



Revenue Signals, Profitability and Stock Mispricing: Evidence from Technology Firms

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ABSTRACT

Focusing specifically on Indonesian technology firms, this paper investigates how profitability dynamics moderate the relationship between revenue-based valuation and future stock returns. Using a quantitative panel framework with a fixed effects model and robust standard errors to control for firm heterogeneity, this paper analyzes 216 firm-quarter observations from 18 technology companies listed on the Indonesia Stock Exchange over the 2022–2024 period. The results show that industry-adjusted price-to-sales deviation (PSDEV) has a negative and significant effect on future stock returns ($\beta = -0.183$, $p < 0.01$), indicating the presence of stock mispricing. Profitability is positively associated with future returns, suggesting that firms with stronger operating performance generate superior stock performance. Crucially, profitability significantly moderates the relationship between valuation deviation and returns, where higher profitability weakens the negative impact of overvaluation. From a practical standpoint, investors can look at profitability as a definitive legitimacy anchor. High profit margins effectively validate steep valuation levels, drastically lowering the odds of walking into a mispricing trap. The present inquiry develops an industry-adjusted revenue-based mispricing framework to show that profitability acts as a critical boundary condition for the relationship between valuation deviation and future returns, especially in the earnings-opaque technology sector.

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1. INTRODUCTION

To evaluate a firm's trajectory and financial condition, capital market investors routinely rely on accounting metrics. Theoretically, under the Asset Pricing Theory and the Efficient Market Hypothesis (EMH), these insights should be fully and instantly priced into the market. Yet, the rapid expansion of the technology sector, where firms operate with substantial intangibles and erratic earnings profiles, disrupts this conventional framework, raising doubts about the relevance of legacy valuation measures. Financial fundamentals such as earnings and retained earnings admittedly maintain their grip on equity valuations (Ball et al., 2020; Fama and French, 2021). Still, the fact that valuation anomalies stubbornly persist suggests that information efficiency in stock pricing is far from absolute.

Valuation anomalies have been widely documented in the literature, yet empirical findings regarding their behavior remain largely inconclusive. Enhanced statistical rigor has been shown to neutralize the significance of many historical anomalies (Bartram et al., 2025; Hou et al., 2017). Conversely, another school of thought argues that these anomaly returns actually stem from distinct economic forces that elude conventional risk-based models (Lochstoer and Tetlock, 2020). When we account for systemic market frictions and structural arbitrage asymmetries that continuously hinder mispricing corrections (Shi et al., 2023; Stambaugh et al., 2015), the persistence of these anomalies becomes clearer. Ultimately, this ongoing theoretical tension underscores the necessity of a more nuanced investigation into valuation-driven stock returns.

Beyond traditional valuation metrics, contemporary literature attributes stock return variations to a complex interplay of behavioral, informational, and structural dimensions. For instance, shifting investor behavior and market sentiment frequently drive return fluctuations (Daniel et al., 2020; Wang, W., et al., 2021). While financial statement-based models hold ground (Penman and Zhu, 2022), the paradigm has clearly shifted toward intangible resources. Intangibles are where the real value lies now. For modern corporations, traditional metrics no longer tell the whole story; instead, intangible investments have become vital for predicting future returns (Li et al., 2025). This shift has opened the floodgates for non-financial data. Today, predicting market performance requires looking at ESG disclosures, integrated reporting (Juniarti et al., 2024), and even how satisfied a company's employees are (Bae and Ha, 2025). But these metrics do not work in a vacuum. They collide directly with macroeconomic forces, meaning that a firm's growth trajectory is always tightly bound to prevailing market conditions (Beckers and Bernoth, 2024; Levine and Warusawitharana, 2021; Sterk et al., 2021).

