Unveiling the Relationship: Earnings Quality and Income Protection Performance through the Hidden Markov Model in Economic Growth Perspectives

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ABSTRACT

Over the past three decades, especially since the recent financial crisis, the volume of academic research analysing banks' efficiency and productivity has grown substantially. The risk-taking behaviour of banks used to be of relatively low interest; however, in recent years, this interest has exploded, especially in regards to its correlation with monetary policy. Measuring credit risk has been and will continue to be a top priority in the banking industry, and the recent global economic crisis has had a direct impact on this process. In this research, the authors of a hidden Markov model-based earnings quality measurement propose and verify its usefulness. Earnings fidelity is a measure of how closely reported earnings correspond to the company's true financial health. The percentage represents the level of accuracy achieved. The impact of earnings management on financial institutions' bottom lines is the focus of this research paper. Within the framework of a Bayesian hierarchical model that allows for cross-sectional heterogeneity, we employ a Markov chain Monte Carlo procedure to estimate the variable in question. The forward earnings response coefficient is positively correlated with earnings fidelity, suggesting a positive relationship between the two.

Keywords: Earnings management, bank performance, risk-taking, corporate governance, Markov model.

INTRODUCTION

Corporate governance research focuses on the factors that influence a company's success. An important focus of this body of work is the role of financial management in organisational performance. Financial statements for businesses include information on a company's earnings, also known as the "bottom line" or "net income" (Akram et al., 2015). It is widely accepted that earnings are a good indicator of a company's financial health as well as its profitability and market strength. Profitability can be measured in a variety of ways by both external and internal users. Managers' pay plans, debt covenants, investors, and creditors, to name a few, all rely on earnings data (Tabassum et al., 2015; Dechow, 1994). Earnings management through manipulation of accounting earnings has been studied in accounting and finance literature. Based on study of Ljubisavljević and Jakobsson (2022), the pandemic caused by the COVID-19 virus has resulted in a number of financial difficulties. In times of financial distress, companies are typically incentivized to use earnings management techniques so that they can alter the picture that they have of their current financial situation. This is because market-based pressure encourages companies to do so.

However, studies have shown that institutional and macroeconomic factors may be more influential during times of crisis. This is due to increased scrutiny and acceptance of abnormal results, both of which may make such practises less attractive.

Earnings management is the tools or processes used by insiders, within the constraints of Generally Accepted Accounting Principles (GAAP), to manipulate earnings or change the reported number against the interests of outsiders (Cimini, 2015; Healy and Wahlen, 1999; Schipper, 1989). Companies, on the other hand, only use earnings management when it is an option (Teoh et al., 1998). Earnings management's primary goal is to smooth out the flow of money. In order to achieve this goal, businesses can use a variety of methods. On the one hand, managers attempt to reduce reported earnings when a company's previous earnings were high. As a result, managers try to boost reported earnings if previous earnings are low (Tabassum et al., 2015; Zang, 2011). In addition, executives use earnings management to maintain a high level of performance and to achieve personal contractual goals linked to the reported accounting figures (El Sood, 2012; Goulart, 2007).

It is possible for executives to inflate or underflate the reported income to demonstrate the performance of the company and obtain higher compensation tied to the firm's expected future performance (eg. firm performance and earning management; Mostafa and Ibrahim, 2019) . As a result, the way managers implement earnings management practise can have either a positive or negative impact on the performance of the company (Bornemann et al., 2012). Earnings reports are impacted by several factors, including the fundamental performance of a company as well as the measurement process, which is governed by reporting standards, auditing technology, and managerial discretion (Dechow et al., 2000; Nikolaev, 2017). In previous studies, the level of earnings quality was evaluated based on statistical properties of earnings (such as smoothness, earnings kinks, and target beating) as well as regression-based abnormal accrual models (Dechow et al., 2010). Researchers use models that are based on regression to differentiate "abnormal" accruals from "normal" accruals based on fundamental performance, and they base the definition of accruals quality on abnormal accruals (Dechow and Dichev, 2002). Recent studies have shown, however, that using proxies for unobservable "true" earnings may lead to confusion between performance shocks and reporting discretion (Guay et al., 1996; Ball, 2013; Dichev et al., 2013; Owens et al., 2017).

