

AI Washing and Stock Returns: Evidence from Chinese A-Share Firms

Chenghui Yu^{1,*}, Minghao Xia², Yufei Li³, Jiaqi Lu⁴

¹*Faculty of Arts & Science, University of Toronto, Toronto, Canada*

²*College of Liberal Arts and Science, University of Colorado Denver, Denver, USA*

³*School of Social Sciences, University of Manchester, Manchester, UK*

⁴*Rutgers Business School, Rutgers University, Piscataway, USA*

**Corresponding Author. Email: ychalice.yu@mail.utoronto.ca*

Abstract. Artificial intelligence has become increasingly prominent in corporate disclosure, yet firms' AI-related narratives may not always be supported by observable investment in technology or human capital. Using AI-related keywords from annual reports, AI patents, and AI-related job postings of Chinese A-share firms from 2020 to 2025, we construct a firm-year measure to examine this disclosure-investment gap. We classify a firm as an AI washer when its AI-related disclosure is above the industry-year median, while both AI patent activity and AI-related recruitment remain below their corresponding medians. Firms meeting this definition are associated with lower annual stock returns, and the result remains qualitatively unchanged when we use alternative methods to identify AI patents. Additional tests point to two related market responses: AI washing is accompanied by more negative media coverage and weaker investor sentiment. The return discount is also more pronounced among firms with higher institutional ownership and among firms in regions with stronger local AI policy support. These results suggest that investors do not treat AI-related disclosure independently of observable corporate activity. Instead, the impact of AI narratives on stock returns appears to depend partly on whether firms can support those narratives with technological development and hiring.

Keywords: AI Washing, Stock Returns, Corporate Disclosure, Institutional Investors, Investor Sentiment

1. Introduction

AI-related language has become increasingly visible in firms' annual reports as companies seek to present themselves as participants in the ongoing development of artificial intelligence. For outside investors, however, such disclosure is much easier to observe than the underlying investment that supports it. A firm's AI capability is largely embedded in intangible assets, technological development, and specialized human capital, none of which can be fully inferred from narrative disclosure alone. As a result, firms may differ substantially in the extent to which their stated AI strategies are matched by observable investment in patents and AI-related recruitment.

Firms with extensive AI disclosure may benefit from greater market attention, particularly when investors expect AI adoption to generate future growth opportunities. Yet the same disclosure may lose credibility when it is not accompanied by observable evidence of technological development or demand for AI-skilled labor. This raises the question of whether firms with high AI disclosure but limited observable AI investment subsequently experience weaker stock performance.

In this study, we use "AI washing" to refer to an observable disclosure-investment mismatch rather than deliberate misrepresentation. To capture this mismatch, we combine information from three dimensions at the firm-year level: AI-related disclosure, AI patent activity, and AI-related recruitment. We classify a firm as an AI washer when its AI disclosure is above the industry-year median, while both its AI patent activity and AI-related hiring fall below their corresponding industry-year medians. This definition therefore identifies firms whose AI-related communication is relatively strong compared with observable indicators of technological and human-capital investment.

The empirical analysis covers Chinese A-share firms from 2020 through 2025. Across the alternative patent definitions, the estimated relation between AI washing and subsequent annual returns is consistently negative. AI washing observations are also associated with more negative media coverage and lower investor sentiment. In the subsample analysis, the return coefficient is more negative for firms with higher institutional ownership and for firms in regions with stronger AI policy support.

Our study contributes to the emerging literature on corporate AI disclosure in three ways. First, we operationalize AI washing as a mismatch between firms' AI-related communication and two observable forms of investment: AI patent activity and AI-related recruitment. Since patent development often takes years to materialize and may not capture contemporaneous investment, we additionally incorporate AI-related job postings as a timelier indicator of firms' investment in AI-related human capital. Second, we use the AI washing measure to show that firms with relatively high AI disclosure but limited observable AI investment are associated with weaker subsequent performance in the Chinese A-share market. Third, we provide evidence on the conditions under which the market response to AI washing is more pronounced.

The rest of the paper is organized as follows. Section 2 develops the hypotheses in relation to the existing literature. Section 3 introduces the data, variable construction, and empirical model. Section 4 presents the baseline results, robustness checks, mechanism tests, and heterogeneity analyses. Section 5 discusses the main findings, implications, and limitations. Section 6 concludes.