Because erratic earnings profiles make technology firms difficult to appraise through conventional earnings lenses, revenue-based metrics have emerged as essential alternatives. Specifically, price-to-sales multiples often serve as more effective valuation benchmarks in this opaque environment (Joshi and Chauhan, 2024). Yet, existing literature typically treats valuation and profitability as independent vectors, offering scarce evidence on how bottom-line profitability conditions the trajectory between valuation deviations and future stock returns (Haboub et al., 2026). Rather than evaluating these factors in isolation, our framework introduces an industry-adjusted Price-to-Sales Deviation (PSDEV) metric. By positioning profitability as a crucial moderating variable, we offer a distinct methodological advancement to the current asset pricing literature.

To bridge the gaps in existing literature, this paper evaluates the predictive power of revenue-based valuation deviations on future stock returns, specifically focusing on how profitability influences this dynamic within Indonesian technology firms. Structurally, our work advances the accounting literature by pushing valuation analysis beyond traditional, earnings-centric models and demonstrating how bottom-line profitability shapes the market's reading of valuation signals. Beyond its theoretical merits, the evidence provides actionable intelligence for market participants navigating equity valuations in high-growth, intangible-heavy sectors.

2. METHODS

To investigate how revenue-based valuation ratios forecast future stock returns and the extent to which profitability moderates this link, we adopt a quantitative panel data regression framework. Utilizing panel data analysis is essential here; as noted by (Baltagi, 2021), it effectively controls for unobserved firm-level and temporal heterogeneity—a critical requirement in asset pricing empirical work. The dataset comprises 18 technology companies listed on the Indonesia Stock Exchange, spanning Q1 2022 to Q4 2024 and yielding 216 firm-quarter observations. Targeting the tech sector is strategically driven by the industry's high-growth yet earnings-volatile nature, environments where conventional valuation indicators face significant friction (Lev and Anup, 2022; Penman and Zhu, 2022). Sample inclusion was strictly restricted to enterprises maintaining complete financial and market records throughout the observation window. Firms are selected based on data availability and completeness of financial and market information.

Empirical data are derived from published financial statements and official stock price records on the Indonesia Stock Exchange, combining accounting metrics with market data to analyze valuation and mispricing dynamics (Ball et al., 2020; Hou et al., 2017). Our primary outcome, future stock return (RET_{t+1}), is specified as the one-period-ahead percentage change in stock price. Utilizing lead returns ($t+1$) serves a dual purpose: it captures subsequent market reactions while mitigating potential reverse causality issues (Fama and French, 2021).

Our core explanatory variable relies on an industry-adjusted approach. Specifically, we use Price-to-Sales deviation (PSDEV), which standardizes the distance between an individual firm's Price-to-Sales multiple and its industry median for each period (Bartram et al., 2025; Stambaugh et al., 2015).

To capture operational efficiency, firm profitability (GPM) is integrated by scaling gross profit against total revenue (Ball et al., 2020; Bedford et al., 2021). We do not look at these variables in a vacuum. The regression model actively controls for financial leverage (LEV, calculated as total debt over total assets) and firm size (SIZE, using the natural logarithm of market capitalization) to strip away confounding corporate traits and align with standard asset pricing literature (Hou et al., 2017; W. Wang et al., 2021).

To test the hypotheses, this study estimates the following panel regression models:

Baseline Model

$$RET_{i,t+1} = \alpha + \beta_1 PSDEV_{i,t} + \beta_2 GPM_{i,t} + \beta_3 LEV_{i,t} + \beta_4 SIZE_{i,t} + \varepsilon_{i,t}$$

Moderation Model

$$RET_{i,t+1} = \alpha + \beta_1 PSDEV_{i,t} + \beta_2 GPM_{i,t} + \beta_3 (PSDEV \times GPM)_{i,t} + \beta_4 LEV_{i,t} + \beta_5 SIZE_{i,t} + \varepsilon_{i,t}$$

To evaluate the conditional dynamics, the empirical framework incorporates an interaction term ($\text{PSDEV} \times \text{GPM}$), matching the standard approach for testing conditional relationships in panel structures (Brambor et al., 2006). This specification captures whether the market's reaction to valuation signals shifts across varying levels of corporate profitability. Choosing the right panel estimator requires a strict elimination process. We weigh pooled OLS, fixed effects, and random effects frameworks against each other using Chow, Hausman, and Breusch–Pagan Lagrange Multiplier tests. The data pointed directly to a fixed effects model. This specific framework won out because it effectively kills off time-invariant, unobserved corporate noise—something other models fail to control for. (Baltagi, 2021).

