Innovations

Risk Management Practices in the Ethiopian Banking Sector: Using the Structural Equation Model

Temesgen Ayenew Birhan
Department of Accounting and Finance, Bahir Dar University, Bahir Dar, Ethiopia
Dr. Jasmindeep Kaur
Professor at Department of Commerce, Punjabi University, Patiala, India

Abstract : *This research assessed risk management practices in the Ethiopian banking sector. This objective was achieved by collecting primary data through a questionnaire. The questionnaire was prepared on a five-point Likert-type scale. It coveredeight aspects of risk management practice: understanding risk management, identification, assessment and analysis, monitoring and controlling, managing credit, market, liquidity, and operational risk.The data was collected from 193 bank officials of banks operating in Ethiopia. The structural equation model was used to study the relationship between risk management practice and its determinants. The researchers performed a confirmatory factorial analysiswith AMOS 26 on the questionnaire data. The regression result showed that all independent variables positively correlate with risk management practice. This study also found that understanding risk management, risk assessment and analysis, and managing credit and liquidity risksweresignificantly related to risk management practices in the Ethiopian banking sector. Finally, the study suggested that the National Bank of Ethiopia establish proper, precise, and objectively measured criteria for guiding risk management.*

Keywords: *Risk management practice, Structural equation model, Confirmatory factor analysis, average variance extracted, AMOS.*

1. Introduction

Banks are financial institutions that serve as engines of the economy which bring economic growth in a nation(Dill, 2020). Because of these activities, risks are an inherent component of the banking industry. Even though risk has no universal definition, some authors likeCrouhy et al.(2001)defined risk as the fundamental element that influences the financial behavior of financial institutions. Many financial decision-making by households, business firms, governments, and especially financial institutions are focused on managing risk. Measuring the influence of risk and analyzing ways of controlling and allocating it requires a wide range of sophisticated mathematical and computational tools.Banking risks in the banking sector refer to the negative effects on the profitability of various sources of uncertainty. To quantify risk, it is necessary to identify the cause of uncertainty and determine the extent to which it could negatively impact profitability(Bessis, 2002).If these risks are not effectively identified and handled, they can result in significant losses and jeopardize the bank's survival.

Banks, in the process of becoming financial intermediaries, are confronted with various kinds of financial and non-financial risks, viz. credit risk, liquidity risk, interest rate risk, foreign exchange rate risk, operating risk, and so on.Risk analysis and risk management have been carried out in many fields for several decades and are increasingly used as integral parts of the overall business management approach and on most major projects; in some cases, they have become a mandatory requirement for financial planning and regulatory approval. Many client organizations now require contractors to identify potential risks in an investment and to state how these risks would be managed should they occur(Merna & AL-Thani, 2015).

According to Gallati (2003), risk management is evolved from corporate insurance management, focuses on unintentional losses to an organization's assets and income. Risk management safeguards assets and revenue. Risk management is a scientific approach to corporate risk. Ghosh(2013) also explainsthat risk management entails detecting and handling financial risks to minimize or eliminate losses. It entails creating tools and methods to discover, assess, and manage risks. It involves creating policies, plans, and financial and benchmark constraints for many operations. Risk management optimizes risk-adjusted returns on assets through business policies and strategies. Risks should be accepted, managed, hedged, or transferred to minimize their impact.

The financial crisis in 2007–2008 highlighted the need for greater risk management in the significant function of banking in the financial system. Risk management inthe Ethiopian banking sector within the national economy has gained the increasing attention of policymakers and researchers. This study provided suggestions topolicymakers, corporate boards, executives, and other stakeholders to improve risk management practices for the Ethiopian banking sector.It also contributed to enhancing and understanding the risk management practices, incredibly clarifying the process of risk management practices in the Ethiopian banking sector. Under this study, risk understanding, risk identification, risk analysis, and risk monitoring were assessed in addition to credit risk management, market risk management, liquidity risk management, and operating risk management covered under this study. The study also provided a significant methodological contribution by using the structural equation model for future research in the Ethiopian banking sector.

