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Developing Enterprise Risk Management Index for Shariah-Compliant Companies

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Abstract

Numerous firms are implementing enterprise risk management (ERM) because it can increase firm value. However, academic research examining the association between ERM and firm value remains limited due to the lack of suitable and comprehensive dimensions available for measuring ERM. This study directly addresses this research gap and proposes a comprehensive dimension of ERM that effectively measures the construct. ERM Index (ERMi) is proposed as an effective measurement for ERM implementation. ERMi was constructed on the basis of data gathered from a thorough review of literature. The effectiveness of ERMi in measuring ERM implementation was assessed through survey questionnaire among Shariah-compliant companies listed in Bursa Malaysia, and tested using the structural equation modeling technique of partial least squares (PLS-SEM). Empirical findings confirm that 42 items in ERMi that measure the eight principal components of ERM are significant and effective dimensions for ERM implementation. Empirical premise of ERMi, such as its reliability and validity assessed using PLS-SEM, is another important contribution of this study attesting that PLS-SEM is an efficient data analysis technique that can be employed in accounting research.

Keywords: Enterprise risk management, Firm value, Partial least square, Structural equation modeling

Introduction

Corporate risk management practices experienced paradigm shift and evolution in the last decade due particularly to the recent financial crisis that led to the downfall of large corporations around the world (Gordon, Loeb, & Tseng, 2009). In response to the catastrophe, stakeholders demand for holistic and effective risk management practices, which can help firms survive a myriad of risks. This pressure generated the concept of the enterprise risk management (ERM), which was introduced as a potential and an effective response to risk management challenges (Paape & Spekle, 2012). ERM is different from the traditional silo-based approach because ERM considers risk management at an enterprise-wide level, and risks are managed holistically. The main objective of ERM is to

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maximize stakeholders' values using a holistic approach that enables firms to manage risks and opportunities simultaneously and do so effectively. This approach eventually creates value for stakeholders (COSO, 2004).

ERM came under spotlight particularly after the Enron debacle that highlighted the limitations of traditional risk management practices in protecting firms from a crisis. Despite the rising number of firms that implemented ERM mainly due to its potential for value creation, the number of empirical research that examines the association between ERM and firm value is limited. Difficulty in measuring ERM implementation is the main obstacle to researching this issue. Measuring ERM implementation using firms' available information is challenging for researchers because of the information on risk management disclosed in firms' reports. This dearth of information is because disclosure of risk management activities remains on a voluntary basis (Gates, Nicolas, & Walker, 2012). Firms rarely publish about their adoption of ERM, and they disclose minimal information about the program. Therefore, evaluating risk management activities based on this limited information is difficult (Gatzert & Martin, 2013; Tufano, 1996). To gauge the extent of ERM implementation, previous research used a simple proxy, such as appointment of chief risk officer (CRO) (Beasley, Pagach, & Warr, 2008; Golshan & Rasid, 2012; Liebenberg & Hoyt, 2003; Pagach & Warr, 2010, 2011) or survey information (Altuntas, Berry-Stolzle, & Hoyt, 2011; Beasley, Branson, & Hancock, 2010; Beasley, Clune, & Hermanson, 2005; Gates et al., 2012; Norhayate, Hasnah, & Ibrahim, 2011).

Lack of an effective dimension for ERM is the main deterrent to research in this area (Beasley et al., 2008; Gordon et al., 2009; McShane et al., 2011; Pagach & Warr, 2010). This limitation has resulted in mixed and inconclusive empirical findings regarding the value creation potential of ERM. The mixed findings are of major concern because ERM, as a value-creating program, is important for its continued development and the main motivation for firms' decisions to implement ERM because it requires substantial resources for implementation. Thus determining an effective dimension of ERM is important. Given the limitations in the ERM dimension, the main objective of this study is to propose an effective measurement for ERM.

To achieve this objective, we proposed ERM Index (ERMi). ERMi is constructed on the basis of data gathered from an extensive review of literature. Initially, ERMi comprised 44 items that measured eight principal components of ERM. The effectiveness of ERMi, as a dimension of ERM implementation, was assessed through survey questionnaire among Malaysian publicly listed companies. Based on data collected from 81 companies, empirical premises of ERMi was tested using the structural equation modelling technique of partial least squares (PLS-SEM). PLS-SEM has become a mainstream technique of analysing quantitative data in numerous fields of business research; however, its use in accounting research remains inadequate, and among reasons for this limitation are lack of understanding of the PLS-SEM's benefits and its applicability in accounting research (Lee, Petter, Fayard, & Robinson, 2011). Thus, this study employed SEM-PLS to assess the reliability and validity of ERMi. A hierarchical component model (HCM) comprising 44 items measuring the eight principal components of ERM was developed. PLS-SEM assessed the reliability and validity of ERMi; then, the empirical results confirmed that 42 items of ERMi are significant dimensions of ERM that effectively measure the construct.

This study aims to fill the gap in the literature and contributes to the body of knowledge in twofold: first, to propose ERMi as an effective ERM dimension, and second, to demonstrate that PLS-SEM is an efficient data analysis technique for accounting research. ERMi has scientific and practical relevance and two different groups, which are practitioners and academics, are foreseen to be the main users

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of ERMi. Practitioners can use ERMi for self-assessment of their ERM programs or utilize the index as a checklist during the initial phase of ERM implementation. Academics can use ERMi in their empirical research for assessing the extent of ERM implementation.

