The Effect of Risk Type on ERM Effectiveness and Bank Performance: An Empirical Analysis Of European Banks

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Keywords: Banking Sector, Contingency Theory, COSO Framework, Corporate Governance, Credit Risk, Enterprise Risk Management, Type of Risks.

Abstract: Ths study aims to provide empirical evidence on the significance of risk types on the effectiveness of ERM and to the relationship between effective risk management and entities' performance by using logistic and residual analysis in European banking sectors in the period 2013-2016. This study provides empirical evidence on the significance of credit risk and off-balance sheet exposure on the effectiveness of enterprise risk management. The significance of credit risk may arise due to the banks close supervision on their credit risks by implementing processes to monitor key risks to ensure they stay within the approved risk appetite and mitigating efforts. Additionally, the significance of off-balance-sheet items may due to the consideration that off-balance-sheet risk is the integral part of banks' risk profile that need to be assessed carefully. While this study does not provide support to contingency theory proposed by Gordon et. al. (2009), it provides support for Kaplan and Mikes (2014) conception that risk management will be most effective when it matches the intrinsic nature and controllability of the different types of risk the organization faces. As this study only focuses on the banking sector, some standard measurement as suggested by previous studies cannot be fully measured. It is possible that these results may not be generalizable to a broader range of risk and risk management research. This study provides the empirical evidence of the significance of different type of risks on the effectiveness of ERM in the European banks.

1 INTRODUCTION

Enterprise risk management (ERM) have been listed by Harvard Business Review as one of their breakthrough ideas (Buchanan, 2004). Most legislative bodies, professional associations, rating agencies, regulators, and stock exchange hold the view that an ERM is an important tool to manage all the risks an organization faces and have actively advised firms to adopt ERM. Nevertheless, the financial crisis of 2008 has cast doubts upon the efficacy of ERM. Serious failures across financial institutions during financial crisis, many ERM best practice firms faced bankruptcy in the 2008 financial crisis (Bromiley et al., 2015), have been link to risk management flaws and low transparency in managing risks (Stulz, 2008). Power (2009) argues that the benefits of ERM are limited to certain states of the world and that ERM is not well equipped to address the complex realities of interconnectedness. Further, Fraser, Schoening-Thiessen, and Simkins (2008) confirmed that many practitioners recognize the lack of information on management of ERM.

Literature on risk management after the financial crisis shows that organisations can improve their performance by implementing an enterprise risk management, a holistic approach to risk management (Gordon, Loeb, & Tseng, 2009; McShane, Nair, & Rustambekov, 2011; Bromiley, McShane, Nair, & Rustambekov, 2015). The efficiency in managing risks can be achieved through a deeper understanding of risk management across the institutions. Gordon et al. (2009) show that the relation between a firm's ERM and its performance is dependent on the proper match between a firm's ERM and the contextual variables surrounding firms. However, they acknowledged that there is a limitation in their study that contingency variables selection is only based on the way the authors' interpretation of the extant literature and there is no theoretical model that could adequately explain which contingency variables

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should be considered in ERM studies. Nevertheless, this limitation also presents opportunities to find more fitting contingency variables in ERM studies. A recent article written by Kaplan and Mikes (2014) concludes that the effective risk management depends on the organization's context and circumstances. Further, they have proposed that risk management will be most effective when it matches the inherent nature and controllability of the different types of risk the organization faces. The primary aim of this paper is to provide empirical evidence for the proposal that the different types of risk is one of the contingency variables that influence the relationship between a firm's ERM and its performance. Additionally, this paper assesses the different risk types in banking sector and their significance on the effectiveness of risk management implementation.

2 LITERATURE REVIEW

Many academic scholars, standards setting organizations, industry publications, industry associations, consulting firms, and rating agencies has offered their ERM definitions and descriptions. The most recognised definition has been proposed by COSO framework (2004) which define ERM as a process that is designed to identify potential events and manage risk in relation to the achievement of entity's objective. It indicates that enterprise risk management addresses internal control need and a fuller risk management process. The framework focus on strategy, which is the key for implementing the right ERM direction. Gordon et al. (2009) show that enterprise risk management assess risks that encompasses all functions and levels in an organization. Additionally, research by Kaplan and Mikes (2014) show that enterprise risk management is an important component of corporate governance reforms in the entities.

