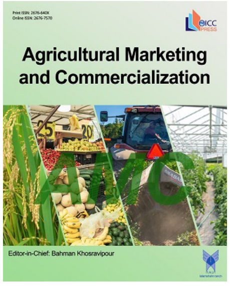

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Original Article

Modeling the Relationship Between Real Earnings Management and Accruals Over Time

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Abstract:

The use of traditional variables and models in explaining the factors affecting real and accrual-based earnings management has faced numerous challenges in the literature. Accordingly, the objective of the present study is to model the relationship between real earnings management and accruals over time. The present research is applied and exploratory. The study's time horizon covers the period 2011-2023. Data from 131 listed companies were used in estimating the model. First, the determinants of real and accrual-based earnings management were theoretically explained; then, using Bayesian econometrics and the "Bayesian Model Averaging" method in MATLAB, the models of real and accrual-based earnings management were estimated. By performing the calculations and examining the effects of 56 factors that had been identified in empirical studies as affecting accrual-based earnings management and 13 factors affecting real earnings management, it was determined that the effects of 8 variables on these two types of earnings management were significant, and that these variables consistently maintained their effects in the presence of other variables; in other words, they were robust. Based on the results of the time-varying parameter model approach, the average net effect over the entire period in the model in which real earnings management is the dependent variable is smaller than in the case where accrual-based earnings management is the dependent variable; in other words, in calculating the net effect, it is observed that, in its overall trend, real earnings management substitutes for accrual-based earnings management. According to the results, in the short term, the relationship between real and accrual-based earnings management is positive and complementary. In contrast, in the medium and long term, it is substitutive.

Keywords: Accrual-based earnings management, Real earnings management, Bayesian averaging, Time-varying parameter

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INTRODUCTION

Today, information plays an effective role in economic decision-making, and the quality of such information undoubtedly depends on the accuracy and precision of its preparation. In this regard, earnings are one of the most essential pieces of information reported by companies(Imeni, 2019). One of the fundamental financial statements that meets part of users' needs is the income statement. Accordingly, the final product of the income statement is net profit, one of the financial statement items with a significant impact on the decisions of investors and other users of financial statements(Zalaghi, 2018). Moreover, some believe that investors place greater value on companies with stable and sustainable earnings; as a result, managers may resort to earnings management to increase their company's share price (Damoori, 2011).

Furthermore, studies in earnings management identify two primary methods for managing earnings. Company managers can manage earnings through the manipulation of accruals and real activities(Mashayekhi, 2016).

Earnings manipulation is a strategy applied by a company's manager for the purpose of manipulating the level of earnings. This process is carried out through the purposeful manipulation of company figures, in a way that ensures the changes are as closely aligned with the company's conditions as possible to avoid detection(Roozbahani, 2017).

Zang, argue that earnings management can be carried out both from the perspective of financial reporting and through other managerial activities; however, researchers such as Healy and Schipper contend that it occurs primarily within the scope of financial reporting and accrual accounting (Zang, 2012).

Accordingly, Cohen et al., redefines earnings management based on Healy and Wahlen's definition (D. A. Cohen, Dey, A., & Lys, T. Z., 2008). According to his view, earnings management occurs when managers use judgment in financial reporting and in structuring transactions to manipulate financial reports, mislead specific stakeholders about the company's business activities, or influence the outcomes of contracts based on reported accounting numbers. It should be noted that motivations for earnings management can be divided into efficient and opportunistic (Karimi, 2015)

Manipulation of real activities is a purposeful action to change reported earnings. This occurs through changes in the timing and/or structure of operating, investing, and/or financing activities, and its underlying cause is weak business performance that has fallen below the optimal level. The idea that firms use real activities manipulation (Graham, 2005) and (Das, 2009).

Real activities manipulation involves a deviation from normal operating practices, and managers engage in it to mislead specific stakeholders into believing that financial reporting objectives have been achieved through everyday activities. Real earnings management is carried out through methods such as granting price discounts and reducing discretionary expenditures such as research and development (Das, 2009).

Shah, et al., defines real earnings management as the deviation from normal operating activities by managers to mislead certain stakeholders into believing that financial reporting objectives have been met in the normal course of operations (Shah, 2024).

Gary, argue that if managers are extensively involved in such activities, this indicates a tendency toward real earnings management, because such activities can affect current-period earnings. Although these deviations enable management to meet reporting objectives, they do not necessarily increase firm value. Prior studies provide evidence that firms have shifted from managing earnings through real activities toward accrual-based earnings management (Gary, 2013).

There is also evidence that firms choose between these two earnings management approaches (D. A. Cohen, Dey, A., & Lys, T. Z., 2008).

Despite the costs associated with real activities manipulation (by which we mean variables related to earnings management approaches), it is unlikely that managers rely solely on accruals manipulation to manage earnings. The results of Burns and Merchant and Graham et al. indicate a strong tendency among executives to manage earnings through real activities rather than through accrual manipulation, because accrual-based earnings management attracts greater attention from auditors and regulators (Hassani, 2024).

Our research question is whether there is a relationship between the two earnings management strategies. To answer this question, the motivations underlying the chief executive officer's equity incentives must first be identified as a determinant of earnings management. Market participants tend to reward accrual-based earnings management with positive stock returns (P. M. Dechow, & Skinner, D. J., 2000).

Recent studies increasingly show that firms increasingly use real activities manipulation as a substitute for accrual-based earnings management (D. A. Cohen, & Zarowin, P. , 2010).

It should be noted that the results of various studies regarding the nature of the relationship between real and accrual-based earnings management are mixed. Some of these studies find a negative relationship between the two (Amini, 2025), some find a positive relationship and in more recent research conducted by Cohen & Lys, no significant relationship between real and accrual-based earnings management was identified (D. A. Cohen, & Lys, T. Z. , 2022).

Some studies, such as Chan et al., view this relationship as variable and state that the interaction between types of earnings management depends on conditions. Consequently, the main issue of the present study is how to model the relationship between real and accrual-based earnings management on the Tehran Stock Exchange. To address this issue, the following two sub-questions must be answered (Chan, 2015).

First, what is the optimal model of real and accrual-based earnings management in the Tehran capital market? Second, does the nature of the relationship between real and accrual-based earnings management depend on the time horizon, or not? In other words, does the nature of the relationship between real and accrual-based earnings management change over time, or is it constant?

THEORETICAL FOUNDATIONS AND RESEARCH BACKGROUND

Theoretical Foundations

Managers implement earnings management through both discretionary accrual manipulation and manipulation of real activities. In other words, these two play complementary roles, and management uses both methods together to achieve earnings management objectives. Since accrual-based earnings management is usually carried out at the end of the financial period, while real earnings management occurs during the period, it is expected that managers' decisions to manipulate real activities will affect

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accrual-based earnings management. However, there are differences between accrual-based earnings management and real earnings management:

1. Accrual-based earnings management is carried out through the selection of accounting methods by management. Changes in operating activities do not accompany it. In contrast, real earnings management is conducted through changes in core operations (including the company's procurement, production, and distribution processes) to increase current-period earnings (Gunny, 2010).

2. Accounting choices related to accruals for earnings management involve greater risk and a higher likelihood of detection in audit examinations. In contrast, the judgmental nature of real earnings management reduces this likelihood. Accordingly, the comparability of financial statements can affect the substitution between these two types of earnings management (Meftah, 2025).

3. Generally, real earnings management occurs during the financial period, while accrual-based earnings management occurs at the end of the period. For this reason, managers tend to use real earnings management during the financial period and before engaging in end-of-period accrual-based earnings management, because relying solely on accrual manipulation entails risk. This is because the end-of-year shortfall between unmanaged earnings and the target threshold may exceed the amount achievable through accrual manipulation. If so, real activities cannot be manipulated at year-end. Typically, managers determine the level of accrual-based earnings management after setting the level of real activities manipulation (Algharaballi, 2008). In other words, managers first employ real activities manipulation and then use accruals for earnings management. Each of these two types of earnings management is carried out sequentially, and the manipulation of real activities encourages managers to engage in accrual-based earnings management. Accrual manipulation may be applied to avoid losses resulting from real activities (Stubben, 2010). Based on the above explanations, the nature of the relationship between types of earnings management is illustrated in (Figure 1).

Research Background

Shah, et al., examined the relationship between accrual-based earnings management and real earnings management using a sample of 150 listed manufacturing firms over the period 2008–2017. Accrual-based earnings management was measured using the original Jones model and Dechow et al., while real earnings management was measured using For empirical analysis, the study estimated simultaneous equations using Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS) techniques. The results of the analysis indicate a negative and significant relationship between accrual-based and real earnings management, suggesting that Pakistani listed firms use the two as substitutes to achieve earnings targets (Shah, 2024).

Nguyen et al., examined the relationship between accrual-based earnings management (AEM) and real earnings management (REM). The results show that real earnings management and accrual-based earnings management have a negative relationship over time, that there is a unidirectional causality from accrual-based earnings management to real earnings management, and that the reverse relationship does not exist (Nguyen, 2023).