Literature Review

Risk Management and ERM Framework

One of the definitions of perceived risk is any negative events or threats to companies achieving their objectives. For example, risk is defined as the possibility of danger, loss, injury, or other adverse consequences (Collier, Berry, & Burke, 2006). In 1999, IFAC positively interpreted risk as an opportunity (Collier & Berry, 2002). The International Organization for Standardization (ISO) later issued an international standard for risk management, ISO 31000:2009, and defined risk as the "effect of uncertainty on objectives." An organization should manage risk to accomplish targeted objectives and ensure business sustainability. Prior to ERM, risk management activities were concentrated on eliminating downside exposures. This style of managing risk is known as traditional risk management (TRM) or silo-based risk management practices wherein risks are managed on a separate or individual basis.

ERM as an evolving concept of managing risks has various definitions. Meulbroek (2002) describes ERM as the identification and assessment of the collective risks that affect firm value and the implementation of a firm-wide strategy to manage those risks. ERM, also known as integrated risk management, means integration of risks and ways to manage risks. This approach evaluates firm's total risk exposure, which is important to the assessment of the firm's value, instead of partial evaluation of each risk. The link between ERM and a firm's value is clearly stated in the definition by the Casualty of Actuarial Society (CAS) Committee. CAS defines ERM as the process by which firms in all industries assess, control, exploit, finance, and monitor risks from all sources to increase firms' short and long-term values to their stakeholders (Gordon et al., 2009).

In 2004, the Committee of Sponsoring Organizations of the Treadway Commission (COSO) issued the ERM-Integrated Framework as a guideline for firms when implementing ERM. COSO (2004) defines ERM as "a process, affected by an entity's board of directors, management and other personnel, applied in strategy setting and across the enterprise, designed to identify potential events that may affect the entity, and manage risks to be within its risk appetite, to provide reasonable assurance regarding the achievement of entity objectives" (p. 8).Therefore, ERM can be used to enhance a firm's share value, growth, return on capital, and consistency of earnings. In addition, ERM can identify any threat to a firm's growth and recognizes risks that represent opportunities for a firm to exploit its competitive advantage.

Since the progress of ERM, professional bodies and practitioners have proposed a number of ERM frameworks to guide firms in implementing the system. Among the most prominent and most quoted frameworks in the literatures are COSO's ERM-Integrated Framework, ISO 31000:2009 (International Organization for Standardization, 2009), CAS Framework, and the Risk Management Framework by Institute of Risk Management (2002).

In 2004, COSO expanded the scope of the earlier issued Internal Control Framework (1992) and provided a more robust and extensive focus on the broader subject of enterprise risk management. The framework is represented as a three-dimensional matrix of eight elements essential for achieving organization's main goals, which are strategic, operational, reporting, and compliant. The eight components consist of (i) internal environment, (ii) objective setting, (iii) event identification, (iv) risk assessment, (v) risk response, (vi) control activities, (vii) information and communication, and (viii)

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monitoring. To ensure the effectiveness of ERM processes, the eight components must function properly where no material weakness is present and risk is managed within a firm's risk inclination. Since its release, COSO's ERM-Integrated framework has been referred to extensively by firms as the main guideline to move towards an integrated risk management process. A survey conducted by Lundqvist (2014) shows that 24% of 153 firms follow this framework's ERM guidelines.

ISO 31000:2009 recommends that organizations develop, implement, and continuously improve a framework that integrates risk management into the organization's overall governance, strategy and planning, management, reporting, policies, values and culture. Accordingly, ISO 31000:2009 assists a firm in managing risks effectively through the application of the risk management process at varying levels and within specific contexts of the firm. The standard also ensures that risk information derived from the risk management process are effectively reported and used as a basis for decision-making and accountability throughout the firm.

ISO 31000:2009 highlights six principles that firms should comply with at all levels to ensure effectiveness of risk management processes. The six principles are as follows:

(i) Risk management creates and protects value of an organization through the achievement of firm's objectives and improvement of performance.
(ii) Risk management is an integral part of all firm processes, it is not a stand-alone activity separate from the main activities.
(iii) Risk management is part of decision making that helps decision makers make informed choices.
(iv) Risk management explicitly addresses uncertainty and how it can be managed.
(v) Risk management is systematic, structured, and timely.
(vi) The input to risk management is based on the best available information.

ISO's risk management framework does not prescribe a specific management system for a firm to implement. This framework only assists firms to integrate risk management to their overall management system. Firms should tailor the framework to their specific needs. Both frameworks (i.e., COSO's ERM-Integrated Framework (2004) and ISO 31000:2009) play an important role in this study.

Issues on ERM Dimensions

Past empirical studies yielded inconclusive findings regarding the value creation potential of ERM. Lundqvist (2014) argues that the main cause of the mixed findings is partly due to flaws and inconsistencies in methods used for measuring the ERM construct. The lack of a suitable and comprehensive dimension available to measure ERM construct is one of the obstacles in researching this area. Inconclusive findings in ERM research are mainly due to different dimensions used for measuring ERM.