Nevertheless, findings by Paape and Speklé (2012) shows that ERM implementation is influenced by the regulatory environment. However, they did not find any support that application of the COSO framework and mechanistic view on risk appetite and tolerance improves risk management effectiveness. In response, COSO (2016) provides clarification on a few misconceptions about its original framework since it was introduced in 2004 that may alter research findings. Further, it offers a more concise definition of enterprise risk management as the culture, capabilities, and practices, integrated with strategy and execution, that organizations rely on to manage risk in creating, preserving, and realizing value.

2.1 Theoretical Paradigm

Gordon, Loeb, & Tseng (2009) show that risk management effectiveness and performance relation is dependent upon the proper match between a firm's enterprise risk management (ERM) and its contextual variables. Additionally, Kaplan and Mikes (2014) indicates that the effective risk management depends on the organization's context and circumstances. Further, they have indicated that risk management will be most effective when it matches the inherent nature and controllability of the different types of risk the organization faces.

The banking sector is chosen because signalling theory suggests that firms within the same sector try to adopt the same level of disclosure to keep pace with their peers and to avoid being perceived as firms that hiding bad news (Craven & Marston, 1999). Additionally, the firms may use internet disclosure to signal high effectiveness disclosures that provide signal to investors that the firm is profitable and keep up with the latest technology (Oyelere et al., 2003). Further, the banking sector has its own unique characteristics and always attempted to diversify its risk to prevent unexpected default from sinking the entire bank.

2.2 Regulatory Context

This study focus on in the banking sector. The banking industry is a heavily regulated industry. Harnay and Scialom (2016) stated that there is a paradigmatic change in the conception of regulatory instruments of banking authorities, in which the regulations have shifted from public interest theory regulation to private interest theory regulation for the substitution of micro-prudential for macro-prudential regulations. They show that micro- prudential regulations have failed to take the global features and caused the 2007-2008 financial crisis. Kaminski and Robu (2016) said that bank managers are often left to their own ways to figure out what specific controls are required to address regulatory requirements which lead to uncertain effectiveness in control activities. Further, they stated that tighter compliance regulations have challenged financial institutions in a variety of ways. In spite of that, those who adapt best may enjoy a distinct competitive advantage and make them more robust and sustainable over time.

Banking industry need more practical guidance that could provide structural answers in detail manner. Basel Committee on Banking Supervision (BCBS) has developed Basel III which is aim to strengthens micro-prudential regulation and supervision, which raise resilience of individual banking institutions to periods of stress, and adds a macro-prudential overlay, which target system wide risks and pro-cyclical amplification overtime (BCBS, 2011). Basel III has three pillars that includes capital buffers, risk coverage, containing leverage, risk management supervision, and market discipline. In relation to risk management, Basel III address firm-wide risk management by capturing risk of off-balance sheet exposures, managing risk concentration, strengthening counterparty credit risk framework by risk coverage, and comprising common equity of 2.5 percent of risk-weighted assets. By meeting the Basel III requirements, individual bank can have greater resilience in the period of stress and global financial institutions can reduce the risk of system wide shocks.

2.3 Hypotheses Development

This study follows Gordon et al. (2009), a firm's choice of ERM system should be properly matched with several key firm-related factors that includes one additional factor, different risk types, proposed by Kaplan and Mikes (2014). Thus, the relation between a firm's ERM and its performance is contingent on the proper match between a firm's ERM and the following six firm-related variables: environmental uncertainty, industry competition, firm size, firm complexity, board of directors' monitoring, and risk types.

This study set out to offer a new model for understanding the relationship between different risk types disclosure on ERM implementation effectiveness and its effect on the fitting level of contingency variables in ERM studies. Thus, the first hypothesis is formulated as follows:

H_1: There is a positive association between the different types of risk disclosure and ERM implementation effectiveness.

Healy and Palepu (2001) shows that disclosure is an important means for management to communicate firm performance and governance to outside investors. Previous studies of risk management provide mixed evidence on the relationship between ERM effectiveness and market performance. Banks and insurers with a strong and independent risk management function have better performance and reduce risk exposure (Ellul & Yeramilli, 2013; McShane, Nair, & Rustambekov, 2011). However, research by Baxter and Vermeulen (2013) shows that there is no relationship between ERM effectiveness and market performance in banking and insurance sector.