An important influence on a company's profitability and performance is earned management practise. Financial performance is the primary source of information for investors and other stakeholders, so an examination of the link between earnings management and performance is critical. In order to prevent future scandals, the demand for research into the causes of accounting figure manipulation and their effects on firm stability has increased since the last financial crisis (Ardekani et al., 2012). Indeed, since the last financial crisis, earnings management has received a growing amount of attention from scholars (Filipa and Raffournierb, 2014; Cimini, 2015; Debnath, 2017).

To mitigate the danger of using unreliable proxies, our approach uses a statistical model called the Markov Model to decouple the two concepts of accounting quality and the process of actual earnings. Each company is thought to undergo state transitions according to a Markov process, at least in our model. The company's underlying performance is represented by the state, which can be either Low (L) or High (H). The status of the company is hidden from view, but at the end of each period (h), it announces whether its earnings were low (l) or high (h). Inferring a company's unobservable state from its earnings signals is possible because the likelihood that it will issue a particular signal depends on the state. As a result, the probabilities that a firm will stay in its current state or switch to the other state and the probabilities that it will emit a given earnings signal are uniquely associated with each firm in each period. Based on the design of this HMM, we can make an educated guess as to how well earnings signals reflect the true health of the business. Earning Fidelity is the name given to this metric.

A consensus has not yet emerged regarding the optimal earnings quality metric (Dechow et al., 2010). New to empirical research that proposes accounting quality measures based on distributional properties of earnings (e.g., smoothness) and reduced-form regression models is the Bayesian hierarchical method (e.g., accruals quality). Our structurally estimated earnings quality measure is theoretically motivated and provides at least two advantages over existing quality measures. Initially, the Bayesian hierarchical method considers firmspecific parameters to be random variables drawn from a distribution. As a result, the method combines firmspecific data with essential prior information (i.e., the distribution of all firms' parameter values). Secondly, this method does not restrict connections between companies. Companies in the same industry or

published in the same year, for instance, need not be connected in a particular way. This hypothesis has the potential to minimise measurement error.

Different conclusions can be drawn from theoretical and empirical studies of accounting quality. In contrast to the static models of financial reporting that have been the focus of the analytical literature (Christensen and Feltham, 2003), the empirical literature has proposed quality measures based on accounting data from multiple periods. The hidden Markov model allows us to make our reporting systems dynamic rather than static. By providing an estimate of the reporting system's properties in a multiperiod setting, the theory of earnings quality is brought closer to practise. Accounting structural estimations typically ignore cross-firm heterogeneity (Bertomeu et al., 2018; Zakolyukina, 2019; Du, 2019), but this is something that can be fixed by employing Bayesian hierarchical modelling. Using Bayesian hierarchical modelling and Markov chain Monte Carlo (MCMC), respectively, Bernhardt et al. (2016) and Zhou (2021) estimate the impact of investor learning on cross-sectional variations in the manager's voluntary disclosure and the stickiness of analyst recommendations in a cross-section of analysts. For the first time, we use a firm- and time-dependent Bayesian method to estimate earnings quality in our study.

2. The Method and Forecasting Model

2.1 Data

Extending previous empirical studies, this paper examines the impact of earnings management on bank profitability. Financial institutions play an important role in maintaining the integrity of the global financial system (Cheng et al., 2011). Aside from that, banks were seen as an important player during the most recent financial crisis (Faulkender et al., 2010; Claessens and Horen, 2015). These findings show how important it is to look into the connection between earnings management and bank performance. Islamic banks that were active between 2000 and 2021 are included in the study's initial sample. In the end, we have a final sample of 150 bankyear observations representing 15 Malaysian Islamic Banks after restricting all banks with the data needed to analyse our primary variables of interest. The Orbis database is where we get the numbers and dates for loan loss provisions. Any information that was missing was gleaned from the annual financial reports. The data analysis is using the R project for statistical computing software version 4.3.0.

2.2. Earnings Management in Markov Model Forecasting

The measure of the earnings' quality that we conceptualise as Earnings Fidelity is the degree to which a company's earnings signal reveals the underlying state of the company, where "state" refers to the economic conditions that have an impact on the company's fundamental performance. The recipients' confidence in their inferences about the state of the company is boosted when the earnings signal contains more accurate information. We need a theoretical model in which earnings serve as a noisy indicator of the firm's underlying condition so that we can formalise earnings fidelity. This will allow us to measure earnings more accurately. For the purpose of this function, we make use of a highly stylized model.