Reviews of literature indicate that ERM implementation was measured using a proxy such as CRO appointment. The use of CRO appointment as a proxy of ERM implementation is due to a lack of disclosure on risk management programs. Using a simple proxy such as a CRO appointment is problematic because hiring a CRO is not a true and robust measurement that accurately represents a well-implemented and effective ERM system. CRO appointment is a vague and debated dimension of ERM, and several sets of literature debated its effectiveness (see Grace; Lundqvist; McShane et al., 2011; Pagach & Warr, 2011; Waweru & Kisaka, 2013) . The primary limitation of this proxy is that it cannot measure robustly the extent to which firms actually embrace ERM (Beasley et al., 2008; Gordon, Loeb, & Tseng, 2009; Pagach & Warr, 2011). Grace et al. (2014) argue that the use of a CRO may lead to biased results in situations where the existence of CRO does not correspond to the implemented ERM system. A firm's appointment of a CRO in this case

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tends to be only for signaling purposes. This proxy ignores the complexity of the system and is regarded as an imprecise identifier of ERM implementation (Lundqvist, 2014).

Another stream of ERM research uses a rating agency database, such as Standard & Poor's (S&P) rating, as an instrument to gauge the level of ERM practices in a firm. This method has its own limitation despite relying on accurate data from reliable sources, such as S&P. Waweru and Kisaka (2013) argue that using measurement criteria developed by consulting firms, such as S&P, restricts research to particular industries because the criteria are developed mainly to evaluate ERM practices in a specific industry, such as the financial and insurance industry. As a result, only insufficient research employed this method to quantify ERM (see e.g., Baxter, Bedard, Hoitash, & Yezegel, 2013; McShane et al., 2011).

Therefore, limitation on ERM dimensions has been the motivation of this study to propose and develop a comprehensive dimension of ERM that can measure the construct effectively. ERMi is proposed as a comprehensive ERM dimension. Table 1 summarizes the ERM dimensions used in previous empirical studies discussed in this section and findings of the studies. Eight out of 13 studies used a survey method to capture the extent of ERM implementation, indicating that survey is the most pertinent method of assessing ERM. CRO appointment was used in three studies, and two studies relied on the S&P database to gauge ERM implementation. ERMi is proposed as an instrument that can measure ERM implementation comprehensively. The instrument development in this study followed a systematic guidelines recommended by Mackenzie, Podsakoff, and Podsakoff (2011) and Lewis, Templeton, and Byrd (2005). Lewis et al. (2005) argue that instrument development is a critical process particularly in a new research area wherein the existence of validated instruments is limited. The instrument development began with an extensive literature review, followed by content adequacy assessments to ensure that a valid and reliable instrument items are produced. The process started with a clear theoretical specification of the ERM construct, which included defining the construct and specifying its premise (purpose) and theoretical domain as well as the dimensions.

The proposed dimension was operationalized by incorporating the important elements and effectiveness of risk management practices as specified in various literature, specifically in COSO's (2004) ERM-Integrated Framework and ISO 31000:2009. ERMi consists of eight principal dimensions that are measured using 44 items which are important and relevant in assessing the extent of ERM implementation. The eight interrelated dimensions of ERM are (i) internal environment, (ii) objective setting, (iii) event identification, (iv) risk assessment, (v) risk response, (vi) control activities, (vii) information and communication, and (viii) monitoring. Table 2 describes the principal components included in ERMi and the total number of items measuring each dimension.

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Table 1: ERM Dimensions used in Previous Studies

Author(s)	ERM Dimension	Objective	Findings
Altuntas, Berry-Stolzle, & Hoyt (2011)	Survey	Extent of ERM implementation	Significant increase in the level of ERM implementation
Beasley, Branson, & Hancock (2010)	Survey	Extent of ERM implementation	The current state of ERM implementation is considered as immature
Beasley, Clune, & Hermanson (2005)	Survey	Determinant of ERM implementation	Determinants are CRO, board independence, CEO or CFO support, size, big four auditors
Baxter, Bedard, Hoitash, & Yezegel, (2013)	S&P Rating	Determine whether ERM quality enhances firm performance	Firm performance and value are enhanced by high quality ERM
Golshan & Rasid (2012)	CRO Appointment	Factor influences ERM adoptions	Financial leverage and auditor type are significant influential factors of ERM adoptions
Grace, Leverty, Phillips, & Shimpi (2014)	Survey	Value creation of ERM	ERM improves firm performance
Kleffner, Lee, & McGannon (2003)	Survey	Factor influences ERM adoptions	Risk manager, board-of-directors support, and compliance with guidelines are the influential factors of ERM adoptions
Liebenberg & Hoyt (2003)	CRO Appointment	Determinant of ERM implementation	Financial leverage is the only factor significant with ERM implementation
McShane, Nair & Rustambekov (2011)	S&P Rating	Value creation of ERM	Positive relation between increasing level of TRM and firm value but no further increasing in value for firm with higher extent of ERM implementation
Pagach & Warr (2011)	CRO Appointment	Firm's characteristic for ERM adoption	Firm's characteristics that are large, volatile, and have a greater institutional ownership influences ERM adoption
Paape & Spekle (2012)	Survey	Factor influences the extent of ERM implementation	Regulatory environment, internal factors, ownership structure, and firm and industry characteristics are the factors influencing ERM implementation
Norhayate, Hasnah, & Ibrahim (2011)	Survey	Factor influences ERM adoption	Quality of BODs positively influence the extent of ERM implementation
Waweru & Kisaka (2013)	Survey	Value creation of ERM	Positive relation between ERM implementation and firm value