2. Literature review

This section reviews the related literature about risk management practices from many researchers.The empirical evidence was discussed as follows:
Hassan Al-Tamimi andMohammed Al-Mazrooei (2007)discovered that banks in the UAE demonstrate a moderate level of efficiency in risk management. Notably, the variables with the most impact on risk management practices are risk identification, risk assessment, and analysis. A notable difference was seen in risk assessment, analysis, and risk monitoring and control between UAE national banks and foreign banks.Hassan (2009) assessed the degree to which Islamic banks in Brunei Darussalam use risk management practices and techniques in dealing with different types of risks. The researcher found foreign exchange, credit, and operating risks are most common types of risks. They also found that Islamic banks are reasonably efficient in managing risks, where risk identification and risk assessment and analysis are the most influencing variables in risk management practices.
Shafiq and Nasr (2010) found that Pakistani commercial bank risk management employees understand risk and risk management. They found that Pakistan's banking system's most significant risks include credit, liquidity, interest rate, foreign exchange, and operations. They noted that Pakistan is part of the Global Village, and international financial crises like foreign currency rate changes and inflation severely impact Pakistan banks. Understanding Risk, Risk Management, Risk Identification, Risk Assessment and Analysis, Risk Monitoring, and Credit Risk Analysis were significantly linked to risk management methods.
In Bahrain, Abu Hussain and Al-Ajmi (2012)observed that banks in Bahrain clearly understood risk and risk management and had efficient risk identification, risk assessment analysis, risk monitoring, and credit risk analysis and management practices. They concluded that credit, liquidity, and operational risk were the main types of risk faced by both conventional and Islamic banks. They also found that Islamic banks differed from conventional banks in understanding risk and risk management. They further pointed out that the risks faced by Islamic banks were significantly higher than those faced by conventional banks.Khalid and Amjad (2012)Pakistani Islamic banks are reasonably efficient in managing risk where understanding risk management, risk monitoring, and credit risk analysisare the most influential variables in risk management practice.
Hafez (2015)compared Islamic and Conventional banks' risk management practices on forty listed banks in Egypt. The researcher indicated that credit and liquidity risks were the biggest challenges for Egyptian Islamic and conventional banks. The

researcher noted that conventional banks managed risk better and employed more advanced methods. Islamic Banks' biggest risk was liquidity. The researcher found a positive relationship between understanding risk, risk management, risk identification, risk assessment and analysis, risk monitoring, and risk management practices in Islamic and conventional banks. The researcher suggested to future researchers include credit risk, which is the most challenging risk faced by banks in Egypt, and liquidity risk management, which is the second most challenging risk faced by banks in Egypt.Ishtiaq (2015) studied different aspects of risk management in Pakistani banks and found that risk management practices are significantly influenced by risk understanding, identification, risk assessment and analysis, risk monitoring and controlling, credit risk, market risk, liquidity risk, and operational risk.

Nade and Sharma (2019) observed that understanding of risk management practices in public sector banks was better than in private sector banks, and the public sector banks in Ethiopia had better risk management practices than private sector banks. They observed that understanding risk and risk management, risk assessment and analysis, risk identification, risk monitoring, and risk management practices in public sector commercial banks were substantially better than in private banks. They suggested that banks need to use specialized risk management methods such as earning at risk, value at risk, and simulation techniques, and private sector banks need to strengthen their risk management practices. They suggested that future researchers include Credit risk management practices, Liquidity risk management practices, Operating risk management practices, foreign exchange risk practices, and Board involvement in the risk management process as additional variables for determining risk management practices. They also suggested including other parties in the Ethiopian commercial banks dealing with risk management besides risk officials at the headquarters level.

Elgharbawy (2020)comparedto conventional banks, Islamic banks faces unique types and levels of risk. They also said Islamic banks have higher operational and Sharia non-compliance risks. In comparison, conventional banks have larger credit and insolvency risks. Islamic and conventional banks face liquidity risk and other concerns. Understanding risk management, risk identification, risk monitoring and control, and credit risk analysis determine risk management strategies, not risk assessment and analysis.Rehman et al. (2020)discovered that subgroup risk identification was significantly different and understanding risk management did not affect either bank. They found that private commercial banks minimized credit risk better than public banks. They proposed that public banks adopt private commercial banks' risk management procedures or revisit and develop new risk management strategies to reduce risk exposure.

Zeleke and Sindhu (2021)noted that private commercial banks assessed and analyzed risk more than state banks. Comparing publicly owned banks with private commercial banks, quantifying risk, credit worthiness analysis, sensitivity analysis, and internal risk rating analysis were significantly different. Ethiopian commercial banks practiced collateral security, credit limit systems, and stress testing.

3. Research Hypotheses

The following hypothesis was developed for investigation by the broad purpose statement. The study's hypothesis is based on a theoretical concept and empirical evidence concerning different aspects of risk management practices in the Ethiopian banking sector. As a result, eight hypotheses were proposed as follows.