This study examines the relationship between the determinants and effectiveness of ERM systems, and the consequences of ERM systems effectiveness on financial and market performance of the entities. The different risk type disclosure in this model is represented by the variable ERWA, which is the incorporation of risk types and risk level of European banks. Thus, this research also seeks to address the following hypothesis.

H_2. There is a negative association between the absolute value of the residuals and performance.

3 RESEARCH METHODOLOGY

3.1 Sample and Data

The risk types data are collected from Orbis Bank Focus database which consist of world banking information source from banks in 28 European Union countries in the year of 2013-2015. After excluding companies with missing data, preliminary sample with complete risk types data consists of 14 variables and 125 observations.

To test for association between risk types and ERM effectiveness, I gather different risk types data (market, credit, operational, counterparty, and off-balance-sheet risk) of European banks annually from Orbis. ERM Advanced data is manually collective from selected European banks' annual reports are publicly available on their websites and Federal Deposit Insurance Corporation (FDIC) websites. The financial information and corporate governance data are collected from DataStream, Reuters, and Financial Times websites for the year 2013-2016.

3.2 Research Method

The first model is regressed using a logistic regression to predict association between risk types, other variables proposed by Gordon, Loeb, & Tseng (2009) and ERM effectiveness. Logistic Regression Models relationship between set of variables or covariates x_i. The advantages of the logit are simple transformation of P(y|x), linear relationship with x, can be continuous (Logit between $-\infty$ to $+\infty$), and known binomial distribution (P between 0 and 1). A logistic regression was chosen since the dependent variable of ERM effectiveness is a binary dependent variable (Wooldridge J., 2012). A binary variable takes on only two values, zero and one. The binary variable in this model is ERMadvanced that takes value of 1 if ERM score is equal to or higher than 4, and 0 if otherwise.

The second model is regressed using ordinary least squares that regressed the absolute residual value of the first model with the dependent variable of bank's performance, return on average assets and Tobin Q. Both models are regressed using STATA 14 software that supports many aspects of logistic regression.

3.3 Research Models and Variables

The first hypothesis is tested using the model in Eq. (1). The coefficients in Eq. (1) describes the proposed best practice match between ERM and the bank-related factors (variables) discussed above:

$$ERMA_{i,t} = \beta_0 + \beta_1 MR_{i,t} + \beta_2 CR_{i,t} + \beta_3 OR_{i,t} + \beta_4 OBS_{i,t} + \beta_5 EU_{i,t} + \beta_6 CI_{i,t} + \beta_7 BC_{i,t} + \beta_8 BS_{i,t} + \beta_9 MBD_{i,t} + \varepsilon_{i,t} \quad (1)$$

where,

ERMA	ERM advanced is a dummy variable equal to 1 if ERM score is equal to or higher than 4, and 0 otherwise, which is a measurement by Florio and Leoni (2017), ERMA is a comprehensive measure for ERM implementation effectiveness, whereas ERM score is the sum of the following variables, chief risk officer, risk committee, risk committee to board of directors, risk assessment frequency, risk assessment level, risk assessment method in bank i at year t.
MR	Market risk is the risk of losses in the bank's trading book due to changes in equity prices, interest rates, credit spreads, foreign-exchange rates, commodity prices, and other indicators whose values are set in a public market, in bank i at year t, in millions of dollars.
CR	Credit risk is the potential risk that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms, in bank i at year t, in millions of dollars.
OR	Operational risk is the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events, in bank i at year t, in millions of dollars.
OBS	Off-balance-sheet items are assets or liabilities that exist, but are not required by IFRS to be included on financial statements, in bank i at year t, in millions of dollars.
EU	Environmental uncertainty that represent the difficulties for organizations due to the increasing unpredictability of the future events affecting the organization, in bank i at year t.
CI	Industry competition that represent an inter-industry variable represent a possible competitive pressure banks face from other sectors which is represented by the measurement of market capital to GDP, in bank i at year t.
BS	Bank size is the bank's average total assets, in bank i at year t.
BC	Bank complexity that captured scope and diversity in business lines of the subsidiaries of an organization, in bank i at year t.
MBD	Monitoring by firm's board of directors which represents the number of directors for each firm divided by the natural logarithm of total assets, in bank i at year t.
β_i	various model parameters, i = 0 to 5
ε	residual or error term.

