EP-JOURNALS

Available on: https://jefrr.ep-journals.org/ E-ISSN: 3051-3650, P-ISSN: 3051-3642

Journal of Economic Finance Research and Review

Volume: 02 Issue: 07 July 2026

Long-Run Evolution and Industry Divergence of Real Activities Earnings Management in Chinese A-Share Listed Firms: Evidence From 58,661 Firm-Year Observations, 1998-2025

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Published Date: July 08, 2026 **Article DOI: 10.65150/EP-jefrr/V2E7/2026-02**

ABSTRACT: Real activities earnings management affects reported earnings through operating decisions such as sales policies, production scheduling and discretionary expenditure. Compared with purely accrual-based adjustments, it is less visible in accounting entries and more likely to alter future cash flows, inventory risk and long-term investment. Using a real earnings management dataset for Chinese A-share listed firms from 1998 to 2025, this study examines the long-run evolution, industry divergence and firm-level persistence of REM based on 58,661 firm-year observations, 5,288 listed firms and 74 detailed industries. The evidence shows that Abs_REM reached its highest level in 2007-2012 and subsequently declined, whereas the median of REM_Total and the share of positive REM continued to rise in recent years. Real activity deviations are stronger in internet services, retail, pharmaceuticals, real estate, wholesale and software services. The explanatory power of firm-level grouping is much higher than that of year or industry grouping, and REM_Total, Abs_REM, REM1 and REM2 all display significant first-order persistence. The contribution of this paper is threefold. First, it provides a long-window measurement of REM in the A-share market over nearly three decades, complementing short-horizon event studies. Second, under a unified measurement design, it distinguishes REM direction, absolute intensity, industry divergence and firm persistence, thereby reducing the interpretive bias created by a single composite indicator. Third, it offers replicable evidence for regulatory enquiries, audit risk assessment and investor screening of earnings-quality risk embedded in operating activities.

KEYWORDS: real activities earnings management; earnings quality; listed firms; industry heterogeneity; firm fixed effects; Chinese A-shares

1 INTRODUCTION

1.1 Research Background

This paper uses the dataset of real earnings management among listed firms for 1990-2025 to examine the long-run evolution of real activities earnings management in Chinese A-share listed companies. The original data package contains 84,586 firm-year records. The final sample available for REM measurement contains 58,661 observations, covering 5,288 listed firms, the period from 1998 to 2025, and 74 detailed industries. Real activities earnings management differs from accrual earnings management. It affects current earnings through real operating decisions, including sales discounts, credit policies, production arrangements, and the timing of research and development, selling and administrative

expenditure. It is therefore more deeply embedded in the operating process than accounting-estimate adjustments and is more likely to generate intertemporal costs. The research value of REM lies in shifting the earnings-quality question from accounting entries to operating behaviour. Sales policy, production rhythm and expenditure decisions may all be commercially reasonable. Yet when they are systematically used to manage reported earnings, financial statements can deviate from the firm's long-term operating substance. The long time series of the Chinese A-share market is particularly suitable for observing such deviations. During the sample period, the market experienced the implementation of new accounting standards, governance changes after the split-share reform, the advancement of the registration-based IPO system, stronger delisting constraints and the COVID-19 shock. A single event study cannot capture these changes, whereas a long panel can provide more stable structural evidence.

This paper does not treat REM as a simple negative label. Instead, it regards REM as an operating deviation that requires interpretation. High REM may reflect opportunistic earnings management, but it may also arise from business model changes, demand shocks or strategic adjustment. The analysis therefore needs a clear chain linking measurement, distribution, industry patterns and firm-level persistence. From the perspective of financial statement users, the risk of REM is that an improved income statement may coincide with deteriorating cash flow, higher inventory exposure and lower long-term investment. If investors focus only on net income, they may underestimate the operating cost paid to deliver current earnings. From the perspective of internal corporate decision-making, REM often does not require an obvious breach of accounting standards. Managers can alter current earnings by accelerating or delaying real operating activities. This appearance of compliance makes REM harder to detect through traditional audit procedures than accrual manipulation.

1.2 Research Questions and Contributions

The paper addresses four questions. What is the overall distribution of REM among A-share firms? Do REM intensity and direction change across periods? Does REM vary across industries? Does REM show persistence at the firm level? The paper does not equate residual deviations directly with misconduct. It treats REM as a replicable measure of earnings-quality risk and operating deviation. Its marginal contribution has three parts. First, the sample covers 1998-2025, which is suitable for observing long-run trends. Second, the paper reports Ab_CFO, Ab_PROD, Ab_DISX, REM1, REM2 and REM_Total at the same time, avoiding over-interpretation of a single indicator. Third, all measurements, regressions and statistics are derived from the workspace data and scripts. The first issue concerns the overall distribution. If the mean of REM is close to zero, does that imply low risk? The paper answers this question by reporting the mean, median, percentiles and Abs_REM together, thereby avoiding the misleading offset of positive and negative residuals. The second issue concerns period change. Institutional and regulatory changes may compress extreme operating deviations, but they may also alter the direction of manipulation. The paper therefore examines REM_Total and Abs_REM together, distinguishing directional change from intensity change. The third issue concerns industry and firm differences. Industry differences reflect business models and operating flexibility, whereas firm persistence reflects inertia that may arise from governance, managerial style and internal controls. If the explanatory power of firm grouping is much higher than that of year and industry grouping, REM risk monitoring cannot remain at the macro level.

The paper also stresses consistency in measurement. If long-run REM changes are reported only through a single composite indicator, directional change, intensity change and channel differences are easily mixed together. The paper therefore presents base residuals, composite indicators, absolute deviations and persistence evidence under the same data design. Unlike an approach that reports only regression significance, this paper places formula checks, descriptive statistics, period comparisons, industry divergence and fixed-effect regressions in one logical chain. This makes the results more replicable and prevents complex models from obscuring the measurement basis.

2 LITERATURE REVIEW AND ANALYTICAL FRAMEWORK

2.1 Earnings Management and Reporting Incentives

Healy and Wahlen (1999) define earnings management as the use of judgement in financial reporting to alter reported information, thereby misleading stakeholders or affecting contractual outcomes. Burgstahler and Dichev (1997) and Degeorge et al. (1999) further show that losses, earnings declines and benchmark thresholds create reporting pressure. Jones (1991) and Kothari et al. (2005) provide the measurement foundation for accrual earnings management, while real activities earnings management extends the object of study from accounting estimates to operating decisions. The survey evidence in Graham et al. (2005) indicates that managers may sacrifice long-term value to meet short-term earnings targets. The common starting point of the earnings management literature is information asymmetry between managers and outside investors. External

parties rely on financial statements to assess performance, debt-servicing ability and future cash flows, whereas managers control operating arrangements and accounting judgements. When external evaluation depends heavily on earnings numbers, managers have incentives to alter reported outcomes. Early studies focused mainly on accrual items such as bad-debt allowances, depreciation estimates, inventory valuation and revenue-recognition judgements. These actions usually occur at the level of accounting recognition and estimation, where auditors can inspect evidence, standards and assumptions. Real activities earnings management is closer to the operating site and is therefore more difficult to identify. Research on earnings thresholds shows that firms do not adjust earnings randomly. They often act around targets such as avoiding losses, avoiding earnings decreases and meeting analyst forecasts. The same logic applies to REM: when the cost of accounting adjustments rises, managers may shift towards sales, production and expenditure decisions. Schipper (1989) placed earnings management within the broader framework of disclosure management and reporting strategy. Later research gradually moved from asking whether earnings management exists to asking which tools managers choose and what economic consequences those tools create. The IPO and SEO studies of Teoh et al. (1998) show that earnings management in financing settings can affect long-run market performance. Although this paper does not examine financing events, such evidence suggests that the economic consequences of earnings management can extend across multiple years.