Cohen & Lys, investigated substitution between accrual-based earnings management and real activities manipulation. The results indicated no relationship between these two variables over the period under study. confirmed a positive relationship among the variables examined (D. A. Cohen, & Lys, T. Z. , 2022).

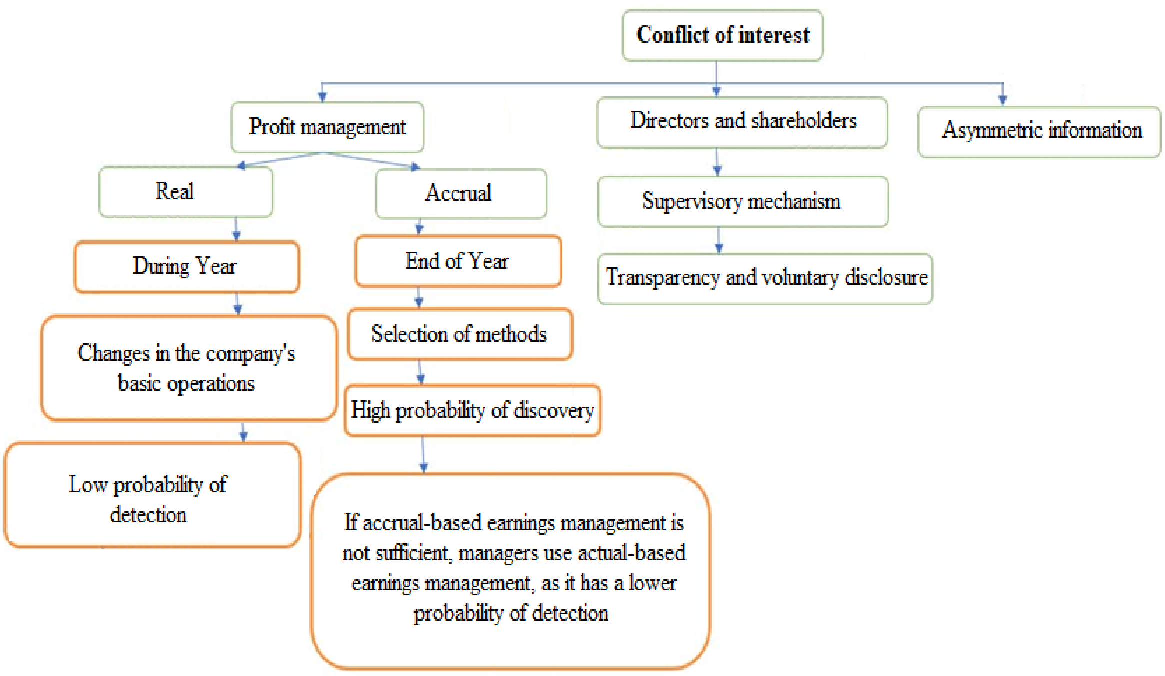

Figure 1. Process of the relationship between types of earnings Source: Ebrahimi, 2021

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Hammami & Hendijani Zadeh, employed two algorithms—the Ant Colony Optimization and Bird Flight algorithms—to predict earnings management. A total of 163 firms were selected using the systematic elimination method over the period 2013–2019. The data were panel data, and 13 variables were considered to examine patterns, of which eight were ultimately identified as effective. The tests were conducted using Python software. The results show that both algorithms can predict earnings management with an accuracy of over 97 percent; however, the Bird Flight model has greater predictive power for accrual-based earnings management, while the Ant Colony Optimization algorithm has greater predictive power for real earnings management. Based on the results, the economic uncertainty variable has a positive and significant effect on both real and accrual-based earnings management (Hammami, 2022).

Ebrahimi et al., examined the relationship between economic uncertainty and earnings management and evaluated the effect of audit quality on this relationship among firms listed on the Tehran Stock Exchange. For this purpose, 113 firms were selected over the period 2010–2019 using the systematic elimination method. The data were analyzed based on a multiple regression model. Audit quality was measured using auditor size, tenure, and report type; earnings management was examined using the Dechow model; and economic uncertainty was measured using the exchange market pressure index. The analysis of the results indicates that, under conditions of financial uncertainty, the use of large audit firms and longer auditor tenure reduces earnings management. In addition, the issuance of a non-standard audit report strengthens the direct effect of economic uncertainty on firms' earnings management (Ebrahimi, 2021).

Koop et al., examined the relationship between real earnings management and accruals management with CEO tenure in firms listed on the stock exchange. In terms of purpose, this research is applied, and in terms of nature, it is an ex post facto study. In this research, 106 firms were selected from among companies listed on the Tehran Stock Exchange over the period 2015–2019 using systematic sampling. The data were collected using the Rahavard Novin software, and a multivariate regression model was used to test the research hypotheses. The statistical method used was panel data, and the research data were ultimately analyzed in EViews. The study's findings indicate that real earnings management has a positive and significant relationship with accruals management, and that both real earnings management and accruals management are positively and significantly associated with CEO tenure (G. Koop, & Korobilis, D. , 2012)

METHODOLOGY

In terms of purpose, this research is applied. Based on the nature of the study, it is descriptive, and in terms of time, it is classified as retrospective research. The time horizon of this study is 19 years, from 2011 to 2023, for firms listed on the Tehran Stock Exchange. Given the research's spatial scope, the nature of the study, and the presence of some inconsistencies, the research population comprises firms listed on the Tehran Stock Exchange, from which the sample was selected after applying the following restrictions. Accordingly, to determine the sample size, after collecting the data and applying the above limits, the number of firms under study was determined. By applying these restrictions and using the systematic elimination method, 131 of the 407 listed and over-the-counter firms with initial information were selected as the sample. It should be noted that all investment funds, fixed-income funds, and ETFs were excluded from the study (Table 1).

In the present study, the variables of real and accrual-based earnings management are simultaneously estimated in a time-varying parameter vector autoregression model. In this model, all variables are treated as endogenous and entered endogenously. To calculate real and accrual-based earnings management, Bayesian averaging and dynamic approaches are employed (Table 2).

The conceptual model of the present study is presented in (Figure 2) as follows:

Based on the conceptual model of the study, the research variables are classified into three levels, as presented in (Figure 2). This classification is intended to highlight that the relationship between different types of earnings management is a complex process, and that modeling it requires consideration of market conditions. The present study was conducted in two main stages. In the first stage, the Bayesian averaging approach was used to model real and accrual-based earnings management. In the next stage, the time-varying parameter approach was employed to identify the nature of the relationship between different types of earnings management over time. In (Table 3), each research question and the required approach for its estimation are presented.

Table 1. Sampling process

Sampling Stages	Number
Total number of firms listed on the Stock Exchange and OTC market	407
Firms whose fiscal year does not end on 29/12	−110
Banks, insurance companies, and investment companies	−43
Firms with a trading suspension exceeding 6 months	−109
Firms with changes in the fiscal year	−14
Selected firms (sample)	131

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Table 2. Research variables

Variable Name	Method of Calculation	Reference
Accrual-Based Earnings Management	Modified version of the model TACCit=b0+b1PPEit+b2ΔSALEit+b3ROAit+εit $TACC_{it}$: Total accruals of the firm, calculated as the difference between cash flows from operations and net income after tax, divided by total assets at the beginning of the period. PPE_{it}: Gross property, plant, and equipment of the firm, calculated as gross property, plant, and equipment at the beginning of the period divided by total assets at the start of the previous period, divided by total assets at the beginning of the period. $\Delta SALE_{it}$: Annual changes in the firm's sales, calculated as the annual change in sales of the current year relative to the previous year, divided by total assets at the beginning of the period. ROA_{it}: Return on assets of the firm in the current period, calculated as pre-tax income divided by total assets. ε_{it}: Since accruals consist of discretionary and non-discretionary components, the ε_{it} component represents non-discretionary management; therefore, it reflects accrual earnings.	(Pincus & Hwang, 2022)
Real Earnings Management	$\frac{CFO_{i,t}}{AT_{i,t-1}} = \alpha_1 \frac{1}{AT_{i,t-1}} + \alpha_2 \frac{Sales_{i,t}}{AT_{i,t-1}} + \alpha_3 \frac{\Delta Sales_{i,t}}{AT_{i,t-1}} + \varepsilon_{i,t}$ CFO: Operating cash flows AT: Total assets SALE: Net sales of the firm ΔSALE: Changes in net sales of the firm ε: The residual of the regression model, which represents the firm's abnormal cash flow variable. For production cost variables and discretionary expense variables, the following models are examined, based on the perspective of, in which the error term represents the unexpected component of the model. $\frac{PROD_{i,t}}{AT_{i,t-1}} = \alpha_1 \frac{1}{AT_{i,t-1}} + \alpha_2 \frac{Sales_{i,t}}{AT_{i,t-1}} + \alpha_3 \frac{\Delta Sales_{i,t}}{AT_{i,t-1}} + \frac{\Delta Sales_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}$ $\frac{DISC_{i,t}}{AT_{i,t-1}} = \alpha_1 \frac{1}{AT_{i,t-1}} + \alpha_2 \frac{Sales_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}$	(Owusu et al., 2022)

