Applying a Profit Health Assessment Model: Evidence from A-Share Listed Firms in the Guangdong Segment of the Greater Bay Area (2020–2024)

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Abstract

Against the backdrop of accelerating the development of new quality productive forces and tightening capital market regulation, accurately assessing firms' earnings quality is crucial for high-quality regional development. This study uses a sample of 569 A-share listed firms in the Greater Bay Area from 2020 to 2024, measures the substance of business operations based on a theoretical profit-health assessment model, and examines structural features using ANOVA and nonparametric tests. The results show, first, that firms' profit health in the Greater Bay Area displays a robust "olive-shaped" pattern—large in the middle and small at both ends—yet top-tier firms with exceptionally high quality remain scarce. Second, overall differences across cities are not significant, supporting the synergy of regional integration, while core cities exhibit a more intense internal selection mechanism. Third, there is significant structural divergence across industries ($p < 0.01$), forming a "new-strong, old-weak" pattern: information technology and materials—both aligned with new quality productive forces—show clear advantages, whereas traditional sectors such as real estate and finance face substantial balance-sheet repair pressure. The study indicates that the model effectively identifies structural risks and provides empirical evidence for regulators to implement differentiated supervision and to promote the transition from old to new growth drivers.

Keywords: Profit Health; the Guangdong Part of the Greater Bay Area (GBA); Earnings Management

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1. Introduction

In recent years, corporate financial fraud and earnings manipulation have remained prominent, posing serious threats to the sound functioning of capital markets and drawing sustained attention from regulators and academia worldwide. Against the dual backdrop of advancing new quality productive forces and the continued tightening of China's capital market regulation, "profit health" has become an important dimension for assessing operating quality and sustainable development capacity. Policies released in 2024, including the "New Nine Measures" and the Guiding Opinions on further strengthening the comprehensive punishment and prevention of financial fraud in the capital market, explicitly call for tighter oversight of financial reporting authenticity and severe crackdowns on earnings manipulation, thereby providing solid policy support for evaluating the quality of new quality productive forces from a micro-level perspective.

Unlike the traditional earnings-management lens that emphasizes compliance screening, "profit health" in this paper is a more inclusive and forward-looking concept. It is no longer confined to the book-level truthfulness of financial figures; instead, it emphasizes compliant profit growth that is driven by technological innovation and improved resource allocation, and that is endogenous and sustainable. This concept is not only a concrete manifestation of new quality productive forces at the firm-level financial micro level, but also an accurate mapping of genuine value-creation capacity, and a key expression of modern corporate governance and high-quality regional development. Under the new dual-circulation development paradigm, the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) is China's most open and dynamic strategic economic region, and a core source of new quality productive forces. The profit health of listed companies in the region not only directly affects the efficiency of resource allocation in the regional capital market, but also carries important demonstration value for deep adjustments in China's economic structure and for high-quality development nationwide. Accordingly, based on the profit-health evaluation model developed by Zhu Wen et al. (Zhu, et al., 2024b), this study uses a sample of 569 GBA listed firms over 2020–2024, evaluates corporate profit health from both regional and industry dimensions, and offers policy recommendations to respond to capital-market regulatory needs and support high-quality regional development.

The study makes three main contributions: first, it extends the research boundary of the profit-health evaluation model by applying it to the GBA, a national strategic hub, and it verifies the model's applicability in a capital market with regional heterogeneity. Second, it systematically estimates profit-health scores for GBA listed firms and implements a star-based tiering scheme, enabling a fine-grained depiction and dynamic monitoring of corporate health in the region. Third, through differentiated comparisons across cities and industries, it reveals the relative advantage of emerging industries that represent new quality productive forces in terms of profit health, as well as the structural transition pains faced by some traditional industries. This provides stratified empirical evidence for regulators to design differentiated policies, for firms to optimize governance structures, and for investors to screen risks.

2. Theoretical Foundations and Literature Review

2.1 Conceptual Definition of Profit Health

Academic inquiry into corporate earnings management has undergone an evolution from curbing

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opportunistic behavior toward a more comprehensive evaluation of firms' capacity for sustainable value creation. Early seminal studies largely concentrated on earnings management and earnings quality. Healy and Wahlen (Healy & Wahlen 1999) and Dechow et al. (Dechow, et al., 1995) developed evaluation frameworks centered on representational faithfulness and predictive ability, primarily aiming to detect managerial earnings manipulation within the constraints of accounting standards. However, in the new phase characterized by high-quality development and the accelerated formation of new quality productive forces, the traditional perspective—dominated by compliance-oriented scrutiny—has become increasingly inadequate for practical needs. On the one hand, an excessive emphasis on the formal legality of reported numbers neglects the role of earnings in driving firms' long-term value. On the other hand, fragmented indicators make it difficult to form an integrated framework capable of guiding sustainable development.

Against this background, the concept of "profit health" proposed by Zhu Wen et al. (Zhu et al. 2024b) extends the research focus from passive, defensive compliance screening to proactive, value-oriented assessment. By definition, profit health refers to sustained, stable, and reasonable profit growth achieved by a firm—on the premise of adhering to market mechanisms and laws and regulations—through technological innovation, optimized resource allocation, improvements in total factor productivity, and industrial transformation and upgrading, among other approaches (Zhu et al. 2024b). This concept broadens the theoretical boundaries of the traditional earnings management literature: it not only considers the compliance of financial outcomes, but also emphasizes the firm's capability to achieve high-quality development through endogenous drivers under compliance constraints, thereby providing a novel analytical perspective for assessing sustainable high-quality development.