2.2 Channels of Real Activities Earnings Management

Roychowdhury (2006) identifies three core channels: abnormally low operating cash flow, abnormally high production costs and abnormally low discretionary expenses. The first is usually associated with price discounts and credit expansion; the second with overproduction that spreads fixed costs over more units; and the third with cuts in research and development, advertising, selling and administrative expenditure. Cohen et al. (2008) show that regulatory changes alter the choice between accrual-based and real activities manipulation, while Zang (2012) further emphasises the cost trade-off between the two. On this basis, the paper understands REM as the joint outcome of firm operations, regulatory environments and capital-market pressure. The operating-cash-flow channel mainly appears as a mismatch between sales and cash flow. Firms can increase current sales through discounts, relaxed credit policies or channel stuffing, but these practices usually reduce the quality of cash collection per unit of sales, making CFO low relative to the industry-year normal level. The production-cost channel is more relevant in manufacturing and inventory-intensive industries. Overproduction can allocate fixed manufacturing overheads to more units, reducing current unit costs and cost of goods sold, but it also raises inventory and may later create impairment, markdown or cash-flow pressure. The discretionary-expenditure channel reflects short-term cost cutting. R&D, advertising, selling promotion and some administrative expenses are often adjustable. Reducing these expenses improves current profit but may damage future innovation, brand value and sales capacity. REM therefore has clear intertemporal costs.

The economic meanings of the three channels differ and should not be mechanically added without interpretation. REM_Total provides a composite direction. REM1 highlights the combination of production costs and cash flow, while REM2 highlights the combination of cash flow and expenditure compression. The paper reports these indicators together to retain channel information. The study by Baber et al. (1991) on R&D expenditure shows that managers may adjust expenditure items with long-term value for reporting purposes. This logic is highly consistent with the discretionary-expenditure channel and also indicates that expenditure cuts should not be evaluated only from the perspective of current earnings. Although McVay's (2006) study of classification shifting is not part of the three-channel REM model, it similarly shows that managers search for adjustment space between financial statement structure and the presentation of operating information. REM research pushes this adjustment space further into actual operating activities.

2.3 The Chinese A-Share Context

The Chinese A-share market has experienced the expansion of listed firms, changes in accounting standards, the advancement of the registration-based IPO system and the strengthening of the delisting regime. At the same time, listed firms still face refinancing constraints, performance commitments, regulatory enquiries and valuation pressure. Long-window REM measurement helps identify the empirical form of real operating deviations under these conditions. The sample period saw substantial expansion of A-share listed companies, with later entrants increasingly coming from pharmaceuticals, electronics, software, internet services and advanced manufacturing. Changes in industry composition alter the benchmark levels of normal operating cash flow, production costs and discretionary expenditure, and they also affect the distribution of REM measures. The Chinese market also features strong regulatory enquiry and performance-constraint environments. Listed firms may face refinancing thresholds, performance commitments, delisting-risk warnings, debt financing pressure and market-value management incentives. Even without violating accounting standards, firms may use real operating arrangements to move reported outcomes closer to external evaluation thresholds. The purpose of this paper is not to prove that a particular institutional event caused changes in REM. It first establishes long-run measurement

facts. Only after identifying when REM is higher, where it is concentrated and whether it has firm-level inertia can later causal studies rest on a reliable foundation. Investor composition and the information environment in the A-share market also changed continuously during the sample period. The rise of institutional investors, analyst coverage, media scrutiny and exchange enquiries may increase the cost of accrual manipulation while encouraging firms to rely more on operating arrangements to meet performance targets.

Stronger regulation does not necessarily reduce all forms of REM. If firms face stronger profit pressure or financing needs, real activities management may spread from a small set of extreme firms to a broader pattern of mild deviations. This is why the paper observes both intensity and direction.

3 DATA, VARIABLES AND FORMULAE

3.1 Data Source and Sample Processing

The data come from the workspace package on real earnings management among listed firms for 1990-2025. The sample excludes financial firms, ST/PT firms and firms not listed in Shanghai or Shenzhen. Industry-year regressions require at least ten observations, and regression input variables are winsorised by year at the 1st and 99th percentiles. The final usable REM panel starts in 1998. The original data include security code, year, industry code, operating revenue, operating cost, inventory, selling expenses, administrative expenses, R&D expenses, operating cash flow and total assets. The final data retain three abnormal residuals and three composite REM indicators, making them suitable for direct long-panel analysis.

The requirement of at least ten observations in each industry-year regression is central to measurement reliability. If an industry-year cell is too small, the normal operating model is strongly affected by individual firms, and the residual no longer represents a deviation from the normal level of comparable peers. The paper maintains the winsorisation, industry classification and sample exclusion rules in the data package, rather than changing the measurement design ex post. This ensures consistency with the original calculation process and reduces interpretive bias arising from researcher choice over samples or parameters. The final sample is smaller than the original sample mainly because the REM model requires lagged assets, lagged sales and industry-year estimation conditions. Early years and small-sample industries are more likely to be excluded because of insufficient data, which is an important reason why the final sample begins in 1998.

The paper does not treat missing sample observations as random missingness. Instead, the entry rule itself reflects the technical boundary of REM measurement: residuals are more appropriate as indicators of abnormal operating activity only when there are enough comparable firms in the same industry and year.