H_1: Understanding risk management significantly related to risk management practices in the Ethiopian banking industry.

H_2:Risk identification is significantly related to risk management practices in the Ethiopian banking sector.

H_3:There is a significantrelationship between risk assessment and analysisand risk management practices in the Ethiopian banking sector.

H_4: Risk monitoring and controllingand risk management practices have a significant relationship in the Ethiopian banking sector.

H_5: There is a significant relationship between managing credit risk and risk management practices in the Ethiopian banking sector.

H_6: Asignificantrelationshipexists between market risk management and risk management practices in the Ethiopian banking sector.

H_7: In the Ethiopian banking sector, managing liquidity risk and risk management practices have a significant relationship.

H_8: In the Ethiopian banking sector, managing operational risk is significantly related to risk management practices.

4. Research Methodology

The target population of this study comprised all the banksthat have been issued licenses by the National Bank of Ethiopia. It consists of commercial banks operating in Ethiopia, both public and private owned banks. As of January 31, 2021, 16 commercial banks were operating in Ethiopia. Using Solvin's formula, 193 samples were taken from the total population, and Purposive sampling techniques were used. The data was collected from 193bank officials.The questionnaire covered understanding risk management, risk identification, risk assessment and analysis, risk monitoring and controlling, credit risk, liquidity risk, operating risk, and market risk. The five-point Likert scale-type questions have been prepared and distributed to the respondents.

Data analysis may be classified as descriptive or inferential (Kothari, 2004). In addition to descriptive analysis, inferential analysis is widely used to make data analysis and infer from collected data. The structural equation model would be used (SEM) to study the relationship between dependent and independent variables. SEM has recently emerged as a prominent statistical method due to its ability to account for multiple variables.It also takes a confirmatory factoranalysis (i.e., hypothesis-testing) approach to analyze a structural theory bearing on some phenomenon(Byrne, 2010). Variables that are observed are also known as indicator variables or manifest variables. Unobserved variables or factors are also referred to as latent variables. The latent variables cannot be directly measured. To be represented, the latent variable must be defined as observed variables. There were nine latent variables in this study.

5. Data Analysis

In this research, data analysis was conducted in two steps. First, measurement model assessment (model fitness) was performed. For measurement model assessment, the researchers performed a confirmatory factorial analysis (CFA) with AMOS 26 on the questionnaire data and used Cronbach's alpha, average variance extracted (AVE) values, and composite reliability to examine model fit and assess validity and reliability. The researcher took three steps to improve model fitness. First, improving the models based on standardized regression estimates (factor loading) and any variable loading on the factor less than 0.5 should be removed. Second, modification indices to improvethe model. Under this step, the model may need to be modified to improve the fit, thereby estimating the most likely relationship between variables. Modification indices report the change in chi-square value. Modification indices less than 20 should not be used. More than three parameters should not be connected to avoid overfitting. Parameters can be connected in a permissible way. Third,using standardized residual covariance. Standardized residual covariance is typically expressed in terms of standard deviation. They indicate the degree to which the observed covariance between two variables deviates from the expected covariance based on the estimated model. A standardized residual covariance of zero suggests that the observed covariance matches the expected covariance, while non-zero values indicate discrepancies. Any variable that has more than 0.4 should be deleted.The researcher deleted 20 questionnaire items in this study to improve model fitness. Second, under structural model assessment, the researcher estimated path coefficient or hypothesis testing and estimated squared multiple correlations (R^2).

5.1. Multicollinearity Test

Multicollinearity occurs because of the highest correlation of independent variables with one another or exists when one independent variable is a linear combination with other independent variables.Independent variables are highly correlated when they are 0.9 and above(Tabachnick &Fidell, 2007). Multicollinearity increases the standard errors of the variable's coefficient, making some independent variables statistically insignificant despite being otherwise significant. This affects the predictive power of the model.Multicollinearity problems can be detected by using VIF and tolerance. As shown in table 1 the maximum and minimum value of VIF was1.032 and 1.289, respectively. This implies that the VIF value for all constructs is below 10. The minimum value for tolerance provided was 0.760. All VIF values are below tenand the tolerance statistics areabove 0.2. This evidenced that the data has no multicollinearity problem.