2.2 A Three-Tier Architecture of Assessment Dimensions

The core of constructing a scientific profit health assessment system lies in transcending the limitations of single financial indicators and establishing a multidimensional verification mechanism that integrates both financial and non-financial signals. Drawing on the classical literature and the theoretical model of Zhu Wen et al. (Zhu et al. 2024b), profit health assessment primarily comprises three key dimensions.

First, the dimension of compliance and cash-flow support constitutes the micro-foundation of profit health. The Jones model (Jones 1991) and its modified versions (Dechow et al. 1995 ; Kothari, et al., 2005) established the methodological basis for identifying abnormal accruals, while Dechow and other scholars emphasized the validating role of cash flows for reported earnings (Dechow, et al., 2002). In the context of China, studies by Lu Jianqiao and Cao Qiong et al. indicate that only profits supported by robust operating cash flows and purged of artificially manipulated components can be regarded as possessing fundamental health attributes (Lu 1999 ; Cao, et al., 2014).

Second, the dimension of endogenous growth and operating substance stresses that profits must originate from core businesses and genuine operating activities. Roychowdhury's perspective on real earnings management suggests that actions taken to embellish short-term performance—such as cutting R&D expenditures or conducting excessive sales promotions—can impair firms' long-term competitiveness (Roychowdhury 2006). Fan, et al., (2013) further demonstrate that high-quality internal control can effectively restrain real earnings management, thereby safeguarding the substantive nature of corporate operations. Consequently, healthy profits should arise from the growth of core operations and

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efficient resource allocation, rather than short-term capital operations.

Third, the dimension integrating non-financial information and ESG constitutes the forward-looking perspective of profit health. With the iterative development of large language models and digital-intelligence technologies, assessment has expanded to include unstructured data. On the one hand, text-analytic techniques enable in-depth mining of latent information such as annual report tone and media attention (Liu, et al., 2021); on the other hand, ESG performance is increasingly becoming a pivotal non-financial factor in evaluating earnings sustainability (Huang 2021), underscoring the influence of environmental and social responsibilities on the sustainability of profits. The model developed by Zhu Wen et al. aligns with this trend of digital transformation. By incorporating non-financial signals, it effectively mitigates the lagging nature of purely financial indicators and enhances the ability to identify firms' latent risks (Zhu et al. 2024b ; Zhu, et al., 2025b).

2.3 Technological Evolution of Econometric Models

As the business environment has become more dynamic and complex, assessment methods have progressed from single linear regressions represented by the Jones model (Jones 1991) to multi-indicator composite evaluation systems typified by the Beneish M-Score (Beneish 1999). Nevertheless, traditional models are limited in explaining complex manipulation behaviors (Dechow et al. 1995), and the determination of indicator weights often relies on subjective judgment (Dichev, et al., 2013).

In the era of deep integration between big data and artificial intelligence, data-driven paradigms based on machine learning and data mining have demonstrated distinctive advantages (Zhu, et al., 2024a). Cutting-edge research has begun to employ deep neural networks to capture nonlinear mapping relationships among variables, thereby substantially improving identification accuracy (Bao, et al., 2020); text analytics has also greatly expanded the boundaries of information acquisition (Meng, et al., 2017). Although machine-learning-based black-box models have achieved breakthroughs in predictive accuracy, their lack of economic interpretability constrains their direct usefulness for regulatory policymaking and investors' valuation judgments. By contrast, the "profit health assessment model" proposed by Zhu Wen et al. [1] balances theoretical completeness with practical operability. By systematically integrating multi-source heterogeneous financial and non-financial data, the model constructs a comprehensive assessment tool with clear logic and explicit attribution, making it particularly suitable for rapid screening of large-sample listed firms and for monitoring long-term trends.

3. Research Design

3.1 Theoretical Model and Indicator System

3.1.1 Theoretical Model

Building on the "profit health assessment model" proposed by Zhu et al. (2024b), this study undertakes a regionalized application and empirical test for listed companies in the Guangdong Part of the Greater Bay Area. The model integrates insights from the earnings management literature, agency theory, and signaling theory, and draws on the econometric specifications of Beneish (1999) and Jansen, et al., (2012). This model addresses the limitations of traditional earnings management approaches that focus narrowly on profit manipulation. By jointly incorporating financial and non-financial indicators, it enables a multidimensional assessment of the authenticity and sustainability of reported profits, together

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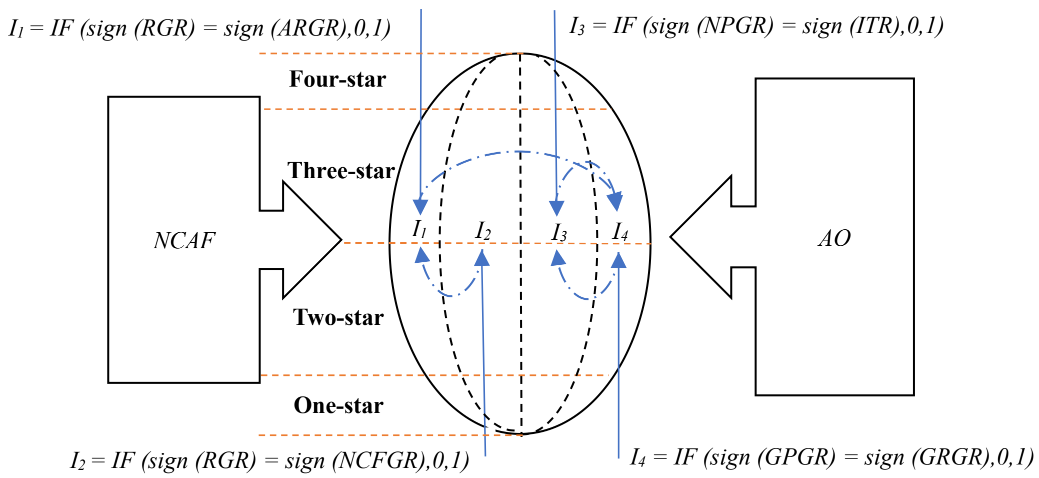
with governance-related factors.