Numerous empirical studies on earnings management can be found in accounting and financial literature. Different measurements, such as discretionary accruals, smoothness, timeliness, loss avoidance, and investor responsiveness, are utilised as proxies for earnings management in these empirical studies (Dechow et al., 2010). For the banking sector, discretionary loan loss provision (DLLP) is one of the most frequently used proxies for measuring earnings management practise (Burstahler and Dichev, 1997; Anandarajan et al., 2003; El Sood, 2012). On the other hand, Hegde and Kozlowski (2021) find that the following year's earnings and loan growth are significantly higher for banks that report higher provisions during prosperous times, while non-performing loans continue to rise for the same banks during recessions. The economic downturn of 2008 had no bearing on these numbers. Investors were already skeptical of DLLP prior to the financial crisis. Regulators need to make sure that bank loss reserves continue to be a reliable source of information even as new accounting standards call for more subjective judgment. Before calculating DLLP, loan loss provision must be separated into discretionary and non-discretionary components. To estimate the non-discretionary

components of loan loss provision, we follow prior research (Beaver and Engel, 1996; Kanagaretnam et al., 2004; Zoubi et al., 2007; Cheng et al., 2011; Ben Othman and Mersni, 2014) and use the following model.

$LLP_{it} = + \square \square_{01} NPL_{it-1} + \square_2 \square NPL_{it} + \square_3 \square TL_{i\,t,} + \square$.....(1)

Where:

LLP_{it} = Total provision for loan losses for bank *i* at year *t*, deflated by beginning loans.

NPL_{it-1} = The beginning balance of non-performing loans for bank *i* at the end of year *t*, adjusted for inflation.

$\square NPL_{it}$ = Variation in the value of non-performing loans for bank *i* at year *t*, deflated by the value of beginning loans.

$\square TL_{it}$ = Change in total loan value for bank *i* at year *t*, deflated by initial loan balances.

The discretionary loan loss provision, also known as $DLLP_{it}$ it is computed by using the residual from

Model 1. According to studies that were conducted in the past (such as the ones conducted by Kanagaretnam et al. (2004) and Ben Othman and Mersni (2014), the loan loss provision has a positive correlation with the levels of non-performing loans, beginning balances of non-performing loans, and total loans. This is because the probability of a loan going into default increases when a bank extends more credit, which forces the bank to increase the amount of money it sets aside to cover bad loans. From the standpoint of earnings quality, banks have incentives to reduce earnings volatility by decreasing earnings in years with an unexpectedly strong performance and increasing earnings in years with a poor performance. A more consistent flow of earnings could help reduce the information asymmetry between managers and outside investors (Beatty et al., 2002; Beatty & Harris, 1999; Liu & Ryan, 2006; Beatty et al., 2002; Beatty & Harris, 1999). There is evidence in many previous studies that managers smooth earnings through LLP and recognise security gains and losses. Consequently, these variables must be considered when evaluating the quality of earnings.

There are many different approaches that can be taken to calculate efficiency indicators that consider the risk-taking behaviour of financial institutions like banks. According to the findings of previous studies, the amount of nonperforming loans can be factored into the production function of a bank as a form of negative output (or, in terms of the profit function, as an expense that reduces total profits). If either the interest payments or the principal payments on a loan are more than ninety days past due, the loan must be categorised as nonperforming in accordance with Spanish accounting standards. In addition, regardless of the status of the borrower's payments, all loans that have been granted to defaulting borrowers are regarded as nonperforming loans.

In accordance with Spanish banking regulations, bank managers estimate LLP based on a stringent set of rules established by the Bank of Spain, which are heavily dependent on the length of time payments are past due. However, Bank of Spain regulations determine the minimum losses a bank must recognise once a loan has been deemed nonperforming, leaving banks with a great deal of leeway. To mitigate the effects of the potential manipulation of LLP, we use anticipated LLPs as expenditures rather than realised LLPs. This reveals whether banks' LLP decisions to manage earnings or capital (and circumvent strict accounting rules by over- or underprovisioning assets or misclassifying them) are effective. According to Pérez et al. (2008), if they were successful, stringent regulations on LLP might be unnecessary, and "there is merit in having more principlesbased accounting standards" (Pérez et al., 2008).