Table 1. Abbreviations and Symbol Definitions

Abbreviation/Symbol	Meaning	Explanation
REM	Real activities earnings management	Earnings management through real operating decisions
CFO_A	Operating cash flow / lagged total assets	Dependent variable in the normal operating cash flow model
PROD_A	Production costs / lagged total assets	Usually operating costs plus the change in inventory
DISX_A	Discretionary expenses / lagged total assets	Adjustable R&D, advertising, selling and administrative expenses
INV_A	Inverse of lagged total assets	Controls for the scaled intercept difference
SALES_A	Operating revenue / lagged total assets	Captures sales scale
DSALES_A	Change in operating revenue / lagged total assets	Captures sales growth shocks
L_SALES_A	Lagged SALES_A	Used to estimate normal discretionary expenses
L_DSALES_A	Lagged DSALES_A	Used to estimate normal production costs
Ab_CFO	Abnormal operating cash flow	Residual from Equation (1)
Ab_PROD	Abnormal production costs	Residual from Equation (2)
Ab_DISX	Abnormal discretionary expenses	Residual from Equation (3)
REM1	Ab_PROD - Ab_CFO	Combined production-cost and cash-flow channel

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Abbreviation/Symbol	Meaning	Explanation
REM2	-Ab_CFO - Ab_DISX	Combined cash-flow and expense-compression channel
REM_Total	-Ab_CFO + Ab_PROD - Ab_DISX	Composite real activities earnings management indicator
Abs_REM	|REM_Total|	Intensity of real activity deviation
Size	Natural logarithm of total assets	Firm-size variable in the auxiliary association model
N	Number of observations	Firm-year sample size
Within R2	Within-group explanatory power	Within goodness of fit in fixed-effect regressions
alpha_i/lambda_t	Firm fixed effects / year fixed effects	Controls for time-invariant firm characteristics and common annual shocks

Note: Subscript i denotes firm and t denotes year; variables with the suffix _A are scaled by lagged total assets.

3.2 Normal Operating Models

Abnormal operating cash flow is obtained from the residual of the industry-year normal operating cash flow model, as follows:

$$CFOA_{it} = \alpha_0 + \alpha_1 INVA_{it} + \alpha_2 SALESA_{it} + \alpha_3 DSALESA_{it} + \varepsilon_{it} \quad (1)$$

where CFO_A is operating cash flow divided by lagged total assets, INV_A is the inverse of total assets, SALES_A is operating revenue divided by lagged total assets, DSALES_A is the change in sales revenue divided by lagged total assets, and the residual eps_it is denoted Ab_CFO. Abnormal production cost is obtained from the residual of the normal production cost model, as follows:

$$PRODA_{it} = \beta_0 + \beta_1 INVA_{it} + \beta_2 SALESA_{it} + \beta_3 DSALESA_{it} + \beta_4 LDSALESA_{it} + \nu_{it} \quad (2)$$

The residual nu_it is denoted Ab_PROD. The abnormal discretionary expense model is:

$$DISXA_{it} = \gamma_0 + \gamma_1 INVA_{it} + \gamma_2 LSALESA_{it} + \eta_{it} \quad (3)$$

The residual eta_it is denoted Ab_DISX. All three models are estimated at the industry-year level. Equation (1) captures the normal level of operating cash flow. Larger sales normally generate higher operating cash flow; sales changes capture growth shocks; and the inverse of total assets controls for intercept differences after scaling. Ab_CFO is the portion of actual CFO_A that deviates from the industry-year normal level. Equation (2) relates production costs to sales level, sales change and lagged sales change. PROD_A is usually defined as operating cost plus the change in inventory, scaled by lagged total assets. If a firm uses overproduction to dilute unit costs, Ab_PROD appears as a positive deviation. Equation (3) uses lagged sales to explain normal discretionary expenses, because R&D, advertising and administrative expenditure are often planned according to prior operating scale. If a firm temporarily cuts expenses, actual DISX_A falls below the normal level and Ab_DISX is usually negative. The three normal models use scaled variables to reduce the effect of firm-size differences on estimation. Using lagged total assets as the scaling base makes operating ratios more comparable across firms of different size within the same industry-year regression. Industry-year estimation means that common shocks within the same industry and year are incorporated into the normal level. The residual represents a firm's deviation from peer firms in the same year, rather than its deviation from the whole market or from its own historical mean.

3.3 Core REM Measures

The data package constructs composite REM indicators according to the three channels. The paper verifies the formulae using the final data, and the maximum absolute calculation error for REM1, REM2 and REM_Total is on the order of 1e-15. The core formulae are as follows:

$$REM1_{it} = AbPROD_{it} - AbCFO_{it} \quad (4)$$

$$REM2_{it} = -AbCFO_{it} - AbDISX_{it} \quad (5)$$

$$REMTotal_{it} = -AbCFO_{it} + AbPROD_{it} - AbDISX_{it} \quad (6)$$

$$AbsREM_{it} = |REMTotal_{it}| \quad (7)$$

REM_Total identifies the direction of real activities earnings management, whereas Abs_REM captures the intensity of deviation. They serve different purposes: directional interpretation and risk-intensity comparison. REM1 combines abnormal increases in production costs and abnormal decreases in operating cash flow in the same direction. If a firm stimulates sales through promotion or relaxed credit while increasing production scale to improve gross margin, REM1 becomes higher. REM2 emphasises the combination of lower cash flow and compressed discretionary

expenditure. It is suitable for identifying firms that sacrifice cash flow through sales policies while cutting expenses to improve profit. REM_Total is the composite measure of the three channels, but its interpretation must still return to the base residuals. An increase in the composite measure does not imply that every channel has increased. One channel may dominate, or different channels may offset one another. Abs_REM addresses the problem of directional cancellation. If some firms use positive REM to increase earnings while others use negative REM to smooth or reduce earnings, the overall mean may be close to zero even when absolute deviations are high. In practice, REM_Total is suited to identifying the direction of earnings management, Abs_REM to building risk rankings, and the base residuals to tracing specific channels. These three types of indicators have different functions and cannot substitute for one another.

3.4 Analytical Design

The sample is divided into four periods: 1998-2006, 2007-2012, 2013-2018 and 2019-2025. The period division is used to describe the empirical trajectory of REM under changes in market institutions and sample composition; it is not used for causal identification. Regression standard errors are clustered by firm. The period model controls for firm fixed effects, while the persistence model controls for both firm and year fixed effects. The auxiliary association model is used only to describe the contemporaneous association between operating fundamentals and REM, not to infer causality. Firm fixed effects absorb time-invariant business models, asset structures, governance environments and managerial styles. Without firm fixed effects, period differences may be confounded by sample expansion and changes in industry entry composition. Year fixed effects absorb macro shocks common to all firms, such as business cycles, capital-market volatility, regulatory intensity and public-health events. After adding year fixed effects to the persistence model, the lagged term better reflects within-firm inertia. The empirical purpose of the paper is to describe long-run facts rather than force causal interpretation in the absence of an external shock. Whenever regressions involve operating fundamentals, the interpretation is expressed in correlational language to avoid mistaking common variables in the measurement model for exogenous causes. The period division balances institutional background and sample size. The period 1998-2006 is the benchmark; 2007-2012 corresponds to the post-new-standards period and the global financial crisis shock; 2013-2018 corresponds to continued market expansion; and 2019-2025 corresponds to the advancement of the registration-based IPO system and the post-pandemic environment.

All regressions in this paper support descriptive judgement. Period coefficients compare changes within the same firm across periods, lagged coefficients assess persistence, and the operating association model describes the synchronous relationship between REM and operating scale or sales volatility.