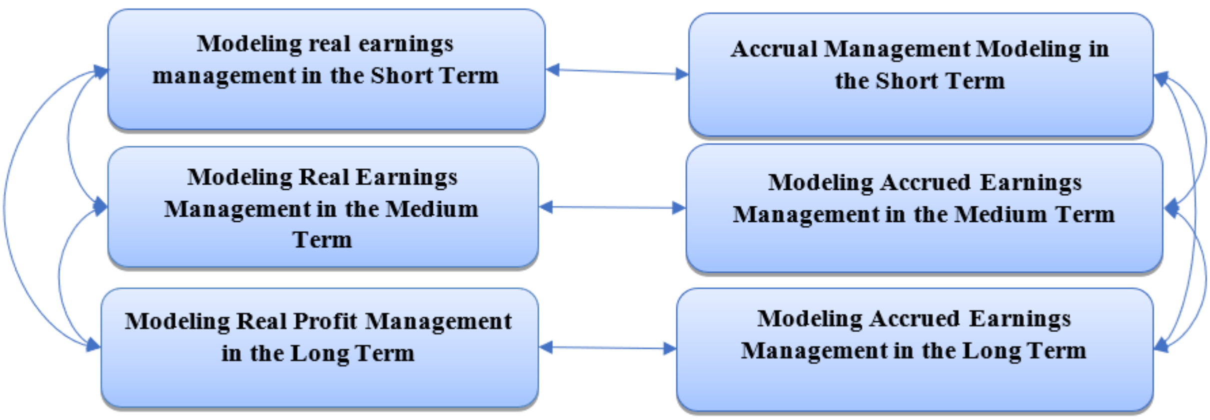

Figure 2. Conceptual model of the study

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Table 3. Estimation models used in the study

Model	Application
Panel data approach and Bayesian dynamic averaging	To determine the optimal model of accrual-based and real earnings management
Time-varying parameter approach	To determine the relationship between accrual-based and real earnings management in the short, medium, and long term

Table 4. LR Test for Comparing the Efficiency of TVP and OLS Models

LR	lnL	Approach	Variable
χ^2 = 22.41 (***)	16.321	OLS	Real earnings management
	93.395	TVP	
χ^2 = 34.99 (***)	19.402	OLS	Real earnings management
	01.503	TVP	

***: Significant at the 1% level.

Source: Author's calculations

RESULTS

Model Estimation

Before estimating the model, it is necessary to examine whether TVP-based estimation is more efficient than traditional OLS. To determine this issue, the log-likelihood values of the two models are presented in (Table 4).

The results of the LR test in (Table 4) indicate that the TVP model has a higher log-likelihood ratio in the real earnings management model (93.395 is greater than 16.321) compared to the OLS model. Therefore, model estimation based on TVP approaches (nonlinear) has higher efficiency than OLS models (linear). These results support the theories proposed by (G. Koop, McIntyre, S., Mitchell, J., & Poon, A., 2020). These researchers argue that allowing time-varying coefficients, compared to the restrictive assumption of coefficient stability (the traditional approach), improves forecasting accuracy. Consequently, models with time-varying parameters perform better at forecasting than those with fixed parameters (G. Koop, McIntyre, S., Mitchell, J., & Poon, A., 2020).

Determining the Optimal Model for Accrual-Based Earnings Management

In recent decades, the financial literature has examined the amount of information required to achieve robust estimates for forecasting economic and financial variables. One of the significant achievements in this regard has been the use of various econometric methods to exploit information from large datasets (big data) for forecasting purposes. In such approaches, factor models have received greater attention and have become widely used. Factor models (specifically PCA-based models, which are examined in the coding of TVP-DMA, TVP-DMS, and TVP-FAVAR models alongside state-space model approaches such as the Kalman filter) summarize information from a large set (big data) of indicators into a small number of unobservable fundamental components (Badertscher, 2011).

Time-varying parameter (TVP) models employ state-space methods (such as the Kalman filter), which are commonly used in empirical macroeconomic research for structural analysis and forecasting. When a large dataset is used to forecast macroeconomic variables, TVP models (on their own) tend to suffer from in-sample overfitting and therefore exhibit weak out-of-sample forecasting performance. To correct these shortcomings in TVP models, DMS and DMA models are used (Stubben, 2010). The testing period for the short-term horizon spans from 2011 to 2022, and the forecast evaluation period is 2023. The testing period for the medium-term horizon spans 2011 to 2019, and the forecast evaluation period spans 2020 to 2022. The testing period for the long-term horizon spans 2011 to 2015, and the forecast evaluation period spans 2016 to 2023. Forecasts are generated using TVP-AR(1)-X DMA and TVP-AR(1)-X DMS models, where "-X" indicates the presence of exogenous predictor variables in addition to AR(1) dynamics. The values of forgotten factors (i.e., factors that affect the primary variable but are not included in the model) are also considered; in this approach, they are incorporated into the model as a percentage of the previous period.

To evaluate forecasting performance, the Mean-Square Forecast Error (MSFE), Mean Absolute Forecast Error (MAFE), Mean Absolute Percentage Error (MAPE), Forecast Error Bias (Bias), Forecast Error Variance (FEV), and the sum of the Logarithm Predictive Likelihoods (Log PL) are used. (Table 5) presents the forecasting performance of accrual-based earnings management across different models at three forecasting horizons (h = 1, 4, 8). Based on the results, given the novelty of the Bayesian averaging approach in the field of accounting, the objective of the calculations is first presented in simple terms before the statistical explanations. In this section, the aim is to regress all possible combinations of the presence of 56 variables affecting accrual earnings management. According to Sala-i-Martin's view, after a certain number of estimations (approximately 1 to 10 million regressions), the ratio of the number of significant variables to all possible combinations converges to a specific value; therefore, there is no need to estimate all possible combinations.

Table 5. Comparison of the accuracy of different models in designing the accrual-based earnings management model

Row	Log(pl)	MAFE	MSFE	MAPE	FEV	Bias
	h=1					
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.99)$	72.406	0.075	0.009	0.196	0.009	0.018
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.95)$	80.124	0.065	0.007	0.192	0.007	0.015
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.90)$	81.901	0.060	0.006	0.176	0.006	0.014
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.99)$	73.226	0.080	0.012	0.201	0.011	0.019
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.95)$	84.507	0.070	0.008	0.177	0.008	0.012
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.90)$	105.313	0.056	0.006	0.160	0.006	0.016
$TVP-AR(2)-X \quad DMA(\alpha=0.99,\lambda=1)$	69.929	0.077	0.011	0.204	0.009	0.017
$TVP-AR(2)-X \quad DMA(\alpha=0.95,\lambda=1)$	74.597	0.070	0.008	0.232	0.007	0.024
$TVP-AR(2)-X \quad BMA(\alpha=\lambda=1)$	115.183	0.015	0.002	0.111	0.022	0.005
$WALS$	83.659	0.051	0.005	0.156	0.004	0.013
	h=4					
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.99)$	68.062	0.078	0.010	0.206	0.010	0.019
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.95)$	76.987	0.063	0.007	0.185	0.007	0.014
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.90)$	75.317	0.068	0.008	0.202	0.008	0.015
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.99)$	68.832	0.084	0.012	0.211	0.011	0.020
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.95)$	79.437	0.074	0.009	0.186	0.009	0.012
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.90)$	98.994	0.058	0.007	0.168	0.007	0.017
$TVP-AR(2)-X \quad DMA(\alpha=0.99,\lambda=1)$	65.733	0.080	0.011	0.214	0.010	0.018
$TVP-AR(2)-X \quad DMA(\alpha=0.95,\lambda=1)$	70.121	0.074	0.009	0.244	0.008	0.025
$TVP-AR(2)-X \quad BMA(\alpha=\lambda=1)$	108.272	0.015	0.002	0.117	0.023	0.006
$WALS$	78.639	0.054	0.006	0.164	0.004	0.013
	h=8					
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.99)$	68.518	0.068	0.007	0.202	0.007	0.016
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.95)$	67.032	0.075	0.008	0.220	0.008	0.017
$TVP-AR(2)-X \quad DMA(\alpha=\lambda=0.90)$	60.575	0.085	0.011	0.225	0.011	0.020
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.99)$	61.261	0.091	0.013	0.230	0.012	0.022
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.95)$	70.699	0.081	0.010	0.203	0.010	0.013
$TVP-AR(2)-X \quad DMS(\alpha=\lambda=0.90)$	88.105	0.064	0.007	0.183	0.007	0.018
$TVP-AR(2)-X \quad DMA(\alpha=0.99,\lambda=1)$	58.503	0.088	0.012	0.233	0.011	0.019
$TVP-AR(2)-X \quad DMA(\alpha=0.95,\lambda=1)$	62.408	0.081	0.010	0.266	0.008	0.028
$TVP-AR(2)-X \quad BMA(\alpha=\lambda=1)$	96.362	0.017	0.002	0.127	0.025	0.006
$WALS$	69.989	0.059	0.006	0.179	0.005	0.014