Variables market risk (MR), credit risk (CR), operational risk (OR), and off-balance-sheet items (OBS), represent different risk types in European banks, proposed by Mike & Kaplan (2013). The other independent variables are contingency variables proposed by Gordon et al. (2009).

The second hypothesis is tested using the model in Eq. (2). Eq. (2) is a residual analysis model. The basis for using a residual analysis is a better test of the holistic relation concerning the way contingency factors interact with ERM in affecting bank performance (Gordon, Loeb, & Tseng, 2009). The Eq. (2) is written below and regressed by an OLS regression.

$$P_{i,t+1} = \beta_0 + \beta_1 ARES_{i,t} + \varepsilon_{i,t} \quad (2)$$

where,

P	Firm performance, measured by accounting measures, ROAA, market measures, Tobin Q, in bank i at year $t+1$.
ARES	absolute value of residuals from Equation 1) that represent "lack of fit", in bank i at year t.
β_i	various model parameters, i = 0 to 5
ε	residual or error term.

In order to see whether the above argument is right and whether ARES, the absolute value of residuals in Eq. (1), is related to performance. The ARES coefficient should show a significant negative association with banks' performance in Eq. (2). The derived coefficients are based on ''minimizing" the sum of the squared deviations of the residual. The negative significance of ARES coefficient in Eq. (2) is critical in assessing the ''lack of fit" in the match between an ERM system and the *sixth* contingency variables.

4 RESULTS

4.1 Main Results

4.1.1 Descriptive Statistics

The table 1 presents descriptive statistics for the dependent and independent variables. Sampled companies present a high operating profitability on average, as mean ROA is equal to 61.4%. Mean Tobin's Q ratio (Q) is 0.11, signalling means that the cost to replace a firm's assets is greater than the value of its stock, which implies that the stock is undervalued. Meanwhile, 87.2% of the sample shows an advanced ERM system, having 4 or more ERM components. The average credit risk is 107,063 million dollars, the highest among all risks measured.

Table 1: Descriptive Statistics.

Variable	Mean	Std. Dev	Min	Max
ROAA	0.614	1.719	-3.420	16.340
TQ	0.110	0.351	0.000	3.930
ERMA	0.872	0.335	0.000	1.000
CR	107063.000	173515.600	49.000	955300.000
MR	9474.480	19544.120	2.000	119731.000
OR	15656.230	27218.830	2.000	119200.000
OBS	81552.780	148014.600	2.000	752775.000
EU	5.158	1.136	2.187	7.016
CI	0.024	0.049	0.000	0.426
BS	10.993	2.586	3.995	14.798
BC	612.840	1185.485	2.000	6024.000
MBD	2.646	0.887	0.760	5.074
N	125			

4.1.2 Logistic regression result

The table 2 below is the logistic regression outcome. I use Stata's predict to obtain the predicted probabilities of the outcome, the value of the logit index, and the standard error of the logit index.

From 125 observations, the model likelihood is -31.7, where null model has a lower value (more negative). The LR $Chi^2(9)$ indicates G-square for 9 degrees of freedom. The Prob > chi^2 or p-value of the first model is 0.0002. The $p < 0.05$ indicates a significantly better model. In other words, the Prob > chi^2 = 0.0002 show that the model as a whole is statistically significant ($p < 0.0001$). The Pseudo R^2 of 0.336 indicates that model explain 33.6% of variation in the effectiveness of ERM. In other words, the McFadden Pseudo $R^2 = 0.336$ indicates that an approximate amount of variability explained by the fitted model is 33.6 percent.

The odds ratio of credit risk is 0.99 ($p = 0.022$). It indicates that the odds of having an effective ERM are increased by a factor of 0.99 for having credit risk rather than not having credit risk, controlling for other variables in the model. In other words, each one-unit increase in credit risk variable increases the odd ratio of ERM advanced by 0.99, when the other independent variables are held constant, and this effect is statistically significant.

The odds ratio of off balance sheet items is 1.00 ($p=0.09$). It indicates that the odds of having an advanced ERM are increased by a factor of 1.00 for having off balance sheet item rather than not having off balance sheet item, controlling for other variables in the model. It means that each one-unit increase in off balance sheet items variable increases the odd ratio of ERM advanced by 1.00, when the other independent variables are held constant, and this effect is statistically significant.