4 EMPIRICAL RESULTS

4.1 Descriptive Statistics

The mean of REM_Total is 0.0001, the median is 0.0092 and the standard deviation is 0.1886. A mean close to zero does not imply that REM is absent, because positive and negative residual deviations offset each other. The mean of Abs_REM is 0.1290, which more directly reflects the intensity of real activity deviation at the firm-year level. Among the three base residuals, the standard deviation of Ab_PROD is 0.1119, higher than 0.0729 for Ab_CFO and 0.0623 for Ab_DISX, indicating that the production-cost channel is more dispersed across firms. The descriptive statistics show that the distribution of REM_Total is highly dispersed. Its near-zero mean mainly reflects the residual nature of industry-year estimation and should not be interpreted as evidence that real activities earnings management is unimportant. By contrast, Abs_REM presents the magnitude of deviation more directly. The greater dispersion of Ab_PROD indicates that the production-cost channel differs more markedly across sample firms. This is consistent with the high share of manufacturing and inventory-intensive firms in the A-share industry structure, and it also warns researchers not to neglect production when interpreting REM_Total. The negative median of Ab_DISX suggests that many firms compress discretionary expenses relative to peers in the same industry-year. Because R&D, advertising, selling and administrative expenses can generate benefits across periods, short-term adjustment through the expense channel may affect future competitiveness.

The distributions of REM1 and REM2 should also be distinguished. REM1 is more affected by production and sales strategies, while REM2 is more affected by cash-flow and expense policies. If both indicators are high, firms may be using multiple channels in combination. Percentile information is more informative than the mean alone. If the median and the mean differ in direction, tail observations strongly affect the mean; if the 75th percentile is much higher than the median, high-REM firms form a right-tail risk. The paper therefore retains the mean, standard deviation and percentiles in the descriptive statistics. The mean helps assess the overall direction, the standard deviation captures dispersion, and percentiles reveal the difference between typical firms and tail firms. The combination is more suitable for REM data than any single statistic.

Table 2. Descriptive Statistics of Main Variables

Variable	N	Mean	Std. dev.	25%	Median	75%
Ab_CFO	58,661	-0.0001	0.0729	-0.0386	-0.0008	0.0391
Ab_PROD	58,661	-0.0000	0.1119	-0.0458	0.0030	0.0480
Ab_DISX	58,661	0.0000	0.0623	-0.0305	-0.0070	0.0182
REM1	58,661	0.0001	0.1557	-0.0742	0.0033	0.0766
REM2	58,661	0.0001	0.1009	-0.0479	0.0056	0.0550
REM_Total	58,661	0.0001	0.1886	-0.0838	0.0092	0.0960
Abs_REM	58,661	0.1290	0.1376	0.0412	0.0902	0.1681

Note: Abs_REM is the absolute value of REM_Total.

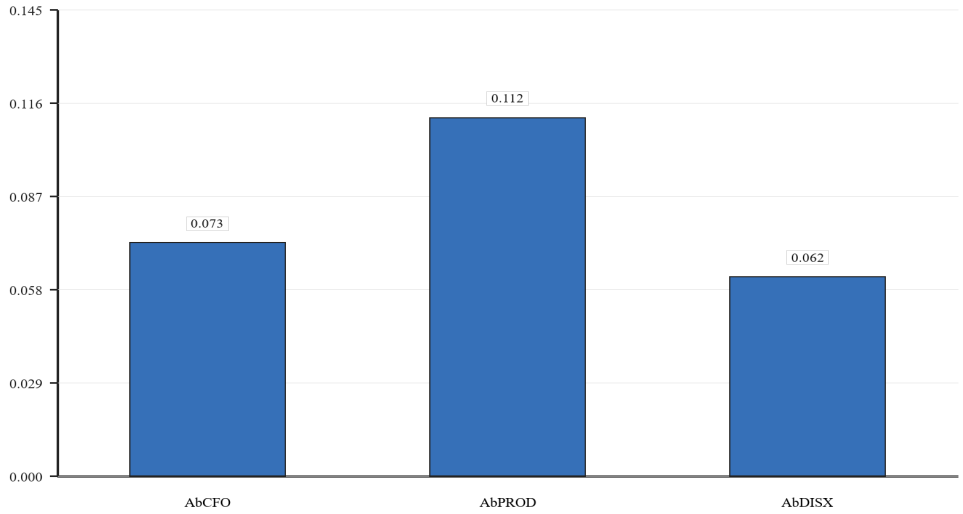

Figure 1. Standard Deviations of Three Base REM Residuals

4.2 Period Trends

Abs_REM reaches 0.1589 in 2007-2012, higher than 0.1184 in 1998-2006. It then falls to 0.1377 in 2013-2018 and further to 0.1180 in 2019-2025. This indicates that the intensity of real activity deviation was elevated after the implementation of new accounting standards and around the global financial crisis, and then converged. Directional indicators did not decline in the same way. The share of positive REM rose from 50.36% in 1998-2006 to 54.24% in 2019-2025, and the median of REM_Total rose from 0.0010 to 0.0120. Intensity decline and directional movement must therefore be interpreted separately. The high Abs_REM in 2007-2012 may be related to the adaptation period after the new accounting standards, the global financial crisis and capital-market volatility. The paper does not interpret these factors causally, but the period trajectory shows that REM was concentrated in specific periods. After 2019, Abs_REM is below its peak, but the number of sample firms increased sharply and industry structure became more complex. Recent risk may therefore take the form not of extreme deviations among a few firms, but of broader and more dispersed operating-level adjustment. The annual trend figures further show that REM intensity is not linear. The annual plot observes the continuous trajectory, whereas the period bar charts compress the comparison of period means. Together, the figures show that the period division does not hide the main direction of change.

The annual mean rises clearly in several years, indicating that REM is not a smooth linear process but fluctuates with market conditions and operating shocks. Annual figures help identify local peaks behind period averages. Period comparisons highlight mean differences across the four periods. The height of the 2007-2012 bar is visibly above the other periods, showing that this period contains not only abnormal individual years but also a higher average intensity. The period trend also shows that improvement in the regulatory environment does not mean the disappearance of risk. Convergence in intensity may reduce extreme deviations, but a positive directional tilt can still affect investors' assessment of earnings persistence and must be tracked in subsequent years.

Table 3. REM Distribution by Period

Period	N	Firms	Mean REM	Median REM	Mean Abs_REM	Positive share
1998-2006	7,921	1,421	-0.0006	0.0010	0.1184	50.36%
2007-2012	8,501	2,006	-0.0017	0.0052	0.1589	51.46%
2013-2018	14,880	3,040	0.0009	0.0102	0.1377	52.93%
2019-2025	27,359	5,047	0.0003	0.0120	0.1180	54.24%

Note: Positive share is the proportion of firm-year observations with REM_Total greater than zero.