2. Literature review and hypothesis development

2.1. Literature review

Corporate disclosures contain information beyond the numerical items reported in financial statements. In particular, the language used in annual reports can reveal how firms describe their strategy, investment opportunities, and expected future developments. A growing body of textual-analysis research shows that such narrative information contains signals relevant to investors and can help identify firm characteristics that are difficult to observe through conventional accounting variables alone [1]. Recent advances in machine learning further demonstrate that these textual signals can be extracted and incorporated into investment decisions [2, 3]. This literature provides the basis for treating AI-related language in annual reports as an observable measure of how strongly firms communicate their involvement in artificial intelligence.

The informational value of corporate narratives, however, does not imply that disclosure always corresponds closely to underlying activity. Managers have discretion over how firms present themselves to external audiences, creating scope for favorable information to receive greater emphasis than less favorable aspects of firm performance. Basnet et al. distinguish actionable AI disclosure from speculative and irrelevant narratives and find that only AI disclosure tied to more concrete activities generates valuation benefits [4]. Their evidence suggests that the market response depends not simply on how much firms discuss AI, but on whether those claims are accompanied by observable AI-related activity.

Measuring the activity behind AI disclosure is difficult because much of firms' investment in artificial intelligence does not appear as conventional physical capital expenditure. Two observable outcomes are particularly useful in this setting. AI-related recruitment reflects firms' demand for specialized human capital, a dimension that Babina et al. use to study corporate AI investment [5]. They find that firms with greater AI-skilled workforce investment achieve stronger growth, innovation, and market valuation. In addition, patent activity provides a complementary signal by capturing realized technological output. Kogan et al. show that patent-based measures capture the economic significance of firms' technological innovations and are associated with subsequent firm growth [6]. Hiring and patents together therefore provide distinct, though imperfect, indicators of whether firms are committing resources to AI-related activity.

2.2. Hypothesis development

AI-related disclosure can affect market expectations even before the underlying investment becomes fully observable. Prior evidence suggests that firms with greater AI exposure may receive higher valuations, indicating that AI narratives can shape investor expectations and asset prices [7]. This creates scope for firms with extensive AI-related communication to attract investor attention even when observable technological or human-capital investment remains limited.

The valuation effect, however, may not persist when disclosure is not supported by subsequent evidence of AI activity. Song et al. document that AI narratives unsupported by patent activity can initially attract investors but are followed by negative market reactions and persistent underperformance [8]. Yang also finds an inverted U-shaped association between AI washing and firm value, with more pronounced disclosure–capability mismatches associated with weaker valuation outcomes [9].

In this study, we focus on relatively pronounced cases of this mismatch. We classify a firm as an AI washer when its AI-related disclosure exceeds the industry-year median, while both AI patent activity and AI-related recruitment fall below their respective medians. If investors eventually revise their expectations when strong AI narratives are not supported by technological output or demand for AI-skilled labor, we expect firms meeting this definition to earn weaker subsequent stock returns.

H1: Firms classified as AI washers are associated with lower subsequent stock returns than other firms.

We propose two market responses that may accompany AI washing and affect stock returns: media coverage and investor sentiment.

The first response operates through media scrutiny. Prior research shows that media coverage plays an important role in transmitting firm-specific information to investors and can affect both sentiment and cross-sectional returns [10,11]. Firms whose AI-related claims lack observable supporting activity may be more exposed to critical reporting. Negative coverage can, in turn, make this mismatch more visible to market participants and increase reputational pressure.

H2a: AI washing is positively associated with negative media coverage.

The second response operates through investor sentiment. Baker and Wurgler show that sentiment has stronger effects on securities whose valuations are more subjective [12]. The expected payoff from AI investment is inherently difficult to assess, as many of its benefits are intangible and materialize over time. This uncertainty makes AI-emphasizing firms particularly sensitive to shifts in investor sentiment. Strong AI-related disclosure may initially support optimistic expectations, but confidence may weaken when investors observe little corresponding evidence of technological development.

H2b: AI washing is negatively associated with investor sentiment.