The odds ratio of competition in inter-industry is 1.6e+201 ($p = 0.024$) show that the odds of having an advanced ERM are increased by a factor of 1.6e+201 for having competition in inter-industry rather than not having competition in inter-industry, controlling for other variables in the model. It means that each one-unit increase in operational risk variable increases the odd ratio of ERM advanced by $1.6*10^{201}$, when the other independent variables are held constant, and this effect is statistically significant.

Table 2: Logistic regression outcome.

	(1) ERMA (odd rat.)
ERMA	
CR	0.999* (-2.29)
MR	0.999 (-0.05)
OR	1.000 (0.84)
OBS	1.00** (1.69)
EUI	1.030 (0.06)
CI	1.6e+201* (2.26)
BS	1.518 (1.43)
BC	0.998 (-1.56)
MBD	1.828 (1.11)
_cons	0.010 (-1.74)
N	125

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

4.1.3 Residual analysis

The residual analysis outcome is shown in table 3 below. The residuals (e) is derived from equation (1), where $e = Y - \hat{Y}$ using a postestimation command in STATA. Variable ($ARES$) is the absolute value of the residual (e) is obtained using an absolute syntax in STATA. The number of observations in table (3) is reduced to 117 observations, due to eight missing values generated in predicting (e) and generating ($ARES$).

The coefficients of ARES (0.579) for ROAA and (0.117) for Tobin Q are positive and significant (at the level of 0.05). In other words, ARES is positively associated with firm performance. These results are contrary to the expected negative sign from Gordon et al., (2009). These results do not support the main argument that the proper match between ERM and the contingency variables is an important driver of firm performance. The different result may due to several factors. First, the different ERM effectiveness and entities performance measurements used, I used Florio and Leoni (2017) measurement instead of Gordon et. Al. (2009) and different sectors observed, instead of multi-sectors observation, this paper only focus on single sector, banking. Secondly, the lack of variable control for different set of rules that varies across countries in Europe. The lack of countries' controls due to rigid application of Gordon et.al. model that contain only the contingency variables.

Table 3: Residual analysis outcome.

	(1) ROAA	(2) Tobin Q
abs res	0.579*	0.117*
	(2.24)	(2.21)
_cons	0.355	0.0573
	(1.78)	(1.41)
N	117	117

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

4.2 Post Estimation Results

The classification model test yields predicted p>.5 for 118 banks, 106 banks actually have an effective ERM. Overall 88% of banks are correctly classified. Out of all banks observation that have an effective ERM 97.25% were correctly predicted to have an effective ERM. Out of all banks observation that do not have an effective ERM 25% were correctly predicted.

The regression collinearity diagnostic procedures (coldiag) were also performed in STATA follow Belsley, Kuh, & Welsch (2005) that examine the "conditioning" of the matrix of independent variables. Coldiag computes the condition number of the matrix. If this number is "large", Belsley et. al. (2005) suggest 30 or higher, then there may be collinearity problems. The condition number is the largest singular value. All "large" singular may be worth investigating. The all condition numbers (singular values) are below 30 which most numbers are relatively smaller than 30, that indicates that there may not be collinearity problems in this model.

Model specification is tested by LR Diagnostics using linktest in STATA. The insignificant *_hatsq* (p = 0.858) indicates the link function is correctly specified. In other words, it indicates that there is no specification error. Additionally, insignificant *_hatsq* means that there are no omitted relevant variables. Moreover, it also indicates that the link function is correctly specified.

A goodness of fit test shows how well the data fits the model. Specifically, the Hosmer-Lemeshow test (HL test) calculates if the observed event rates match the expected event rates in population subgroups (Hosmer, Lemeshow, & Sturdivant, 2013). The HL test is a goodness of fit test for logistic regression, especially for risk prediction models. The output returns a chi-square value (a Hosmer-Lemeshow chi-squared) and a p-value (e.g. Pr > Chi^2) are the main concerns in this test. Small p-values (usually under 5%) mean that the model is a poor fit. The large insignificant p-value (0.8349), suggests that the model fits the data reasonably well.

The AIC in this result show a smaller value of 0.66, that indicates the better fit of the model. Meanwhile, the current model is preferred when BIC is negative. The more negative the BIC, the better the fit. The BIC in this result is large negative that show a better fit of the model.