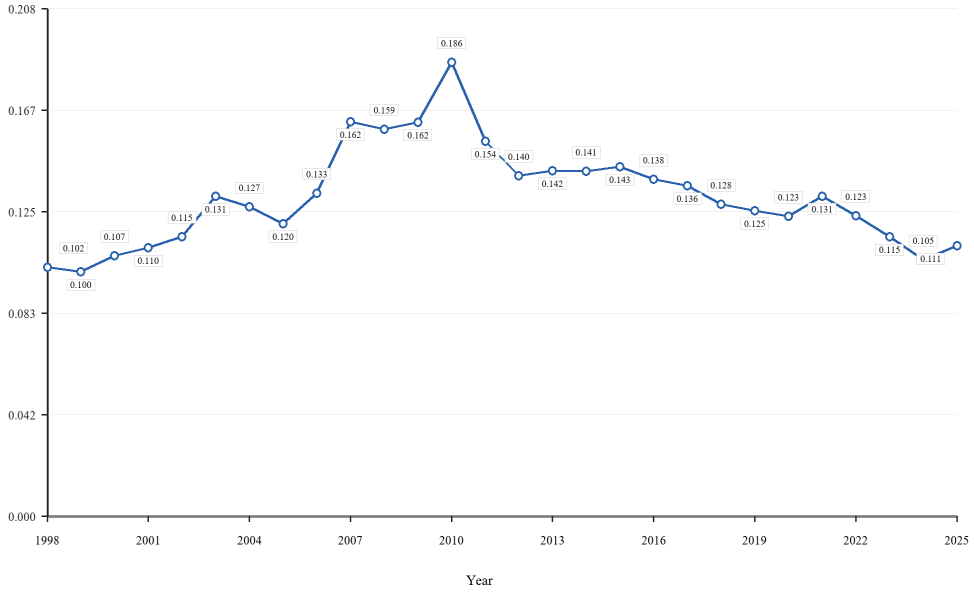

Figure 2. Annual Mean Abs_REM

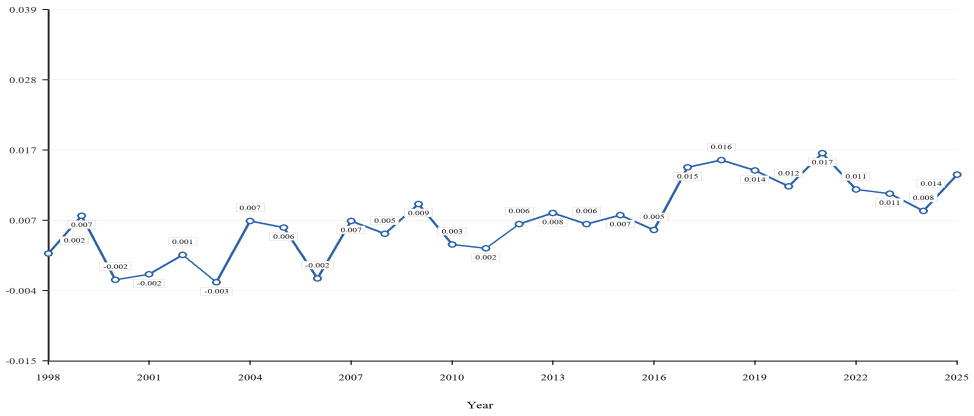

Figure 3. Annual Median REM_Total

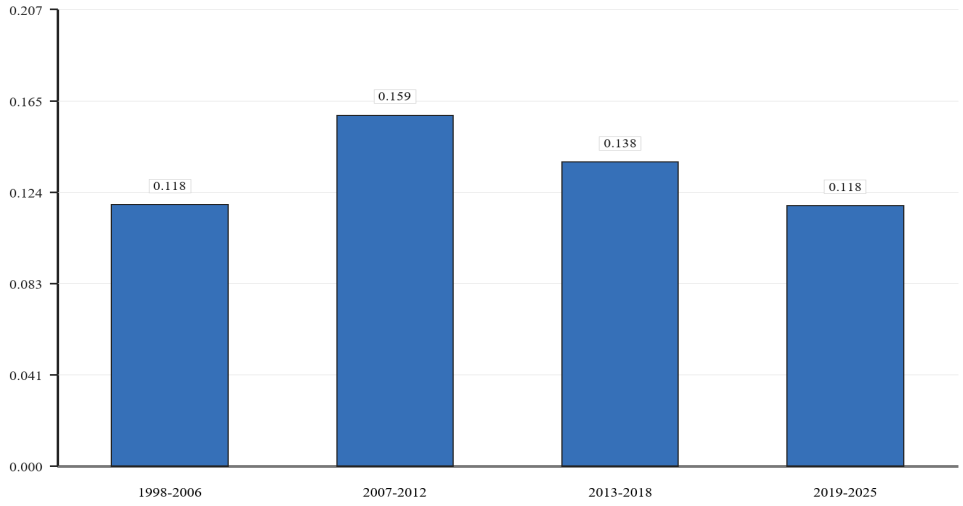

Figure 4. Mean Abs_REM by Period

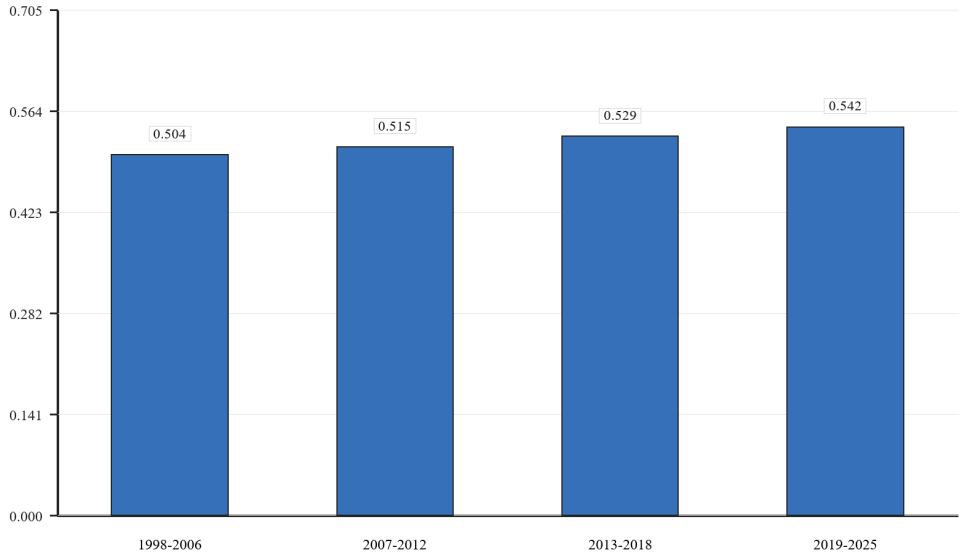

Figure 5. Positive REM Share by Period

4.3 Industry Heterogeneity

Among detailed industries with at least 300 observations, internet and related services has the highest Abs_REM, with a mean of 0.1980; water production and supply has the lowest value, with a mean of 0.0725. High-intensity industries are concentrated in internet services, retail, pharmaceuticals, real estate, wholesale and software services. These industries usually feature complex revenue-recognition timing, flexible expenditure deployment, stronger demand volatility or greater scope for channel management. Utilities and infrastructure-related industries have lower REM, possibly because of price regulation, capacity constraints and more stable operating processes. The high REM in retail and wholesale has a clear operating meaning. These firms often have multiple channel layers, frequent promotions, and flexible credit and collection arrangements, making short-term mismatches between revenue growth and operating cash flow more likely. In pharmaceuticals and software services, high REM is more closely related to the flexibility of expenditure inputs. R&D, sales promotion and project delivery schedules affect discretionary expenses and revenue recognition, so REM in these industries should be interpreted together with expense structure and project cycles. High Abs_REM in real estate is related to development cycles, inventory scale and financing constraints. Real estate firms have concentrated revenue recognition, high inventory proportions and volatile cash flows, making them more likely to show real activity deviations in the REM model. Industry codes are used in the figure instead of long industry names to keep the visual clean; Table 4 provides full names and values, so the figure and table jointly support readability and precision.