The effect of AI washing on stock pricing may also depend on investors' ability to assess disclosure credibility. Institutional investors, generally with stronger incentives and greater resources to collect and process firm-specific information, are better positioned to detect inconsistencies between AI narratives and firms' actual capability [13,14]. Where institutional ownership is higher, discrepancies between AI communication and observable AI-related activity may therefore be identified and incorporated into prices more quickly.

H3a: The negative association between AI washing and stock returns is stronger for firms with higher institutional ownership.

The local policy environment may introduce a second source of variation in how investors evaluate AI-related disclosure. In regions where AI receives stronger policy support, greater market attention to AI may incentivize firms to emphasize their AI involvement, while simultaneously increasing investor scrutiny of such claims. Disclosure not backed by patents or recruitment is therefore more likely to be exposed in these regions. If stronger policy support improves the visibility of such discrepancies, the return discount associated with AI washing should be more pronounced in these regions.

H3b: The negative association between AI washing and stock returns is stronger in regions with greater local AI policy support.

3. Research design

3.1. Sample and data

Our sample comprises Chinese A-share firms from 2020 to 2025, spanning two years before and after the ChatGPT shock of late 2022. Financial, governance, institutional ownership, and sentiment data are obtained from the China Stock Market and Accounting Research Database (CSMAR). AI disclosure data are extracted from firms' annual reports on CNINFO. AI patents and media coverage data are drawn from the Chinese Research Data Services Platform (CNRDS). AI-related job postings are collected from 51Job, a major Chinese online recruitment platform. The initial sample includes 39,442 firm-year observations, which reduces to 24,885 after excluding missing values.

3.2. Variable construction

3.2.1. AI measures

We construct three core AI-related measures: *AI Talk*, *AI Walk*, and *AI Washing*.

AI Talk captures AI disclosure intensity measured by the frequency of AI-related keywords in the Management Discussion and Analysis (MD&A) section of annual reports. It follows the dictionary-based approach established in the textual analysis literature.

AI Walk captures substantive AI capability using AI-related patents and AI-related recruitment. AI patents are identified using keyword- or classification-based approaches and classified as either independent or collaborative, yielding four alternative measures. AI-related hiring is measured by the number of AI-related job postings.

AI Washing is our primary independent variable. Following the definition established in Section 2.2, a firm is classified as an AI washer ($AI_washing = 1$) if its AI disclosure is above the industry-year median, while both its AI patents and AI hiring are below their respective industry-year medians. For robustness, we construct four alternative washing indicators using different patent-identification methods ($AI_washing1$ – $AI_washing4$).

3.2.2. Dependent variables

The primary dependent variable is AnnualRet, measured as the firm's annual stock return.

For mechanism analyses, we employ two additional dependent variables:

Negative: the natural logarithm of one plus the number of negative media reports, capturing negative media attention. Higher values indicate more negative media coverage.

SentimentQ: a market-based measure of investor sentiment, constructed following Baker and Wurgler using a valuation decomposition approach [12]. Higher values indicate more optimistic investor sentiment, whereas lower values indicate more cautious investor sentiment.

3.2.3. Control variables

Following the asset-pricing and disclosure literature, we control for a set of firm characteristics: Size (natural logarithm of total assets), Lev (total liabilities divided by total assets), Age (natural logarithm of the number of years since listing plus one), Board (natural logarithm of the number of board directors plus one), Indep (proportion of independent directors), Big4 (indicator for Big Four auditor), Top1 (shareholding proportion of the largest shareholder), and ROA (return on assets).

3.3. Empirical model

We estimate firm-year fixed-effects panel regressions to examine whether AI washers earn lower stock returns. The baseline specification is:

$$Ret_{i,t} = \alpha + \beta AI_Washing_{i,t} + \gamma Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

where $Ret_{i,t}$ is the annual stock return for firm i in year t , $AI_Washing_{i,t}$ is the AI washing indicator, $Controls_{i,t}$ is the vector of control variables, μ_i denotes firm fixed effects, λ_t represents year fixed effects, and $\varepsilon_{i,t}$ is the error term. The coefficient β captures whether firms with a significant talk-action mismatch subsequently earn lower returns.