Ensuring statistical validity required rigorous diagnostic screening. We assessed potential multicollinearity via Variance Inflation Factors (VIF), heteroskedasticity through the Breusch–Pagan test, and serial correlation using the Wooldridge specification. To safeguard our inferences against remaining heteroskedasticity and within-firm error clustering, the estimation utilizes clustered robust standard errors at the firm level (Colin Cameron and Miller, 2015). Finally, to ensure our core insights are not artifacts of model specifications, we executed several robustness checks: substituting PSDEV with raw Price-to-Sales ratios, extending the return horizon to two periods ahead, and performing subsample splits based on profitability medians. The core empirical findings hold firmly across these alternative setups, confirming their stability against potential model sensitivities (Bartram et al., 2025; Hou et al., 2017).

3. RESULTS AND DISCUSSION

3.1. Descriptive Analysis

The numbers tell a story of immense variance behind a deceptively calm surface. A positive average future return (RET) of 0.058 for Indonesian tech enterprises actually hides a massive standard deviation of 1.74. What this tells us is that extreme volatility functions as a permanent structural reality, not just a passing anomaly. Such deep fragmentation is driven by the unpredictable earnings and systemic growth struggles typical of the tech sector (Lev and Anup, 2022; Sterk et al., 2021). Table 1 shows descriptive statistics.

Table 1. Descriptive statistics

Variable	Mean	Median	Std.Dev	Min	Max
RET	0.058	0.052	1.74	-3.20	4.10
PSDV	0.12	0.05	0.89	-2.10	2.45
GPM	0.34	0.31	0.18	0.05	0.78
LEV	0.46	0.44	0.21	0.08	0.89
SIZE	28.7	28.6	1.95	24.9	32.1

Source: Processed Data, 2026

The wide dispersion in PSDEV, ranging from -2.10 to 2.45, underscores substantial cross-sectional variation in market valuations. This gap points to heterogeneous investor expectations and localized informational frictions typical of emerging capital markets, ecosystems where pricing efficiency is frequently compromised and valuation spreads are more pronounced (Beckers and Bernoth, 2024; Stambaugh et al., 2015). Looking at operational indicators, the technology sector exhibits moderate earning power, marked by a mean gross profit margin (GPM) of 0.34, alongside a considerable reliance on debt financing, as reflected by a average leverage ratio (LEV) of 0.46. Organizational scale also varies significantly across the sample, with

firm size (SIZE) averaging 28.7. This data exposes a deeply fragmented industry. When evaluating tech firms, assuming they all follow the same playbook is a mistake. The way their growth paths, capital frameworks, and profit margins split apart is simply too drastic. It is this internal fragmentation that plays a direct role in creating uneven future stock returns, showing that the industry cannot be boxed into a single, predictable standard (Demerjian et al., 2020; Fama and French, 2021; Lev and Gu, 2016).

3.2 Correlation Analysis

Table 2. Correlation matrix

Variable	RET	PSDV	GPM	LEV	SIZE
RET	1.000	-0.21	0.18	-0.15	0.12
PSDV	-0.21	1.000	-0.10	0.09	0.14
GPM	0.18	-0.10	1.000	-0.22	0.20
LEV	-0.15	0.09	-0.22	1.000	0.25
SIZE	0.12	0.14	0.20	0.25	1.000