After estimating the extent of earnings manipulation in the Spanish banking system, we estimate a nonconvex model of the short-run profit frontier. This model follows Fare et al. (1994) by classifying the inputs as variable (*xv*) and fixed (*xf*) based on the original variables (in the case of a bad output, only considering the realised LLPs) Primont, (1993), for a short run cost frontier definition). We will therefore model variable profit maximisation.

$manip \qquad \square_M \qquad V \qquad O \qquad \square$

$$(r_{jm}, P_{jv}, P_{jo}) = \max(z u_m, x npl_v, o) \left[\sum_{m=1} r u_{jmm} - \sum_{v=1} p x_{jv} u - \sum_{o=1} p npl_{jo} o \right] \quad \ldots(2)$$

Where:

j

$$\sum_{j=1} z u_j jm \leq u_m, m = 1,\ldots\ldots\ldots,M,$$

j

$$\sum_{j=1} z x_j jv \leq x v_v, = 1,\ldots\ldots\ldots,V,$$

j

$$\sum_{j=1} z x_j jf \leq x_{jf}, f = 1,\ldots\ldots\ldots,F,$$

j

$$\sum_{j=1} z npl_j jo \leq npl o_o, = 1,\ldots\ldots\ldots,O,$$

j

$$\sum_{j=1} z_j = 1,\ldots\ldots\ldots,M,$$

$z_j = [0,1]$ where $r_{jm} \in R_+^M$ is the vector of output prices for bank j, $r_{jm} \geq 0$, and we also have variable inputs (netputs) with prices $p_{jv} \in R_+^V, v = 1,\ldots\ldots\ldots,V$. Analogously $u_j \in R_+^M$ is the vector of output quantities for j $x_{jv} \in R_+^V$ are the variable net puts for bank j and $x_{jf} \in R_+^F$ are the fixed netputs for the same bank. However, compared with the contributions of Färe et al. (1994) and Primont (1993), we are considering here the role of risk via LLPs. Therefore, we have $npl_j \in R_+^O$ is the amount of NPLs for bank j $o, = 1,\ldots,O$, and $p_{jo} \in R_+^O$ will be their prices.

2.3 Indicators of Income Performance

The goal of this study is to see if bank earnings management has an effect on the bottom line. The return on assets (ROA) and return on equity (ROE) ratios are therefore used to assess a company's financial performance in line with previous empirical research (Kothari et al., 2016; Akram et al., 2015; Alhadab and Alsahawneh, 2016). A company's ROA is an important measure of profitability. It measures a company's total assets divided by total income. These assets can be used to generate income for the company, and this ratio measures that ability. As a result, this ratio provides insight into the efficiency with which a company's assets are turned into revenue. The more efficiently a company utilises its own resources, as according to Wen (2010), the higher the ROA ratio. In the context of financial reporting, ROE is the ratio of a company's net income to its total shareholder equity. In other words, it's a way of quantifying how much of their money they're getting back in terms of profit. Internal cash flow is expected to be a strength of a company with a high return on equity (ROE). As a result, a higher ROE signifies better business performance. The ROE ratio measures a company's ability to generate a profit for its shareholders. ROE is also a measure of a company's executive's ability to manage shareholder capital (Ongore and Kusa, 2013).

We estimate a model in which the dependent variable is a proxy for banks' performance (ROA/ROE) and the main explanatory variable is a proxy for discretionary loan loss provision in order to examine whether earnings management (via manipulation of loan loss provision) has an impact on banks' current and future performance (DLLP). Determinants of performance are included in the study, following previous research (Moyer et al.; Collins et al.; Ahmed et al., 1999; Kanagaretnam et al., 2004; Liu and Ryan, 2006). The ($EBTP_{it}$), risk-

adjusted Tier 1 capital ratio (CAP_Tier1_{it}), firm size ($SIZE_{it}$), and leverage ratio (LR) are all adjusted for (LEV_{it}). There is no way to predict the sign (+/-) of direction for these determinant variables because prior research Darjezi (2006) showed that the discretionary loan loss provision could be measured with errors. Using these models, we look at the relationship between DLLP and performance (ROA/ROE).

