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Financial Valuation of Artificial Intelligence Firms: A Panel Data Approach Based on the Modified Ohlson Model

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Abstract:

This study investigates the determinants of market valuations for Artificial Intelligence (AI) firms to determine whether the recent surge in technology stock prices reflects a behavioral speculative bubble or rational pricing of financial fundamentals. Using a Modified Ohlson Model, the research analyzes a balanced panel data sample of 30 leading U.S. AI-centric technology firms from Q1 2020 to Q4 2025. Econometric estimation via a robust Fixed Effects model reveals a paradigm shift in value relevance. Traditional accounting metrics, such as tangible Book Value Per Share (BVPS), lost statistical significance, while current Earnings Per Share (EPS) exhibited a negative valuation impact. Conversely, Research and Development (R&D) expenditures demonstrated a significant positive premium, indicating that financial markets actively reward innovation intensity and penalize short-term profit maximization.

The findings conclude that the 'AI premium' is not merely speculative noise but a rational market response to aggressive technological reinvestment. Consequently, the study recommends recalibrating traditional valuation multiples and reforming accounting standards to better capture intangible assets.

Keywords: Artificial Intelligence, Financial Valuation, Modified Ohlson Model, Panel Data, R&D Expenditures.
JEL Classification Codes : G12 ; M41 ; O33

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التقييم المالي لشركات الذكاء الاصطناعي: دراسة قياسية باستخدام نموذج أولسون المعدل وبيانات البانل

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ملخص:

تهدف هذه الدراسة إلى استقصاء محددات التقييم السوقي لشركات الذكاء الاصطناعي (AI)، وذلك لتحديد ما إذا كان الارتفاع الأخير في أسعار أسهم شركات التكنولوجيا يعكس فقاعة مضاربة سلوكية أم تسعيراً عقلانياً للأساسيات المالية. بالاعتماد على نموذج أولسون المعدل، يحلل البحث عينة متوازنة من البيانات المقطعية الزمنية (Panel Data) تضم 30 شركة تكنولوجية أمريكية رائدة ترتكز على الذكاء الاصطناعي، وذلك خلال الفترة من الربع الأول لعام 2020 إلى الربع الرابع لعام 2025. أظهرت نتائج التقدير القياسي باستخدام نموذج التأثيرات الثابتة الحصين (Robust Fixed Effects) حدوث تحول جذري في الملاءمة القيمية. فقدت المقاييس المحاسبية التقليدية، كالقيمة الدفترية للسهم (*BVPS*) الملموسة، دلالتها الإحصائية، في حين أظهرت ربحية السهم (*EPS*) تأثيراً سلبياً على التقييم. وعلى النقيض من ذلك، أظهرت نفقات البحث والتطوير (*R&D*) معاملات موجبة وذات دلالة إحصائية، مما يشير إلى أن الأسواق المالية تكافئ بنشاط الكثافة الابتكارية وتعاقب التوجه نحو تعظيم الأرباح قصيرة الأجل.

وتخلص النتائج إلى أن "علاوة الذكاء الاصطناعي" ليست مجرد ضوضاء مضاربية، بل هي استجابة سوقية عقلانية لإعادة الاستثمار التكنولوجي المكثف. وبناءً على ذلك، توصي الدراسة بضرورة إعادة معايرة مضاعفات التقييم التقليدية، وإصلاح المعايير المحاسبية لتتمكن من عكس قيمة الأصول غير الملموسة بشكل أفضل.

الكلمات المفتاحية: الذكاء الاصطناعي، التقييم المالي، نموذج أولسون المُعدل، بيانات البانل، نفقات البحث والتطوير.

رموز تصنيف JE: G12 ; M41 ; O33

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1. INTRODUCTION

The global economy is currently undergoing an accelerated structural transformation driven by the revolution in Artificial Intelligence, particularly following the large-scale commercial deployment of Generative Artificial Intelligence technologies in late 2022. These technologies are no longer perceived merely as advanced software tools; rather, they are increasingly classified as General Purpose Technologies capable of generating positive productivity shocks with far-reaching implications across virtually all economic sectors. Amid this profound transformation, global financial markets rapidly incorporated these innovations into asset pricing mechanisms, leading to massive capital inflows into technology stocks and driving the market valuations of major technology firms (Tech Giants) to unprecedented historical levels.