The model combines seven financial indicators and two non-financial indicators to analyze the dynamic evolution of corporate profits (Zhu, et al., 2025a). The seven financial indicators are organized into four paired diagnostics to examine their interrelationships. Scores are assigned according to whether the directions of change within each pair are consistent, thereby identifying varying degrees of profit health. The financial indicators capture the sources of profits, operational efficiency, and the cash realizability of earnings. The non-financial indicators are evaluated along the dimensions of governance stability and audit opinions. The scores from the four financial diagnostic pairs are then aggregated with the two non-financial scores to form an annual Profit Health Score (PH), which characterizes the firm's level of profit health.

In addition, drawing on Maslow's hierarchy of needs and the balanced scorecard framework (Maslow 1943 ; Kaplan 2009), the model aggregates annual PH scores over a five-year horizon to derive a Profit Health Total Score (PHT). Firms are classified into star ratings based on the PHT, providing an intuitive stratification of profit conditions and associated risk identification. The theoretical framework of the model is presented in Figure 1.



$$PH = \sum_{m=1}^{4} I_m + NCAF + AO$$

Figure 1: Theoretical Model of Profit Health Assessment

Source: Zhu Wen, Wu Chengcheng, Li Meiling, and Yao Fengmin. "Profit Health Assessment: Theoretical and Practical Exploration." Friends of Accounting, 2025(8): 52–62.

Compared with traditional accrual-based tools such as the Jones model, the Modified Jones model, and the Beneish M-Score, the present model achieves a more comprehensive identification of profit health by incorporating non-financial signals and modeling dynamic trends. First, it moves beyond the single-source focus on accruals in financial statements by innovatively integrating financial signals with non-financial signals (e.g., audit opinions and auditor changes as governance-related variables), thereby substantially enhancing the joint identification of profit authenticity and sustainability. Second, by employing multi-period trend scoring and a star-based stratification scheme, the model enables dynamic monitoring of corporate profit health, remedying the limitation of traditional models that chiefly uncover short-term manipulation. Third, drawing on signaling theory and agency theory, the model underscores the roles of governance, innovation, and resource allocation in shaping profit health, which strengthens

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its forward-looking nature and policy relevance.

Overall, the profit health assessment framework not only identifies earnings management risks but also emphasizes high-quality development and sustainable value creation. By combining local adaptability with a practice-oriented design, it provides robust theoretical and empirical support for capital-market regulation and for refining regional capital-market health assessment systems.

3.1.2 Indicator System

To measure corporate profit health in a systematic manner, the model specifies a composite evaluation framework consisting of four financial signal detectors and two non-financial indicators.

(1) Financial Signal Detectors

These detectors test the quality, cash realizability, and reasonableness of profits. The financial indicators cover key dimensions related to profit generation, operating efficiency, and profitability:

I_1: Revenue Growth Rate (RGR) and Accounts Receivable Growth Rate (ARGR)

This detector assesses the quality of revenue growth. If revenue growth is not accompanied by a concurrent increase in accounts receivable, the case is classified as abnormal and assigned 1 point; otherwise, 0 points.

I_2: Revenue Growth Rate (RGR) and Net Cash Flow from Operating Activities Growth Rate (NCFGR)

This detector examines the cash realizability of revenue growth. If the two indicators move in opposite directions, the case is classified as abnormal and assigned 1 point; otherwise, 0 points.

I_3: Net Profit Growth Rate (NPGR) and Inventory Turnover Ratio Growth Rate (ITR)

This detector evaluates the operational basis and reasonableness of profit growth. Divergent directions are classified as abnormal and assigned 1 point; otherwise, 0 points.

I_4: Gross Profit Growth Rate (GPGR) and Gross Revenue Growth Rate (GRGR)

This detector tests the consistency between profit growth and revenue growth. Opposing directions are classified as abnormal and assigned 1 point; otherwise, 0 points.

Taken together, the four detectors capture profit health risks at different stages and, through their logical interrelations, form a coherent financial evaluation loop that reduces the probability of misclassification by any single indicator.

(2) Non-Financial Indicators

These indicators reflect governance stability and the reliability of financial reporting, compensating for traditional models' neglect of governance and compliance factors.

Frequency of Audit Firm Changes (NCAF): switching the audit firm during the year is assigned 1 point; otherwise, 0 points, capturing governance stability and potential risks.

Type of Audit Opinion (AO): a standard unmodified opinion is assigned 0 points; an unmodified opinion with an emphasis-of-matter paragraph is assigned 1 point; a qualified opinion is assigned 3 points; and an adverse opinion or a disclaimer of opinion is assigned 5 points. Higher scores indicate greater risk.

(3) Profit Health Score (PH)

Aggregating the scores from the four financial detectors and the two non-financial indicators yields the Profit Health Score (PH) for a given year:

$$PH = I_1 + I_2 + I_3 + I_4 + NCAF + AO$$

(4) Star-Based Stratification Mechanism

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To reveal long-term characteristics of profit health, the annual PH scores for 2020–2024 are summed to obtain the Profit Health Total Score (PHT). Firms are then classified into four levels (Table 1).

