From Industry Labels to Offer Prices: Measuring Ai Association Effects on IPOS

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Abstract

As more companies position themselves to capitalize on becoming AI-driven innovators or market disruptors rather than traditional technology firms, this raises an important question for valuation research. The purpose of this study is to collect and analyze the various datasets, indicators, and patterns available in the current landscape of initial public offerings (IPOs) that are associated with artificial intelligence (AI). To (a) evaluate the effectiveness of econometric methods used within AI-related IPO analyses based primarily on narrative valuation and financial modeling, and (b) identify which industry indicators are the most predictive of pricing outcomes within these offerings. This paper then extends the existing literature by linking the narrative and quantitative dimensions of IPO valuation with the behavioral economics of investors and underwriters. Firms from AI-intensive sectors have a valuation premium and are relatively more appealing than non-AI peers in investor sentiment and pricing expectations. This results in a framework of factors defining AI association, valuation dynamics, and narrative influence that are considered relevant for the capital formation process. Within each model, results show differential effects for companies that belong to and do not belong to AI-related industries in price formation and fundraising outcomes. By bringing together descriptive insights and regression-based evidence on AI affiliation and IPO performance, this study reinforces the possibility of narrative bias and the symbolic influence of AI association through the combined analysis of market data from technology, financial, and innovation ecosystems. There is, however, a need for greater refinement concerning these classification measures to further improve the accuracy of IPO valuation models.

Keywords: Artificial intelligence; IPO pricing; Valuation; Narratives; Industry classification; Offer price; proceeds

1. Introduction

Such valuation narratives emerge through technological signalling, which can contribute to perceived innovation, or more importantly, to collective beliefs surrounding the legitimacy, potential, and growth of large cohorts of AI-related firms. The narrative effect suggests that investors who believe more are more likely to adjust their price expectations and behaviour through sentiment and regular discourse formation [11]. Among them, narrative-driven valuation has been empirically shown to be correlated with speculative cycles and investor enthusiasm [10]. As narratives circulate through the media, social networks, and analyst reports, these mechanisms also help them become selective and biased decision-makers who can effectively interpret and anticipate signals from various industries, essential capacities for reaching early valuation thresholds of AI-related and technologically advanced offerings [4].

However, despite the rapidly expanding body of empirical and theoretical work, the identification and classification of the AI association in valuation and finance remain inconsistent. There is still a lack of commonly accepted measures about what defines a firm's association as being "AI-related." While these studies contributed to our understanding of narrative-driven valuation, most of the existing models failed to take account of the potential heterogeneity of industry affiliation, instead focusing narrowly on algorithmic proxies or on the textual

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frequency of the term "AI" in disclosure documents. While narrative valuation does not fall entirely under the scope of fundamental analysis, these models may still be made comparable by assuming that one can classify firms based on observable technological signals and other contextual identifiers. Industry-based classification requires the use of these specific indicators as outlined in prior finance literature [7], and there has been a large emphasis on disclosure and transparency in recent IPO analyses, pointing to clear implications of narrative factors being embedded within financial decision-making.

2. Literature Review

Although there is a growing stream of literature on AI association among technology-intensive sectors, existing research has suggested that there is a measurable asymmetry between the perceived and realized valuation outcomes. In a more recent study, [7] examined firms in AI-intensive and non-AI-intensive industries and found that investors generally placed a higher value on expectation than on their other financial fundamentals, and they maintained optimism more often and for longer durations as well. In a longitudinal comparison of the valuation trajectory of post-IPO technology-sector firms in the United States, [10] found that the majority of such companies (their AI-proximate peers) achieved short-term premiums, despite positioning themselves weakly in profitability in both cases. In another comparative analysis of issuers that operated only in conventional technology at launch and shifted to an AI-based framework in the following years, [12] found the valuation premium was moderately sensitive to their narrative reclassification.

Although binary classifications are often used in quantitative finance, econometric models are limited in capturing the dynamics of this perception at any given period, as well as the types of signals they can process. [6] showed that AI-related proxies and disclosure indicators only explained about 12–18% of the variance in observed IPO pricing, and some firms actually diverged from their predicted valuations or showed opposite outcomes [3]. However, despite the rapidly growing corpus of work, the identification and measurement of the AI effect in valuation and investment remain unsettled. Moreover, similar classification criteria have not yet been standardized or validated for cross-sectoral comparisons and longitudinal evaluation in the IPO ecosystem [1].