Source: Processed Data, 2026

The correlation matrix presented in **Table 2** offers preliminary support for our core hypothesis, revealing a negative correlation between PSDEV and future returns (RET = -0.21). This negative link ties directly to the asset pricing mispricing framework. Under this view, stocks priced above their fundamental anchors cannot hold their ground forever; they inevitably hit a downward slide as market values collapse back toward intrinsic worth (Daniel et al., 2020; Kumar et al., 2024; Stambaugh et al., 2015). Why do these pricing anomalies stick around? Mostly because structural limits to arbitrage and deep investor disagreement stall the correction process, a problem that intensifies when severe informational frictions muddy the waters (Shi et al., 2023; Van Binsbergen et al., 2023). Looking at the explanatory variables, the cross-correlations are generally muted, spanning between -0.22 and 0.25. The strongest co-movement occurs between financial leverage and organization scale (LEV and SIZE at 0.25), a value that sits comfortably below the conventional thresholds that signal multicollinearity. Consequently, these independent metrics appear to capture distinct, non-overlapping dimensions of firm profiles without threatening the stability of our subsequent regression estimates. This structural independence is consistent with established empirical designs that utilize profitability, leverage, and firm size as independent control vectors (Hou et al., 2017; W. Wang et al., 2021).

3.3 Regression Results: Baseline Model

Table 3. Regression result model-1

Variable	Coefficient	t-Statistic
PSDV	-0.183***	-3.12
GPM	0.096**	2.04
LEV	-0.071	-2.21
SIZE	0.052*	1.78
Constant	-	-

Notes: ***p<0.01, **p<0.05, *p<0.10

Source: Processed Data, 2026

Table 3 shows Regression result model-1. The baseline regression numbers deliver a very clear message. Most notably, our industry-adjusted valuation metric, PSDEV, actively depresses future stock performance, carrying a negative and highly significant coefficient ($\beta = -0.183$, $p < 0.01$). This downward pressure solidifies the mispricing hypothesis. It proves that when tech equities drift too far from fundamental anchors, market forces eventually trigger a harsh downward price correction. Rather than a random fluctuation, this return reversal mirrors classic asset pricing literature on market inefficiencies and the inevitable hangover that follows overvaluation (Bartram et al., 2025; Daniel et al., 2020; Stambaugh et al., 2015; van Binsbergen et al., 2023; Zhang et al., 2024). Investors closely watch operating profitability (GPM) as a direct indicator of corporate quality. With a positive and significant coefficient ($\beta = 0.096$, $p < 0.05$), the data shows that stronger earning power is a major driver behind future equity gains (Ahmed et al., 2024; Ball et al., 2020; Penman and Zhu, 2022). What this means is the results push back against the traditional arguments surrounding profitability.

The controls add necessary friction to the framework. Financial leverage (LEV) pushes returns down ($\beta = -0.071$, $p < 0.05$, a direct warning that aggressive debt loads drag down subsequent market performance. Conversely, corporate scale (SIZE) offers a marginal, weak positive bump to returns ($\beta = 0.052$, $p < 0.10$), pointing to a slight edge for larger firms. These baseline dynamics verify that valuation anomalies hold heavy predictive power, while leverage, size, and earnings remain essential pieces of the asset pricing puzzle (Dang et al., 2023; Fama and French, 2021; Hou et al., 2020).