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Table 2: Description of ERMi Dimensions and Number of Items

No	Component	Description	Item
1.	Internal Environment	How risk is viewed and addressed by an entity's people, including risk management philosophy, integrity, ethical values, and the environment in which they operate.	7
2.	Objective Setting	ERM ensures that objectives are established at the strategy level and the chosen objectives' support, align with the entity's mission and vision, and are consistent with organization's risk appetite.	5
3.	Event Identification	Internal and external events affecting achievement of an organization's objectives are identified and distinguished between risks and opportunities.	5
4.	Risk Assessment	Risks assessed from two perspectives, which are likelihood for risks to occur and risk impact on the organization, as a basis for determining how it should be managed.	5
5.	Risk Response	Having assessed relevant risks, companies determine how they will respond. Responses include risk avoidance, reduction, sharing, and acceptance.	5
6.	Control Activities	Policies and procedures are established and implemented to ensure the risk responses are effectively performed.	5
7.	Information and Communication	Significant information is identified, captured, and communicated in a form and time frame that enable people to perform their responsibilities.	6
8.	Monitoring	ERM process is monitored by assessing the presence and functions of its components over time.	6
		Total	44

Methodology

Sample

This study focused on Malaysian Shariah-compliant companies listed in Bursa Malaysia. The increasing number of firms granted with the status of Shariah-compliant shows the significance of Shariah-compliant companies in Malaysian capital market. Although the number of companies classified as Shariah-compliant over the years has been on the rise, empirical research on the business conduct of these firms is limited, particularly on risk management. Risk management is an important activity in Shariah-compliant companies so that it is consistent with the Islamic fundamental principles wherein managers should save guard invertors' investment due to the trust between them. To date, very few studies carried out in Malaysia assessed ERM practices among these companies. The sample was selected from the list of Shariah-compliant companies issued by the Shariah Advisory Council (SAC) of the Securities Commission Malaysia (SC). The sample was selected from the population using simple random sampling method, and the final sample comprised 201 Malaysian Shariah-compliant companies from seven industries.

Data Collection

The effectiveness of the ERMi as a dimension of ERM implementation was assessed through survey questionnaire. Previous literature showed that survey is the common method used for assessing ERM practices. This method is adopted mainly due to difficulty in accessing risk management information directly from firms' published reports.

The questionnaire was designed with the focus on identifying the level of ERM implementation in a firm. Survey questions were constructed according to the ERMi developed earlier in which the dimensions were transformed into questions designed to assess the extent of implementation of each ERM's component

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based on a seven-point Likert scale ranging from one (strongly disagree) to seven (strongly agree). The questionnaire was sent to personnel responsible for risk management activities in the company, such as CRO, accountant, management accountant, and internal audit officers. A total of 105 responses were received at the end of the data collection period. However, 24 were rejected and removed from the sample because the respondents left a substantial number of questions unanswered. The final usable sample consisted of 81 respondents.

Analytical Methods: PLS-SEM

The effectiveness of ERMi in measuring ERM implementation was tested using the PLS-SEM. SEM is known as the second-generation of multivariate analysis that permits data to be analyzed simultaneously among multiple independent and dependent constructs. The main advantage of SEM is that it supports the hypothetical construct known as latent variable (LV). LV is an unobservable construct that cannot be measured directly. Thus, researchers use observable and empirically measurable indicator variables to estimate LV (Urbach & Ahlemann, 2010), (Urbach & Ahlemann, 2010. In this study, ERM is an unobservable construct that is measured using ERMi.

This study developed a hierarchical component model (HCM). HCM comprises multidimensional constructs that have two elements: high-order component (HOC) that captures the more abstract construct and the lower-order component (LOC) that captures the sub-dimensions of the abstract construct (Hair, Hult, Ringle, & Sarstedt, 2014). Jarvis, Mackenzie, and Podsakoff (2003) argue that most construct has a high level of abstraction that requires multiple dimensions for measurement. The use of HCM allows for theoretical parsimony and reduces model complexity (Wetzels, Odekerken-Schroder, & Oppen, 2009).

HCM in this study is established on the basis of a top-down approach, in which a general construct consists of several sub-dimensions (Hair & Hult et al., 2014). This study adopts a type II HCM known as a reflective-formative model (Becker, Klein, & Wetzels, 2012)or partial least squares path modeling (PLS. In a reflective-formative type II model, the LOC are deemed as reflectively measured constructs that do not share common cause but instead form a general concept; hence, HOC. A path relationship diagram shows that ERM is a HOC that formed from a combination of eight LOC (e.g., internal environment, objective setting, event identification, risk assessment, risk response, control activities, information and communication, monitoring) which formatively measure ERM. Figure 1 shows the HCM model and its HOC and LOC measurements.