Table 1: Multicollinearity test

Variables in the study		Collinearity statistics result	
Independent Variables	Symbol	Tolerance	VIF
Understanding Risk Management	URM	0.776	1.289
Risk Identification	RI	0.933	1.072
Risk Assessment and Analysis	RAA	0.922	1.085
Risk Monitoring and Controlling	RMC	0.949	1.054
Managing Credit Risk	MCR	0.760	1.317
Managing Market Risk	MMR	0.919	1.088
Managing Liquidity Risk	MLR	0.902	1.109
Managing Operational Risk	MOR	0.969	1.032

Source: SPSS Output, 2023. Dependent variables: Risk Management Practices (RMPs)

5.2. Normality test

SEM assumes all data have a multivariate normal distribution (Hooley & Hussey, 1994). The T-test and F statistics require this assumption for significant testing (Tabachnick & Fidel, 2007). Skewness and kurtosis can validate an assumption. The absence of normality affects goodness-of-fit indices and standard errors (Hulland et al., 1996).Chou & Bentler (1995) suggest that skewness indices greater than 3.0 and kurtosis indexes more than 10.0 can indicate a more serious issue.As shown in Appendix 1,none had skewness greater than 3.0,and all kurtosisindicesare below 10.

5.3. Measurement Model, DataReliability, and ValidityTest

The general SEM model can be divided into two sub-models: a measurement model and a structural model. The measurement model defines relations between the observed and unobserved variables.In contrast, the structural model defines relations among the unobserved variables.

Table2: Confirmatory factor loadings, data reliability,and convergent validity

Factor/Items	Factor loading	Alpha	CR[1]	AVE[2]
Understanding Risk Management (Item1,2,3 and 4)		0.738	0.772	0.532
URM1	0.603			
URM2	0.724			
URM3	0.826			
URM4	0.540			
All factor loadings exceed 0.5 and significant at $p>0.001$.The model fit Indices(X^2/df=1.983, NFI=0.981, IFI=0.990, TLI=0.971, CFI=0.990, PNFI=0.527, PCFI=0.630, RMSEA=0.07, PCLOSE=0.267)[3]were showed best goodness of model fit.				
Risk identification(Items 4,5 and 6)		0.618	0.633	0.514
RI4	0.566			
RI5	0.669			
RI6	0.573			
Factor loadings ranged between 0.566 and 0.669, significant at $p<0.001$. X^2/df=1.539, NFI=0.959, IFI=0.9985, TLI=0.953, CFI=0.984, PNFI=0.620, PCFI=0.528, RMSEA=0.05, PCLOSE=0.364				
Risk assessment and analysis (Items 2,3 and 4)		0.681	0.798	0.569
RAA2	0.912			
RAA3	0.783			
RAA4	0.788			
The factor loadings ranged between 0.783 and 0.912, significant at $p<0.001$. the data showed satisfactory goodness of- fit indices (X^2/df=3.59, NFI=0.945 IFI=0.948, CFI=0.948, PNFI=0.658, PCFI=0.558, RMSEA=0.028, PCLOSE=0.364)				
Risk Monitoring and Controlling (Items 3,4,5 and 6)		0.617	0.863	0.615
RMC3	0.959			

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[1]Composite reliability (CR), computed as $CR= \sum (Xi^2/ (\sum (Xi^2 +\sum\delta)$, Xi→The value of regression weight under each construct. N→Number of observed variables under each construct. **δ** refers to the error term.

[2]Average Variance Extracted (AVE), computed as $AVE= \sum(Xi^2/N)$

[3]X^2/df→ the normed chi-square statistic, NFI→Normed Fit Index, IFI→Incremental Fit Index, CFI→Comparative Fit Index, PNFI→Parsimony Normed Fit Index, PCFI→Parsimony Comparative Fit Index, RMSEA→Root Mean Square of Approximation.