Table 1: Rating Intervals for the Profit Health Total Score

Rating	Score Interval	Profit Health Status
4-star	[0, 4]	Excellent
3-star	[5, 9]	Good
2-star	[10, 14]	Fair
1-star	[15, +∞)	Poor

3.2 Data Sources and Sample Selection

This study initially selects firms located in the Guangdong Part of the Greater Bay Area (GBA) that had been listed on the A-share market by the end of 2020. In accordance with the *Outline Development Plan for the Guangdong–Hong Kong–Macao Greater Bay Area*, the sample scope covers nine core cities—Shenzhen, Guangzhou, Foshan, Dongguan, Zhuhai, Zhongshan, Huizhou, Jiangmen, and Zhaoqing (including their county-level cities under respective jurisdictions). The research dataset comprises both financial and non-financial information from 2020 to 2024, all obtained from the Wind database.

To eliminate potential distortions from abnormal operating conditions and to enhance the robustness and generalizability of the empirical findings, firms subject to "ST" and "*ST" special treatment during the sample period are excluded in line with common practice. In addition, given the requirements on statistical power for between-group heterogeneity tests, extremely small subsamples may induce bias in variance estimation. Accordingly, sub-industries with fewer than five observations are removed; specifically, the "Energy" industry (with only one firm) is excluded. After screening, the final sample consists of 569 listed firms across ten industries (based on Wind's first-level industry classification).

During data cleaning, a small number of missing values are imputed using the industry-year median, so as to maximize information retention while maintaining unbiased estimation. Given that the core variables in this study are largely constructed from growth rates or relative ratios, and that extreme values may contain important information regarding abrupt changes in firms' operations, conventional winsorization is not applied to the original continuous variables.

In particular, because the principal measurement in this study transforms continuous variables into binary dummy variables reflecting the direction of change (taking values of 0 or 1), this discretization process inherently mitigates potential noise from outliers in subsequent regressions.

To examine the structural characteristics and regional representativeness of the sample, Tables 2 and 3 report distributional statistics across cities and industries, respectively. Descriptive statistics indicate that, in terms of city distribution, Shenzhen and Guangzhou jointly account for more than 70% of the observations, underscoring their central roles in the GBA capital market. In terms of industry distribution, firms in information technology and industrial sectors together represent more than 55% of the sample. This distribution is highly consistent with the GBA's strategic orientation toward the deep integration of advanced manufacturing and the digital economy. Overall, the sample exhibits strong representativeness across both regional and industrial dimensions. It should be noted that Table 3 excludes the Energy industry due to its extremely small sample size; although heterogeneity in sample

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size remains across other industries, each satisfies the basic assumptions required for large-sample statistical inference.

Table 2: Distribution of Listed Companies by City in the Guangdong Part of the Greater Bay Area

City	No. of Listed Companies	Proportion (%)
Shenzhen	312	54.83
Guangzhou	108	18.98
Foshan	37	6.50
Dongguan	33	5.80
Zhuhai	26	4.57
Zhongshan	22	3.87
Huizhou	12	2.11
Jiangmen	11	1.93
Zhaoqing	8	1.41
Total	**569**	**100.00**

Table 3: Distribution of Listed Companies by Industry in the Guangdong Part of the Greater Bay Area

Industry	No. of Listed Companies	Proportion (%)
Information Technology	178	31.28
Industrials	147	25.83
Consumer Discretionary	76	13.36
Materials	46	8.08
Health Care	42	7.38
Real Estate	25	4.39
Consumer Staples	16	2.81
Communication Services	14	2.46
Utilities	13	2.28
Financials	12	2.11
Total	569	100.00

3.3 Research Methods

Based on the PHT and star-rating data, this study follows a "description–test–inference" empirical logic to provide an in-depth examination of heterogeneity in profit health among listed companies in the Guangdong Part of the Greater Bay Area.

A one-way analysis of variance (one-way ANOVA) is employed to test differences in profit health across regions and industries. To ensure the reliability of statistical inference, stringent ex ante assumption checks are conducted. Although the Shapiro–Wilk test indicates that certain grouped data deviate from normality, the relatively large overall sample size ($N = 569$) implies—by virtue of the central limit theorem—that the sampling distribution of the sample mean converges asymptotically to normality, thereby supporting the robustness of the F-statistic to violations of normality.

Meanwhile, Levene's test for homogeneity of variances shows that the between-group variances satisfy the equal-variance assumption in both the city dimension ($p = 0.657$) and the industry dimension

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(p = 0.271). Consequently, no degrees-of-freedom adjustment is required (i.e., Welch's ANOVA is unnecessary), and the standard ANOVA specification can be directly applied to obtain main-effect test results with optimal statistical power.

To further ensure robustness, sensitivity analyses are additionally conducted using the Kruskal–Wallis nonparametric test as a parallel validation of the ANOVA results, thereby addressing potential distributional skewness. Because the Kruskal–Wallis test does not rely on the normality assumption and is less sensitive to extreme values, it provides an effective cross-check of the reliability of the ANOVA-based conclusions.

4. Empirical Results Analysis

4.1 Descriptive Statistics

Based on the profit health total score (PHT) and rating grades for 569 listed firms in the Guangdong Part of the Greater Bay Area from 2020 to 2024, this study characterizes the distributional pattern of overall profit health in the GBA; the results are reported in Table 4.

As shown in Table 4, Panel A, the sample firms exhibit a mean PHT of 8.78, a median of 9, and a standard deviation of 2.61, with scores ranging from 2 to 21. The skewness statistic is 0.72, indicating a typical right-skewed distribution. Because PHT is a reverse-coded indicator, this implies that most firms cluster in the left-hand, low-score (i.e., healthier) region, whereas the right tail suggests that a subset of firms face very high accumulated risk. The kurtosis statistic is 4.62, indicating a leptokurtic shape with a pronounced peak and fat tails. Overall, these features suggest a high degree of homogeneity in profit health among GBA firms, rather than extreme polarization.