The marginal effect outcome for the first model indicates the following, one-unit increase in credit risk from the baseline mark of 107063 increases the probability of ERMA improvement by -1.44e-09, one-unit increase in the off balance sheet items from the baseline (81552.8) increases the probability of ERMA improvement by 8.08e-10, and one-unit increase in the competition in inter-industry from the baseline (0.023) increases the probability of ERMA improvement by 0.012 or 1.2 percent. (Basel Committee on Banking Supervision (BCBS), 1986).

The robust estimate of variance of the first model estimates the standard errors that are robust to the fact that the error term is not identically distributed. The standard errors in the robust regression can be used to make valid statistical inference on the coefficients, even though the data are not identically distributed. The model likelihood and Pseudo R^2 has the same value with the standard logistic regression, -31.7 and 0.336 respectively. The Prob > chi^2 or p-value of the robust model is slightly higher, 0.004, nevertheless, it still below $p < 0.05$ that indicates a significant model. The odds ratio of credit risk, off balance sheet items, and competition in inter-industry have the same value with the standard logistic regression. However, the robust regression has the lower p-value that indicates the higher odds of having an effective ERM are increased by a factor of 0.99, 1.00, and 1.6e+201 for having credit risk, off balance sheet items, and competition in inter-industry rather than not having those variables, when the other independent variables are held constant, and this effect is statistically significant.

5 CONCLUSIONS

5.1 Key Findings

This study provides empirical evidence on the significance of credit risk, off-balance sheet exposure on the relationship between effective risk management using measurement by Florio and Leoni (2017) and entities' performance. The significance of credit risk on enterprise risk management (ERM) may due to that ERM takes a broader view of risk that identify risks that could impact the institution's ability to achieve their goals. It implements processes to monitor key risks to ensure they stay within the approved risk appetite. Further, it seeks to identify all aspects of credit risk that might be present throughout the institution, regardless of where the risk occurs. The credit risk needs to be identified, aggregated, and managed that contributes to the effectiveness of ERM (Hoover, 2016). Meanwhile, the significance of off balance sheet items can be explained by the paper conclusion of Basel Committee on Banking Supervision (1986) that stated the individual types of risk associated with most off-balance-sheet business are in principle no different from those associated with on-balance-sheet business. The off-balance-sheet risks should not be analysed separately from the risks arising from on-balance-sheet business, but should be regarded as an integral part of banks' overall risk profiles. Thus, the existence of off-balance-sheet risks contributes to the effectiveness of ERM, since it considered as integral part of banks' risk profile that need to be assessed carefully.

Additionally, it also provides support for Kaplan and Mikes (2014) findings that the effective risk management depends on the organization's context and circumstances. However, this study does not provide support to contingency theory proposed by Gordon et. al. (2009).

5.2 Limitations and Further Research

There are limitations in this study. First, the study is unable to encompass the different industries, since it only focus on the banking sector. The measurement as suggested by Gordon et al. (2009) cannot be fully measure due to single industry study. It is possible that these results may not be generalizable to a broader range of risk and risk management study. In other words, the generalisability of these findings is limited to the banking sectors. Thus, the further studies need to be carried out in a cross-industry study involving different sectors to investigate the association between risk types and ERM effectiveness. A second limitation is that a theoretical model with selected contingency variables is based on subjective interpretation of the literature. Schoonhoven (1981) suggests that the contingency theory has several problems lack of clarity in its theoretical statements to the embedding of symmetrical and non-monotonic assumptions in the theoretical arguments. Thus, it is recommended that further research be undertaken from different theoretical perspectives. A third limitation to this study is that banks with complete risks data are more likely to have more funding in risk management which implies higher assets. It may hinder the inclusion of banks sample with moderate or lower assets. Further studies should assess different periods beyond the year of 2018 to include more banks with different assets range, as the upcoming 2018 Basel III requirements will generate more complete risks data in banking industry. The forth limitation is the ERM components may not be a complete representation of ERM effectiveness. Thus, more research is needed to account for other potentials representation of ERM effectiveness, e.g. risk committee experiences and risk assessment complete disclosures. The last limitation is the lack of variable control for different set of rules that varies across countries in Europe. Thus, the future research need to consider the inclusion of controls for countries' rules, such as a rules index.

Hopefully, this study could offer some important insights into the significance of credit risk, off-balance sheet exposure, and competition in industry in incentivizing banks to better manage their risk by meeting the upcoming 2018 Basel III requirements that are in line with the new 2016 COSO framework.

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* Data not shown, available upon request.

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