The meteoric rise in the valuations of technology companies has generated extensive academic and professional debate regarding the efficiency of financial markets in pricing technological innovation shocks. From a traditional financial perspective, stock prices are expected to reflect the present value of anticipated future cash flows, thereby justifying elevated valuations as a rational response to the substantial investments undertaken by these firms in Research and Development (R&D) activities, as well as the expected growth in their operating revenues. According to this view, artificial intelligence constitutes a sustainable engine of growth, while the price premium enjoyed by these firms reflects the value relevance of their intangible assets and continuous innovation capabilities.

Conversely, the literature on Behavioral Finance offers a more cautious and critical interpretation. It argues that excessive optimism surrounding emerging technologies frequently generates investment hype, leading market prices to diverge from firms' underlying economic and accounting fundamentals. Drawing parallels with the Dot-com Bubble of the late 1990s, serious concerns have emerged that current valuations may be driven by herd behavior and the fear of missing out (FOMO), thereby creating a speculative bubble that could expose financial markets to severe volatility and systemic instability.

Although numerous recent studies have attempted to assess the short-term impact of artificial intelligence announcements on stock returns, there remains a notable scarcity of empirical studies aimed at decomposing these valuations and examining the extent to which they are structurally linked to genuine financial fundamentals—particularly R&D expenditures and revenue growth—over a longer time horizon encompassing the post-generative AI era. Accordingly, the present study seeks to address this research gap by adopting an econometric framework that integrates accounting-based asset valuation models (specifically a modified Ohlson Model) with behavioral market indicators, in order to provide a rigorous empirical assessment of the contemporary technology sector.

Based on the foregoing discussion, the central research problem of this study can be formulated as follows:

"Do the current market valuations of major AI-related technology firms reflect sustainable growth supported by the value relevance of innovation and financial fundamentals, or do they represent a speculative bubble detached from actual financial performance?"

This main research question gives rise to the following sub-questions:

1- 1 To what extent do fundamental components—namely Research and Development (R&D) expenditures and revenue growth—explain the sharp increases in the stock prices of leading technology companies during the study period?

1- 2 To what extent does the inclusion of Research and Development intensity (RDPS) enhance the explanatory power of the traditional Ohlson Model in valuing AI firms, compared to conventional accounting metrics alone?

2. Theoretical Framework and Previous Studies

The issue of financial valuation in technology companies, particularly amid the rapid expansion of artificial intelligence, has attracted growing attention within contemporary financial and economic literature. In order to comprehensively address the different dimensions of this issue, previous studies may be classified into three major strands reflecting divergent interpretations of the current surge in market valuations.

2.1 The Behavioral Perspective: Market Reaction and the Impact of Technological "Hype"

A growing body of recent studies has focused on the behavioral dimension of investors' responses to innovation shocks. **Lopez-Lira and Tang** (Lopez-Lira & Tang, 2023) demonstrated that artificial intelligence models possess predictive capabilities regarding stock market movements, thereby encouraging markets to react rapidly to AI-related developments. Within the same context, **Pietrzak** (Pietrzak, 2025) examined the short-term market reaction through an Event Study methodology for firms whose financial disclosures referenced "ChatGPT" technologies, documenting positive abnormal returns that reflected excessive investor optimism.

This argument was further reinforced by the findings of **Da, Engelberg, and Gao** (Da et al., 2011), who identified a strong positive relationship between search intensity for the term "Generative AI" and market price levels, supporting the hypothesis that valuations are significantly influenced by investor sentiment and herd behavior. These findings are consistent with the theory of Diagnostic Expectations developed by **Bordalo et al.** (Bordalo et al., 2021), which explains how investors tend to overreact to salient positive news, thereby generating speculative price overshooting. Similar conclusions were highlighted in the comprehensive review conducted by (Barberis et al., 1997; De Long et al., 1987) which emphasized the possibility that market prices may become detached from underlying fundamentals due to excessive informational noise.