RMC4	0.692			
RMC5	0.545			
RMC6	0.612			
The factor loadings for this model range between 0.545 and 0.959, significant at $p<0.001$. The model goodness of- fit indices (X^2/df=3.73, NFI=0.927IFI=0.934, CFI=0.928, PNFI=0.658, PCFI=0.548, RMSEA=0.048, PCLOSE=0.284)				
Managing credit risk (Items 1,2,3,4 and 5)		0.838	0.840	0.56
MCR1	0.841			
MCR2	0.672			
MCR3	0.692			
MCR4	0.691			
MCR5	0.674			
The factor loadings for this model range between 0.674 and 0.841, significant at $p<0.001$. The model goodness of- fit indices such as X^2/df=1.233, NFI=0.983 IFI=0.997, CFI=0.997, PNFI=0.491, PCFI=0.498, RMSEA=0.035, PCLOSE=0.539 indicates the model well fitted.				
Managing market risk (Item1,2 and 3)		0.667	0.670	0.664
MMR1	0.753			
MMR2	0.596			
MMR3	0.543			
The factor loadings ranged between 0.543 and 0.753, significant at $p<0.001$. The indices such as X^2/df=1.940, NFI=0.958 IFI=0.917, CFI=0.937, PNFI=0.479, PCFI=0.500, RMSEA=0.013, PCLOSE=0.690 indicates the adequate model goodness of- fit.				
Managing liquidity risk (Item2,3,4 and 5)		0.811	0.794	0.570
MLR2	0.588			
MLR3	0.826			
MLR4	0.717			
MLR5	0.661			
The factor loadings ranged between 0.588 and 0.826, significant at $p<0.001$. The model goodness of- fit indices such as X^2/df=3.850, NFI=0.967,IFI=0.975, TLI=0.924 CFI=0.975, PNFI=0.489, PCFI=0.525, RMSEA=0.012, PCLOSE=0.069 indicates the model well fitted.				
Managing operating risk (Items 1,2 and 3)		617	0.737	0.536
MOR1	0.676			
MOR2	0.560			
MOR3	0.613			
The factor loadings for this model range between 0.560 and 0.676, significant at $p<0.001$. The model goodness of- fit indices (X^2/df=0.264, NFI=0.994, RFI=0.981, CFI=0.978, PNFI=0.631, PCFI=0.533, RMSEA=0.0013, PCLOSE=0.354)				
Risk management practices(Item1,2,3 and 4)		0.738	0.801	0.503
RMP1	0.795			

RMP2	0.556			
RMP3	0.823			
RMP4	0.641			
All factor loadings exceed 0.5 and significant at p>0.001. The model fit Indices (X^2/df=4.265, NFI=0.948, IFI=0.960, TLI=0.923, CFI=0.959, PNFI=0.618, PCFI=0.520, RMSEA=0.0356, PCLOSE=0.05) were showed best goodness of model fit.				

Source: Amos output, 2023.

Cronbach alpha estimates the proportion of systematic or consistent variance in test scores. It can range from 00.0 (if no variance is consistent) to 1.00 (if all variance is consistent), with all values between 00.0 and 1.00 also possible. As we seein the above table, all alpha values exceed 0.5,showingthat the data is more reliable. In addition to reliability, convergent validity was tested using Composite Reliability (CR), Average Variance Extracted (AVE), and factor loading.

Table 2shows that the AVE of all constructs exceeds 0.5, and the CR exceeds 0.6. This indicates that convergent validity was established.Composite Reliability (CR), Average Variance Extracted (AVE), and factor loading. CR is considered an appropriate tool to measure internal consistency reliability. CR is a value in the ranges between 0 and 1, the higher the value, the higher the reliability. Hair et al. (2014) suggests that a CR value of less than 0.6 means a lack of consistent internal reliability. They also suggested that AVE value over 0.5 means that the construct explains more than half of the variance of its indicators while more error remains in the items than the variance explained by the construct when AVE is less than 0.5.

5.4. Discriminant Validity

To test it, the researcher compares the average variance extracted (AVE) values for two constructs with the square of correlation estimate between them. Discriminant validity is significant when the average variance extracted exceeds squared correlation estimates between constructs. A significant level of discriminant validity was established as AVE > than the squared correlation estimates for all the constructs. The average variance extracted is calculated and provided as 0.761326. Asshownin the table below, the value of AVE exceeds all squared correlation values. So, the discriminate validity is established.

Table3:Discriminate valididity

Correlation squared(r^2)	URM	RI	RAA	RMC	MCR	MMR	MLR	MOR
URM		0.016384	0.023104	0.010609	0.023716	0.007225	0.003721	0.0016
RI			0.0196	0.002809	0.002025	0.151321	0.008464	0.010404
RAA				0.000004	0.000016	0.020449	0.024964	0.014641
RMC					0.000529	0.000064	0.000784	0.024336
MCR						0.001225	0.000225	0.006241
MMR							0.001225	0.000625
MLR								0.391876
MOR								

Source: Amos output, 2023

5.5. Structural ModelAssessment

After assessing the measurement model and confirming that the model was good and fit to perform a structural model assessment, the researcher usedthe structural equation model(SEM) to test the pre-established hypothesis. Table 4 reportsthe structural path estimates and squared multiple correlations. Indices such as degrees of freedom = 490, x^2=668.516, the normed chi-square statistic (x2/df) = 1.364, the comparative fit index (CFI) = 0.972, TLI=0.924, IFI=0.901, NFI=0.934, PNFI=0.619, PCFI= 0.784, and the root mean square error of approximation (RMSEA) = 0.044, PCLOSE=0.904 evidenced that data presented a good fit. Cronbach's coefficients were between 0.617 and 0.883, which were higher than the 0.6 acceptable level recommended by the literature.