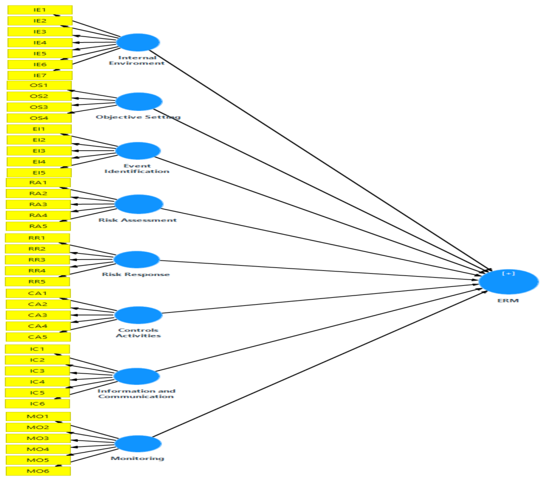

Figure 1: hierarchical component model (HCM)

Justifications for Using PLS-SEM

The use of PLS-SEM remains limited, particularly in accounting research, and, therefore, a justification for using PLS-SEM is necessary. A meta-analysis study conducted by Hair et al. (2014) identifies the three most prominent factors that influence the use of PLS-SEM. The following reasons for using PLS-SEM in this study follow the suggestion made by Hair et al. (2014).

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Non-normal data

Data collected in social science research often follow a multivariate normal distribution. PLS-SEM is less stringent when working with the non-normal data because the PLS algorithm analyses the data in accordance with the central limit theorem. PLS-SEM is a non-parametric statistical method that does not require the data to be normally distributed. Although PLS-SEM is flexible in data normality, researchers need to be cautioned that highly skewed data can reduce the statistical power of the analysis. The Kolmogorov–Smirnov and Shapiro–Wilks tests were conducted in this study to assess the normal distribution of data. The results of Kolmogorov–Smirnov and Shapiro–Wilks tests show significant values of .001 and .000 respectively, suggesting the violation of normality assumption because a non-significant value of more than .05 is assumed normal. The results show violation of normality assumption, i.e., data are not normally distributed. A non-parametric test needs to be used in data analysis.

Small sample sizes

PLS-SEM can be utilized with small sample sizes even when the models are highly complex. The overall complexity of a structural model has minimal influence on the sample size. PLS estimates the model parameters using the original sample and to statistically validate the estimated model, a resampling method is performed using random subsets of data such as bootstrapping (Aibinu & Al-lawati, 2010). PLS-SEM works efficiently when small samples are used to estimate path models comprising many constructs, which are normally more than five, with several structural path relationships and many indicators per construct (Sarstedt, Ringle, Smith, Reams, & Hair, 2014). Thus, PLS-SEM is the suitable data analysis method for this study since there are 44 indicators, eight components, and 81 samples.

Scale of measurement

In general, the construct in a PLS-SEM model can be classified into reflective or formative constructs. The main difference between reflective and formative constructs is that formative measures indicate the assumption that the indicator variables cause the measurement of the construct, which is shown by the direction of the arrows coming from the indicator variables to the construct. On the contrary, reflective indicators are caused by the construct where the arrows point from the construct to the indicators. PLS-SEM has received considerable support as the recommended method for estimating formative constructs. This study analyzes a reflective-formative HCM (type 11) (Jarvis et al., 2003; Wetzels et al., 2009) that consists of eight LOC constructs, reflectively measured by 44 indicators, and HOC formatively measured by eight LOC; thus, PLS-SEM is the most appropriate method of analysis.

Results & Discussion

Model estimation using PLS-SEM

PLS-SEM is a component-based estimation method. PLS-SEM path models are formally defined by two sets of linear equations: (i) the measurement model (outer model) and (ii) the structural model (inner model). The measurement model specifies the relations between a construct and its observed indicators, which are also known as manifest variables, whereas the structural model specifies the relationships between the constructs (Henseler, Hubona, & Ash, 2016). PLS-SEM model estimation procedures are empirical measures of the relationship between the indicators and the constructs (measurement model) as well as between the constructs (structural model).

LOC Measurement Model

Measurement model assessment established whether the instrument items that were used to gather the data actually measured what they were intended to gauge. ERM constructs

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are reflectively measured constructs. The reflectively measured constructs assume that the indicators are caused by the underlying construct; and therefore, should be evaluated with regards to its reliability and validity. The first inspection of the reflective measurement model was the assessment of the composite reliability and convergent validity of the constructs. The composite reliability assessing the construct internal consistency means that the construct is internally consistent due to the consistency of measures used. Meanwhile, convergent validity is assessed by evaluating the reliability of each item used to measure the constructs. Convergent validity was evaluated using three analyses: (i) item reliability, (ii) composite reliability, and (iii) average variance extracted (AVE).

The reflectively measured LOC measurement model assumes that the indicators are caused by the underlying construct and therefore should be evaluated with regard to reliability and validity. Therefore, reflective indicators comprising a set of indicators within the conceptual domain of a construct are interchangeable, highly correlated, and could be omitted from the construct without affecting the construct meaning (Hair & Sarstedt et al., 2014). The first inspection of reliability for the reflective measurement model is the assessment of composite reliability to evaluate the construct measure's internal consistency reliability.