From an empirical standpoint, a negative relationship emerges between leverage (LEV) and future stock returns ($\beta = -0.069$, $p < 0.05$). This suggests that enterprises carrying higher financial risk are more prone to underperformance in the following periods. This dynamic corroborates the risk-based paradigm in asset pricing, where severe financial risk intensifies distress threats and consequently depresses expected returns. Conversely, firm size (SIZE) exhibits only a marginally significant positive influence ($\beta = 0.049$, $p < 0.10$), reflecting the operational advantages—such as enhanced market share and data transparency—enjoyed by larger enterprises. Collectively, these baselines underscore the established consensus that cross-sectional return variations are rooted in firm-specific characteristics (Green et al., 2017; Hou et al., 2017; W. Wang et al., 2021). Within this specific context, the interaction between valuation deviation and profitability (PSDEVxGPM) yields a positive and statistically significant coefficient ($\beta = 0.094$, $p < 0.05$). This indicates that the impact of valuation anomalies is fundamentally conditional on a firm's internal performance metrics. This result highlights firm profitability as a pivotal moderating variable that alters the relationship between valuation anomalies and future stock returns. Essentially, strong profit margins serve as a shock absorber against valuation deviations, shielding fundamentally robust companies from mispricing vulnerabilities. Such dynamics support the premise that robust earnings anchor a firm's core fundamentals, allowing investors to gauge intrinsic worth more precisely and insulating the stock from steep price discrepancies (Ahmed et al., 2024; Penman and Zhu, 2022). This protective mechanism echoes the perspective of (Bedford et al., 2021; Fama and French, 2021), who argue that operational resilience and reduced valuation ambiguity in highly profitable enterprises effectively neutralize market anomalies. Taken together, these baseline results confirm that revenue-based valuation deviations serve as a potent predictor of future equity returns. **Table 4** shows regression results model-2.

Table 4. Regression results model-2

Variable	Coefficient	t-Statistic
PSDV	-0.165***	-2.85
GPM	0.082*	1.76
PSDVxGPM	0.094**	2.12
LEV	-0.069**	-2.10
SIZE	0.049*	1.72

Notes: ***p<0.01, **p<0.05, *p<0.10

Source: Processed Data, 2026

The inverse nexus between PSDEV and stock returns signals that valuation dispersion is a byproduct of market mispricing rather than a reflection of core fundamental variances. This highlights the critical role of valuation-anchored indicators in asset pricing models, particularly in emerging economies where information frictions are typically severe. This line of thought is further reinforced by global empirical evidence indicating that mispricing forces possess a lasting capacity to forecast subsequent returns (H. Chen et al., 2024). Additionally, prior research attributes the persistence of such mispricing to arbitrage constraints, divergent investor expectations, and information asymmetry, all of which obstruct the timely adjustment of stock prices to underlying fundamentals (Z. Chen et al., 2025; Van Binsbergen et al., 2023).

3.4 Robustness Tests

To ensure the validity of the core findings, the analysis incorporates several robustness checks. Initially, substituting PSDEV with the raw Price-to-Sales (PS) ratio generates highly consistent outcomes. The main conclusions also remain unchanged when evaluating a two-period-ahead return ($t+2$) as the dependent variable. In tandem with these tests, the study employs a subsample analysis segmented by profitability levels, allowing for a detailed examination of whether these observed patterns vary across distinct firm characteristics. **Table 5** shows robustness test results.

Table 5. Robustness test results

Model Specification	PSDV/PS	t-Statistic
Baseline Model	-0.183***	-3.12
Using PS (raw)	-0.167***	-2.95
Lag $t+2$	-0.141**	-2.21
Low Profitability	-0.201***	-3.45
High Profitability	-0.098*	-1.75

Notes: ***p<0.01, **p<0.05, *p<0.10

Source: Processed Data, 2026

Across all alternative specifications, the core insights demonstrate qualitative resilience, evidenced by the consistently negative and statistically significant coefficient of PSDEV (or PS). Neither the adoption of the raw Price-to-Sales ratio nor the shift to alternative return horizons alters these conclusions, confirming that specific variable measurements or model designs do not artifactualize the documented relationship. In tandem with this, the more pronounced coefficient within the low-profitability subsample implies that mispricing intensifies among fundamentally weaker firms, which are typically plagued by heightened valuation ambiguity and information asymmetry.

These checks confirm that the documented relationship between revenue-based valuation and future stock returns is remarkably stable, rather than being an artifact of specific model choices. Instead of fading under different empirical conditions, Such outcomes are highly consistent with established literature regarding the enduring nature of market anomalies and the role of firm-specific features in shaping cross-sectional dynamics (Baba-Yara et al., 2024; Bartram et al., 2025; Hou et al., 2017; Shi et al., 2023). This alignment is further underscored by international evidence showing that market mispricing tends to persist when structural frictions and arbitrage constraints slow down the incorporation of fundamental data into asset values (H. Chen et al., 2024; Van Binsbergen et al., 2023; C. Wang, 2024).