Table 6. First stage of the sampling process and calculations assuming $\bar{K}$ = 8

Variable	First sample including 4 million regressions		First sample including 5 million regressions	
	Prior coefficient	Prior probability	Posterior coefficient	Posterior probability
DEP	0.00208	0.053	-0.00122	0.019
X	0.00375	0.021	0.00319	0.020
TA_{it-1}	0.02181	0.306	0.02145	0.394
$\frac{1}{Asset_{t-1}}$	0.2956	0.4952	0.1632	0.81327
S_t	-0.3862	0.3194	-0.1173	0.1843
S_{t-1}	-0.3964	0.2017	-0.1935	0.0975
$\frac{1}{A_{it-1}}$	-0.0926	0.2749	-0.0073	0.0312
$\frac{\Delta REV_{it}}{A_{it-1}}$	0.0273	0.1573	0.03127	0.8157
$\frac{\mathrm{PPE}_{it}}{A_{it-1}}$	0.0738	0.1916	0.0472	0.6371
$\frac{TA_{t-1}}{S_t}$	0.1027	0.1846	0.06328	0.0576
$\frac{TA_{t-1}}{S_{t-1}}$	-0.00021	0.141	-0.00037	0.136
$\frac{\Delta REV_{iP} - \Delta AR_{ip}}{A_{ip-1}}$	0.00546	0.206	0.00603	0.408
$(\Delta CA_{it} - \Delta Cash_{it})$	-0.00555	0.094	-0.01172	0.010
$\left(\frac{AR_{t-1}}{REV_{t-1}} REV_{i,t}\right)$	0.03651	0.491	0.02002	0.307
$\left(\frac{APB_{t-1}}{EXP_{t-1}} EXP_{i,t}\right)$	0.64039	0.999	0.66442	0.999
$\left(\frac{DEP_{t-1}}{GPPE_{t-1}} GPPE_{i,t}\right)$	0.01427	0/068	0.02290	0.028
$\frac{\Delta CFO_{it}}{TA_{i,t-1}}$	0.00021	0.141	0.00037	0.236
$\left(\frac{ART_{t-1}}{REV_{t-1}}\right)\left(\frac{REV_{i,t}}{A_{t-1}}\right)$	0.05450	0.068	0.17365	0.213
$\left(\frac{OCAL_{t-1}}{EXP_{t-1}}\right)\left(\frac{EXP_{i,t}}{A_{t-1}}\right)$	-0.45250	0.057	-0.88385	0.011
$\frac{1}{A_{t-2}}$	-0.17470	0.083	0.04092	0.023

Table 6. (Continued)

$\frac{\mathrm{Disc}_t}{A_{t-2}}$	0.00005	0.036	0.00026	0.091
$\frac{\mathrm{Disc}_{t-1}}{A_{t-2}}$	-0.01191	0.114	-0.00506	0.044
$\frac{\mathrm{PPE\ SALES}_t}{A_{t-2}}$	0.01556	0.220	0.01322	0.213
$\frac{\mathrm{PPE\ SALES}_{t-1}}{A_{t-2}}$	0.00179	0.098	0.03117	0.091
$\frac{\Delta REV_{it} - \Delta REC_{i,t}}{TA_{it-1}}$	0.05577	0.640	0.02885	0.367
$\frac{PPE_{it}}{TA_{it-1}}$	0.03135	0.059	0.01816	0.114
$\frac{CFO_{it}}{A_{it-1}}$	0.1729	0.3863	0.0529	0.5484
$\frac{\mathrm{WCA}_{it-1}}{A_{i,t-2}}$	0.00220	0.068	0.00230	0.058
REV_{it}	0.00005	0.036	0.00026	0.091
PPE_{it}	0.00546	0.206	0.00603	0.208
CF_{t-1}	0.00555	0.094	0.01172	0.210
CF_t	-0.03651	0.491	-0.02002	0.307
$\Delta Sales_t$	0.00208	0.053	0.00122	0.119
$\Delta Sales_t - \Delta REC$	0.01427	0.068	0.02290	0.028
$\Delta Sales_t - \Delta AR$	0.05450	0.068	0.17365	0.013
TACC_{it-1}	0.66762	1.000	0.66786	1.000
$\frac{1}{Asset_{t-1}}$	0.32051	0.933	0.33928	0.955
ROA_t	0.17470	0.083	0.04092	0.123
$DCFO_t$	0.18784	0.611	0.18918	0.602
$DCFO_t * CFO_t$	0.32051	0.733	0.33928	0.625
$\frac{\Delta REV_i - \Delta REC_i}{REV_i}$	0.07664	0.239	0.14061	0.426
$\frac{\Delta EXP_i - \Delta PAY_i}{REV_i}$	-0.00179	0.098	-0.03117	0.091
$\frac{DEP_i - \Delta RET_i}{REV_i}$	0.01191	0.114	0.00506	0.104
$\mathrm{LOG(TA)}$	0.03135	0.059	0.01816	0.114
$GRSales$	0.45250	0.057	0.88385	0.111
$InfIndex$	0.00220	0.068	0.00230	0.088
$ROA_{i,t-1}$	0.00018	0.129	0.00018	0.103

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Table 6. (Continued)

$NCWC_{i,t-1}$	0.00258	0.080	0.00209	0.077
$NCWC_{i,t}$	0.00544	0.098	0.00478	0.091
$NCWC_{i,t-1} * \Delta REV_{it}$	0.00188	0.024	0.00142	0.021
$\Delta DEP_{i,t-1}$	0.07664	0.239	0.14061	0.126
$\Delta DEP_{i,t-1} * \mathrm{PPE}_{it}$	0.00164	0.031	0.00131	0.028
$\frac{REV_t}{A_{t-1}}$	0.64039	0.099	0.66442	0.199
$\frac{\Delta NREC}{A_{t-1}}$	0.11711	0.152	0.13440	0.148
PPE_{t-1}	0.29700	0.028	0.22027	0.026
$NetIncome_{i,t}$	0.12173	0.027	0.16091	0.021

Source: Researcher's calculations

Ultimately, a decision threshold is required for eliminating variables. To determine the optimal threshold, the ratio k/ total variables is used (where k is the number of variables the researcher proposes as having the highest impact on the dependent variable). This *k* is empirical and is selected based on the researcher's judgment.

To obtain the results, computations must be performed over all models in the model space. Given the number of variables examined, the total number of possible models (based on the presence or absence of each variable) in the model space is 256, which amounts to more than 72 trillion regression models. In other words, the model space consists of 2^{56} models, and under the assumption of model uncertainty, meaning avoidance of subjective judgment in model selection, all models must be examined, and information from all models must be utilized to obtain the results.

Following Sala-i-Martin et al., the value of *k* in this study is set equal to 8. This number indicates the expectation that, ultimately, eight variables will be identified as robust through the computational process; however, the final number of robust variables may be fewer or greater than 8. Initially, a sample of 1 million regressions from the model space was obtained, and the coefficients and posterior probabilities for each variable were calculated. Subsequently, 1 million regressions were added to the first sample, and calculations were performed for 8 million regressions, yielding coefficients and posterior probabilities. By continuing this process, convergence was achieved after 5 million regressions. Accordingly, there is no need to increase the sample size to determine non-fragile variables. To introduce a variable as non-fragile, two conditions must be met: 1) An increase in the posterior probability of each variable compared to the prior probability, and 2) The posterior probability level must be higher than the defined threshold level (initial threshold level = 8 divided by 56 = 0.142). It is worth noting that in the first stage, due to the assumption of model uncertainty, non-data information was used, and in the second stage, due to the faster achievement of convergence, data information was used; Also, variables that had a posterior probability lower than the considered prior probability were removed from the model due to being fragile compared to other variables (in the first stage, 16 variables were non-fragile, and in the second stage, we continue the calculations with these variables that had a posterior probability higher than the prior probability) (Table 6).

In the first stage, using the above dual conditions to identify robust variables, 25 variables were selected. That is, 25 variables had posterior probabilities higher than their prior probabilities, and these 25 variables had posterior probabilities above the threshold of 0.142. Subsequently, all procedures carried out in the first stage were applied to the remaining 25 variables in the second stage. In the second stage, an initial sample of 4 million regressions was applied to the 25 selected variables, and coefficients and posterior probabilities were calculated. Thereafter, by using the two aforementioned conditions (secondary threshold level = 8 ÷ 25 = 0.32), the most important variables affecting accrual earnings management were identified. The results are shown in (Table 7).