$ROA_{t\,i+} = +\square\ \square_{0\,1}DLLP_{it} + \square_2 EBTP_{it} + \square_3 CAP\ Tier\_\ 1_{it} + \square_4 SIZE_{it} + \square_5 LEV_{it} + \square$.....(3)

$ROE_{t\,i+} = +\square\ \square_{01}DLLP_{it} + \square_2 EBTP_{it} + \square_3 CAP\ Tier\_1_{it} + \square_4 SIZE_{it} + \square_5 LEV_{it} + \square$.....(4)

Where:

i = 1

ROA= Return on assets for bank i at the year t.

ROE = Return on equity for bank i at the year t.

$DLLP_{it}$ = Discretionary loan loss provision that is calculated as the residual from model (1) for bank i at the year t.

$EBTP_{it}$ = Earrings before tax and loan loss provision for bank i at the year t.

$CAP\ Tier\_\ 1_{it}$ = Risk-adjusted Tier 1 capital ratio for bank i at the year t.

$SIZE_{it}$ = Natural logarithm of market value for bank i at the year t.

LEV_{it} = leverage ratio that is calculated as total debt divided by total assets for bank i at the year t.

2.4 Advantages and Drawbacks of The Method

Our approach would be severely lacking without the use of the hidden Markov model and the Bayesian hierarchical framework. Each prototype is out of sight. Both have the potential to enhance the quality of earnings measurement. To make use of the hidden Markov model, it is not necessary to monitor surrogate measures for the true states. Because it does not rely on empirical proxies for the underlying states, our approach to decoding earnings signals is less vulnerable to misspecification and variable omission. The likelihood of inaccurate results is reduced as a result. Developing firm-level empirical measures is a common task in the accounting literature, and there are two common approaches that need to be compared in order to understand the relative benefits of the Bayesian hierarchical framework. These techniques are employed in the creation of firm-level empirical measures. To begin, a researcher may assume that the unidentified parameters are the same across all companies in a given group. Cross-sectional or panel regressions could then be used to estimate the parameters (Dechow and Dichev, 2002; Hribar et al., 2014).

On the other hands, it's possible that this approach won't work if the parameters change along a crosssection. Second, researchers can estimate parameters for each company using firm-specific time-series regressions (Lipe et al., 1998). Firm-specific analysis relaxes the assumption that model parameters are the same for all firms, but it requires a long sequence of observations to reliably estimate firm-level parameters, which is frequently impractical. There is no guarantee that a time series will remain stationary, even if it is very long. Firm-specific estimates should be "shrunk" to the population mean when there is a dearth of firm-specific data.

The reliability of our measure is based on the assumption that the financial reporting process has a hidden Markov structure. Nevertheless, there is no reason to believe that this structure is less plausible than those underlying reduced-form accounting quality measures, which could lead to measurement error if not described accurately. There is no a priori reason to assume that accounting signals are a linear function of proxy values for the underlying states, which is why some measures using reduced-form relationships are derived.

Firm-specific parameters are selected from a distribution using a hierarchical Bayesian framework. These estimates are based on a combination of company data and population distribution. The importance of the first

is inversely proportional to the volume of data collected specifically from the company. Using long-term data sets is the most important factor in determining firm-specific estimates. Relatively close estimations occur when time series constraints are applied. Studies show that Bayesian hierarchical estimates have a significant advantage over conventional estimates in terms of precision (Greenland, 2000). As a result, a Bayesian hierarchical framework can significantly improve firm-specific estimates for firms with limited time series. Readers are referred to prior research in Bayesian analysis. Check out the article to learn more about the advantages of the Bayesian hierarchical framework in terms of technology (Gelman, 2006; Gelman et al., 2013).

There are three potential costs associated with the Bayesian method. First, even though Bayesian hierarchical model estimates frequently have a lower variance than firm-specific estimates, they may have a greater bias (Greenland, 2000). Any misspecification of the prior distributions of unknown parameters can result in biased parameter estimates. The influence of priors may not be negligible when the ratio of data-based information to "parameters" is low (Rossi et al., 2005). Lastly, the estimation algorithm utilised in MCMC simulation is frequently computationally demanding. This is especially true for firm-level parameters for which each iteration of the Metropolis-Hasting algorithm implementation requires the calculation of the likelihood function. In spite of these potential costs, we believe the Bayesian hierarchical model can be a valuable tool for accounting researchers interested in estimating firm-level measures.