We apply the same specification to mechanism tests, replacing the dependent variable with *Negative* and *SentimentQ*, respectively, to examine whether AI washing increases negative media coverage and reduces investor sentiment.

4. Empirical results

4.1. Summary statistics

Table 1. Summary statistics

Panel A						
	count	mean	sd	min	median	max
AnnualRet	24885	0.083	0.367	-0.496	0.016	1.683
AI_washing1	24885	0.317	0.465	0.000	0.000	1.000
AI_washing2	24885	0.298	0.457	0.000	0.000	1.000
Panel B						
Industry				Frequency	Percent	
Computer, Communication & Other Electronic Equipment				1,333	18.14%	
Special Purpose Equipment Manufacturing				525	7.15%	
Software & IT Services				429	5.84%	
Electrical Machinery & Equipment				365	4.97%	
Pharmaceutical Manufacturing				328	4.46%	
Chemical Raw Materials & Products				300	4.08%	
Other Industries				4,067	55.35%	
Total				7,347	100.00%	

Panel A of Table 1 summarizes the main variables used in the baseline regressions. The estimation sample contains 24,885 firm-year observations, with a mean annual stock return of 8.3%. The average values of *AI_washing1* and *AI_washing2* are 0.317 and 0.298, so the two definitions classify roughly three out of ten observations as AI washing.

Panel B shows that the largest share of AI washing observations comes from Computer, Communication & Other Electronic Equipment (18.14%), followed by Special Purpose Equipment Manufacturing (7.15%) and Software & IT Services (5.84%).

Across provinces, Shanghai and Guangdong have the highest reported AI washing ratios, at 36.54% and 36.30%, while Hainan and Shanxi have the lowest, at 17.34% and 16.24%.

4.2. Main results

Table 2. Main regression results

	(1) AnnualRet	(2) AnnualRet	(3) AnnualRet	(4) AnnualRet
washing1	-0.022***	-0.017***		

Table 2. (continued)

	(-3.48)	(-2.87)		
washing2			-0.015**	-0.011*
			(-2.37)	(-1.83)
Size		-0.271***		-0.271***
		(-16.14)		(-16.14)
Lev		0.388***		0.388***
		(9.15)		(9.16)
Age		0.188***		0.188***
		(16.21)		(16.25)
Board		0.039***		0.039***
		(2.79)		(2.80)
Indep		-0.013		-0.013
		(-0.33)		(-0.33)
Big4		-0.021		-0.022
		(-0.88)		(-0.91)
Top1		-0.164*		-0.165*
		(-1.87)		(-1.88)
ROA		1.543***		1.542***
		(24.34)		(24.32)
_cons	0.090***	5.546***	0.088***	5.552***
	(48.26)	(14.98)	(40.41)	(14.98)
Year_FE	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes
N	24885	24885	24885	24885
r2_a	0.102	0.154	0.102	0.154

Table 2 reports the main regression results examining the relationship between AI washing and stock returns. For *AI_washing1*, the coefficient increases from -0.022 to -0.017 after firm-level

controls are added, with both estimates statistically significant at the 1% level. The corresponding estimates for *AI_washing2* are -0.015 and -0.011 , respectively, with the specification including controls statistically significant at the 10% level.

Adding the controls reduces the magnitude of the estimated coefficients but does not change their negative sign. The results are statistically stronger for *AI_washing1*, while both measures point to a negative association between the disclosure-investment gap and subsequent annual returns. This result accords with H1.

4.3. Robustness checks

Table 3. Robustness checks

	(1) AnnualRet	(2) AnnualRet	(3) AnnualRet	(4) AnnualRet
washing3	-0.024^{***} (-3.56)	-0.019^{***} (-2.87)		
washing4			-0.019^{***} (-3.05)	-0.016^{**} (-2.53)
Size		-0.271^{***} (-16.13)		-0.271^{***} (-16.15)
Lev		0.387^{***} (9.14)		0.388^{***} (9.15)
Age		0.187^{***} (16.17)		0.188^{***} (16.22)
Board		0.040^{***} (2.82)		0.039^{***} (2.80)
Indep		-0.013 (-0.32)		-0.013 (-0.33)
Big4		-0.021 (-0.87)		-0.021 (-0.89)
Top1		-0.164^* (-1.87)		-0.164^* (-1.87)