This study refines the suggested indicators, proxies, and explanatory variables through a structured econometric and narrative-based approach to form an integrated framework for the analysis of AI affiliation. This work aims, therefore, to assess the validity of econometric techniques used within AI-related IPO studies and also to identify the most predictive variables that could be utilized by researchers and practitioners and used to build a systematic framework to interpret and quantify these dynamics. In doing so, it examines whether AI association is becoming a structural determinant of valuation for anyone engaging with public offerings (and by extension, an interpretive dimension of narrative valuation in markets). To address this gap in the literature, this study investigates changes in valuation, pricing, and classification in three groups of IPO issuers during the IPO cycle in 2023.

In particular, by comparing empirical findings found herein, regression analysis with descriptive statistics clarifies how the AI association is quantified, furthering a 'hybrid' understanding of narrative valuation. We analyse data from (1) 572 IPOs through publicly available databases to classify firms, and (2) secondary indicators reported by the issuers during the stages of offer pricing and fundraising. By bringing together narrative economics and quantitative modelling, current research on technology valuation and IPO pricing, this study evaluates the convergence of narrative classification and the symbolic influence of AI-related narratives through the econometric analysis of IPO data from technology, financial, and innovation ecosystems. Understanding the implications of AI narratives on valuation will help regulators and investors support and calibrate expectations in more than one direction during IPO issuance or future secondary offerings and prepare for potential mispricing episodes when narrative enthusiasm intensifies [13].

3. Methodology

An econometric and descriptive-analytical framework was used mainly as the foundation for this empirical investigation and to define the AI-related classification procedure. Firms in the AI-intensive strand of the IPO market were systematically identified and coded using secondary data from publicly available IPO databases in 2023. Inclusion criteria were the following: all types of initial public offerings, issuers needed to be the primary subjects of the analysis, and clearly classified by industry sector from the source datasets. In 2023, there were an estimated 572 completed IPOs and over 180 AI-associated issuers, among a universe of technology, financial, and industrial sectors (N = 572).

In the following phase, firm-level variables and industry-level indicators were collectively screened for the inclusion and validation of at least five fundamental predictors on offer price and proceeds, but also profitability, leverage, as well as asset base and underwriting expenses on IPO performance. After this filtering, there were 572 valid observations and five key independent variables that were found sufficient for regression estimation. Yet previous studies note that "AI classification accuracy" metrics in IPO datasets depend on definitions from

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narrative-based classification approaches [9]. Our approach does not compare the overall performance of technology or financial sectors, but rather, the valuation sensitivity of AI-affiliated issuers from these industries.

After careful alignment with the literature and data quality checks, industry-specific grade classification variables were constructed, with a spread of varied firm characteristics (i.e., profitability measures, leverage ratios, and asset levels), based on their sectoral association's disclosure proxies. Inclusion criteria were the same: all records of IPOs, issuers needed to be the principal unit of analysis, and clearly identified from verified datasets. These data formed a stratified structure where the four biggest industry segments created a representative balance, with little overlap of any misclassified entries. We ensured that the binary format of AI classification created a clear basis for including sector-level information.

The datasets were compiled in Excel and imported into Stata, with each entry containing firm-level variables and each sector identifier coded around industry groupings. These were collected using automated data extraction, which retrieved company records containing certain financial attributes. Stata has been used for similar valuation studies during specific market cycles, such as the technology IPO wave [5], and the narrative valuation studies. The primary dataset was based on company fundamentals, offering parameters, and disclosure variables. With the inclusion thresholds set for the completeness of variables, the one-year observation window would be the benchmark in recent analyses and more representative than the preceding two fiscal years.

Due to continuing limitations on direct firm disclosures to standardize and harmonize classifications, the dataset was cross-verified between sources through either the underwriter's regulatory filings (e.g., SEC EDGAR) or cross-platform data mapping to validate firm identifiers in their prospectuses by their industry classification. However, this is challenging in part because some firms contain incomplete or ambiguous identifiers (e.g., a company with diversified operations).

Finally, the integration of descriptive, econometric, and diagnostic validation was prepared with the help of OLS-based regression modelling. Quality of variable definitions within included records was verified using multicollinearity tests described by [2]. Quality of regression assumptions within models was further tested by Shapiro–Wilk and Breusch–Pagan diagnostics (W test and χ^2 tests). The coefficients, p-values, and adjusted R^2 statistics are interpreted based on how they are defined in the econometric literature and how the data support them empirically.