3. Analysis of The Results

3.1 Descriptive Statistics

Table 1 below described the descriptive statistics for variables included in the Model 1 and Model 2 and assuming that the total loan loss provision ranges from RM -1,069,832 to RM 35,120,480 and has a mean value of RM 1,028,756.8; non-performing loans range from RM 2,933 to RM 42,563,000 and have a mean value of RM 19,646,287.9; and total loans range from RM 450,650 to RM 3,498,000,000 and have a mean value of RM 431,400,000. These statistics indicate that the average percentage of nonperforming loans for Islamic banks is approximately 2%; the lower this percentage, the lower the risk of bank failure. Table 1 also provides statistics for the aforementioned variables scaled by the initial loan balance.

Table 1. Descriptive Statistics for Variables of Loan Loss Provisions.

Model	Mean	Standard Deviation	Min	Max
LLP_{it}	1028756.841	4525463.900	-1069832.140	35120480.000
NPL_{it}	19646287.872	1365478.916	2933.000	42563000.000
TL_{it}	431,400,000.000	596,200,000.000	450650.000	3,498,000,000.000
$LPP\ TL_{it}/\ _{it-1}$	0.005	0.005	-0.002	0.065
NPL_{it-1}/TL_{it-1}	0.085	0.061	0.000	0.415
$\Delta NPL\ TL_{it}/\ _{it-1}$	0.037	0.017	-0.954	2.369
$\Delta TL\ TL_{it}/\ _{it-1}$	0.056	0.023	-0.421	1.262
N	150			

Table 2 provides descriptive statistics for the dependent and independent variables utilised in Models 3 and 4, which are used to investigate the relationship between earnings management and performance. The main independent variable of interest, $DLLP_{it}$ has a mean value of 0.006 and a range of 0.008 to 0.045. In contrast,

ROA and ROE (our performance proxies) have mean values of 1.056 and 9.084, minimum values of -4.230 and -98.021, and maximum values of 8.415 and 42.071, respectively. Earnings before tax and loan loss provision $EBTP_{it}$ ranges from RM -45,620,000 to RM 35,644,159 with a mean value of RM 1369,5411.2; adjusted risk Capital Tier 1 ratio *CAP Tier_ 1* ranges from 6.150 to 30.109, with a mean of 11.352; banks size ratio *SIZE* ranges from 12.329 to 23.754, with a mean of 20.105; and leverage ratio *LEV* (LEV) ranges from 3.960 to 94.652 with a mean value 34.092.

Table 2. Descriptive Statistics for Variables of Association between Earnings Management and Performance.

Model	Mean	Standard Deviation	Min	Max
$DLLP_{it}$	0.006	0.004	0.008	0.045
ROA	1.056	0.104	-4.230	8.415
ROE	9.084	15.419	-98.021	42.071
EBTP	1369541.213	7048563.281	-4.562e+09	35644159.000
CAP Tier_ 1	11.352	4.514	6.150	30.109
SIZE	20.105	2.583	12.329	23.754
LEV	34.092	15.265	3.960	94.652
N	150			

3.2 Regression Coefficient DLLP with ROA

Results of our primary investigation into how earnings management affects the current and future performance of banks are presented in this section (Models 2). Earnings management has a significant negative impact on current and future operating performance, as shown in Table 3 (the first performance proxy). Specifically, in Table 3, column 1 shows that the $DLLP_{it}$ coefficient is negative (-42.764) and statistically significant at a 1% level for the current ROA_{it}. At the 1% level, the coefficients of the other explanatory variables $EBTP_{it}$, *CAP Tier_ 1*$_{it}$, $SIZE_{it}$, and LEV_{it} show that they are significant predictors of current operating performance ROA_{it}. Explanatory power (Adj.R^2) for the model is 0.590, which means that explanatory variables account for 59.0% of the variance in current operating performance ROA_{it}, as shown in Column 1 of Table 3.

In addition, the results for future performance ROA_{it+1} can be found in column 2 of Table 3. Earnings management in the current year has a negative effect on operating performance in the following year, according to the $DLLP_{it}$ coefficient (-42.119) which is statistically significant at 1%. Prior studies have shown that earnings management has a negative impact on a company's bottom line. The explanatory variables, as shown in Table 6's column 2, are also good indicators of future performance, as shown in the table. Column 3 of Table 3 shows that earnings management has a negative impact on future performance when ROA_{it+2} is the dependent variable. At the 1% level, we can see a negative (- 46.811) correlation coefficient in column 3 of Table 3 for the measure of $DLLP_{it}$.