When we see the regression weight for understanding risk management (Hypothesis1), the critical ratio is 4.107, and the probability of getting above this absolute value is less than 0.001. In other words, the regression weight for understanding risk management in predicting risk management practicesignificantly differs from zero at the 0.001 level (two-tailed). This implies that this study supported the first hypothesis.When we see risk identification(H_2),the probability of getting a critical ratio as large as 0.184 in absolute value is .854. In other words, the regression weight for risk identification in the prediction of risk management practice is not significantly different from zero at the 0.05 level (two-tailed).This study did not support the second hypothesis even though the relation between risk identification and risk management practices was positive.The study found that in significant coefficient.

In risk assessment and analysis (H_3),the probability of getting a critical ratio as large as 2.251 in absolute value is .024. This implied that the regression weight for risk assessment and analysis in predictingrisk management practicessignificantly differs from zero at the 0.05 level (two-tailed).This study supported this finding.For risk monitoring and controlling(H_4),the probability of getting a critical ratio as large as 1.476 in absolute value is .140, and it indicates that the regression weight for risk monitoring and controlling in the prediction of risk management practices is not significantly different from zero at the 0.05 level (two-tailed).The study did not support this finding because of a significant coefficient between risk monitoring and controlling and risk management practices.

The other latent variable for this study is managing credit risk (H_5). The regression weight for managing credit risk in the prediction of risk management practice is significantly different from zero at the 0.01 level (two-tailed), in which the probability of getting a critical ratio as large as 2.633 in absolute value is .008. The study supports this hypothesis.Managing market risk is the sixth hypothesis (H_6), and the probability of getting a critical ratio as large as 0.059 in absolute value is .953. It implied that the regression weight for managing market risk in the prediction of risk management practice is not significantly different from zero at the 0.05 level (two-tailed).This study did not support this hypothesis because of the insignificant coefficient. For managing liquidity risk (H_7),the probability of getting a critical ratio as large as 3.99 in absolute value is less than 0.001. This indicates thatthe regression weight for managing liquidity risk in the prediction of risk management practice is significantly different from zero at the 0.001 level (two-tailed).The coefficient was significant; as a result, this hypothesis was supported. The last hypothesis for this study was managing operational risk (H_8). For this latent variable, the probability of getting a critical ratio as large as 0.941 in absolute value is .347. This impliesthat the regression weight for managing operational risk in predictingrisk management practice is not significantly different from zero at the 0.05 level (two-tailed).An insignificant coefficient between managing market risk and risk management practices indicates that this study did not support this hypothesis.

The squared multiple correlation of a variable is the proportion of its variance that is accounted for by its predictors. It understands risk management,identification, assessment and analysis, monitoring and controlling, credit risk, market risk, liquidity risk, and operational risk for 77.1 % of the variance of risk management practices. In other words, the error variance of risk management practices is approximately 22.9percent of the variance of risk management practices itself. See Appendix 2 for regression weights and p-value.

Table 4: Structural path estimations

Path from	Path to	H	Estimate	S.E.	C.R.	p-value
Understanding risk management	Risk management practices	H_1	0.579	0.141	4.107	***
Risk identification	Risk management practices	H_2	0.020	0.107	0.184	0.854
Risk assessment and analysis	Risk management practices	H_3	0.137	0.061	2.251	0.024
Risk monitoring and controlling	Risk management practices	H_4	0.156	0.106	1.476	0.140
Managing credit risk	Risk management practices	H_5	0.225	0.085	2.633	0.008
Managing market risk	Risk management practices	H_6	0.009	0.153	0.059	0.953
Managing liquidity risk	Risk management practices	H_7	0.349	0.087	3.990	***
Managing operating risk	Risk management practices	H_8	0.084	0.089	0.941	0.347
Squared multiple correlations (R^2)				0.771		

Source: Amos output, 2023. See Appendix 3 for path estimates and R^2. Note: *** $p < 0.001$

5.6. Conclusion and Recommendation

This study assessed the relationship betweenthe dependent variable, risk management practice, and eight independent variables in the Ethiopian banking sector. Thus, the research tried to show bank risk officials' perception of the risk management practice in line with understanding risk management, risk identification, risk assessment and analysis, risk monitoring and controlling, managing credit risk, market risk, liquidity risk, and operational risk.