Although the raw data display mild skewness, the sample size is sufficiently large (N = 569). Under the law of large numbers and the central limit theorem (CLT), the distribution of the sample mean converges asymptotically to normality, thereby supporting the statistical convergence and robustness of subsequent parametric tests (ANOVA).

Table 4: Descriptive Statistics of the Profit Health Total Score

Panel A. Full Sample (N = 569)

Mean	P50	SD	P25	P75	Min	Max	Skew.	Kurt.
8.78	9	2.61	7	10	2	21	0.72	4.62

Panel B. Star-Rating Distribution

Rating	Freq.	Percent	Cum.
4-star (Excellent)	14	2.46	2.46
3-star (Good)	352	61.86	64.32
2-star (Fair)	189	33.22	97.54
1-star (Poor)	14	2.46	100
Total	569	100	-

Considering the star-rating composition in Table 4, Panel B, the sample exhibits a typical "large middle and small ends" olive-shaped structure. Firms rated 4-star and 3-star total 366, accounting for 64.32% of the sample, indicating that the majority of GBA listed firms maintain relatively solid profit health. In contrast, 2-star and 1-star firms total 203, representing 35.68%, suggesting that a non-negligible proportion of firms still face insufficient profit quality or elevated operating risk.

Notably, only 14 firms fall at each extreme—4-star and 1-star—each accounting for 2.46% of the sample. This indicates that there are relatively few exceptionally strong or weak firms within the region, and that there remains substantial room to further cultivate and expand the pool of high profit-health firms.

4.2 Regional Differences Analysis

4.2.1 Overall Test

This study first examines the prerequisite assumptions. Levene's test for homogeneity of variances indicates that the variances across city groups satisfy the equal-variance assumption ($W_0 = 0.739$, $p = 0.657$), ruling out heteroskedasticity as a source of bias and confirming the applicability of the standard ANOVA model.

The ANOVA results show that inter-city differences in profit health among listed firms in the Greater Bay Area are not statistically significant ($F(8, 560) = 0.51$, $p = 0.849 > 0.1$). The effect-size estimate ($\eta^2 = 0.0072$) further suggests that city-level geographic factors explain only a negligible share of the variation in profit health. Overall, the findings imply convergence in profit health across GBA cities, with no pronounced regional stratification—consistent with the region's advancing market and economic integration.

4.2.2 Mean Comparisons

Although the overall statistical test points to convergence, small fluctuations in city-level mean PHT still reflect underlying heterogeneity in local industrial structures at the micro (numerical) level.

Table 5: Mean PHT of Listed Companies by City, 2020–2024 (Lower PHT Indicates Better Profit Health)

City	Number of Firms	Share (%)	Mean PHT	Rank
Huizhou	12	2.11	7.67	1
Zhaoqing	8	1.41	8.25	2
Dongguan	33	5.8	8.42	3
Zhuhai	26	4.57	8.58	4
Foshan	37	6.5	8.62	5
Jiangmen	11	1.93	8.64	6
Guangzhou	108	18.98	8.80	7
Shenzhen	312	54.83	8.89	8
Zhongshan	22	3.87	8.95	9

As shown in Table 5, the mean PHT across cities fluctuates within a relatively narrow range, from 7.67 to 8.95, indicating limited dispersion in profit health at the city level.

Huizhou (7.67) and Zhaoqing (8.25) report comparatively lower mean PHT, which is largely attributable to survivor bias arising from small sample sizes. When considering within-city industrial structure and firm-level performance, although the subsamples for these two cities are small, the presence of leading firms—such as EVE Energy, TCL Technology, and Fenghua Advanced

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Technology—pulls down the overall mean PHT (i.e., improves the implied profit health, given that PHT is reverse-coded).

In contrast, Shenzhen (8.89) and Guangzhou (8.80) exhibit mean PHT values slightly above the overall average. As the two core cities account for a large share of the listed-firm sample (73.8% in total) and host a broad industry mix, they not only concentrate many high-growth firms but also include firms undergoing transformation or experiencing greater earnings volatility. This more complex economic ecosystem plausibly leads to slightly higher average PHT, consistent with the risk–return profile often observed in highly competitive and diversified core-city markets.

4.2.3 Structural Characteristics

Combining Figure 1, the internal structure of profit health across cities (i.e., star-rating distribution) shows the following features:

First, high-quality firms concentrate in core cities. Although 4-star ("excellent") firms are scarce overall, more than 70% are clustered in Guangzhou, Shenzhen, Dongguan, and Foshan. This suggests that the creation of exceptionally high-quality profits still relies heavily on the stronger economic foundations and more complete industrial-chain support systems in core cities.

Second, the middle tier constitutes the region's stable backbone. In most cities, the distribution is dominated by 3-star firms. The share of 3-star firms exceeds 70% in Huizhou, Zhaoqing, and Jiangmen, while Shenzhen, Guangzhou, and Foshan remain around 60%. This again confirms that listed firms in the GBA generally maintain relatively sound profit health, with limited extreme-risk exposure.

Third, core cities face more intense market selection. Most 1-star ("poor") firms are found in Shenzhen (8 firms) and Guangzhou (3 firms). This does not imply a weaker business environment in core cities; rather, it reflects their role as financial and competitive hubs where market competition is more intense and survival-of-the-fittest mechanisms are more pronounced—hence a non-trivial presence of low-health firms. Meanwhile, cities such as Zhongshan and Jiangmen may not host many 1-star firms, but they show a relatively higher share of 2-star firms, indicating that upgrading efficiency and profitability among mid-tier firms should remain a key focus going forward.