Industry differences also suggest that later studies should avoid explaining all industries together. If the focus is expenditure compression,

pharmaceuticals, software and internet services are more suitable settings. If the focus is the production-cost channel, detailed sub-industries within manufacturing are more informative. Industry heterogeneity also affects the allocation of regulatory resources. When regulatory and audit resources are limited, attention should first be directed to industries with high REM intensity and clear channel interpretation, followed by the identification of firms with persistent deviations within those industries.

Table 4. Detailed Industries with the Highest Abs_REM (N >= 300)

Industry code	Industry name	N	Firms	Mean REM	Median REM	Mean Abs_REM
I64	Internet and related services	809	87	0.0100	0.0432	0.1980
F52	Retail	1,851	151	-0.1044	-0.0654	0.1960
C27	Pharmaceutical manufacturing	3,797	332	0.0007	0.0173	0.1933
K70	Real estate	2,735	152	-0.0007	-0.0256	0.1902
C18	Textile, apparel and accessories	431	44	0.0038	0.0063	0.1849
F51	Wholesale	1,603	105	0.1220	0.1320	0.1815
I65	Software and information technology services	2,949	346	-0.0035	0.0306	0.1563
B09	Non-ferrous metal mining and dressing	404	26	0.0324	0.0402	0.1516
L72	Business services	857	68	-0.0012	0.0159	0.1495
C14	Food manufacturing	741	73	0.0017	0.0031	0.1491

Note: Industries are ranked by the mean of Abs_REM.

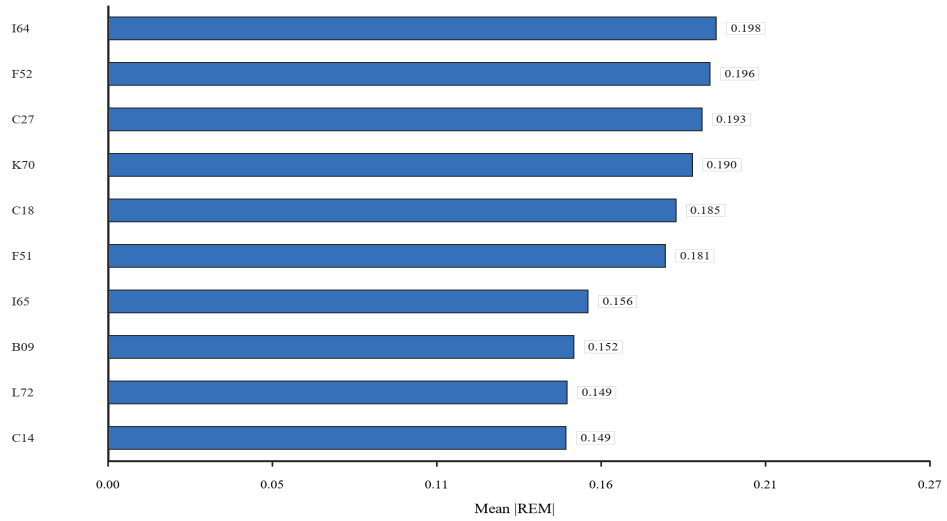

Figure 6. Top Ten Detailed Industries by Abs_REM

4.4 Variance Decomposition

To compare explanatory power at the year, industry and firm levels, the paper calculates single-factor group explanatory power as follows:

$$R^2g = 1 - \Sigma(y_{it} - mean(y|g))^2 / \Sigma(y_{it} - mean(y))^2 \quad (8)$$

The results show that year grouping alone explains only about 0.01% of the variance in REM_Total, detailed industry explains about 2.55%, and firm grouping explains about 47.00%. Firm differences are much larger than year and industry differences, indicating that REM risk identification must reach the firm level. Equation (8) is not a causal model. It compares the descriptive explanatory power of different grouping variables for REM variation. The low explanatory power of year grouping indicates that macro annual shocks are not the main source of REM differences. Industry grouping explains more, but its explanatory power remains limited. The much higher firm-level explanatory power indicates that firm-specific characteristics occupy the central position in REM. Business model, internal control, managerial incentives, supply-chain position and governance quality may all create long-term differences. Future research can build mechanism tests around these variables. High firm-level

explanatory power does not mean that year and industry are unimportant. It means that they cannot substitute for firm-level information. In practice, high-risk industry lists can serve as an initial screen, but the firm's historical trajectory is the key to further identification. This result also supports the need for fixed-effect models. If time-invariant firm characteristics explain a large share of REM differences, period comparisons without firm fixed effects may mistake firm-composition differences for time variation. Methodologically, variance decomposition provides evidence between descriptive statistics and regression models. It does not rely on complex identification assumptions, but it indicates that later models should treat firm fixed effects as a basic specification.

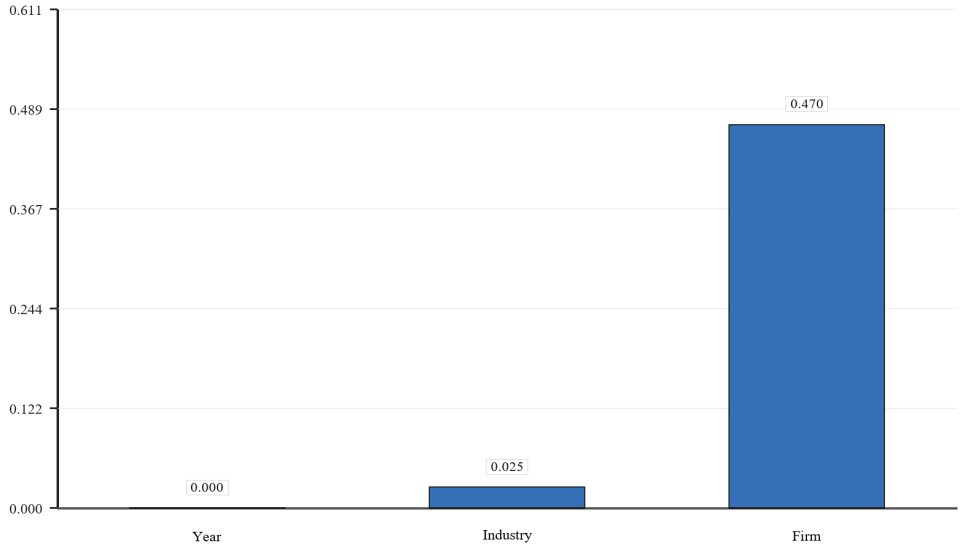

Figure 7. Single-Factor Explanatory Power in the Variance Decomposition of REM_Total