According to Table 3, the manipulation of the loan loss provision $DLLP_{it}$ has a significant and long-lasting impact on current ROA_{it} and future operating performance. This supports our first hypothesis that banks' earnings management negatively impacts their current and future operating performance. Earlier studies (Cohen and Zarowin, 2010, Kothari et al., 2016) have shown that earnings management has a detrimental effect on future operating results.

Table 3. The Relationship between Earnings Management and Performance by ROA

Variables	ROA_{it}
Constant	1.287* (1.811)
$DLLP_{it}$	-35.628*** (-2.111)
EBTP	0.000*** (6.548)
*CAP Tier_* 1	0.534*** (2.644)
SIZE	-0.048** (-1.997)
LEV	0.011*** (7.202)
N	150
Adj. R-squared	0.879

Note: ***, **, * Significant at the 1%, 5%, and 10% level.

DISCUSSION AND CONCLUSION

An investigation into the current and future effects of earnings management on bank performance is presented in this study. Few studies have examined how earnings management practises in Europe's banking industry affect current and future performance. This study is one of those few. An analysis of 150 bank-year observations from 2000 to 2021 from 15 Islamic Banks in Malaysia is presented in this article, which adds to the body of knowledge. The new data demonstrates that Malaysian Islamic Banks that use discretionary loan loss provisions to manage earnings have lower current and future operating performance (as measured by ROA or return on assets). This evidence is consistent with previous studies that show a negative correlation between earnings management and future performance (Cohen and Zarowin, 2010, Kothari et al., 2016)..

Therefore, the findings of this paper have important implications for Malaysian regulators who want to reform the regulatory environments of the Malaysian banking industry to reduce practises of earnings management involving the manipulation of provisions for loan losses. These banks' current and future performance has been adversely affected by the manipulation of their loan loss provision, which has been discovered to be a problem in Malaysian Islamic Banks. For this reason, it is imperative that all parties involved (such as government regulators, financial institutions, and independent audit firms) work together to address these reforms.

Based on the method that we discover for Markov Model with earning fidelity; we've created an entirely new way to assess the quality of an individual's earnings. Estimates of the firm's economic condition are based on a structural model that separates it from its reporting system. To arrive at the Fidelity estimate, all that is needed is one measure of earnings and no additional information beyond what is already available (such as smoothness and accruals quality). Even small businesses can benefit from using this method. There is a significant conceptual difference between our study and previous research on earnings persistence in that we did not make a distinction between earnings signals and underlying states. If a company's past earnings are

used to infer its current state, then valuing it must be a filtering problem. We believe that both economic persistence and earnings consistency are related, but that earnings persistence is distinct from them.

Even though we've focused on earnings, our methodology can be applied to other research contexts. An advantage of this method is that it can be used when empirical proxies fail to capture latent states accurately enough. Other types of accounting information (such as recognising a loss contingency) could also be used to estimate the accuracy of the firm's underlying condition. Because it does not rely on empirical surrogates for latent states, this method has a significant advantage over other approaches. A less reliable source of earnings signal is not considered by our metric. Managers' decisions within a given framework of accounting rules and the specifics of that framework influence the fidelity of earnings in an intuitive way. Future studies could focus on separating these components and determining how important they are.

Extensive attention is paid to credit risk from both theoretical and empirical perspectives. Nevertheless, despite the growing number of contributions, most of this research has focused on specific topics, such as how to evaluate the risks of individual loan operations and or borrowers, and how lenders (banks) respond to these evaluations (Salas & Saurina, 2002). In this paper, we examine the relationships between bank performance and risk-taking behaviour, i.e., how various (non-financial) firm characteristics, particularly creditworthiness, are related to various measures of bank performance. Our study differs from previous contributions that have emphasised the significance of the relationship between banks and their (non-financial) borrowers in that we attempt to model explicitly the links between the financial situation of the borrowing firms and the risk banks assume, as well as how bank performance influences this link.

Research in this area is promising because the analysis can be improved from multiple angles, resulting in more accurate and precise economic policy recommendations. Even though our study was innovative because of the proposed efficiency measures, additional measures can be used to further strengthen the analysis. The potential for LLP manipulation is often overlooked when evaluating these measures, and we believe it is critical to take a similar approach when defining efficiency. By considering various time lags, we can examine how bank inefficiency and the risk characteristics of their customers interact over time.

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