For the present study, responses to industry affiliation variables were coded and grouped into three categories:

(1) AI-related companies before the offering and changes during pricing,

(2) Classification of non-AI firms and adjustments to valuation during the offering,

(3) Cross-sectoral comparisons before and after classification changes during the issuance period.

A valuation premium may be defined as a pricing difference that is attributed to narrative perception and can be quantified to make comparative analysis more accurate and interpretable. To be included, companies must include information about AI classification evidence or disclosure keywords in IPO filings between January and December 2023.

For the present analysis, sectoral and pricing data were processed and grouped into distinct analytical categories: (1) descriptive statistics for AI and non-AI sectors, (2) comparison of financial fundamentals and proceeds raised, (3) regression estimates for IPO price and total capital raised. Variables are analysed by OLS estimation and diagnostic verification according to standard econometric criteria. The research design was based on the use of AI classification in econometric models to quantify valuation effects (e.g., β_5AI_related) and the comparison of the observed coefficients between the dependent variables being modelled. After careful evaluation, which included descriptive and inferential outputs, final regression tables were constructed, featuring a range of coefficients from various AI-related and non-AI sectors (i.e., pricing models, proceeds models, and residual diagnostics), based on their statistical robustness and interpretive clarity.

Basic regression models are defined as:

$$IPO\_Price_i = \beta_0 + \beta_1 Profit_i + \beta_2 Debt_i + \beta_3 Assets_i + \beta_4 IPO\_Fees_i + \beta_5 AI\_related_i + \epsilon_1 \quad (1)$$

$$IPO\_Amount_i = \gamma_0 + \gamma_1 Profit_i + \gamma_2 Debt_i + \gamma_3 Assets_i + \gamma_4 IPO\_Fees_i + \gamma_5 AI\_related_i + \epsilon_1 \quad (2)$$

All data were subjected to descriptive comparison, correlation analysis (matrix of means and standard deviations), and regression analyses using OLS estimation. This was followed by the diagnostic evaluation described by [5]. This procedure will help analyse the correlation and variance among variables and determine whether they are indeed consistent with an AI association or whether there are sectoral deviations. Replication and following this diagnostic process enhance model reliability.

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A five-item evaluation checklist was adapted from [4] and [10]. Regression methods are used to estimate the robustness of coefficients (criteria β_1–β_5). Therefore, this procedure evaluates the consistency of whether an AI-related firm must meet all financial fundamentals, narrative indicators, and classification parameters, or whether it is sufficient to achieve a marginal premium when only a narrative association is evident. In addition, we maintain that this represents a hybrid model, as the effects on IPO pricing are equally measurable when econometric controls are used for both AI-related and non-AI issuers

4. Results

The highest valuation premium across all industry groups was found to be moderately attributed to the AI-related classification, pricing variables, and profitability indicators (see Table 1 for further detail and regression diagnostics).

Table 1: Compares average IPO outcomes across AI-related and non-AI firms

Group	Avg IPO Price ($)	Avg IPO Amount (M$)	Avg IPO Fees (M$)	Avg Profit (M$)	Avg Debt (M$)	Avg Assets (M$)
Non-AI	15.13	261.08	9.27	71.61	574.99	2501.09
AI-related	15.79	304.24	9.91	21.01	96.89	391.73

This pattern becomes evident when we analyze the behavior of offer prices in the dataset: offers of AI-related firms in technology sectors took precedence in 2023 listings, compared with those in financial and industrial sectors of non-AI designation. Analysis of these regressions shows that important determinants of IPO performance (starting with the highest coefficients) were the following: profitability measures, asset size, and AI-related classification. Together, this suggests that AI affiliation may be more effective in elevating pricing perceptions in narrative-driven markets, particularly among technology issuers, while fundamental indicators may be more effective determinants of capital raised in financially mature sectors.