Since eight variables were selected in the presence of the remaining variables, these variables are called strong or non-fragile, and the remaining variables, which have a lower posterior probability of entry than the prior probability, are called fragile. According to (Table 8), it is evident that the inverse variables of the total assets of the previous period, changes in the company's sales revenue over the total assets of the previous period, the ratio of the company's gross amount of property, machinery, and equipment over the total assets of the previous period, changes in the company's sales revenue minus changes in accounts receivable divided by the total assets of the previous period, changes in cash flow from operations divided by the total

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Table 7. Second stage of the sampling process and calculations assuming $\bar{K} = 8$ in accrual earnings management

Variable	First sample including 1 million regressions		First sample including 2 million regressions	
	Prior coefficient	Prior probability	Posterior coefficient	Posterior probability
TA_{it-1}	0.00491	0.428	0.0121	0.362
$\frac{1}{Asset_{t-1}}$	0.0976	0.302	0.0813	0.515
$\frac{\Delta REV_{it}}{A_{it-1}}$	0.0301	0.319	0.0242	0.795
$\frac{\mathrm{PPE}_{it}}{A_{it-1}}$	0.0135	0.539	0.0182	0.721
$\frac{\Delta REV_{iP} - \Delta AR_{ip}}{A_{ip-1}}$	0.0802	0.219	0.00964	0.327
$\left(\frac{AR_{t-1}}{REV_{t-1}} REV_{i,t}\right)$	0.0138	0.129	0.0391	0.101
$\left(\frac{APB_{t-1}}{EXP_{t-1}} EXP_{i,t}\right)$	0.00836	0.0824	0.0385	0.0685
$\frac{\Delta CFO_{it}}{TA_{i,t-1}}$	0.0827	0.163	0.0739	0.718
$\left(\frac{ART_{t-1}}{REV_{t-1}}\right)\left(\frac{REV_{i,t}}{A_{t-1}}\right)$	0.0914	0.821	0.072	0.947
$\frac{\mathrm{Disc}_t}{A_{t-2}}$	0.0351	0.282	0.0129	0.204
$\frac{\mathrm{PPE\ SALES}_t}{A_{t-2}}$	0.0319	0.173	0.0083	0.812
$\frac{PPE_{it}}{TA_{it-1}}$	0.0315	0.813	0.0523	0.095
$\frac{CFO_{it}}{A_{it-1}}$	0.0298	0.038	0.0029	0.015
REV_{it}	0.0293	0.062	0.0029	0.018
PPE_{it}	0.0218	0.192	0.0119	0.013
CF_{t-1}	0.0210	0.978	0.0391	0.008
$\Delta Sales_t$	0.0392	0.229	0.0237	0.169
$\frac{1}{Asset_{t-1}}$	0.0381	0.0384	0.0261	0.0274
ROA_t	0.0548	0.682	0.932	0.741
$\frac{\Delta REV_i - \Delta REC_i}{REV_i}$	0.0592	0.182	0.012	0.128
$\mathrm{LOG(TA)}$	0.684	0.924	0.239	0.762
$GRSales$	0.792	0.291	0.012	0.185
$InfIndex$	0.0405	0.339	0.0389	0.113
$NCWC_{i,t-1}$	0.0413	0.394	0.0134	0.197
$\frac{REV_t}{A_{t-1}}$	0.0229	0.602	0.0221	0.212

Source: Researcher's calculations

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Table 8. Results of the sampling and calculation process based on two stages, including 2 million regressions for accrual earnings management

Column one	Column two	Column three	Column four	Column five
Variable	Posterior coefficient	Posterior probability	Posterior standard deviation	Regressions with 2≥ $\lvert t-stat \rvert$
TA_{it-1}	0.0021	0.562	0.1573	0.132
$\frac{1}{Asset_{t-1}}$	0.0813	0.515	0.1982	0.752
$\frac{\Delta REV_{it}}{A_{it-1}}$	0.0242	0.795	0.1359	0.871
$\frac{\mathrm{PPE}_{it}}{A_{it-1}}$	0.0182	0.721	0.1294	0.653
$\frac{\Delta REV_{iP}-\Delta AR_{ip}}{A_{ip-1}}$	0.00964	0.127	0.0625	0.837
$\left(\frac{AR_{t-1}}{REV_{t-1}}REV_{i,t}\right)$	- 0.0391	0.201	0.0954	0.214
$\left(\frac{APB_{t-1}}{EXP_{t-1}}EXP_{i,t}\right)$	- 0.0385	0.0685	0.0826	0.042
$\frac{\Delta CFO_{it}}{TA_{i,t-1}}$	0.0739	0.818	0.0381	0.993
$\left(\frac{ART_{t-1}}{REV_{t-1}}\right)\left(\frac{REV_{i,t}}{A_{t-1}}\right)$	0.072	0.947	0.7548	0.893
$\frac{\mathrm{Disc}_t}{A_{t-2}}$	0.0129	0.204	1.0185	0.394
$\frac{\mathrm{PPE\ SALES}_t}{A_{t-2}}$	0.0083	0.812	0.1827	0.683
$\frac{PPE_{it}}{TA_{it-1}}$	0.0523	0.095	0.0427	0.204
$\frac{CFO_{it}}{A_{it-1}}$	0.0029	0.075	0.0217	0.112
REV_{it}	0.0029	0.018	0.0129	0.095
PPE_{it}	0.0119	0.013	0.0062	0.075
CF_{t-1}	0.0391	0.008	0.0183	0.018
$\Delta Sales_t$	0.0237	0.169	0.0721	0.013
$\frac{1}{Asset_{t-1}}$	0.0261	1	0.1195	0.249
ROA_t	0.932	0.741	0.0281	0.681
$\frac{\Delta REV_i-\Delta REC_i}{REV_i}$	0.012	0.628	0.0284	0.093
$\mathrm{LOG(TA)}$	0.239	0.762	0.0184	0.061
$GRSales$	0.012	0.785	0.0027	0.075
$InfIndex$	0.0389	0.513	0.0295	0.044
$NCWC_{i,t-1}$	0.0134	0.497	0.8134	0.391
$\frac{REV_t}{A_{t-1}}$	0.0221	0.912	0.2215	0.036

Source: Researcher's calculations

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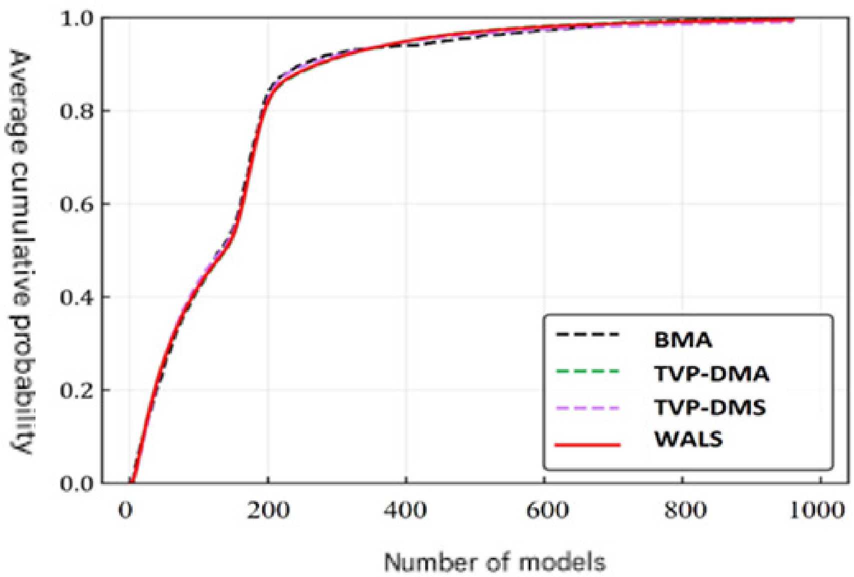
Table 9. Comparison of posterior probabilities based on different assumptions of $\bar{K}$ for accrual earnings management

Variable	Posterior probability $\bar{K} = 8$	Posterior probability $\bar{K} = 10$	Posterior probability $\bar{K} = 12$
$\frac{1}{Asset_{t-1}}$	0.515	0.518	0.522
$\frac{\Delta REV_{it}}{A_{it-1}}$	0.795	0.783	0.775
$\frac{PPE_{it}}{A_{it-1}}$	0.721	0.787	0.795
$\frac{\Delta REV_{iP} - \Delta AR_{ip}}{A_{ip-1}}$	0.827	0.811	0.821
$\frac{\Delta CFO_{it}}{TA_{i,t-1}}$	0.818	0.828	0.828
$\left(\frac{ART_{t-1}}{REV_{t-1}}\right)\left(\frac{REV_{i,t}}{A_{t-1}}\right)$	0.947	0.954	0.935
$\frac{PPE\ SALES_{t}}{A_{t-2}}$	0.812	0.8675	0.8685
ROA_t	0.741	0.744	0.761

Source: Researcher's calculations



Source: Research calculations

Figure 3. Simple and cumulative mean posterior probability of the top 1,000 models

accruals, the ratio of accounts receivable of the previous period divided by changes in the company's sales revenue of the previous period multiplied by the company's sales revenue of the current period divided by the total assets of the previous period, the ratio of the sales amount of property, machinery, and equipment of the previous period divided by the total assets of the two previous periods, and the rate of return on assets have found a higher posterior probability of entry than their prior probability in the presence of all variables, and due to the increase in our guess for the presence of these 8 variables in the model, the effect of these variables on earnings management can be examined, in other words, these variables are significant. The third and fourth columns, respectively, present the posterior coefficients and posterior standard deviations of the variables, and the last column presents the t^8-statistic ratio of each variable.