Next is the assessment of construct validity, namely convergent and discriminant validity. Convergent validity is the extent to which a measure correlates positively with alternative measures of the same construct, whereas discriminant validity represents the extent to which the construct is empirically distinct from other constructs, essentially meaning that the construct measures what it is supposed to measure (Hair & Sarstedt et al., 2014). Individual indicator loadings and AVE are the assessments for convergent validity and discriminant validity established using the Fornell–Larcker criterion.

The reliability of the reflectively measured measurement model was evaluated from composite reliability (CR) test results. Hair and Sarstedt et al. (2014) argue that CR provides a more conservative measure of internal consistency reliability because CR, unlike Cronbach's alpha, does not assume that all indicator loadings are equal in the population. AVE is the measurement for convergent validity of the measurement model. The AVE measures convergent validity at the construct level, which is also known as communality of a construct. It estimates the degree to which a construct explains the variance of its indicators with the threshold value of AVE being 0.50 or higher. An AVE value of 0.50 or higher indicates that the construct explains more than half of the variance of its indicators (Hair & Hult et al., 2014). Another measurement of convergent validity is the indicator external loadings. Higher indicator external loadings on a construct indicate that the associated indicators have many in common, which is captured by the construct. An established rule of thumb is that a construct should explain at least 50% of each indicator's variance. An indicator's outer loading should be above 0.708 since the square of the number equals 0.50 (0.708^2). Indicators with outer loading below the threshold of 0.708 but above 0.40 should only be considered for removal from the scale when deleting the indicators results in an increase in the composite reliability or AVE (Hair & Hult et al., 2014).

Table 3 displays the result of the measurement model of LOC. From the assessment of indicators' external loadings, two of the indicators representing internal environment construct, IE1 and IE2, were deleted. These indicators were excluded from the construct because they have the lowest loadings of 0.518 and 0.572. By removing them, AVE value for the construct increased from 0.435 to 0.507, which is above the threshold value. The loadings for other indicators exceeded the recommended value of 0.708; and indicators with values below the threshold were retained since the AVE for

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the constructs were above the cut off value. The AVE values range from 0.562 and 0.702 exceeded the recommended value of 0.50 (Hair & Hult et al., 2014).

Table 3: Results of the LOC measurement model

Construct	Code	Loadings	CR	AVE
Internal Environment	IE3	0.650	0.835	0.507
	IE4	0.678		
	IE5	0.805		
	IE6	0.798		
	IE7	0.606		
Objective Setting	OS1	0.800	0.863	0.559
	OS2	0.796		
	OS3	0.696		
	OS4	0.624		
	OS5	0.805		
Event Identification	EI1	0.628	0.881	0.599
	EI2	0.783		
	EI3	0.848		
	EI4	0.827		
	EI5	0.764		
Risk Assessment	RA1	0.791	0.921	0.702
	RA2	0.743		
	RA3	0.900		
	RA4	0.898		
	RA5	0.848		
Risk Response	RR1	0.821	0.873	0.585
	RR2	0.850		
	RR3	0.789		
	RR4	0.810		
	RR5	0.500		
Controls Activities	CA1	0.907	0.892	0.626
	CA2	0.731		
	CA3	0.884		
	CA4	0.637		
	CA5	0.763		
Information and Communication	IC1	0.805	0.884	0.562
	IC2	0.619		
	IC3	0.734		
	IC4	0.788		
	IC5	0.841		
	IC6	0.686		
Monitoring	MO1	0.844	0.929	0.686
	MO2	0.789		
	MO3	0.888		
	MO4	0.855		
	MO5	0.721		
	MO6	0.861		

Notes: CR, composite reliability; AVE, average variance extracted; IE1 and IE2 were deleted due to low loadings

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The next process was measuring discriminant validity of the LOC measurement model. Discriminant validity is the extent to which a construct is truly distinct from other constructs. This is indicated by the low correlations between the measure of interest and the measures of other constructs. Establishing discriminant validity shows that the construct is unique and captures the phenomena not represented by other constructs in the model. The Fornell–Larcker criterion is a conservative approach to assessing discriminant validity. This method compares the square root of the AVE values with the latent variable correlations. The square root of each construct's AVE should be greater than its highest correlation with any other construct (Hair & Hult et al., 2014). Table 4 shows that the square root of the AVE (diagonal values) of each construct is larger than its corresponding correlation coefficients, indicating adequate discriminant validity (Fornell & Larcker, 1981). Overall, the measurement model of LOC demonstrated adequate convergent validity and discriminant validity.