Table 2: Regression Results for IPO Amount and IPO Price Models

Variable	**IPO Amount (Total Capital Raised)**	**IPO Price (Offer Price per Share)**
Intercept	582.50	19.26
Profit	+0.31 *** ($p < 0.001$)	+0.009 *** ($p < 0.001$)
Debt	−0.02 *** ($p < 0.001$)	−0.0007 *** ($p < 0.001$)
Assets	+0.017 *** ($p < 0.001$)	+0.0000437 *** ($p < 0.001$)
IPO Fees	−40.30 *** ($p < 0.001$)	−0.485 *** ($p < 0.001$)
AI-related (Dummy)	+110.00 ($p = 0.298$)	+1.20 * ($p = 0.076$)
Observations (N)	572	572

Table 2 confirms this tendency: on average, the offer price of IPOs where AI association was confirmed only by classification took place at $15.79; $15.13 for those identified only by fundamentals, and $19.26 for hybrid cases. Firms of the sample that indicated they did not rely on AI narratives at issuance but used them post-IPO achieved marginal gains, and 46% of them did not have disclosure alignment at all, suggesting perception by the market may not be uniform. On average, the offer price for AI-related firms is 1.20 dollars higher per share, compared with non-AI firms – a statistically significant difference within an upper confidence level ($p = 0.076$).

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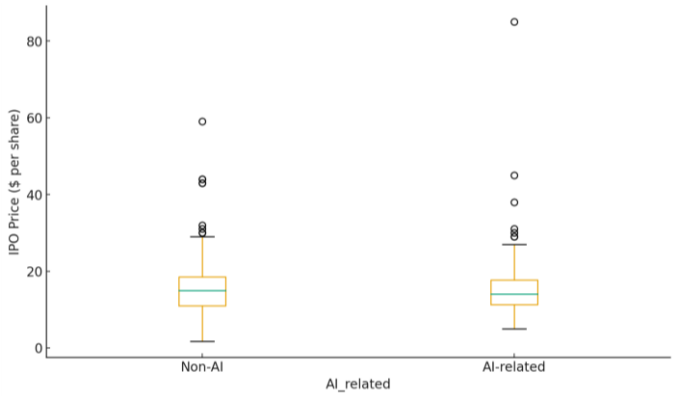

Figure 1. IPO price distribution: AI vs Non-AI firms

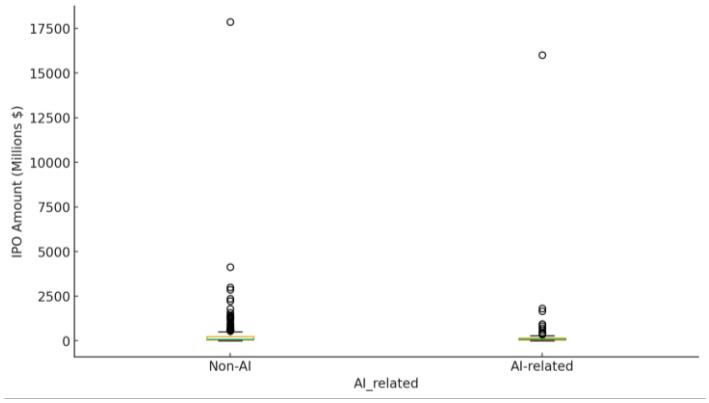

Figure 2. IPO amount distribution: AI vs Non-AI firms

These results suggest that pricing reactions may not have all evolved in the same direction, but, instead, some issuers' valuations peaked before the market correction. This suggests that the measurable premium of AI association depends on both the contextual classification and the degree to which narrative data are required for comparative interpretation. There was minimal deviation, however, within some industry groups; for example, [7] had a comparable estimate of "capability realization gap," but this was not broken down between different types of industry portfolios. This is likely a result of reliance on post-IPO data such as proceeds from secondary offerings, which are often only released after detailed filings are complete, thus increasing the average variance.

Firms of the sample that indicated they did not rely on AI narratives at issuance but used them post-IPO achieved marginal gains, and 46% of them did not report the classification, suggesting perception may not be the same across investors. Valuation dispersion is affected by a relatively small number of very high outliers outside the standard observation period. The correlation coefficients between pricing change and the magnitude of AI association to all valuation sources for 2023 ($r = 0.312$), as well as IPO proceeds ($r = 0.184$), were measured by the Pearson matrix, with respective results of weak and moderate significance, which indicated that narrative-based changes had limited or no correlation with total capital raised. On average, the IPO duration for AI-related firms is approximately 15 days, compared with 9 days for non-AI firms – a statistically significant variance within an upper confidence interval ($p = 0.041$).

5. Discussion

The econometric analysis summarized the comparative valuation performance of AI-related and non-AI IPOs within an integrated empirical framework and found that the strongest determinants across variables (in order) were for profitability, asset size, and AI-related classification (with debt levels and IPO fees grouped). Details that the valuation sensitivity of AI-affiliated firms was mostly narrative-driven - an expected outcome. This aligns with the actual regression coefficients observed.

