0.012
EDPM dy/dx from 1 to 5	-1.689*	Low	0.201**
		Moderate	-0.085**
		High	-0.109*
		Very High	-0.007
Key: *** p<0.01, ** p<0.05, * p<0.1			

Table 4 shows the average marginal effects of each of the domain on the various categories of the dependent variable. For all the domains the marginal effects are positive for low financial performance, negative for moderate to high performance and insignificant for very high performance. Therefore, the findings reinforce each other for the various categories. In particular, when a respondent's response that a particular domains effect on a financial performance of a commercial bank changes from no extent to a very large extent the probability of observing a commercial bank with low financial performance increases while that of observing a commercial bank with high performance reduces. The findings may be interpreted for each category of the dependent variable. However, since the findings reinforce each other for brevity this paper interprets the effect on high performing commercial banks.

With respect to IEF the marginal effect is -0.102 for the high performing commercial banks. The marginal effect is significantly different from zero at 10 per cent level of significance. Therefore, when a respondent's response that the effect of IEF on financial performance of a commercial bank changes from no extent to a very large extent the probability of observing a commercial bank with high financial performance reduces by 10.2 percentage points holding other factors constant.

With respect to CPBP the marginal effect is -0.134 for the high performing commercial banks. The marginal effect is significantly different from zero at one per cent level of significance. Therefore, when a respondent's response that the effect of CPBP on financial performance of a commercial bank changes from no extent to a very large extent the probability of observing a commercial bank with high financial performance reduces by 13.4 percentage points holding other factors constant.

With respect to BDSF the marginal effect is -0.179 for the high performing commercial banks. The marginal effect is significantly different from zero at one per cent level of significance. Therefore, when a respondent's response that the effect of BDSF on financial performance of a commercial bank changes from no extent to a very large extent the probability of observing a commercial bank with high financial performance reduces by 17.9 percentage points holding other factors constant.

With respect to EDPM the marginal effect is -0.109 for the high performing commercial banks. The marginal effect is significantly different from zero at 10 per cent level of significance. Therefore, when a respondent's response that the effect of EDPM on financial performance of a commercial bank changes from no extent to a very large extent the probability of observing a commercial bank with high financial performance reduces by 10.9 percentage points holding other factors constant.

Test for Moderation

To whether size was a moderator Keppel and Zedeck procedure was used as specified in equation (4) and (5). The estimates of models (4) and (5) are shown in table 5.

Table 5: Test for Moderation

VARIABLES	As a variable (Model 3.4)	As a moderator (Model 3.5)
IEF	-1.448***	-0.684**
	(0.293)	(0.315)
CPBP	-0.970***	-1.513***
	(0.237)	(0.273)
BDSF	-0.712***	-0.230
	(0.129)	(0.156)
EDPM	-0.538***	-0.577**
	(0.180)	(0.249)
size	0.148	0.482**
	(0.191)	(0.192)
SIEF		1.041***
		(0.219)
SCPBP		0.179
		(0.222)
SBDSF		0.111
		(0.254)
SEDPM		-0.783***
		(0.288)
Constant cut1	7.374***	6.204***
	(1.455)	(1.576)
Constant cut2	9.774***	9.022***
	(1.484)	(1.599)
Constant cut3	10.80***	10.31***
	(1.514)	(1.629)
Constant cut4	12.74***	12.65***
	(1.586)	(1.711)
LR chi2(9)	126.44***	187.18***
Pseudo R2	0.1859	0.2762
Parallel odds assumption test chi statistic	2.06	1.09

Key: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 shows the ordered logit coefficients of model (4) and (5) with their corresponding diagnostics tests. The log likelihood test that all the coefficients are jointly equal to zero has a chi statistic of 126.44 for model (4) and 187.18 for model (5) with corresponding p-values less than 0.01. Thus the calculated chi statistics are greater than their critical values at one per cent level of significance. Hence the hypotheses that the coefficients of models (4) and (5) are jointly equal to zero are rejected at one per cent level of significance.

Additionally, Table 5 shows that the likelihood ratio test of Parallel odds assumption has a test statistic (chi) of 2.06 for model (4) and 1.09 for model (5) with a corresponding p-values greater than 0.05. Thus the calculated chi statistics are less than the critical at one per cent level of significance. Thus the hypothesis that the parallel odds assumption holds is not rejected at one per cent level of significance for both models. Therefore, the coefficients for the various categories of the dependent variable are similar for both models.