In summary, GBA listed firms exhibit a pattern of "macro-level convergence and micro-level differentiation." The absence of statistically significant mean differences supports the effectiveness of regional integration policies in promoting more balanced resource allocation, while structural differences reveal sharper competitive sorting within core cities and more industry-reliant stability in peripheral cities.

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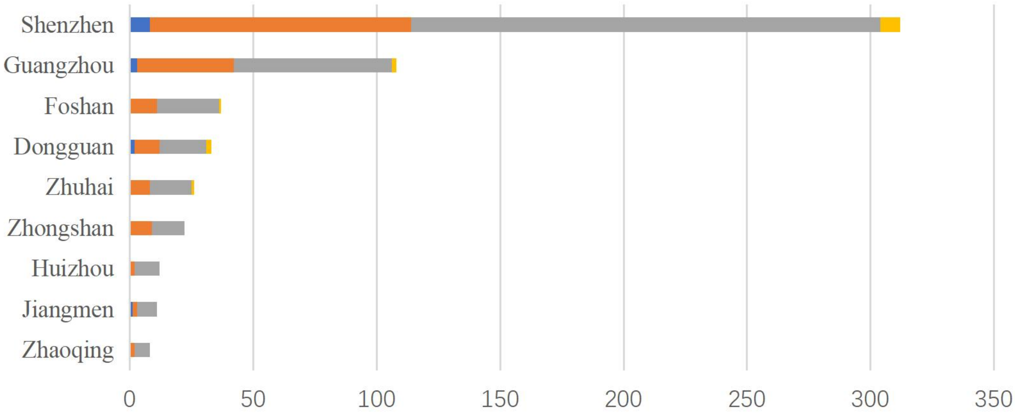

	Zhaoqing	Jiangmen	Huizhou	Zhongshan	Zhuhai	Dongguan	Foshan	Guangzhou	Shenzhen
1-star		1				2		3	8
2-star	2	2	2	9	8	10	11	39	106
3-star	6	8	10	13	17	19	25	64	190
4-star					1	2	1	2	8

Figure 2: Distribution of Profit Health Star Ratings by City

4.3 Industry Differences Analysis

4.3.1 Overall Test

Following the statistical strategy outlined above, Levene's test confirms homogeneity of variance across industry groups ($W = 1.234$, $p = 0.271$), satisfying the prerequisite for ANOVA. Unlike the non-significant differences observed at the regional (city) level, the ANOVA results indicate a highly significant structural disparity across industries ($F(9, 559) = 3.33$, $p = 0.001 < 0.01$). The effect size ($\eta^2 = 0.051$) suggests that industry affiliation is a core determinant of variation in profit health, with a moderate explanatory power.

4.3.2 Mean Comparisons and Post-hoc Tests

To pinpoint the relative strengths and weaknesses of specific industries, and given substantial differences in sample sizes across sectors, this study applies Tukey's HSD for post-hoc multiple comparisons, supplemented by Bonferroni correction as a robustness check.

The results show that the Materials sector exhibits significantly better profit health than Financials ($p=0.01$) and Real Estate ($p=0.029$), confirming the pronounced advantage of the real-economy segment over traditional capital-intensive industries. The Health Care sector also outperforms Financials ($p=0.042$); even under the stringent Bonferroni correction, this difference remains at the margin of 10% significance ($p=0.058$). While Information Technology does not differ significantly from the top-ranked Materials and Health Care sectors ($p>0.05$), its overall mean performance is solid and it outperforms Financials and Real Estate, serving as a stabilizing pillar of the regional economy.

These findings remain highly robust under multiple-comparison procedures, further supporting the conclusion that emerging sectors (Materials and Health Care) significantly outperform traditional sectors

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(Financials and Real Estate).

Table 6: Mean Profit Health Total Score (PHT) by Industry, 2020–2024

Industry	No. of Firms	Share (%)	Mean PHT	Rank
Materials	46	8.08	7.78	1
Health Care	42	7.38	8.12	2
Information Technology	178	31.28	8.51	3
Consumer Discretionary	76	13.36	8.91	4
Industrials	147	25.83	8.96	5
Consumer Staples	16	2.81	9.00	6
Communication Services	14	2.46	9.64	7
Real Estate	25	4.39	9.92	8
Utilities	13	2.28	10.00	9
Finance	12	2.11	10.83	10

Judging from the mean ranking in Table 6, listed firms in the Greater Bay Area exhibit a clear pattern of industry stratification.

First, the Materials (7.78) and Health Care (8.12) sectors have mean values that are significantly lower than (i.e., better than) the overall level. The former benefits from the ongoing wave of domestic substitution, which has enabled the conversion of higher technological content into greater value added. The latter, supported by inelastic demand and a less cyclical profile, effectively smooths macroeconomic fluctuations and builds relatively robust earnings "moat."

Second, Information Technology (8.51) ranks third. As a core representative of new-quality productive forces, this sector maintains strong R&D intensity while still achieving a healthy alignment between cash flows and profits, embodying the essence of high-quality development. Notably, Industrials (8.96)—the foundation of the manufacturing base—perform slightly worse than the overall mean. This may reflect the transitional pains of digital transformation in traditional manufacturing, where heavy capital expenditures and depreciation burdens temporarily suppress current profitability.

Third, Financials (10.83), Utilities (10.00), and Real Estate (9.92) rank near the bottom. This suggests that under the macro deleveraging cycle, highly leveraged and asset-intensive industries are facing severe balance-sheet repair pressures; inventory impairments and liquidity constraints have materially weighed on their profit health.