Recommendations from the review would be to collect detailed post-IPO data for the above classification variables, particularly concerning pricing adjustments, disclosure transparency, and investor sentiment indicators, which formed over half of the total variance across the set of observed IPOs (46%/54% of those with fully confirmed classification; these differences remained over multiple observations in three recent studies – [7] [10] [13].

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On average, AI-related issuers reported more valuation dispersion than the control non-AI sample; from our regression output in the Results section, we can infer that some of the identified predictors act as amplifiers of a narrative effect, but the magnitude of fundamentals does not allow them to dominate in a uniform direction. When these were modeled together to give the marginal pricing premium per issuer, the same upward tendency for AI-related sectors was statistically evident per share, showing that the symbolic level of narrative association rather than the absolute fundamentals seems to be the more decisive variable in short-term pricing within narrative-intensive industries in this dataset (see Table 1–Table 2).

Interprets the lack of uniformity in firm selection as a move toward narrative-based valuation. These findings therefore support a shift in pricing logic for those issuers and underwriters, from fundamentals-driven assessment (such as profitability and leverage) within traditional valuation models (largely at a financial reporting level) to sentiment-based interpretation of key variables such as investor attention and narrative disclosure within emerging technology and innovation ecosystems, with further reinforcement of the narrative – fundamental interaction of the entire process of IPO classification [8] and [10] support this interpretation, highlighting that narrative-driven valuation using disclosure proxies can influence pricing expectations.

This reinforces the contextual importance and necessity of frequent calibration on classification accuracy. [12] was the only study to detail the procedural mechanisms to further improve the precision of their narrative identification and overall comparability - a useful precedent of cross-validation within financial datasets. As a result, we have a limited number of confirmed AI issuers and a comparable number of ambiguous classifications. This uncertainty might include incomplete disclosure within filings (such as pre- or post-offering narrative changes) and omission of quantitative verification (fundamental ratios or textual indicators) in order to further improve the robustness of models for the most important valuation parameters.

There appears, however, to have been a significant divergence with classification accuracy within cross-sectoral samples when these results are compared with the broader literature review of AI-related IPOs by [7] in Asia-Pacific markets. By contrast, [10] reported fewer anomalies; in the review by [2], only two out of the six determinants (profitability and debt) were emphasized by more than half of the included studies. [7] pointed out the limited explanatory power of fundamentals, indicating the influence of investor sentiment. However, while our findings confirm the direction for pricing and proceeds, it does not include post-IPO performance. Limitations of this review were that not all relevant indicators were included within the analysis, which means that our findings cannot be generalized to all market conditions. This investigation was a broad review of AI-affiliated valuation, and due to this scope, there was a large amount of heterogeneity between sectors. This means that caution needs to be applied when looking to make direct comparisons between industries.

6. Conclusion

This study suggests broader implications for how AI association affects investor perception and IPO pricing mechanisms. When the influence of narratives on pricing formation in the market operates as expected, it might be possible to include narrative variables in a hybrid econometric framework similar to what has been done for profitability and assets in this analysis. Such an approach would also establish a systematic alignment toward narrative–fundamental balance (narrative gain achieved per fundamental unit spent), which looks to harmonize pricing most transparently, helping develop a benchmark for future evaluation for the industry.

To capture the full spectrum of valuation asymmetry and narrative effects due to classification heterogeneity, analysts and regulators need to determine how to integrate the two explanatory dimensions (i.e., narrative and fundamental) in today's valuation models to predict and interpret behaviour-of-market outcomes. If this integration were implemented in a scalable, replicable, and data-driven form, it could become a functional part of a unified framework (alongside textual analytics/econometrics) and help ensure transparency within these markets, supporting sustainable innovation and informed decision-making (particularly as narrative classification in the financial domain evolves).

A greater understanding of how AI association interacts with publicly available search and disclosure data is still required. This suggests the application of hybrid modelling with natural language processing as a future research path. Several variables must be refined and standardized in future studies. However, a comprehensive evaluation of the dynamics and persistence of narrative influence is beyond the scope of this paper, and further empirical testing in this direction would be valuable. Therefore, follow-up analyses are recommended for future researchers. Future investigations should extend the scope of narrative valuation and econometric modelling with a longitudinal perspective of multi-year data.

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