As shown in Table4, a clear understanding of risk management and risk assessment and analysis in the Ethiopian banking sector significantly related torisk management practice. This study did not support this theory even if risk identification and risk monitoring and controlling are prominent factors for effective risk management practice in the banking industry.Even though those factors coefficient was insignificant, this study disclosed that risk identification and monitoring have a positive relationship with risk management practice. In addition, managing credit risk and liquidity risk significantly determined risk management practices. At the same time, managing market risk and operational risk hasan insignificantbut positive relationship with risk management practices.

This study's result confirmed Ishtiaq's finding that risk management practices are significantly influenced by risk understanding, assessment, and analysis. The finding is also consistent with risk management practices significantly impacted by managing creditand liquidity risks. Whereas risk identification, monitoring and controlling, and managing market and operational risksdid not significantly affect risk management practices in the Ethiopian banking system. Unlike the finding by Elgharbawy (2020), this study revealed that risk management practices are determined by risk assessment and analysis. However, this research finding is consistent with Elgharbawy (2020), which is risk management practice substantially determined by understanding risk management. This study also found the same result with Shafiq and Nasr (2010)that a significant relationship existed between understanding Risk management, risk assessment and analysis, and credit risk analysis with risk management practice. Contrary to this research finding, Shafiq and Nasr (2010) proved that risk management practice is also determined by risk identification and monitoring.Hafez (2015)also evidenced a positive relationship between understanding risk management and risk assessment and analysis and risk management practice, consistent with this research findings.Hassan Al-Tamimi and Mohammed Al-Mazrooei (2007)also found that UAE banks are somewhat efficient in managing risk, and risk identification, risk assessment, and analysis are the most influential variables in risk management practices.Abu Hussain and Al-Ajmi (2012)also observed that banks in Bahrain clearly understood risk and risk management and had efficient risk identification, risk assessment analysis, risk monitoring, and credit risk analysis and risk management practices.Khalid and Amjad (2012)found that Islamic banks are reasonably efficient in managing risk where understanding risk management, risk monitoring, and credit risk analysis are the most influential variables in risk management practice.

After in-depth analysis, the researcher finally concluded that having a standard and clear understanding of risk management across the bank risk officials helps the Ethiopian banking sector with effective risk management practices. In addition, a clear establishment of responsibility for risk personnel enables them to understand risk management and makes prudent risk management practice. For risk assessment and analysis,the bank’s risk assessment by using quantitative and qualitative analysis methods significantly contributed to effective risk management practice. The study also concluded that managing credit and liquidity risk adequately determined risk management practices inthe Ethiopian banking sector.

Not only in Ethiopia but also in the world, a critical risk is credit risk. Thecollapse of many banks comes from the failure to collect loans principal and interestgranted to customers(NBE, 2010). Managing banking activitiesthat create credit risk exposures significantly reduces the likelihood of such activities negatively impacting a bank's earnings and capital.In line with liquidity risk management, it ensures that every bank can fully meet its contractual commitments with depositors, businesses, and other stakeholders. When we see the reality, banks in Ethiopia fail to meet this contractual agreement and force the savers and businesses to withdraw a limited amount of money from a bank. Theycannot provide loans for organizations and individuals because of liquidity problems. Finally, the study recommended that the last resort bank of Ethiopia, the National Bank of Ethiopia, establish proper, clear, and objectively measured criteria for guiding risk management. Risk management guidelines are very loose and fail, providing structured risk management procedures such as risk understanding, identification, risk assessment and analysis, and risk monitoring and controlling.

Reference

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Appendix 1: Assessment of normality