2.2 The Fundamental Perspective: The Value Relevance of Innovation and R&D

In contrast to the behavioral interpretation, another strand of literature argues that the valuations of AI-related firms are grounded in rational economic justifications associated with intangible assets. Building upon the classical valuation framework introduced by Ohlson Model and developed by **James Ohlson** (Ohlson, 1995), which links book value and earnings to market value, **Baruch Lev and Feng Gu** (Lev & Gu, 2016) argued that traditional financial statements fail to adequately capture the true value of technology companies, thereby necessitating greater emphasis on innovation-related expenditures.

Prior to the current AI boom, recent empirical studies, such as **Babina et al.** (Babina et al., 2024), demonstrated that corporate investment in artificial intelligence contributed significantly to enhancing firm growth and market value. This perspective is grounded in established financial literature; for instance, **Chan et al.** (Chan et al., 2001.) employed extensive empirical data to conclude that Research and Development (R&D) expenditures exert a decisive positive effect on market valuation. Such findings provide accounting legitimacy for the elevated valuations observed among innovation-driven technology firms.

2.3 The Bubble Debate and Historical Comparisons

Another group of studies sought to resolve the debate by comparing the current AI-driven market environment with previous speculative episodes and by testing for explosive price behavior using advanced econometric methodologies such as those developed by Phillips, Shi, and Yu (Phillips et al., 2015).

Within this framework, a report issued by Janus Henderson ('AI versus the Dotcom Bubble', 2024.) compared the financial structure of contemporary AI firms with that of firms during the Dot-com Bubble, whose consequences were extensively documented by Burton Malkiel (Malkiel, 2020). The report concluded that current AI-oriented firms possess substantially stronger cash flows, making them comparatively less vulnerable to collapse.

Similarly, recent empirical studies, such as **Eisfeldt, Schubert, and Tullis** (Eisfeldt et al., 2023), have analyzed technology firms with high exposure to generative AI, arguing that their recent market value increases are largely supported by rational expectations of future productivity and solid financial fundamentals rather than constituting a pure speculative bubble. This rational valuation stands in stark contrast to the findings reported by **Xiong and Yu** (Xiong & Yu, 2011) concerning the pure speculative nature of the Chinese warrants bubble. Nevertheless, recent macroeconomic analyses, such as **Acemoglu** (Acemoglu, n.d.), reach mixed conclusions, indicating that the market may be overestimating overall impacts, and the distinction between “real economic growth” and “behavioral noise” varies significantly depending on the specific tasks, subsectors, and firm capabilities within the artificial intelligence market."

2.4 Research Gap: A critical review of the existing literature reveals a clear polarization in interpretations. Behavioral studies -e.g., (**Barber & Odean, 2008**);**(Da, Z., Engelberg, J., & Gao, P., 2011**)- tend to explain the rise in trending technology stocks as an exaggerated market reaction driven primarily by heightened investor attention, often overlooking the fundamental role played by financial performance and R&D investments. Conversely, fundamental-oriented studies in the AI space - e.g.,**(Babina et al., 2024**); (**Eisfeldt et al., 2023**)- emphasize the value relevance of innovation; however, they either rely on data preceding the widespread diffusion of generative artificial intelligence or restrict their primary focus to a very limited sample of leading firms, thereby limiting the generalizability of their findings to the broader technology sector.

The core research gap, therefore, lies in the absence of an integrated econometric analysis combining measures of “fundamental value” — based on a modified Ohlson Model incorporating revenues and technology-related expenditures — with indicators of “behavioral noise,” applied to a broad and comprehensive Panel Data sample of artificial intelligence technology firms during the effective adoption period of these technologies (2020–2025).