4.5 Period Fixed-Effect Regressions

The period-difference model is specified as follows:

$$Y_{it} = \alpha_i + \beta_1 D_{2007-2012} + \beta_2 D_{2013-2018} + \beta_3 D_{2019-2025} + u_{it} \quad (9)$$

Using 1998-2006 as the benchmark, the coefficients of REM_Total for 2007-2012, 2013-2018 and 2019-2025 are 0.0083, 0.0186 and 0.0366, respectively, all positive. For Abs_REM, the period coefficients show that 2007-2012 is 0.0429 above the benchmark period, 2013-2018 is 0.0210 above it, and 2019-2025 is not significantly different. The alpha_i term in Equation (9) controls for firm fixed effects, so the period coefficients more strongly reflect changes within the same firm across periods rather than static differences across firms. This helps mitigate structural bias caused by sample expansion. The results show that the later-period coefficients of REM_Total are positive and significant, indicating that typical firms are more inclined towards positive REM in later periods. Abs_REM is no longer significantly above the benchmark in 2019-2025, implying that a positive directional tilt and intensity convergence coexist. This combination has practical importance. Regulation and auditing cannot focus only on the decline in overall intensity; they should also attend to the earnings-direction risk created by the rising share of positive REM. The significantly positive later coefficients for REM_Total indicate that the same firm is more likely to display positive composite deviation relative to the benchmark period. This conclusion is consistent with the rising positive REM share and increases the credibility of the directional result.

Abs_REM is significantly higher in 2007-2012, showing that this period saw not only a change in direction but also a real increase in deviation intensity. The insignificant result for 2019-2025 suggests that recent risk is more likely to be mild, widespread and directionally positive. The period-regression results are consistent with the period-mean results, indicating that the conclusions are not driven only by changes in sample composition. After comparing the same firm across time, period differences remain, strengthening the judgement on long-run trends.

Table 5. Firm Fixed-Effect Regressions of Period Differences

Dependent variable	Period variable	Coefficient	Std. error	t-stat.	N	Firms	Within R2
REM_Total	2007-2012	0.0083**	(0.0041)	2.02	58,661	5,288	0.0066
REM_Total	2013-2018	0.0186***	(0.0041)	4.59	58,661	5,288	0.0066
REM_Total	2019-2025	0.0366***	(0.0039)	9.32	58,661	5,288	0.0066
Abs_REM	2007-2012	0.0429***	(0.0030)	14.22	58,661	5,288	0.0189
Abs_REM	2013-2018	0.0210***	(0.0029)	7.34	58,661	5,288	0.0189
Abs_REM	2019-2025	-0.0017	(0.0028)	-0.60	58,661	5,288	0.0189

Note: The benchmark period is 1998-2006; standard errors are clustered by firm.

4.6 Persistence and Operating Associations

The persistence model is specified as follows:

$$Y_{it} = \alpha_i + \lambda_t + \rho Y_{i,t-1} + u_{it} \quad (10)$$

The first-order lag coefficient of REM_Total is 0.2594, with a clustered robust standard error of 0.0120 and a t-statistic of 21.68, significant at the 1% level. Abs_REM, REM1 and REM2 also show significant positive persistence, indicating that REM is not one-year random noise. The auxiliary association model is specified as follows:

$$Y_{it} = \alpha_i + \theta_1 Size_{it} + \theta_2 SALESA_{it} + \theta_3 DSALESA_{it} + u_{it} \quad (11)$$

Abs_REM is significantly positively associated with SALES_A and DSALES_A, with coefficients of 0.0718 and 0.0392, respectively; the coefficient on Size is -0.0027. Because these variables also participate in the normal REM models, the paper interprets the results only as evidence of associations with operating fundamentals. Equation (10) tests whether REM has firm-level inertia. The lagged coefficient is significantly positive, indicating that firms with higher REM in the previous year are more likely to maintain higher deviations in the following year. This persistence makes historical trajectories important for risk screening. Persistence does not imply persistent misconduct. It may arise from managerial style, business model, budgeting systems, channel arrangements or governance constraints. The conclusion of the paper is that REM is traceable, not that any single firm should be morally judged. Size, SALES_A and DSALES_A in Equation (11) help interpret operating fundamentals. Firms with higher sales intensity and sales changes are more likely to deviate from the industry-year normal level; larger firms show lower deviations, possibly because monitoring, processes and internal controls are more stable. For auditors, persistence means that prior-year risk assessment should not be reset to zero in the new year. Firms with continuous deviations should be included in rolling monitoring, especially when cash flow, inventory and expense ratios move consistently with the REM direction. The association results also show that sales expansion and sales volatility amplify deviations measured by REM. Growth firms are not necessarily opportunistic, but their operating changes more easily move actual outcomes away from industry-year normal relations.

The persistence results further suggest that REM indicators are suitable for early-warning stratification. A single year of high REM can be used as an attention signal, while consecutive high REM should trigger deeper analysis of operating rationality and adjustments to audit procedures.

Table 6. REM Persistence Regressions

Dependent variable	Lagged variable	Coefficient	Std. error	t-stat.	N	Firms	Within R2
REM_Total	L.REM_Total	0.2594***	(0.0120)	21.68	53,373	5,033	0.0765
Abs_REM	L.Abs_REM	0.2120***	(0.0114)	18.56	53,373	5,033	0.0724
REM1	L.REM1	0.2030***	(0.0112)	18.19	53,373	5,033	0.0465
REM2	L.REM2	0.2113***	(0.0084)	25.09	53,373	5,033	0.0545

Note: The model includes firm fixed effects and year fixed effects.

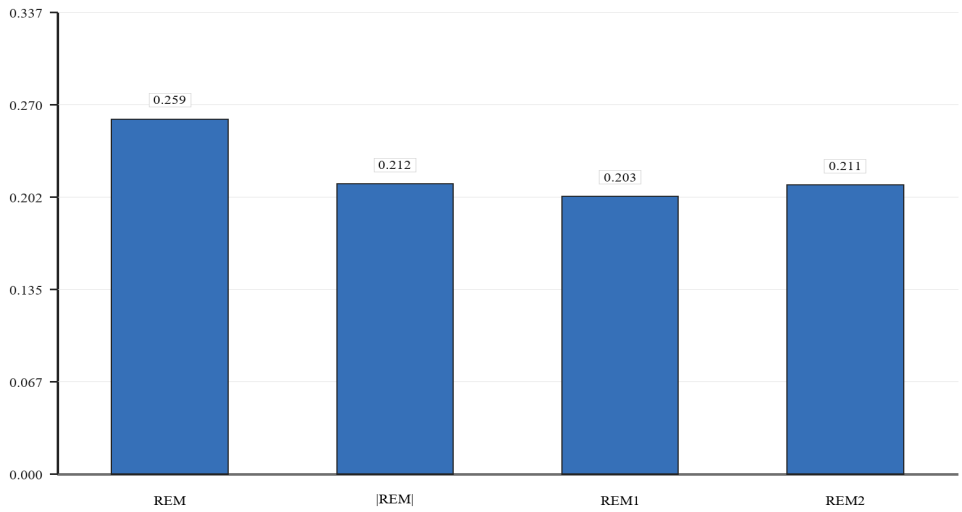

Figure 8. First-Order Persistence Coefficients of REM Indicators

Table 7. Auxiliary Association Regressions between Operating Fundamentals and REM