Table 3. (continued)

ROA		1.543*** (24.35)		1.543*** (24.33)
_cons	0.088*** (64.65)	5.545*** (14.97)	0.089*** (46.07)	5.549*** (14.99)
Year_FE	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes
N	24885	24885	24885	24885
r2_a	0.102	0.154	0.102	0.154

To ensure robustness, we reconstruct the AI washing indicator using classification-based patent measures (*AI_washing3* and *AI_washing4*) rather than the keyword-based measures used in the baseline analysis. As shown in Table 3, the coefficients on *AI_washing3* and *AI_washing4* remain negative and statistically significant with and without firm-level controls. The negative return pattern is therefore not limited to the patent-identification approach used in the baseline measure.

4.4. Mechanism tests

The estimates for media coverage and investor sentiment are consistent with the predicted directions.

For negative media coverage, the coefficients on *washing1* and *washing2* are 0.018 and 0.024, respectively. The positive coefficients indicate that AI washers tend to appear more frequently in negative media reports.

For *SentimentQ*, the coefficients are -0.029 for *washing1* and -0.025 for *washing2*, both significant at the 5% level. The negative coefficients suggest that investor sentiment is lower, on average, for observations classified as AI washing.

Overall, the media coverage and sentiment estimates accord with H2a and H2b. We interpret these findings as two observable market responses accompanying AI washing, rather than formally established causal channels.

Table 4. Mechanism tests

	(1) negative	(2) negative	(3) SentimentQ	(4) SentimentQ
washing1	0.018* (1.73)		-0.029** (-2.48)	
washing2		0.024** (2.23)		-0.025** (-2.13)

Table 4. (continued)

Size	0.018 (0.78)	0.018 (0.78)	-0.494*** (-12.04)	-0.494*** (-12.04)
Lev	0.370*** (5.31)	0.370*** (5.30)	0.883*** (8.79)	0.883*** (8.80)
Age	-0.071*** (-3.46)	-0.072*** (-3.51)	-0.211*** (-7.76)	-0.211*** (-7.74)
Board	0.158*** (7.11)	0.157*** (7.11)	0.091*** (3.49)	0.091*** (3.50)
Indep	-0.256*** (-3.86)	-0.257*** (-3.87)	-0.069 (-0.98)	-0.069 (-0.98)
Big4	0.036 (0.71)	0.036 (0.71)	-0.030 (-0.49)	-0.031 (-0.50)
Top1	-0.060 (-0.42)	-0.060 (-0.42)	-0.403** (-2.12)	-0.403** (-2.12)
ROA	-0.178* (-1.81)	-0.179* (-1.81)	0.278* (1.84)	0.277* (1.84)
_cons	2.790*** (5.50)	2.788*** (5.49)	11.034*** (12.17)	11.037*** (12.18)
Year_FE	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes
N	20673	20673	23487	23487
r2_a	0.693	0.693	0.663	0.663

4.5. Heterogeneity analyses

Table 5 reports the heterogeneity test results, examining whether the negative effect of AI washing varies with institutional ownership and local AI policy support. For firms with above-median institutional ownership, the coefficient on *washing1* is -0.021 and significant at the 5% level. The corresponding estimate for the low-ownership group is smaller in magnitude (-0.009) and statistically insignificant. The policy split yields a similar pattern: the coefficient is -0.030 in

regions with stronger AI policy support and -0.010 in the remaining regions, with statistical significance observed only in the former group.