3.5 Integrated Discussion

Taken together, these insights validate the core premise outlined initially: revenue-based valuation plays an indispensable role in mapping stock mispricing within tech-focused enterprises. The inverse connection between PSDEV and upcoming returns confirms that these valuation anomalies represent transitory market inefficiencies instead of permanent fundamental values, aligning with established anomaly literature (Fama and French, 2021; Stambaugh et al., 2015). This mechanism proves that we cannot evaluate valuation metrics in isolation; the moderating role of profitability is simply too critical. True, revenue figures show immediate growth potential, but whether those market expectations are economically viable over time depends heavily on actual firm profitability. Merging these two aspects gives us a more realistic diagnostic tool for corporate valuation. This approach is highly relevant for emerging economies, where firms constantly grapple with severe uncertainty and information asymmetry (Beckers and Bernoth, 2024; Daniel et al., 2020).

Looking at asset pricing from another angle, recent studies suggest that classic linear frameworks often fail to capture how complex anomaly-driven predictability can be. Instead, modern methods that rely on machine learning and non-linear frameworks provide much stronger evidence of lasting market inefficiencies (Azevedo et al., 2023).

4. CONCLUSION

Focusing on the landscape of technology enterprises within Indonesia, this research investigates how revenue-based valuation accounts for subsequent stock returns, while deeply analyzing the moderating influence of corporate profitability. The empirical data reveals that valuation deviation (PSDEV) exerts a negative, statistically significant impact on upcoming stock returns, implying that corporations carrying higher relative valuations typically face a notable decline in their subsequent market performance. This structural slide aligns heavily with the mispricing hypothesis, pointing to a reality where deviations from intrinsic value face slow, inevitable market corrections (Fama and French, 2021; Stambaugh et al., 2015). Yet, staring solely at these forward-looking growth expectations leaves out a massive piece of the puzzle.

Trading data indicates that companies holding onto a superior Gross Profit Margin (GPM) effectively bypass these downward trends, proving that day-to-day operational health serves as the true baseline for sustaining actual market gains. Navigating complex equity return dynamics requires a deeper look; ignoring these core accounting-based valuations leaves analysts with an incomplete picture (Ball et al., 2020; Penman and Zhu, 2022).

Operational profitability fundamentally reshapes this equation by acting as a substantial buffer between initial valuation mismatches and actual market performance. A positive interaction effect emerges from the data, demonstrating that strong bottom-line execution safeguards overvalued firms from the severe price corrections that typically cripple financially weaker counterparts. Consequently, evaluating standalone valuation multiples proves ineffective since realized earnings heavily dictate how market participants interpret growth signals. By bridging the traditional divide between pricing anomalies and fundamental health, this framework links top-line expansion metrics directly to underlying corporate resilience. This integrated approach offers a fresh empirical view on how growth expectations and fundamental execution jointly determine equity mispricing, particularly within an emerging market characterized by distinct structural frictions.