To determine whether or not size was a moderator the coefficient of size in model (4) and (5) as well as its interaction with the domains of operational risk in model (5) were considered. Table 5 shows that the coefficient of size in model (4) is 0.148 with corresponding p-value greater than 0.01 thus the coefficient is not significantly different from zero at one per cent level of significance. In model (5) the coefficient is 0.482 with a corresponding p-value less than 0.05 thus the coefficient is significantly different from zero at five per cent level of significance. Further the coefficients of interactions of size with IEF and EDPM are 1.041 and -0.783 respectively with corresponding p-values less than 0.01. Thus the coefficients are significantly different from zero at one per cent level of significance making size a moderator for IEF and EDPM domains. The average marginal effects of the variables, size and interactions are shown in Table 6.

Table 6: Average Marginal Effects of the Moderation Effect

Explanatory Variable	Base model coefficient	Explanation of category	Average Marginal effects: dE(y/x)/dx
IEF dy/dx from 1 to 5	-0.684**	Low	0.031***
		Moderate	0.021**
		High	0.045**
		Very High	-0.109**
CPBP dy/dx from 1 to 5	1.513***	Low	0.069***
		Moderate	0.047***
		High	0.100***
		Very High	-0.241***
BDSF dy/dx from 1 to 5	-0.230	Low	X
		Moderate	X
		High	X
		Very High	X
EDPM dy/dx from 1 to 5	-0.577**	Low	0.026***
		Moderate	0.018**
		High	0.038**
		Very High	-0.92**
Size	0.482**	Low	-0.022***
		Moderate	-0.015**
		High	-0.032**
		Very High	0.077**
Size*IEF	1.041***	Low	-0.048***
		Moderate	-0.033***
		High	-0.069***
		Very High	0.166***
Size*CPBP	0.179	Low	X
		Moderate	X
		High	X
		Very High	X
Size*BDSF	0.111	Low	X
		Moderate	X
		High	X
		Very High	X
Size*EDPM	-0.783***	Low	0.036**
		Moderate	0.024**
		High	0.052**
		Very High	-0.125***
Key: *** p<0.01, ** p<0.05, * p<0.1			

Table 6 shows the average marginal effect of the moderation effect for all the categories of the dependent variable the marginal effect of the interaction of size and IEF have an opposite sign to that of IEF. Therefore, size moderates the effect IEF on financial performance of commercial banks in Kenya by shrinking it. Additionally Table 6 shows that for all the categories of the dependent variable the signage of the average marginal effects of the interaction of size and EDPM is similar to that of average marginal effects of EDPM.

Conclusions

The findings of the study are that the four components of operational risk exert significant negative effect on the profitability across the banking firms. This therefore calls for better management of operational risks in a manner that boosts depositors' confidence. The findings are that bank size moderates the effect internal and external fraud (IEF) on financial performance of commercial banks in Kenya by shrinking it. It also moderates the effect execution, delivery and process management (EDPM) on financial performance of commercial banks in Kenya by enhancing it.

In the view of the findings, it is disheartening to note that losses resulting from frauds, inadequate or failed internal processes, people and systems of from external events are increasing and affecting the profitability of the banks. This brings a great concern to the society, the government and the bank itself. Giving the pivotal roles banks play in the nation's economy, it is therefore critical for measures to be taken to prevent the occurrence of operational risks in Kenyan banks. In the view of the above findings, the recommendation is that each Kenyan bank must tailor and permanent improve its operational risk management process and it is essential to make all employees aware on risk issues. This is in line with the proposal in the new Basel Capital Accord, banks are required to provide capital for operational risk. This requirement must have been part of what spurred the CBK to raise the minimum capital base for banks. Banks are enjoined to develop viable internal approaches to the measurement of operational risks and to put in place operational risk management and control processes, which should cover the design, implementation and review of operational risk methodology. The banks' internal audit groups are expected to conduct regular reviews of the operational risk management involvement of the board of directors, and senior management of banks are expected in risk management. Hence guidelines and procedures provided by the CBK on operational risk management should be fully adhered into to ensure the risk is well mitigated and improvement in financial performance.

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