Accordingly, the present study seeks to bridge this gap through the development of a hybrid analytical framework that does not merely test for the existence of a “bubble” as a purely statistical phenomenon, but rather investigates its structural determinants in order to assess whether the prevailing price premium represents a market reward for genuine R&D investment and innovation, or merely reflects elevated behavioral optimism detached from accounting realities.

3. Methodology and Research Procedures

To achieve the objectives of the study and test its hypotheses concerning the value relevance of financial fundamentals versus speculative behavior in the valuation of artificial intelligence firms, this study adopts a descriptive-analytical approach supported by quantitative econometric analysis. Specifically, Panel Data models are employed due to their ability to capture both cross-sectional and time-series variations, thereby reducing multicollinearity problems and providing higher degrees of freedom compared to pure time-series models (Baltagi, 2021).

3.1 Population and Sample

The study population consists of all technology firms listed on U.S. financial markets, particularly NASDAQ and NYSE, that publicly disclose ownership, development, or implementation of artificial intelligence technologies. Owing to the difficulty of defining the full population, a purposive sample of 30 leading firms was selected to represent the entire AI value chain, including semiconductor manufacturing, cloud infrastructure, and software development. The sample also includes the so-called “Magnificent Seven” technology firms.

The study period extends from the first quarter of 2020 to the fourth quarter of 2025, thereby encompassing both the pre-ChatGPT phase and the subsequent generative AI expansion period. Using quarterly data, the total number of firm-quarter observations in this balanced panel amounts to approximately:

$$\textbf{30 firms} \times \textbf{24 quarters} = \textbf{720 observations}$$

This sample size is considered statistically adequate and representative for empirical financial studies (Wooldridge, 2010).

3.2 Model Specification

To analyze the determinants of market valuation, the study builds upon the theoretical framework of the Ohlson Model developed by **James Ohlson** (Ohlson, 1995), which links a firm’s market value to its book value and current earnings. Since conventional financial statements often fail to fully capture the economic value of intangible assets in technology firms (Lev & Gu, 2016), the present study develops a Modified **Ohlson Model** by incorporating Research and Development (R&D) expenditures as a proxy for innovation, in addition to a variable measuring revenue growth.

The econometric specification of the proposed model is expressed as follows:

$$P_{it} = \beta_0 + \beta_1\, BVPS_{it} + \beta_2\, EPS_{it} + \beta_3\, RDPS_{it} + \beta_4\, REV\_G_{it} + \varepsilon_{it}$$

Where:

P_{it}: Closing stock price of firm *i* at the end of quarter *t*.

β_0: Intercept term.

$\beta_1, \beta_2, \beta_3, \beta_4$: Estimated model coefficients.

$BVPS_{it}$: Book Value Per Share.

EPS_{it}: Earnings Per Share.

$RDPS_{it}$: Research and Development Expenditure Per Share.

REV_G_{it}: Quarterly Revenue Growth Rate.

ε_{it}: Random error term.

3.3 Variables Measurement

Financial and accounting data were collected from firms' quarterly reports (Form 10-Q) available through open financial databases such as https://www.macrotrends.net/ and U.S. Securities and Exchange Commission EDGAR https://www.sec.gov/data-research/sec-markets-data filings. Variables were operationalized in accordance with prior literature as follows:

Dependent Variable: Market Value (P_{it}): Measured using the stock closing price on the last trading day of each fiscal quarter, reflecting the market's immediate valuation of the firm (Lopez-Lira & Tang, 2023);

Independent Variables:

- **Book Value ($BVPS_{it}$):** Calculated by dividing total shareholders' equity by the number of outstanding shares, representing the firm's net tangible assets (Ohlson, 1995);
- **Earnings Per Share (EPS_{it}):** Measured as quarterly net income divided by the weighted average number of outstanding shares, capturing the firm's ability to generate current cash flows;
- **R&D Intensity ($RDPS_{it}$):** Calculated by dividing quarterly R&D expenditures by the number of shares outstanding. This variable serves as a direct indicator of innovation efforts and AI algorithm development activities;
- **Revenue Growth (REV_G_{it}):** Measured as the percentage change in revenues relative to the corresponding quarter of the previous year, capturing the firm's sales momentum.