5. REFERENCES

- Ahmed, A., Neel, M., and Safdar, I. (2024). Why does operating profitability predict returns? new evidence on risk versus mispricing explanations. *Accounting and Finance*, 64(2), 1243–1276. <https://doi.org/10.1111/acfi.13178>
- Azevedo, V., Kaiser, G. S., and Mueller, S. (2023). Stock market anomalies and machine learning across the globe. *Journal of Asset Management*, 24(5), 419–441. <https://doi.org/10.1057/s41260-023-00318-z>
- Baba-Yara, F., Boons, M., and Tamoni, A. (2024). Persistent and transitory components of firm characteristics: implications for asset pricing. *Journal of Financial Economics*, 154, 103808. <https://doi.org/10.1016/j.jfineco.2024.103808>
- Bae, J., and Ha, Y. S. (2025). Employee satisfaction, firm performance, and stock returns: evidence from the korean stock market. *Pacific-Basin Finance Journal*, 93, 102847. <https://doi.org/10.1016/j.pacfin.2025.102847>
- Ball, R., Gerakos, J., Linnainmaa, J. T., and Nikolaev, V. (2020). Earnings, retained earnings, and book-to-market in the cross section of expected returns. *Journal of Financial Economics*, 135(1), 231–254. <https://doi.org/10.1016/j.jfineco.2019.05.013>
- Baltagi, B. H. (2021). *Econometric analysis of panel data* (pp. 187–228). Springer. https://doi.org/10.1007/978-3-030-53953-5_8
- Bartram, S. M., Grinblatt, M., and Nozawa, Y. (2025). Book-to-market, mispricing, and the cross section of corporate bond returns. *Journal of Financial and Quantitative Analysis*, 60(3), 1185–1233. <https://doi.org/10.1017/S0022109024000048>
- Beckers, B., and Bernoth, K. (2024). Monetary policy and mispricing in stock markets. *Journal of Money, Credit and Banking*, 56(7), 1887–1904. <https://doi.org/10.1111/jmcb.13090>

- Bedford, A., Ma, L., Ma, N., and Vojvoda, K. (2021). Future profitability and stock returns of innovative firms in Australia. *Pacific-Basin Finance Journal*, 66, 101508. <https://doi.org/10.1016/j.pacfin.2021.101508>
- Brambor, T., Clark, W. R., and Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis*, 14(1), 63–82. <https://doi.org/10.1093/pan/mpi014>
- Chen, H., Dou, W. W., and Kogan, L. (2024). Measuring “dark matter” in asset pricing models. *The Journal of Finance*, 79(2), 843–902. <https://doi.org/https://doi.org/10.1111/jofi.13317>
- Chen, Z., Liu, B., Wang, H., Wang, Z., and Yu, J. (2025). Investor sentiment and the pricing of characteristics-based factors. *The Review of Financial Studies*, 38(12), 3580–3625. <https://doi.org/10.1093/rfs/hhaf053>
- Colin Cameron, A., and Miller, D. L. (2015). A practitioner’s guide to cluster-robust inference. *Journal of Human Resources*, 50(2), 317–372. <https://doi.org/10.3368/jhr.50.2.317>
- Dang, T. D., Hollstein, F., and Prokopczuk, M. (2023). Which factors for corporate bond returns? *The Review of Asset Pricing Studies*, 13(4), 615–652. <https://doi.org/10.1093/rapstu/raad005>
- Daniel, K., Hirshleifer, D., and Sun, L. (2020). Short-and long-horizon behavioral factors. *The Review of Financial Studies*, 33(4), 1673–1736. <https://doi.org/10.1093/rfs/hhz069>
- Demerjian, P., Lewis-Western, M., and McVay, S. (2020). How does intentional earnings smoothing vary with managerial ability? *Journal of Accounting, Auditing and Finance*, 35(2), 406–437. <https://doi.org/10.1177/0148558X17748405>
- Fama, E. F., and French, K. R. (2021). The value premium. *The Review of Asset Pricing Studies*, 11(1), 105–121. <https://doi.org/10.1093/rapstu/raaa021>
- Green, J., Hand, J. R. M., and Zhang, X. F. (2017). The characteristics that provide independent information about average u.s. monthly stock returns. *The Review of Financial Studies*, 30(12), 4389–4436. <https://doi.org/10.1093/rfs/hhx019>
- Haboub, A., Kartsaklas, A., and Sarafidis, V. (2026). Residual income valuation and stock returns: evidence from a value-to-price investment strategy. *Financial Review*. <https://doi.org/10.1111/fire.70059>
- Hou, K., Xue, C., and Zhang, L. (2017). Replicating anomalies. *National Bureau of Economic Research*. <https://doi.org/10.3386/w23394>
- Hou, K., Xue, C., and Zhang, L. (2020). Replicating anomalies. *The Review of Financial Studies*, 33(5), 2019–2133. <https://doi.org/10.1093/rfs/hhy131>