4.3.3 Structural Characteristics

Drawing on Figure 2 to further examine the within-industry star-rating distribution of profit health, the following features emerge:

First, high-quality firms cluster in emerging and manufacturing-related sectors. The distribution of 4-star ("excellent") firms is highly concentrated across industries, appearing mainly in Information Technology (6 firms), Industrials (4 firms), and Materials (3 firms)—sectors associated with high tech and advanced manufacturing. This indicates that real-economy firms with core technological barriers possess stronger value-creation capabilities and serve as a key engine of high-quality regional development.

Second, emerging sectors display an overall highly robust structure. The share of 3-star firms reaches 69.57% in Materials and 71.43% in Health Care, while the proportion of low-star firms (2-star

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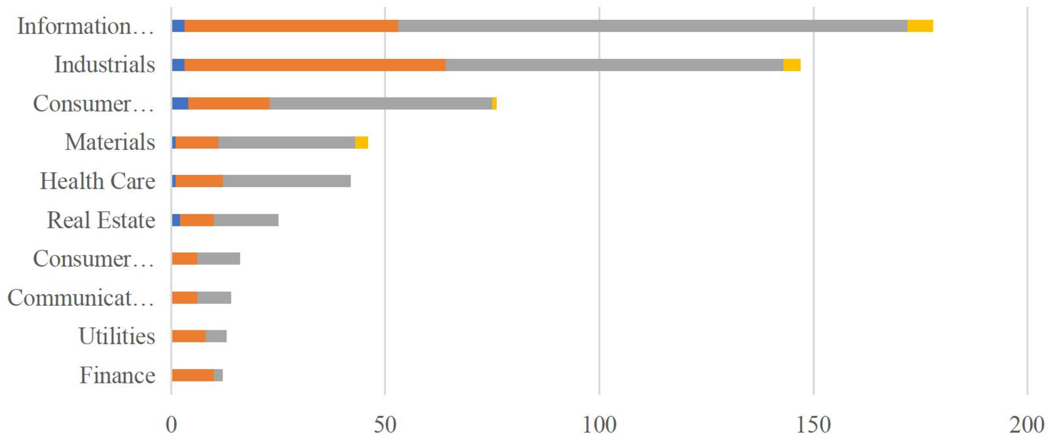
and below) remains relatively small. In particular, Health Care is heavily concentrated in the middle tier and rarely exhibits extremely poor cases, suggesting strong operational stability when facing external uncertainty.

Third, traditional sectors face pronounced structural risks. Financials and Utilities show clear clustering in the mid-to-low tiers, with 2-star firms accounting for 83.33% and 61.54%, respectively, and a lack of leading top-tier firms—reflecting generally weak profit quality. Risk exposure is even more evident in Real Estate, where 2-star and 1-star firms together account for 40%, indicating that the sector is undergoing intense market sorting and risk unwinding. Some firms urgently need balance-sheet repair through debt restructuring or strategic business transformation.

In summary, GBA listed firms exhibit a pronounced industry-level pattern of "new-economy strength versus old-economy weakness," closely aligned with China's policy direction of fostering new-quality productive forces. The empirical evidence not only validates the positive effects of industrial upgrading, but also quantifies the transitional pains in traditional industries, highlighting that regulators and investors should pay particular attention to structural risks in the real estate and financial sectors.



	Finance	Utilities	Communication Services	Consumer Staples	Real Estate	Health Care	Materials	Consumer Discretionary	Industrials	Information Technology
1-star					2	1	1	4	3	3
2-star	10	8	6	6	8	11	10	19	61	50
3-star	2	5	8	10	15	30	32	52	79	119
4-star							3	1	4	6

Figure 3: Distribution of Profit Health Star Ratings by Industry

4.4 Robustness Checks

To ensure the reliability of the findings above, this study conducts robustness checks along two dimensions—non-parametric alternatives and sample-sensitivity tests—to rule out potential distortions in statistical inference arising from deviations from normality and imbalanced group sizes.

4.4.1 Non-parametric Tests

Given that some industry groups exhibit skewed distributions, relying solely on a parametric test (ANOVA) may entail a loss of power. Accordingly, this study introduces the Kruskal–Wallis non-parametric test as a robustness alternative. This method does not require the normality assumption; instead, it infers whether populations differ significantly based on ranked observations.

The results show that differences across cities are not statistically significant ($\chi^2(8) = 4.91$, $p = 0.767$), whereas differences across industries are highly significant ($\chi^2(9) = 32.56$, $p < 0.001$), consistent with the baseline ANOVA conclusions. This indicates that the core findings do not hinge on any particular distributional assumption and are therefore robust.

4.4.2 Sensitivity Analysis for Small-sample Bias

Because some city and industry groups contain relatively few observations (a small-sample issue) that could bias inference, the study re-tests the results after adjusting the sample structure.

(1) Removing the influence of marginal cities.

To eliminate the potential leverage effect of very small groups on overall means, the three cities with the smallest samples—Zhaoqing ($n = 8$), Jiangmen ($n = 11$), and Huizhou ($n = 12$)—are excluded. The analysis retains only the six core cities such as Shenzhen and Guangzhou ($n = 538$).

ANOVA re-check results indicate that profit-health differences among the major cities remain non-significant ($F(5, 532) = 0.29$, $p = 0.917$), with a negligible effect size ($\eta^2 = 0.003$). The Kruskal–Wallis test yields a consistent conclusion ($p = 0.948$), confirming that the city-level finding is not driven by marginal samples.

(2) Regrouping small-sample industries.