Table 5. Heterogeneity analyses

	(1) AnnualRet	(2) AnnualRet	(3) AnnualRet	(4) AnnualRet
washing1	-0.021** (-2.51)	-0.009 (-0.96)	-0.030** (-2.49)	-0.010 (-1.24)
Size	-0.257*** (-10.93)	-0.326*** (-12.67)	-0.231*** (-8.13)	-0.280*** (-13.12)
Lev	0.507*** (7.41)	0.324*** (5.56)	0.316*** (3.53)	0.357*** (6.55)
Age	0.157*** (9.46)	0.218*** (12.64)	0.184*** (7.92)	0.190*** (12.41)
Board	0.046** (2.29)	0.026 (1.30)	0.028 (1.00)	0.033* (1.83)
Indep	-0.090 (-1.59)	0.073 (1.23)	0.099 (1.20)	-0.023 (-0.44)
Big4	-0.037 (-1.41)	0.016 (0.27)	0.008 (0.17)	-0.043 (-1.20)
Top1	-0.276** (-2.22)	-0.197 (-1.34)	-0.503*** (-3.04)	0.012 (0.12)
ROA	1.667*** (15.62)	1.459*** (18.22)	1.396*** (10.79)	1.560*** (19.06)
_cons	5.396*** (10.23)	6.625*** (11.90)	4.802*** (7.71)	5.694*** (12.21)
Year_FE	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes
N	12487	12398	8526	16359
r2_a	0.146	0.188	0.163	0.159

These estimates are in line with H3a and H3b, indicating that the negative effect of AI washing is more pronounced in firms with higher institutional ownership and in regions with stronger local AI policy support.

5. Discussion and implications

5.1. Summary of findings

Based on a sample of Chinese A-share listed firms from 2020 to 2025, our results consistently show that a larger gap between AI disclosure and observable AI investment is associated with weaker subsequent stock performance. This association is robust to the alternative patent-identification measures tested. These findings support the view that investors evaluate AI-related disclosure jointly with observable signals of firms' underlying AI activities.

The additional analyses provide context for these findings. AI washers are associated with more negative media coverage and lower investor sentiment, while the return coefficient is more negative in the high-institutional-ownership and strong-policy-support subsamples. Although these patterns do not establish causal mechanisms, they help identify settings in which the AI disclosure–investment gap is more closely associated with market outcomes.

5.2. Contributions

The main contribution of this study is the joint use of disclosure, patents, and hiring to characterize AI washing. Patent activity and hiring capture different aspects of corporate AI activity, so using both reduces reliance on any single proxy when evaluating firms' AI-related statements.

The findings also provide evidence from the Chinese A-share market that the market response to AI disclosure depends on the observable activities accompanying such disclosure. High AI-related disclosure alone is not associated with stronger subsequent stock performance when observable patent and hiring activity remain limited. The results involving media coverage, investor sentiment, institutional ownership, and local policy further suggest that the information environment and institutional context matter when investors evaluate AI-related claims.

5.3. Limitations

Our measure of AI washing depends on relative thresholds within each industry-year. Firms are classified according to whether AI disclosure, patent activity, and AI-related recruitment fall above or below their corresponding medians. This design allows the measure to account for differences across industries and years, but the resulting classification may still be sensitive to the choice of cutoff. Although the main findings remain similar across four patent-identification methods, alternative threshold definitions could produce different sets of AI washing firms.

A second limitation concerns the coverage of recruitment data. Hiring information is available for only 8,488 of the 39,442 firm-year observations in the initial sample, and only 1,583 of these observations involve AI-related hiring. The hiring dimension therefore contains substantially less information than the disclosure and patent measures. This uneven coverage may reduce the precision with which human-capital investment is captured and should be considered when interpreting the AI washing classification.

Finally, the empirical results identify systematic associations rather than intentional misrepresentation by individual firms. A firm classified as an AI washer may have reasons for limited patenting or recruitment that are not observable in our data, and the analysis does not establish that firms deliberately exaggerate their AI capabilities. The fixed-effects specifications and control variables account for several observable and time-invariant firm characteristics, but they

cannot rule out all unobserved factors that may influence both AI-related disclosure and stock returns.

6. Conclusion

We use disclosure, patent, and recruitment data for Chinese A-share firms from 2020–2025 to identify firms that discuss AI more intensively than their observable investment would suggest. These firms have lower subsequent annual returns across the alternative patent definitions considered in the analysis. They are accompanied by more negative media coverage and lower investor sentiment, and the return relation is more pronounced in the high-institutional-ownership and stronger-AI-policy subsamples.

The classification captures a discrepancy in observable firm behavior, not evidence of deliberate deception. Recruitment data coverage is also incomplete, and the median-based definition represents only one approach to identify the disclosure–investment gap. These limitations leave room for future research to use other measures of AI investment and research designs to further examine the relationship between AI disclosure, observable AI activity, and market outcomes.

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