Variable	Min	Max	Skew	C.R.	Kurtosis	C.R.
RMP4	1.000	5.000	-.639	-3.625	-.790	-2.241
RMP3	1.000	5.000	-.637	-3.613	-.494	-1.401
RMP2	1.000	5.000	-.738	-4.184	-.387	-1.098
RMP1	1.000	5.000	-.781	-4.431	-.507	-1.437
MOR3	1.000	5.000	-.344	-1.953	-1.055	-2.992
MOR2	1.000	5.000	-.506	-2.871	-.851	-2.414
MOR1	1.000	5.000	-.488	-2.767	-.746	-2.116
MLR5	1.000	5.000	-.363	-2.058	-.965	-2.737
MLR4	1.000	5.000	-.538	-3.052	-.795	-2.254
MLR3	1.000	5.000	-.681	-3.862	-.663	-1.879
MLR2	1.000	5.000	-.393	-2.231	-.961	-2.724
MMR4	1.000	5.000	-.777	-4.409	-.333	-.943
MMR3	1.000	5.000	-.450	-2.555	-1.011	-2.867
MMR1	1.000	5.000	-.605	-3.430	-.932	-2.643
MCR5	1.000	5.000	-.834	-4.730	-.488	-1.384
MCR4	1.000	5.000	-.787	-4.461	-.470	-1.334
MCR3	1.000	5.000	-.575	-3.262	-.671	-1.903
MCR2	1.000	5.000	-.595	-3.373	-.881	-2.498
MCR1	1.000	5.000	-.558	-3.162	-.959	-2.719
RM6	1.000	5.000	-.082	-.468	-1.300	-3.687
RM5	1.000	5.000	.127	.721	-1.414	-4.010
RM3	1.000	5.000	-.224	-1.268	-1.393	-3.951
RA4	1.000	5.000	-.512	-2.903	-1.188	-3.369
RA3	1.000	5.000	-.589	-3.340	-.951	-2.697
RA2	1.000	5.000	-.377	-2.136	-1.032	-2.926
RI6	1.000	5.000	-.844	-4.787	-.347	-.984
RI5	1.000	5.000	-1.491	-8.457	2.198	6.233
RI4	1.000	5.000	-.611	-3.468	-.618	-1.751
URM4	1.000	5.000	-.513	-2.912	-.760	-2.155
URM3	1.000	5.000	-.658	-3.730	-.645	-1.829
URM2	1.000	5.000	-.501	-2.843	-.957	-2.712
URM1	1.000	5.000	-.487	-2.762	-.853	-2.418
Multivariate					21.310	3.173

Appendix 2: Regression Weights

			Estimate	S.E.	C.R.	P	Label
RMP	<---	URM	.579	.141	4.107	***	par_24
RMP	<---	RI	.020	.107	.184	.854	par_25
RMP	<---	RAA	.137	.061	2.251	.024	par_26
RMP	<---	RM	.156	.106	1.476	.140	par_27
RMP	<---	MCR	.225	.085	2.633	.008	par_28
RMP	<---	MMR	.009	.153	.059	.953	par_29
RMP	<---	MLR	.349	.087	3.990	***	par_30
RMP	<---	MOR	.084	.089	.941	.347	par_31
URM1	<---	URM	1.132	.186	6.076	***	par_1
URM2	<---	URM	1.412	.209	6.758	***	par_2
URM3	<---	URM	1.555	.219	7.105	***	par_3
URM4	<---	URM	1.000				
RI4	<---	RI	.964	.202	4.762	***	par_4
RI5	<---	RI	.994	.208	4.781	***	par_5
RI6	<---	RI	1.000				
RA2	<---	RAA	.123	.115	1.072	.284	par_6
RA3	<---	RAA	1.077	.302	3.570	***	par_7
RA4	<---	RAA	1.000				
RM3	<---	RM	2.087	.453	4.609	***	par_8
RM5	<---	RM	1.393	.271	5.134	***	par_9
RM6	<---	RM	1.000				
MCR1	<---	MCR	1.267	.131	9.666	***	par_10
MCR2	<---	MCR	1.023	.126	8.123	***	par_11
MCR3	<---	MCR	.944	.113	8.332	***	par_12
MCR4	<---	MCR	.927	.111	8.322	***	par_13
MCR5	<---	MCR	1.000				
MMR1	<---	MMR	2.163	.553	3.910	***	par_14
MMR3	<---	MMR	1.587	.401	3.958	***	par_15
MMR4	<---	MMR	1.000				
MLR2	<---	MLR	.900	.131	6.880	***	par_16
MLR3	<---	MLR	1.297	.150	8.657	***	par_17
MLR4	<---	MLR	1.114	.138	8.062	***	par_18

			Estimate	S.E.	C.R.	P	Label
MLR5	<---	MLR	1.000				
MOR1	<---	MOR	1.096	.244	4.493	***	par_19
MOR2	<---	MOR	.822	.185	4.450	***	par_20
MOR3	<---	MOR	1.000				
RMP1	<---	RMP	1.238	.146	8.497	***	par_21
RMP2	<---	RMP	.777	.119	6.518	***	par_22
RMP3	<---	RMP	.736	.119	6.188	***	par_23
RMP4	<---	RMP	1.000				

Appendix 3: Results for path estimates and R-square.