3.4 Estimation Strategy and Statistical Procedures

The econometric analysis is conducted using specialized statistical software and proceeds through four sequential stages to ensure the reliability and consistency of the estimated parameters:

Descriptive Analysis and Diagnostic Tests

Descriptive statistics—including mean, standard deviation, and skewness—are first computed, followed by the construction of a Pearson Correlation Matrix to test for multicollinearity among the explanatory variables. In addition, the Variance Inflation Factor (VIF) is calculated, where values below 10 indicate the absence of serious multicollinearity problems (Gujarati, D.N. and Porter, D.C. (2009)

Panel Unit Root Tests

To avoid the problem of spurious regression, the stationarity properties of the variables are examined using the panel unit root tests developed by Levin, Lin, and Chu (2002), as well as the test proposed by Im, Pesaran, and Shin (Im et al., 2003).

Model Selection

Given the panel nature of the data, the Hausman Test proposed by **Hausman** (1978) is employed to choose between the Fixed Effects Model—which assumes correlation between unobserved firm-specific effects and the explanatory variables—and the Random Effects Model (Jeffrey M. Wooldridge, 2010)

Addressing Econometric Problems

In the event that heteroskedasticity or autocorrelation is detected through the Modified Wald Test, the model will be corrected using Robust Standard Errors in order to ensure the statistical reliability and consistency of the estimated results (Baltagi, 2021).

4. RESULTS AND DISCUSSION

This section presents an analytical and econometric evaluation of the study's hypotheses concerning the determinants of market valuation for Artificial Intelligence (AI) firms listed on U.S. financial markets. Relying on the Modified Ohlson Model, Panel Data estimation techniques were employed due to their capacity to capture both time-series and cross-sectional variations across a purposive sample of 30 leading firms from the first quarter of 2020 to the fourth quarter of 2025.

4.1 Descriptive Analysis and Diagnostic Tests

The descriptive statistics (Table 1) reveal that the average stock price (P) for the sampled firms stands at $192, accompanied by a high standard deviation (172). This reflects the significant volatility and speculative nature inherent in the technology sector's valuations. Furthermore, the mean Research and Development expenditure per share (RDPS) is $1.15, peaking at an upper bound of $39.8, underscoring the extreme divergence in innovation strategies and algorithmic development among the firms.

Table 1. Summary Statistics, using the observations 1:01 - 30:24

Variable	Mean	Median	S.D.	Min	Max
P	192.44	151.00	172.41	2.13	1070.00
BVPS	18.60	14.30	17.10	-3.62	85.90
EPS	1.11	0.710	1.59	-3.88	10.00
RDPS	1.15	0.703	2.29	0.0004	39.80
REV_G	0.179	0.074	0.249	0.001	0.996

***Source**: Author's calculations using **Gretl** software.*

Regarding the Pearson correlation matrix (Table 2) and the Variance Inflation Factor (VIF) test, the results confirm the absence of severe multicollinearity. The bivariate correlation coefficients among the independent variables did not exceed the 0.65 threshold (the highest being 0.6440 between BVPS and EPS), while all VIF values remained well below the critical threshold of 10, ranging between 1.05 and 1.37.

This verifies the independence of the explanatory variables and the econometric validity of the proposed model (Gujarati & Porter, 2009).

Table 2. Correlation coefficients

	P	**BVPS**	**EPS**	**RDPS**	**REV_G**
P	1.0000	0.5366	0.6440	0.2170	0.1012
BVPS		1.0000	0.5117	0.1732	-0.1119
EPS			1.0000	0.2104	-0.0559
RDPS				1.0000	-0.0135
REV_G					1.0000

***Source**: Author's calculations using **Gretl** software.*

4.2 Panel Unit Root Tests

To circumvent the risk of spurious regression, the stationarity of the variables was tested using the Levin, Lin & Chu (2002) panel unit root test. The results indicated that the dependent variable (*P*) and revenue growth *(REV_G*) are stationary at their level I(0) at a 5% significance level. Conversely, Book Value Per Share (*BVPS*), Earnings Per Share (*EPS*), and RDPS were non-stationary at level but became strictly stationary upon taking their first differences I(1) (p-value = 0.0000 for all three variables). Consequently, the stationary forms (*d_BVPS*, *d_EPS*, *d_RDPS*) were utilized in the regression to ensure the reliability and consistency of the estimated parameters (Baltagi, 2021).