Table 4: Discriminant validity of construct (Fornell–Larcker Criterion)

	CA	EI	IE	MO	OS	RA	RR
CA	**0.791**						
EI	0.647	**0.774**					
IC	0.726	0.706					
IE	0.599	0.636	**0.712**				
MO	0.769	0.647	0.675	**0.828**			
OS	0.649	0.650	0.615	0.614	**0.748**		
RA	0.767	0.677	0.645	0.818	0.622	**0.838**	
RR	0.754	0.626	0.695	0.816	0.661	0.809	**0.825**

Notes: Square root of the AVE on the diagonal

HOC measurement model

The path modeling of this study comprises HOC that should be evaluated separately for its measurement model quality. HOC is a formatively measured construct formed from the repeated indicators approach; thus, the reflective measurement model assessment is not appropriate for evaluating HOC validity and reliability. The content validity of HOC was first examined before assessing the empirical quality of the model. This process is important to ensure that formative indicators capture most of the important domains of the construct. To accomplish the content validity of HOC, a thorough literature review was conducted to ensure a reasonable theoretical foundation in the process of developing instruments (Jarvis et al., 2003). HOC developed an ERM resulting from an in depth research of literature, following a detailed process of measurement development as explained in the previous section, and thus ensuring content validity of the construct.

The second process was the empirical evaluation of the HOC measurement model. This study followed guidelines in Hair and Hult et al. (2014) that involves three main examinations, namely (i) convergent validity, (ii) collinearity, and (iii) statistical significance as well as the relevance of the indicator weights. The process started with an assessment of convergent validity of HOC. HOC is a formatively measured construct and as such, an analysis known as a redundancy test was conducted to ensure that the convergent validity was achieved. A redundancy test is an assessment where each of the formatively measured constructs are correlated with an alternative, reflective, or single-item measurement of the same construct (Hair & Sarstedt et al., 2014). The indicator in the model used more than once means that the indicator was used in the formative and reflective construct. This test measures whether a formative construct is highly correlated with a reflective measure of the same construct. A single-item (global item) approach was applied to conduct the redundancy test where an endogenous single-item construct was used to validate each of the formative measured constructs that formed HOC. The strength of the path coefficient in linking the two constructs is indicative of the validity of the formative indicators in measuring the construct (Hair & Hult et al., 2014). Table 5 demonstrates the t-values ranging from 5.423 to 23.563, indicating that all formatively measured constructs have sufficient degrees of convergent validity.

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Table 5: Convergent validity results of HOC

Path Relationship	t-Value	*p* Value	Significance Level
CA □CA_Global	23.563	0.000	***
EI →EI _Global	5.423	0.000	***
IC →IC_Global	8.976	0.000	***
IE →IE_Global	6.023	0.000	***
MO →MO_Global	14.645	0.000	***
OS →OS_Global	9.033	0.000	***
RA →RA_Global	17.082	0.000	***
RR →RR Global	11.083	0.000	***

*** p< .01

Once convergent validity was established, the next assessment was checking collinearity issues. For a formative construct, high correlations among indicators are undesirable and indicate a methodology problem known as collinearity, which could bias the results. Collinearity arises when two or more indicators are highly correlated. To assess collinearity, a problem in the formative measurement model, the variance inflation factor (VIF) was calculated. VIF was used to quantify the severity of collinearity among the indicators in the formative measurement model (Hair & Hult et al., 2014). Table 6 exhibits the values of VIF that range from 2.540 to 4.616, which are below the cut-off value of 5, indicating that no major collinearity problem occurs in the HOC model.

Table 6: VIF results

Construct	**VIF Values**
Controls Activities (CA)	3.282
Event Identification (EI)	2.540
Information & Communication (IC)	3.609
Internal Environment (IE)	2.340
Monitoring (MO)	4.616
Objective Setting (OS)	2.693
Risk Assessment (RA)	4.121
Risk Response (RR)	4.602

The third empirical test conducted in evaluating formatively measured constructs was examining the significance and relevance of the formative indicators. The significance and relevance of the indicators is determined by comparing the weights of the indicators to indicate their relative contribution to forming the construct (Hair & Hult et al., 2014). PLS-SEM is a non-parametric procedure that does not make any distributional assumptions regarding the indicators or error terms that can facilitate the direct testing of the indicator's weight (Sarstedt et al., 2014). Thus, the bootstrapping technique was performed to determine the outer weights of formatively measured constructs. Bootstrapping is a resampling technique that draws a large number of subsamples from the original data (with replacement) and estimates models for each subsample. It is used to determine standard errors of coefficient estimates to assess the coefficient's statistical significance without relying on distributional assumptions (Hair & Hult et al. 2014, p. 163).

Bootstrap results indicate t-values (p-values) for each indicator weight. Based on t-values, the significance of the weight was determined. Three rules are stated in Sarstedt et al. (2014) and Hair and Hult et al. (2014) whether to retain or remove indicators from the formative construct. First, the indicators are retained if the weight is statistically significant. Second, if the weight is non-significant but the indicator's loading is 0.50 or higher, the indicator is still retained as long as it is supported with theory. Third, if the weight is non-significant and the loading is low (i.e., below 0.50), the indicator should be removed from the measurement model. Deleting formative indicators based on statistical results should done with care since eliminating formative indicators would affect content validity of the model where the measures failed to capture the entire domain of the construct (Sarstedt et al., 2014). Therefore, we retained the indicators in the formative constructs even though their outer weights are not significant, provided that the outer loadings were above the threshold value of 0.50. The analysis of outer weights concludes the evaluation of the formative measurement model. Considering the result from both measurement models, LOC (reflective) and HOC (formative), all reflective and formative constructs exhibit satisfactory levels of quality. Thus, we proceeded with

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the analysis to the second stage, evaluation of structural model.