To smooth the extreme imbalance in group sizes, four industries with relatively small samples—Financials, Utilities, Communication Services, and Consumer Staples—are merged into a "Services & Utilities" group (hereafter, the "Other" group).Industry affiliation remains a significant explanatory factor for firms' profit health (PH total score) ($F(6, 562) = 4.38$, $p < 0.001$), with the effect size staying in the moderate range ($\eta^2 = 0.045$). Tukey's HSD post-hoc comparisons further reveal a clear industry pattern: the "Other" group has a significantly higher PH mean than Information Technology (mean difference = 1.29) and Materials (mean difference = 2.02). The non-parametric result ($\chi^2(6) = 27.64$, $p < 0.001$) again corroborates this differentiation.

In sum, whether by relaxing distributional assumptions or by adjusting the sample structure, the empirical conclusion—no significant differences across cities, but significant differentiation across industries—remains highly robust and is not driven by distributional form or sample-selection bias.

5. Discussion and Policy Recommendations

5.1 Conclusions

Based on the theoretical model of Profit Health Evaluation (Zhu et al. 2024b), this paper uses a sample of 569 A-share listed companies in the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) from 2020 to 2024 to empirically test the model's applicability in a regional capital-market context. The results show that:

First, GBA listed firms exhibit a robust "olive-shaped" distribution, though the leading-firm (champion) effect remains to be strengthened. Empirical evidence indicates that over 60% of firms fall into the moderate health category (3-star), suggesting strong overall operational resilience and risk resistance. However, the shares of both high-health (4-star) and high-risk (1-star) firms are relatively small, with most firms concentrated in the middle range. This implies that profit health is relatively balanced across firms, yet truly high-quality firms remain scarce, and the earnings quality of some firms is still insufficient.

Second, the dividends of regional integration policies have become visible, while structural differentiation across cities is notable. The results show no significant differences in profit health across cities, confirming that since the implementation of the Outline Development Plan for the Guangdong–Hong Kong–Macao Greater Bay Area, market barriers within the region have gradually weakened and both the business environment and regulatory regimes have become more homogeneous. Notably, core cities (Guangzhou and Shenzhen) do not display an overwhelming mean advantage; instead, node cities such as Huizhou and Zhaoqing have demonstrated late-mover advantages by leveraging specific industrial chains. This suggests that the GBA has formed a coordinated development pattern characterized by core-city leadership with multi-point support.

Third, industry heterogeneity is pronounced: emerging industries show clear advantages, whereas traditional industries face substantial transformation pressure. Tests of industry heterogeneity reveal distinct “track” differentiation. Emerging sectors represented by Materials, Health Care, and Information Technology—supported by intensive R&D investment and technological barriers—exhibit significantly better profit health than traditional industries such as Financials and Real Estate. This finding quantitatively demonstrates the superiority of “new-quality productive forces” at the micro financial level, and indicates that the traditional growth model—reliant on leverage and scale expansion—is encountering profound pressures from capacity reduction and balance-sheet repair.

Fourth, the profit-health evaluation model has strong regulatory applicability and early-warning value. This paper confirms that, compared with conventional single financial indicators, a comprehensive evaluation model that incorporates non-financial signals (e.g., audit opinions and auditor changes) can not only smooth short-term earnings fluctuations but also identify potential operational anomalies more accurately. By converting complex financial information into intuitive star ratings, the model provides regulators with a scientific methodological tool for low-cost, high-efficiency, penetrating supervision.

5.2 Policy Recommendations

Based on these findings, and to further enhance the quality of GBA capital-market development, this paper proposes the following policy recommendations:

First, deepen digital regulatory reforms and build a dynamic monitoring system for profit health across the region. Regulators should fully leverage the GBA’s digital-technology strengths to establish a dynamic profit-health monitoring platform, breaking geographical barriers to enable cross-region and penetrating supervision. For firms with low ratings or sharp volatility, a tiered and classified support mechanism should be established, shifting regulation from passive ex post punishment to proactive ex ante warnings and in-process intervention. At the same time, disclosure standards should be refined, and big data and AI technologies should be used to detect abnormal financial signals—especially to prevent earnings manipulation—thereby safeguarding orderly capital-market operation.

Second, implement differentiated industrial policies to promote synergy between new and old growth drivers. Given the significant industry-level divergence in profit health, the government should adopt differentiated guidance policies. For emerging industries such as Materials and Information Technology, support for core technology R&D and collaborative innovation along the industrial chain

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should be strengthened to consolidate the leading advantage of high-star firms. For traditional industries such as Financials, Utilities, and Real Estate, policies should guide firms to reduce costs and improve efficiency through digital transformation and refined management, transition toward new-quality productive forces, and proactively divest inefficient assets. In addition, industry leaders should be encouraged to play a “lead goose” role, using supply-chain coordination to lift the operational quality and efficiency of SMEs and narrow within-industry divergence.

Third, strengthen internal control and compliance to enhance firms’ long-term value-creation capacity. Listed companies should formulate targeted improvement pathways based on their profit-health ratings. High-star firms need to guard against strategic inertia and proactively invest in frontier technologies; mid-star firms should identify financial and operational weaknesses and optimize business processes; low-star firms should refocus on core businesses and repair earnings quality by divesting inefficient assets and cutting loss-making operations. Firms should embed the profit-health concept deeply into corporate governance, shifting from a narrow pursuit of accounting-profit growth to high-quality profitability supported by cash flows, while proactively improving financial transparency and ESG governance to enhance resilience amid external uncertainty.

Fourth, cultivate a rational investment culture and strengthen the market’s “survival of the fittest” function. Investors should treat profit-health ratings as a key input to asset allocation and pay attention to rating dynamics, using market mechanisms to direct capital toward high-star, high-growth quality firms, thereby pressuring inefficient firms to improve operations or exit. Intermediaries and analysts should also recognize the value of non-financial signals in valuation, guiding the market toward a healthier ecosystem focused on long-term value, and jointly promoting high-quality and sustainable development of the GBA capital market.

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