4.3 Model Selection

To choose between the Fixed Effects (FE) and Random Effects (RE) estimators, the Hausman Test was conducted. The test yielded a Chi-square statistic of 16.88 with a p-value of 0.0020. Given that the p-value is less than the 0.05 threshold, the null hypothesis is rejected, indicating that the Random Effects estimators are inconsistent and the Fixed Effects model is the statistically appropriate choice. This econometric decision reflects a crucial economic reality: unobserved firm-specific characteristics—such as management quality, brand equity, and algorithmic robustness—are structurally correlated with the explanatory variables and fundamentally drive market valuations.

4.4 Robust Estimation and Discussion

A preliminary estimation of the Fixed Effects model revealed a low Durbin-Watson statistic (0.31), signaling the presence of autocorrelation in the error terms. To rectify this diagnostic issue and ensure valid statistical inference, the Fixed Effects model was re-estimated using Robust Standard Errors clustered by unit (Table 3).

The overall explanatory power of the robust model is excellent, with an LSDV R-squared of 77.39%. This demonstrates that the variables of the Modified Ohlson Model, alongside firm fixed effects, successfully explain the vast majority of the variance in the market values of the sampled AI firms.

Table 3. Robust Fixed-Effects Model Estimation Results

Variable	Coefficient	Robust Std. Error	t-ratio	p-value
Constant	184.946	8.07543	22.90	<0.0001 ***
d_BVPS	4.11426	2.82215	1.458	0.1556
d_EPS	-3.84526	2.11487	-1.818	0.0794 *
d_RDPS	1.64875	0.73131	2.255	0.0319 **
REV_G	52.2977	41.9247	1.247	0.2222

*Note: *** p<0.01, ** p<0.05, * p<0.1.*

Source*: Author's calculations using Gretl software.*

Regarding the individual coefficients, the analysis yielded profound results that offer a qualitative addition to financial literature in the context of the AI industry:

1. R&D Expenditures (*d_RDPS*): This variable exhibits a positive coefficient (1.64) and is statistically significant at the 5% level (p-value = 0.0319). This pivotal finding validates the proposed modification to the classic Ohlson model. It proves that financial markets actively price AI firms based on their innovation intensity. Investors perceive R&D spending not merely as an expense that reduces current profits, but as a core intangible asset that secures competitive advantage and future cash flows (Lev & Gu, 2016; Chan et al., 2001).
2. Earnings Per Share (*d_EPS*): In a departure from traditional corporate finance fundamentals, EPS demonstrated a negative impact (-3.84) and is statistically significant at the 10% level (p-value = 0.0794). Economically, this implies that investors in the AI sector—particularly during this generative AI expansion phase—penalize firms that prioritize maximizing and distributing current earnings over reinvesting in infrastructure and model development. Sacrificing short-term profitability for future growth is a positively priced behavior in this paradigm.
3. Book Value and Revenue Growth (*d_BVPS & REV_G*): Both variables lost their statistical significance after employing robust standard errors. This indicates that tangible assets (represented by book value) and short-term revenue momentum are no longer the primary drivers of value in the generative AI era. The intrinsic value of these firms resides in their intangible knowledge assets, which traditional balance sheets fail to accurately capture (Ohlson, 1995).

5. CONCLUSION

The unprecedented surge in the market capitalizations of technology firms during the generative Artificial Intelligence boom has sparked intense academic and professional debate regarding the rationality of these valuations. This study aimed to demystify this phenomenon by empirically testing whether the AI stock premium is driven primarily by a behavioral speculative bubble or is genuinely anchored in tangible financial fundamentals. By deploying a Modified Ohlson Model across a robust panel of 30 leading AI-centric firms from 2020 to 2025, the findings reveal a profound paradigm shift in how financial markets conceptualize and price value within the contemporary tech ecosystem.