In the Bayesian averaging method, since the results are obtained based on the value of the hyperparameter k (in the above calculations, *k* was assumed to be 8), the

Table 10. Comparison of the accuracy of different models in designing the real earnings management model

Row	h=1					
	Log(pl)	MAFE	MSFE	MAPE	FEV	Bias
$VP-AR(2)-X \quad DMA(\alpha=\lambda=0.99)$	60.387	0.080	0.010	0.208	0.010	0.019
$P-AR(2)-X \quad DMA(\alpha=\lambda=0.95)$	66.823	0.069	0.007	0.204	0.007	0.016
$P-AR(2)-X \quad DMA(\alpha=\lambda=0.90)$	68.305	0.064	0.006	0.187	0.006	0.015
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.99)$	61.070	0.085	0.013	0.213	0.012	0.020
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.95)$	70.479	0.074	0.008	0.188	0.008	0.013
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.90)$	87.831	0.059	0.006	0.170	0.006	0.017
$-AR(2)-X \quad DMA(\alpha=0.99,\lambda=1)$	58.321	0.082	0.012	0.216	0.010	0.018
$-AR(2)-X \quad DMA(\alpha=0.95,\lambda=1)$	62.214	0.074	0.008	0.246	0.007	0.025
$TVP-AR(2)-X \quad BMA(\alpha=\lambda=1)$	96.063	0.016	0.002	0.118	0.023	0.005
$WALS$	69.772	0.054	0.005	0.165	0.004	0.014
	h=4					
$VP-AR(2)-X \quad DMA(\alpha=\lambda=0.99)$	56.764	0.083	0.011	0.218	0.011	0.020
$P-AR(2)-X \quad DMA(\alpha=\lambda=0.95)$	64.207	0.067	0.007	0.196	0.007	0.015
$P-AR(2)-X \quad DMA(\alpha=\lambda=0.90)$	62.814	0.072	0.008	0.214	0.008	0.016
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.99)$	57.406	0.089	0.013	0.224	0.012	0.021
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.95)$	66.250	0.078	0.010	0.197	0.010	0.013
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.90)$	82.561	0.061	0.007	0.178	0.007	0.018
$-AR(2)-X \quad DMA(\alpha=0.99,\lambda=1)$	54.821	0.085	0.012	0.227	0.011	0.019
$-AR(2)-X \quad DMA(\alpha=0.95,\lambda=1)$	58.481	0.078	0.010	0.259	0.008	0.027
$TVP-AR(2)-X \quad BMA(\alpha=\lambda=1)$	90.299	0.016	0.002	0.124	0.024	0.006
$WALS$	65.585	0.057	0.006	0.174	0.004	0.014
	h=8					
$VP-AR(2)-X \quad DMA(\alpha=\lambda=0.99)$	57.144	0.072	0.007	0.214	0.007	0.017
$P-AR(2)-X \quad DMA(\alpha=\lambda=0.95)$	55.905	0.080	0.008	0.233	0.008	0.018

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Table 10. (Continued)

$P-AR(2)-X \quad DMA(\alpha=\lambda=0.90)$	50.520	0.090	0.012	0.239	0.012	0.021
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.99)$	51.092	0.096	0.014	0.244	0.013	0.023
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.95)$	58.963	0.086	0.011	0.215	0.011	0.014
$P-AR(2)-X \quad DMS(\alpha=\lambda=0.90)$	73.480	0.068	0.007	0.194	0.007	0.019
$-AR(2)-X \quad DMA(\alpha=0.99,\lambda=1)$	48.792	0.093	0.013	0.247	0.012	0.020
$-AR(2)-X \quad DMA(\alpha=0.95,\lambda=1)$	52.048	0.086	0.011	0.282	0.008	0.030
$TVP-AR(2)-X \quad BMA(\alpha=\lambda=1)$	80.366	0.018	0.002	0.135	0.027	0.006
$WALS$	58.371	0.063	0.006	0.190	0.005	0.015

Table 11. Comparison of posterior probabilities based on different assumptions of $\bar{K}$ for real earnings management

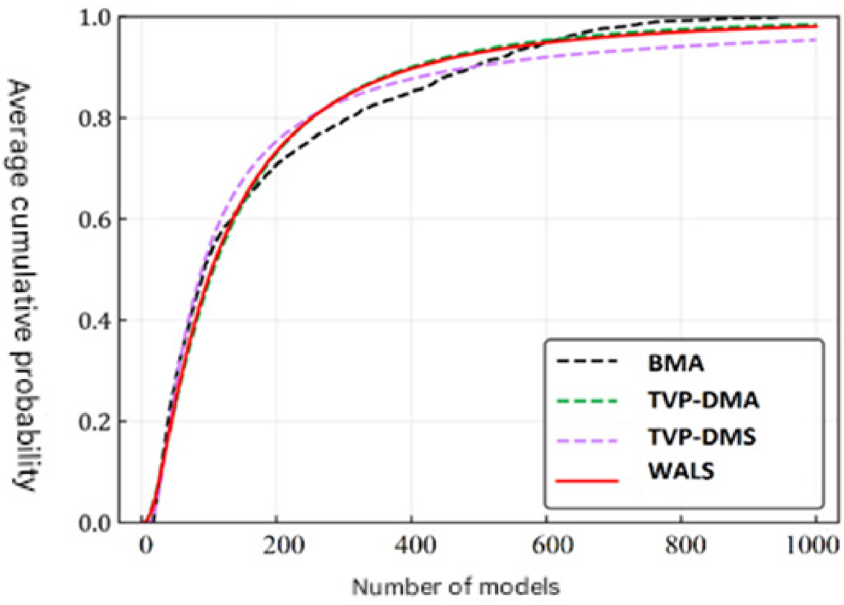
Variable	Posterior probability $\bar{K}=8$	Posterior probability $\bar{K}=10$	Posterior probability $\bar{K}=12$
$\frac{R\&D_{it-1}}{S_{it-1}}$	0.673	0.682	0.680
$LOG\left(\frac{S_{it}}{S_{it-1}}\right)$	0.832	0.842	0.846
$\frac{AssetSale_{it}}{MV_{it-1}}$	0.893	0.902	0.889
$LOG(S_{it})$	0.769	0.777	0.773
$PROD$	0.895	0.905	0.908
$\frac{1}{TA_{it-1}}$	0.947	0.936	0.894
$\frac{S_{it}}{TA_{it-1}}$	0.733	0.738	0.735
$\frac{\Delta S_{it}}{TA_{it-1}}$	0.815	0.809	0.813

Source: Researcher's calculations

question arises as to whether changing the value of the hyperparameter would alter the research results, and if so, to what extent this change would occur. In other words, does the choice of the expected model size affect the results?

Accordingly, by selecting different values of $\bar{K}$ and repeating the entire sampling and calculation process, a comparison of results was conducted. It should be noted that in these three cases, the model space, and thus the variables and data, are identical, and the only difference among them is the expected model size. However, it is entirely clear that by changing the scheduled model size, the samples and consequently the results will differ; that is, variables may be fragile (or robust) under all three values of $\bar{K}$, or the fragility of some variables may change with changes in $\bar{K}$, such that a variable that was fragile under one assumed value of $\bar{K}$ becomes robust with an increase in the expected model size (Table 9).

Given that the robust variables under $\bar{K}$ = 12 and $\bar{K}$ =



Source: Research calculations

Figure 4. Simple and cumulative mean posterior probability of the top 1,000 models in real earnings management

Table 12. Akaike Information Criterion values

Lag	Akaike statistic
First lag	−1.3320
Second lag	−1.1143
Third lag	−0.9394

Source: Research findings

10 are identical to those under $\bar{K}$ = 8, the analyses were not extended to higher values of $\bar{K}$. In (Figure 3), the explanatory power of the variables with the highest explanatory capacity in the top 1,000 models is illustrated. Based on the figure, the top 1,000 models, cumulatively, explain more than 98 percent of the variation in accrual earnings management.

Determination of the optimal model for real earnings management

In this section of the study, the factors affecting real earnings management are modeled. Given the objective of determining the optimal model, an in-sample forecasting approach is employed. To achieve stability of results, forecasting of the factors affecting this type of earnings management is conducted over three time horizons: 1 period (h = 1), 4 periods (h = 4), and 8 periods (h = 8). The test period for the short-term horizon spans from 2011 to 1401, and the forecast performance evaluation period is 2023. The forecasting test period for the medium-term horizon spans 2011 to 2019, and the forecast performance evaluation period spans 2020 to 2023. The forecasting test period for the long-term horizon spans from 2011 to 2015, and the forecast performance evaluation period from 2016 to 2023. To evaluate the forecasting performance of the models, the sum of the logarithms of predictive likelihoods (PL)Log is used (Table 10).