- Joshi, H., and Chauhan, R. (2024). Determinants of price multiples for technology firms in developed and emerging markets: variable selection using shrinkage algorithm. *Vision*, 28(1), 55–66. <https://doi.org/10.1177/09722629211023011>
- Juniarti, J., Santoso, A. C., Hermawan, C. F., Darmasaputra, A., and Wright, J. (2024). Voluntary adoption of integrated reporting and firm valuation: the moderating effect of esg performance. *Jurnal Akuntansi Dan Keuangan*, 26(2), 131–141. <https://doi.org/10.9744/jak.26.2.131-141>
- Kumar, A., Motahari, M., and Taffler, R. J. (2024). Skewness sentiment and market anomalies. *Management Science*, 70(7), 4328–4356. <https://doi.org/10.1287/mnsc.2023.4898>
- Lev, B., and Anup, S. (2022). Explaining the recent failure of value investing. *Critical Finance Review*, 11(2), 333–360. <https://doi.org/10.1561/104.00000115>
- Lev, B., and Gu, F. (2016). The end of accounting and the path forward for investors and managers. *John Wiley and Sons*. <https://doi.org/10.1002/9781119270041>
- Levine, O., and Warusawitharana, M. (2021). Finance and productivity growth: Firm-level evidence. *Journal of Monetary Economics*, 117, 91–107. <https://doi.org/10.1016/j.jmoneco.2019.11.009>
- Li, X., Li, D., Li, T., and Chen, M. (2025). Saliency, fundamentals, and mispricing. *Journal of Behavioral Finance*, 26(4), 485–505. <https://doi.org/10.1080/15427560.2024.2353598>
- Lochstoer, L. A., and Tetlock, P. C. (2020). What drives anomaly returns? *The Journal of Finance*, 75(3), 1417–1455. <https://doi.org/10.1111/jofi.12876>
- Penman, S., and Zhu, J. (2022). An accounting-based asset pricing model and a fundamental factor. *Journal of Accounting and Economics*, 73(2–3), 101476. <https://doi.org/10.1016/j.jacceco.2021.101476>
- Shi, Y., Wang, H., Xia, Y., and Zhen, H. (2023). Mispricing and anomalies in china. *Pacific-Basin Finance Journal*, 79, 102038. <https://doi.org/10.1016/j.pacfin.2023.102038>
- Stambaugh, R. F., Yu, J., and Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance*, 70(5), 1903–1948. <https://doi.org/10.1111/jofi.12286>
- Sterk, V., Sedláček, P., and Pugsley, B. (2021). The nature of firm growth. *American Economic Review*, 111(2), 547–579. <https://doi.org/10.1257/aer.20190748>
- Van Binsbergen, J. H., Boons, M., Opp, C. C., and Tamoni, A. (2023). Dynamic asset (mis) pricing: Build-up versus resolution anomalies. *Journal of Financial Economics*, 147(2), 406–431. <https://doi.org/10.1016/j.jfineco.2022.11.005>
- Wang, C. (2024). Stock return prediction with multiple measures using neural network models. *Financial Innovation*, 10(1), 72. <https://doi.org/10.1186/s40854-023-00608-w>

- Wang, W., Su, C., and Duxbury, D. (2021). Investor sentiment and stock returns: global evidence. *Journal of Empirical Finance*, 63, 365–391.
<https://doi.org/10.1016/j.jempfin.2021.07.010>
- Zhang, T., Li, J., and Xu, Z. (2024). Speculative trading, stock returns and asset pricing anomalies. *Emerging Markets Review*, 61, 101165.
<https://doi.org/10.1016/j.ememar.2024.101165>