The empirical evidence conclusively challenges the pure "behavioral bubble" narrative. Instead, it highlights a highly rational, forward-looking market mechanism where traditional accounting metrics are superseded by innovation indicators. The statistical insignificance of Book Value Per Share (*BVPS*) and the negative valuation impact of current Earnings Per Share (*EPS*) signify that tangible assets and short-term profit maximization are no longer the primary drivers of technology valuations. In stark contrast, the significant positive premium placed on Research and Development (*RDPS*) underscores that investors fundamentally treat innovation expenditures not as sunk operational costs, but as the core intangible assets that guarantee future market dominance, algorithmic superiority, and sustained cash flows.

Regarding the second question, the empirical evidence demonstrates that incorporating R&D intensity substantially improves the model's explanatory power, indicating that traditional accounting frameworks miss a crucial component of AI firm value.

Ultimately, the current valuation of AI firms reflects a structural macroeconomic transition from tangible capitalism to a knowledge-and-data-driven economy. While behavioral hype and market momentum undoubtedly play secondary roles in short-term price fluctuations, the structural core of the AI market boom is fundamentally grounded in the rational pricing of aggressive technological reinvestment. Markets are consciously penalizing short-term earnings distribution in favor of long-term capital expenditure in AI infrastructure, confirming that the "AI premium" is predominantly an innovation reward rather than mere speculative noise.

6. RECOMMENDATIONS

Drawing upon the econometric findings and the broader theoretical framework, this study offers the following strategic recommendations for various market stakeholders:

- **For Institutional Investors and Financial Analysts:** Traditional valuation multiples, such as Price-to-Book (*P/B*) and Price-to-Earnings (*P/E*) ratios, have lost much of their explanatory power in the generative AI era and should be systematically recalibrated. Analysts must pivot towards innovation-adjusted metrics—primarily R&D-to-Market-Capitalization and technological intensity ratios—to accurately gauge a firm's intrinsic value and future growth trajectory.

- **For Corporate Management in the Technology Sector:** Executive boards should actively resist the pressure of short-termism. The empirical penalty observed on current earnings (*EPS*) demonstrates that the market actively supports and rewards aggressive reinvestment. Firms must prioritize long-term capital expenditures in AI infrastructure, computational power, talent acquisition, and algorithmic research over stock buybacks or short-term dividend payouts.
- **For Financial Accounting Standard Setters (FASB & IASB):** The lack of statistical significance for tangible book value highlights a critical deficiency in current financial reporting frameworks. Standard setters are strongly encouraged to accelerate the reform of accounting standards (such as ASC 730 or IAS 38) to allow for the better capitalization of internally generated intangible assets. Accurately reflecting proprietary algorithms, large datasets, and R&D pipelines on the balance sheet is essential to ensure that financial statements represent true economic realities.
- **For Future Academic Research:** While this study successfully isolated the impact of financial fundamentals, future econometric research should aim to quantify the behavioral dimension directly. Developing composite indices of "Investor Attention" (e.g., utilizing natural language processing on financial news, search engine trends, or social media sentiment) and integrating them as explanatory variables within the panel data model would provide a more granular, dual-factor decomposition of the behavioral versus fundamental pricing drivers in the AI sector.