Subsequently, for brevity, (Table 11) presents the results of the real earnings management model for the robust variables.

Based on the results, the variables ratio of research and development expenditures in the previous period to sales in the last period, logarithm of the ratio of current-period sales to previous-period sales, amount of sales of non-current assets divided by the natural logarithm of the market value of shareholders' equity in the previous period, logarithm of sales, production cost, which equals cost of goods sold plus inventory changes, inverse of total accruals of the previous period, sales divided by total accruals of the previous period, and changes in sales divided by total accruals of the previous period were identified as the most essential robust variables affecting real earnings management. In (Figure 4), the explanatory power of the variables with the highest explanatory capacity in the top 1,000 models is illustrated. Based on the figure, the top 1,000 models, cumulatively, can explain more than 95 percent of the variation in real earnings management.

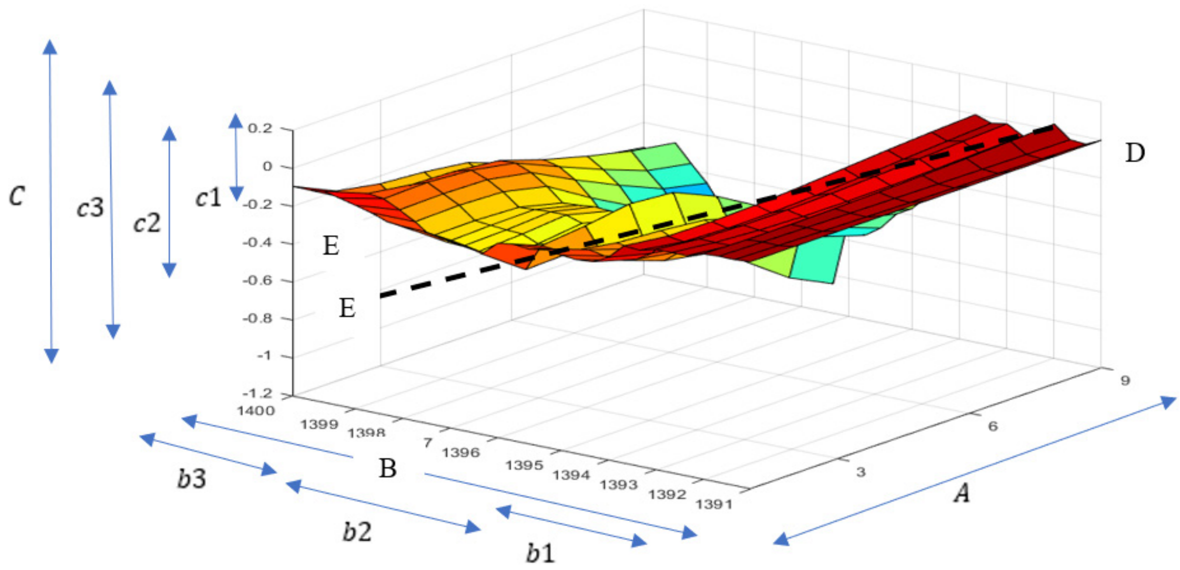
Relationship between real and accrual earnings management across different time horizons

Before estimating the model in the nonlinear framework, it is necessary to determine the optimal lag. Given the nature of the research data and the time period under review, the Akaike Information Criterion (AIC) is used to determine the optimal model. (Table 12) summarizes the AIC results. Based on the results, the optimal lag was the second. To

Table 13. Forecast performance criteria at different forecasting horizons

Research models	h=1		h=4		h=8	
	MSFEs	ALPLs	MSFEs	ALPLs	MSFEs	ALPLs
$TVP-VAR(DLP)$	0.124	118.455	0.161	115.792	0.226	104.360
$TVP-VAR(CC09)$	0.150	94.418	0.175	88.558	0.352	80.813
$TVP-FAVAR(DLP)$	0.144	137.408	0.187	134.319	0.262	121.057
$TVP-\mathrm{FA}VAR(CC09)$	0.174	109.525	0.204	102.727	0.409	93.744

Source: Research findings



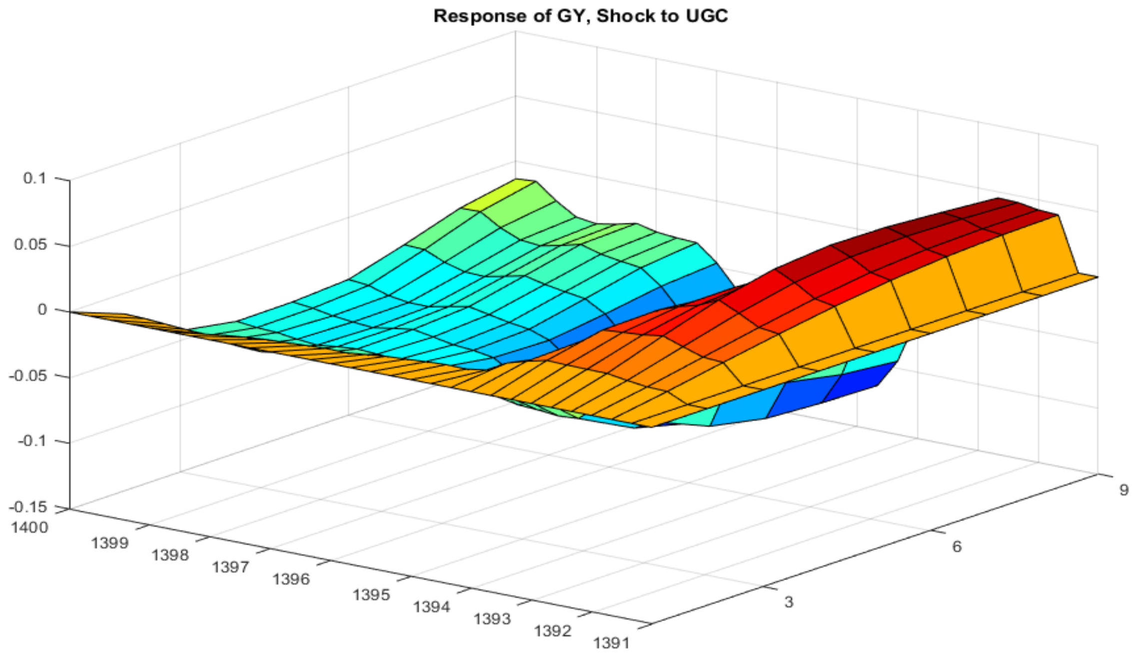
Source: Research findings

Figure 5. Graphical analysis of the response of accrual earnings management in PTVP-FAVAR models to changes in accrual earnings management

determine the optimal model in the nonlinear framework, Mean Squared Forecast Errors (MSFEs) and Average Log-Predictive Likelihoods (ALPLs) are used. (Table 13) summarizes these results.

The results indicate that the TVP-FAVAR Dynamic Learning Prior (DLP) approach has higher accuracy than the TVP-PVAR Canova and Ciccarelli (CC09) model. The difference between these two approaches lies in whether the variance among the examined variables is accounted for. In the TVP-PVAR (DLP) approach, this variance is considered. In the following, the results are computed based on the TVP-FAVAR (DLP) approach.

Subsequently, after estimating the PTVP-FAVAR model in MATLAB, the results of the impulse response analysis of the model variables to one another over 9 periods are presented. Given that the impulse response function in the present study is time-varying, before describing the research figures, (Figure 5) presents the analysis of the impulse response between real and accrual earnings management. In econometrics, the significance of an explanatory variable for a dependent variable depends on the t-statistic's level. In PTVP-FAVAR models, shocks to variables have a significant effect if the impulse response function lies below or above the equilibrium point (zero). If the graph coincides with the equilibrium line, the variable's significant effect is eliminated. As observed in the figure, real earnings management has a positive impact at the beginning of the period and an adverse effect in the middle and later periods on accrual earnings management, because the graph initially lies above the equilibrium level and subsequently below it. In the (Figure 6), vector A represents the length of the effect period, vector B represents the entire time span under investigation, which is divided into three time horizons: short term b1 (30 percent of the time span examined in the present study, three years, i.e., 2012 to 2014), medium term b2 (40 percent of the time span examined, four years, i.e., 2015 to 2018), and long term b3 (30 percent of the time span examined, three years, i.e., 2019 to 2021). Vector C represents the response of the accrual earnings management variable to changes in the variable across the three aforementioned time horizons. For example, the magnitude of vector c1 equals



Source: Research findings

Figure 6. Graphical analysis of the response of real earnings management in PTVP-FAVAR models to changes in accrual earnings management

Table 14. The impact of real earnings management on accrual earnings management in different time periods Course

Period	Short term	Medium term	Long term	Total period average
Average coefficient	0.1148	-0.3792	-0.2693	-0.1779
Relationship type	Real earnings management increases accrual earnings management. (Complementarity relationship)	Real earnings management reduces accrual earnings management. (Substitution relationship in favor of increasing real earnings management)	Real earnings management reduces accrual earnings management. (Substitution relationship in favor of increasing real earnings management)	Real earnings management reduces accrual earnings management. (Substitution relationship in favor of increasing real earnings management)

the response of accrual earnings management to the real earnings management variable in the short-term b1. c2 represents the response of accrual earnings management to changes in the real earnings management variable in the medium term b2, and c3 represents the response of accrual earnings management to changes in the real earnings management variable in the long term b3. Given that c1 is smaller than c2 and c2 is smaller than c3 in magnitude, the trend is downward, represented by vector DE, with the beginning of the movement in the short-term period b1 and its end in the long-term period b3.