Assessment of Structural Model

Once the reliability and validity of the HCM measurement model was established, the next process was evaluating the structural (inner) model. Assessment of the structural model is important to determine how well empirical data supported the theory and thus to decide if the theory has been empirically confirmed (Hair & Hult et al., 2014). The first important criterion for the assessment of the PLS-SEM is latent variable coefficient of determination (R^2). R^2 is a measure of the model's predictive accuracy, that is, it measures the proportion of an endogenous construct's variance that is explained by its predictor (exogenous) constructs (Hair & Sarstedt et al., 2014). A rough rule of thumb on the acceptable values of R^2 are 0.75, 0.50, and 0.25, which indicates substantial, moderate, and weak levels of predictive accuracy (Henseler, Ringle, & Sinkovics, 2009).

The second evaluation of the structural model was assessing the path coefficient between the variables. Path coefficient wass determined using bootstrapping (resampling) procedures as in the previous section. A path coefficient's magnitude indicates the strength of the relationship between two variables. Estimated path coefficient t-values closer to +1 specify strong positive relationships and coefficient values closer to –1 indicate a strong negative relationship. Figure 2 and Table 10 shows the result of the analysis. The adjusted R^2 in Figure 2 refers to the explanatory power of the predictor variables on the respective construct. Internal environment, objective setting, event identification, risk assessment, risk response, control activities, information and communication, and monitoring explain 93.4% of variation in ERM. The co-efficient (β) range from 0.107 to 0.198, and all are significant, and $p<0.001$ that support the eight principal components of ERMi are the significant measurement of ERM. Table 7 shows the results of the structural model of ERM dimensions.

Table 7: Results of structural model

Path	Path Coefficient (β)	t-value	p-value	Significance Levels
IE→ERM	0.107	6.148	.000	***
OS→ERM	0.116	5.373	.000	***
EI→ERM	0.129	8.431	.000	***
RA→ERM	0.168	13.375	.000	***
RR→ERM	0.139	13.863	.000	***
CA→ERM	0.144	9.471	.000	***
IC→ERM	0.156	11.861	.000	***
MO→ERM	0.198	14.138	.000	***

Notes: *** p< 0.001

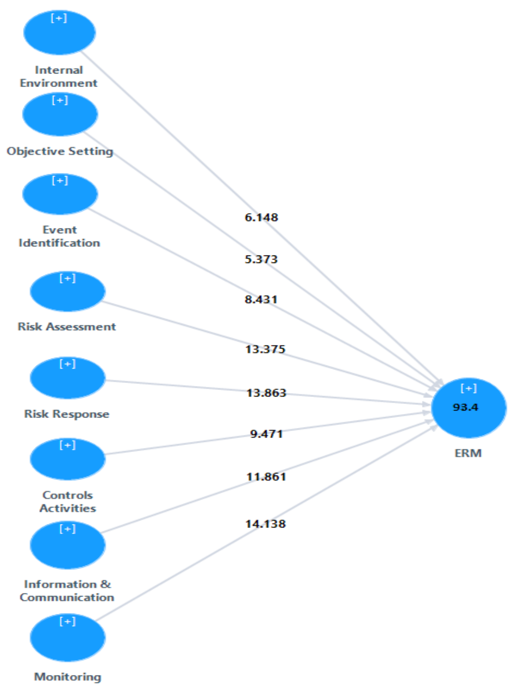

Figure 2: Structural model results

Conclusion

Recent years have observed a paradigm shift in corporate risk management practices that evidenced a shift from a silo-based approach to an enterprise risk management (ERM) approach. Increasing numbers of organizations implement ERM and the main motivation for this decision is due to the claim that ERM has a potential for value creation. Despite the growing number of firms implementing ERM, a limited number of

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empirical research examines the value creation claim of ERM. One of the main barriers of research in this area is to measure the extent of ERM implementation in a firm. Thus, this study proposed an effective measurement for ERM implementation named ERMi, which consists of eight principal components and 42 elements that are important and relevant in measuring ERM.

The empirical premise of ERMi, such as its reliability and validity, was assessed using PLS-SEM. PLS-SEM has become a mainstream technique in many fields of business research but its use in accounting research is still limited. Due to this lag, PLS-SEM was employed in this study to show that PLS-SEM is an efficient data analysis technique that can be used in accounting research. Two types of analyses were conducted using PLS-SEM, that is, measurement (outer) model and structural (inner) model. The measurement model evaluates the relationship between the indicator and construct and results for both LOC and HOC measurement model indicate that 42 items in the ERMi are significant indicators for the eight main components of ERM.

The structural model displays the relationship between the constructs. Structural model results were assessed from path coefficient values that range from 0.107 to 0.198 and confirmed that the eight principal dimensions, which are internal environment, objective setting, event identification, risk assessment, risk response, control activities, information and communication, and monitoring as well as its 42 indicators are significant and effective measurement of ERM.

ERMi is a tool that can be used by practitioners in assessing the maturity level of ERM program in their organizations and by academics in their empirical research. To achieve a successful and sustainable development, an organization should manage risks effectively and ERMi is one of the solutions that may help the organization in achieving its stated goal. ERMi contributes to the body of knowledge in measurement of ERM implementation in organizations.

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