Dependent variable	Variable	Coefficient	Std. error	t-stat.	N	Firms	Within R2
REM_Total	Size	0.0126***	(0.0016)	7.81	58,661	5,288	0.0212
REM_Total	SALES_A	-0.0238***	(0.0066)	-3.60	58,661	5,288	0.0212
REM_Total	DSALES_A	-0.0466***	(0.0078)	-5.96	58,661	5,288	0.0212
Abs_REM	Size	-0.0027**	(0.0011)	-2.48	58,661	5,288	0.0858
Abs_REM	SALES_A	0.0718***	(0.0047)	15.34	58,661	5,288	0.0858
Abs_REM	DSALES_A	0.0392***	(0.0061)	6.45	58,661	5,288	0.0858

Note: The table reports correlations only.

5 DISCUSSION AND IMPLICATIONS

5.1 Interpretation of the Results

The paper finds that REM in Chinese A-share firms exhibits a pattern of period-specific convergence in intensity, a recent positive directional tilt, clear industry differences and significant firm-level persistence. The decline in period intensity may be related to improved regulation, a better information environment and sample expansion, while the increase in the positive REM share indicates that directional earnings adjustment still requires attention. The firm-level explanatory power and persistence results are especially important. They show that REM risk cannot be judged only by the annual environment or industry labels. Firms in the same industry and year may still differ substantially, making the firm's historical REM trajectory useful for audit and regulatory risk screening. The period results indicate that A-share REM intensity is more likely to rise under pressure and volatility, but extreme deviations have converged as regulation, disclosure and market structure changed. At the same time, the rising proportion of positive REM shows that profit-oriented real activities management has not disappeared. The industry results remind researchers that REM is not uniformly distributed across the market. Differences in revenue models, cost structures and expenditure flexibility determine the importance of different channels. Explaining all industries with a market average easily conceals real risk. The persistence results push the issue towards governance. If a firm remains in a high-REM range for several years, auditors and regulators should monitor cash flow, inventories, expense ratios and managerial performance pressure continuously. The paper maintains a conservative interpretation. Because no external shock or instrumental variable is introduced, period and industry differences cannot be interpreted directly as causal effects of institutional change or industry characteristics. They are first and foremost replicable empirical facts.

This conservative interpretation does not reduce the research value. On the contrary, accurately describing long-run facts is the precondition for later causal identification. Without stable measurement, mechanism tests can easily rest on unreliable indicators. Another implication is that earnings-quality research should not stop at financial statement items. Real operating activities themselves can become part of reporting strategy, so accounting research needs to be connected with operations management and industry analysis.

5.2 Practical Implications

Regulators can transform REM indicators into explanatory enquiries. When operating cash flow is abnormally low, attention should be paid to credit policies and subsequent cash collection. When production costs are abnormally high, capacity utilisation and inventory ageing should be examined. When discretionary expenses are abnormally low, regulators should ask whether R&D, advertising and selling expenditure have been compressed in a way that affects long-term operations. Auditors should incorporate REM into risk-oriented analytical procedures. For firms with persistently high REM, auditors should jointly examine year-end sales, channel inventories, expense cut-off, inventory impairment and managerial performance pressure. Investors should assess earnings quality by combining REM with cash flow, inventory turnover, expense ratios and industry conditions. Stock-exchange enquiries can be organised around the three REM channels. When operating cash flow is abnormally low, firms should explain credit policy, major customer collection and subsequent receipts. When production costs are abnormally high, firms should explain capacity utilisation, inventory ageing and impairment allowances. When expenses are abnormally low, firms should explain whether expenditure reductions affect long-term operations. In audit practice, REM analysis should be combined with traditional testing of financial statement items. Revenue growth, improved gross margin, declining cash flow and compressed expenses should be treated as one risk chain rather than as isolated anomalies. Investors should also use REM cautiously. High REM is not direct evidence of financial fraud, and low REM does not guarantee high earnings quality. A more reasonable approach is to use REM as a screening indicator and cross-check it with accrual quality, operating cash flow and industry prosperity.

Regulatory enquiries should not ask only about changes in profit; they should ask about the operating actions behind those changes. REM indicators translate the abstract issue of earnings quality into concrete questions about cash flow, capacity, inventory, expenses and customer collection. In investment analysis, REM can serve both as a negative screening signal and as an entry point for further due diligence. When REM is persistently high and operating cash flow worsens, inventory rises or R&D and selling expenses fall abnormally, earnings-quality risk deserves closer attention. For listed firms themselves, continuous reliance on REM to improve short-term profit is undesirable. Sales stimulation, overproduction and expense compression may later appear as collection pressure, inventory risk and insufficient innovation, ultimately damaging firm value.

5.3 Limitations and Extensions

The main limitation of this paper is that the database mainly provides REM measures and basic operating variables. It lacks governance, audit, financing-constraint and market-pressure variables, so the mechanisms behind the results cannot be directly identified. Residuals from the Roychowdhury model may also contain normal strategic adjustment as well as opportunistic manipulation and must be interpreted with industry background. Future research can merge the REM data with internal control, auditors, analysts, institutional investors, regulatory enquiries and institutional reform events to examine governance mechanisms, institutional shocks and the economic consequences of REM. The paper does not include corporate governance, auditors, analysts, institutional investors or regulatory enquiries, and therefore cannot explain the specific mechanisms behind REM differences. The current results should be regarded as measurement facts and a basis for later mechanism research. At the model level, Roychowdhury residuals depend on industry-year normal relations. If an industry experiences technological change or business model reconstruction, residuals may contain both normal strategic adjustment and earnings management components. Industry results must therefore be interpreted together with sectoral context. Future research can test the economic consequences of REM, such as future operating cash flow, innovation investment, stock-price crash risk, credit spreads and firm value. It can also compare REM with accrual earnings management to judge whether firms change their tool mix after regulatory tightening. Another limitation is that annual data cannot identify concentrated operations around quarter-end or year-end. Real activities management may occur in shorter windows, and annual data smooth part of this timing behaviour. Future research may also combine firm cases and industry cases. Quantitative REM indicators can identify abnormal positions, while case analysis can explain why and how firms influence earnings through operating arrangements. In addition, this paper does not distinguish state-owned and privately owned enterprises, main-board and growth-board firms, or traditional and growth industries. Subsequent studies can conduct group tests within the current framework.

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