The average impact in each of the time periods is as follows (Table 14).

The following examines the impact of accrual earnings management on real earnings management.

The average impact in each time period is as shown in (Table 15).

Based on the results, it is observed that the net effect of the entire period average in the model where real earnings management is the dependent variable is smaller than when the accrual earnings management variable is the dependent variable; in other words, in calculating the net effect, it is observed that in the long run, real earnings management is an alternative to accrual earnings management.

DISCUSSION

The use of traditional variables and models in explaining the factors affecting real and accrual earnings management has faced many challenges in the literature. This study attempts to fill this gap by considering different variables in the context of traditional and new theories, and by using Bayesian econometrics and panel data on listed companies for the period 2011-2023. First, we explained the determinants of real and accrual earnings management theoretically (Beaver, 1968). We estimated the real and accrual earnings management model using Bayesian

Table 15. Impact of accrual earnings management on real earnings management in different time periods

Period	Short term	Medium term	Long term	Total period average
Average coefficient	0.0366	-0.0584	-0.0473	-0.0230
Relationship type	Accrual earnings management increases real earnings management. (Complementarity relationship)	Accrual earnings management reduces real earnings management. (Substitution relationship in favor of increasing accrual earnings management)	Accrual earnings management reduces real earnings management. (Substitution relationship in favor of increasing accrual earnings management)	Accrual earnings management reduces real earnings management. (Substitution relationship in favor of increasing accrual earnings management)

Source: Research findings

econometrics and the "Bayesian model averaging" method in MATLAB. Given that conventional econometric methods cannot examine the effects of a wide range of explanatory variables on real and accrual earnings management, the aforementioned averaging methods have been used. The weights in this averaging are determined by Bayes' rule, i.e., the posterior probability of each model. The aforementioned methods overcome the uncertainty in selecting the model and its variables by estimating and sampling all possible models based on different combinations of explanatory variables, and then averaging them according to the prior distribution function, providing an estimate of all existing coefficients (Bruns, 1990).

By performing calculations and examining the effect of 56 factors that were known to be effective in empirical studies on accrual earnings management and 13 factors that were effective on real earnings management, it was determined that the effect of 8 variables on these two types of earnings management was significant and that these variables always maintained their impact in the presence of other variables and, in other words, were non-fragile. (Caylor, 2010).

These variables were determined and ordered by posterior probability (i.e., they are most important in explaining earnings management and, in other words, have the most significant likelihood of being present in the correct model). For the management of accrued earnings, the variables are: 1. The inverse of total assets from the previous period, 2. Changes in the company's sales revenue relative to total assets in the previous period, 3. The ratio of the company's gross amount of property, machinery, and equipment to the total assets of the previous period, 4. Changes in the company's sales revenue minus changes in accounts receivable divided by the total assets of the previous period. Cash flow changes from operations divided by total accruals 6. Ratio of accounts receivable from the previous period divided by changes in the company's sales revenue from the previous period, multiplied by the company's sales revenue from the current period, divided by total assets from the previous period 7. Ratio of the amount of sales of property, machinery, and equipment from the previous period divided by the total assets of the two previous periods and 8. Return on assets and real profit management rate 1. Ratio of research and development expenses in the previous period to sales from the previous period 2. Logarithm of the current period sales ratio divided by the previous period 3. Amount of sales of non-current assets divided by the natural logarithm of the market value of equity in the previous period 4. Logarithm of sales 5. Cost of production, which equals the cost of goods sold plus inventory changes, 6. Inverse of the sum of the previous period's accruals 7. Sales divided by the sum of the previous period's accruals and 8. Changes in sales divided by the sum of the previous period's accruals. Comparison of the posterior probabilities of the variables shows that, across all three model runs, the variables under study exhibit the necessary non-fragility (D. A. Cohen, Dey, A., & Lys, T. Z. , 2008). Given the significant variables in the model, it is concluded that earnings management on the Iranian Stock Exchange is a multidimensional problem, as variables related to earnings, liquidity, and debt have a positive and significant effect on this indicator. As a result, it is necessary to consider policy packages that include time and implementation inconsistencies in presenting policy solutions to reduce earnings management (D. A. Cohen, & Zarowin, P. , 2010).

It is worth noting that, in this method, the coefficients of the variables in each model (even in the final model) are not the sole criterion and do not reflect the degree of influence of each variable on the dependent variable. However, rather than the weighted average of the coefficients for each variable across all models using the Bayesian method (with specific weights), the Bayesian method should be used to obtain the posterior distribution of each variable (P. M. Dechow, & Skinner, D. J., 2000). This method shows which variables we should pay more attention to develop an appropriate model to explain a specific (dependent) variable. Another point is that, in this method and under the assumption of model uncertainty, no prior beliefs are incorporated into the economic model, so that all variables, and in fact all models, are examined (P. M. Dechow, Sloan, R. G., & Sweeney, A. P. , 1996).

Based on the results, the net effect of the entire period average in the model where real profit management is the dependent variable is smaller than when the accrual profit management variable is dependent; in other words, in calculating the net effect, it is observed that in its general trend, real profit management replaces accrual profit management. Based on the results, in the short term, the relationship between real and accrual earnings management is positive and complementary, whereas in the medium and long term, it is substitutional. The following research suggestions are presented (P. M. Dechow, Sloan, R. G., & Sweeney, A. P. , 1996).

Considering that theoretically all variables considered in the model affect accrual earnings management, and the number of 48 variables compared to 8 variables (5 variables compared to 8 real earnings variables) obtained in the second stage calculations became fragile and lost their effect, it should be noted that the way in which such variables affect the obtained non-fragile variables was in a way that they did not have much impact on earnings management. Therefore, the fact that such a variable is fragile does not mean that it is unimportant, but rather indicates the need for more attention to the appropriate effect of this variable (Islam, 2011).

Given that the substitution relationship between real and accrual earnings management has been established, it is suggested that auditors should place greater emphasis on the components of real profit management to identify profit management in companies (Kothari et al., 2005).

Based on the Bayesian averaging model, real profit management places great emphasis on sales. Given Iran's economic, social, and cultural environment, companies are likely to experience significant sales fluctuations, prompting them to focus on profit management. As a result, companies need to adopt policies that stabilize the company's sales. For example, turning to exports, diversifying product offerings and production to meet customer needs, and keeping product offerings up to date can reduce fluctuations in sales (Korobilis, 2013).

Based on Bayesian averaging, the asset factor is an essential indicator for accrual profit management. As a result, policies such as maintaining a balance sheet and improving current and immediate liquidity ratios will be crucial factors in reducing accrual-based profit management (Rahman, 2013)

Based on the results, it was found that, in studying real and accrual earnings management, a systemic perspective is necessary; simply considering a specific model or a set of variables cannot provide a comprehensive perspective for determining the optimal model of real and accrual earnings management (Lee, 2020).

CONCLUSION

In this study, by examining the empirical columns, we showed that defining alternative transfer models and analyzing uncertainty in real and accrual earnings management models will help select the best, most appropriate model to interpret the empirical columns and improve predictions. The results show that, given the different probabilities calculated across alternative models, relying on a single conceptual model in the modeling process for real and accrual earnings management will lead to incorrect predictions, and ultimately, management decisions based on that model will face the risk of failure. Considering the dependence of earnings management on time conditions and the variability in the intensity of impact across time intervals, it is suggested that different models be designed for short-, medium-, and long-term periods, so that a policy package is used rather than a fixed policy. Given the changing nature of the relationship between real and accrued earnings management over time, it is proposed to provide policy packages to control the types of earnings management based on the company's life cycle.

Author's contribution
Niloofar Hashemian and Mohsen Sadeghi developed the study concept and design. Farzad Karimi and Niloofar Hashemian acquired the data. Niloofar Hashemian and Mohsen Sadeghi analyzed and interpreted the data, and wrote the first draft of the manuscript. All authors contributed to the intellectual content, manuscript editing and read and approved the final manuscript.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interest
The authors declare that they have no conflict of interests.

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