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8. Appendices

Appendix 1: List of Artificial Intelligence and Technology Firms Included in the Study Sample (30 Firms)

No.	Company Name	Ticker
1	Microsoft Corporation	MSFT
2	Apple Inc.	AAPL
3	NVIDIA Corporation	NVDA
4	Alphabet Inc.	GOOGL
5	Amazon.com, Inc.	AMZN
6	Meta Platforms, Inc.	META
7	Tesla, Inc.	TSLA
8	Advanced Micro Devices, Inc.	AMD
9	Intel Corporation	INTC
10	Broadcom Inc.	AVGO
11	Qualcomm Incorporated	QCOM
12	Micron Technology, Inc.	MU
13	Super Micro Computer, Inc.	SMCI
14	International Business Machines Corporation	IBM
15	Oracle Corporation	ORCL
16	Salesforce, Inc.	CRM
17	Adobe Inc.	ADBE
18	Palantir Technologies Inc.	PLTR
19	ServiceNow, Inc.	NOW
20	Snowflake Inc.	SNOW
21	C3.ai, Inc.	AI
22	CrowdStrike Holdings, Inc.	CRWD
23	Palo Alto Networks, Inc.	PANW
24	Datadog, Inc.	DDOG
25	UiPath Inc.	PATH
26	Arista Networks, Inc.	ANET
27	Marvell Technology, Inc.	MRVL
28	Applied Materials, Inc.	AMAT
29	Cisco Systems, Inc.	CSCO
30	Dell Technologies Inc.	DELL

Appendix 2: Variables Measurement and Data Sources

Variable	Symbol	Measurement / Calculation	Data Source
Market Value	***P***	Stock closing price at the end of the fiscal quarter.	Macrotrends
Book Value Per Share	***BVPS***	Total Shareholders' Equity / Total Outstanding Shares.	Macrotrends
Earnings Per Share	***EPS***	Quarterly Net Income / Weighted Average Shares Outstanding.	Macrotrends
R&D Intensity	***RDPS***	Quarterly Research & Development Expenditures / Total Outstanding Shares.	Macrotrends SEC EDGAR Form 10-Q
Revenue Growth	***REV_G***	Percentage change in quarterly revenue compared to the same quarter of the previous year.	Macrotrends SEC EDGAR Form 10-Q

Appendix 3: Baseline Econometric Models (Pooled OLS and Random Effects)

Table A3.1: Pooled OLS Estimation (Model 1)

Dependent variable: P
Included 30 cross-sectional units, Time-series length = 24
Observations = 720

Variable	Coefficient	Std. Error	t-ratio	p-value	
const	54.0887	7.8376	6.901	<0.0001	***
BVPS	2.95111	0.3114	9.475	<0.0001	***
EPS	53.1922	3.3642	15.81	<0.0001	***
RDPS	4.20218	2.0376	2.062	0.0395	**
REV_G	109.568	18.3405	5.974	<0.0001	***

R-squared: 0.501830 Adjusted R-squared: 0.499043
F(4, 715): 180.0633 P-value(F): 1.2e-106

Table A3.2: Random-effects (GLS) Estimation (Model 3)

Dependent variable: P
Included 30 cross-sectional units, Time-series length = 23
Observations = 690

Variable	Coefficient	Std. Error	z	p-value	
const	184.693	23.6580	7.807	<0.0001	***
d_BVPS	4.32596	1.7204	2.514	0.0119	**
d_EPS	-3.85492	2.7562	-1.399	0.1619	
d_RDPS	1.72829	2.0957	0.8247	0.4096	

REV_G 53.0022 17.4125 3.044 0.0023 ***

Hausman test p-value: 0.00203454 (Indicates Fixed Effects is preferred)

Appendix 4: Multicollinearity Diagnostics

Table A4.1: Variance Inflation Factors (VIF)

Minimum possible value = 1.0. Values > 10.0 may indicate a collinearity problem.
BVPS: 1.377
EPS: 1.383
RDPS: 1.057
REV_G: 1.017
Conclusion: No evidence of excessive collinearity.

Appendix 5: Panel Unit Root Tests (Levin-Lin-Chu)

Table A5.1: LLC Unit Root Test Results

Variable	Level I(0) p-value	First Difference I(1) p-value	Decision
P	0.9881	-	Stationary at I(0) in some specs, treated as I(0)
BVPS	1.0000	0.0000 ***	Stationary at I(1)
EPS	0.2259	0.0000 ***	Stationary at I(1)
RDPS	0.9896	0.0000 ***	Stationary at I(1)
REV_G	0.0000 ***	-	Stationary at I(0)