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Comparing the AI-boom with the dot-com bubble: Are we in a bubble?

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Abstract

The rapid rise of artificial intelligence (AI) has triggered a substantial revaluation of technology stocks and renewed concerns about the emergence of a speculative bubble comparable to the dot-com episode of the late 1990s. As AI-related firms increasingly dominate equity market performance, understanding whether current valuations reflect irrational exuberance or genuine economic transformation has become an important question for investors, policymakers and academics. This paper investigates whether the current AI boom resembles the dot-com bubble by comparing the two episodes along two complementary dimensions: the relationship between firm valuations and fundamentals, and the behaviour of institutional investors. The analysis first examines whether valuation multiples are explained by observable fundamentals during the dot-com period (1998–2000) and the AI boom (2022–2025) and then studies whether institutional investors actively contributed to the expansion of AI-related equity prices. The results show that, unlike during the dot-com bubble, AI-era valuations remain significantly linked to profitability, firm scale and capital structure, suggesting that current prices are more closely anchored to fundamentals. At the same time, hedge funds and other active institutional investors play a central role in increasing exposure to AI-related firms, exhibiting behavioural patterns similar to those observed during past speculative episodes. Overall, the findings suggest that while the AI boom shares speculative and behavioural features with the dot-com bubble, it cannot be interpreted as a direct repetition of it, as stronger underlying fundamentals distinguish the current episode from the late-1990s technology bubble.

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1. Introduction

1.1 Contribution and Structure of the Paper

The rapid rise of artificial intelligence has triggered a substantial revaluation of technology stocks, drawing comparisons to previous episodes of speculative excess, most notably the dot-com bubble of the late 1990s. In 2025, AI-related firms appeared to have contributed to major equity indices' record highs, with valuations reaching levels that, on some metrics, approach those observed during past periods of market exuberance ([Financial Times, December 9, 2025](#)). At the same time, policymakers and central banks have warned that such valuations may pose risks to financial stability if expectations around AI's economic impact were to reverse abruptly ([Financial Times, October 8, 2025](#)). These developments raise a central question: does the current AI boom represent a new instance of a dot-com style speculative bubble, or does it reflect fundamentally different economic dynamics?

This paper addresses this question by separating the comparison between the dot-com bubble and the AI boom into two channels: whether valuations are supported by firm fundamentals, and whether institutional investors are actively amplifying the boom. The first channel examines whether AI-related valuations remain connected to observable firm characteristics, such as profitability, growth, scale and capital structure, or whether they display the weaker link with fundamentals that characterised the dot-com period. This is tested through cross-sectional valuation regressions and a structural-break test comparing the two eras. The second channel analyses the behaviour of institutional investors, since evidence from the dot-com episode suggests that sophisticated investors may contribute to bubble dynamics rather than simply correcting mispricing. Using quarterly institutional holdings, the paper decomposes changes in AI portfolio exposure into passive price effects and active trading decisions, allowing the analysis to distinguish mechanical exposure increases from deliberate accumulation by institutional investors.

The structure of the paper is as follows: [Section 2](#) reviews the literature on technology bubbles, focusing on an explanation of the dot-com bubble and investor behaviour. [Section 3](#) provides descriptive evidence on the AI boom, comparing price dynamics, valuation multiples and firm fundamentals to the dot-com period. [Section 4](#) presents the data and methodology for the two empirical exercises. [Section 5](#) reports the empirical results, first analysing the relationship between valuations and fundamentals, and then examining institutional trading behaviour. [Section 6](#) concludes.

1.2 Findings

The empirical analysis yields two main findings. First, the relationship between firm fundamentals and valuation multiples differs substantially between the dot-com and AI periods. During the dot-com bubble,

valuations are only weakly related to observable fundamentals, with most variables failing to explain cross-sectional differences in valuation multiples. By contrast, in the AI period, valuations are significantly associated with profitability, firm size and capital structure, indicating that prices are more closely anchored to underlying economic characteristics. This result is confirmed by the structural-break test, which rejects the hypothesis that the two periods share the same pricing relationship.

Secondly, the behaviour of institutional investors in the AI boom exhibits similarities to that observed during the dot-com bubble, but also important differences. Hedge funds and other active investors play a central role in increasing exposure to AI-related firms, consistent with a rational “bubble-riding” strategy in which investors participate in rising markets while anticipating future corrections. However, unlike the dot-com period, where institutional investors remained net buyers even close to the market peak, the AI period shows evidence of partial rebalancing and more heterogeneous behaviour across investor types.

Taken together, these findings suggest that while the AI boom shares behavioural features with past speculative episodes, it differs in a key dimension: valuations are more closely linked to fundamentals than during the dot-com bubble. This does not imply that current valuations are necessarily justified or that a correction cannot occur. Rather, it indicates that the AI boom cannot be interpreted as a direct repetition of the dot-com bubble. Instead, it reflects a more complex interaction between strong underlying fundamentals, technological uncertainty and strategic investor behaviour.

2. Literature Review

This section reviews the literature on technology bubbles, focusing on the dot-com episode as a benchmark and examining the role of investor behaviour. It synthesizes evidence on how prices can diverge from fundamentals, how behavioural biases and limits to arbitrage sustain such deviations, and how changing valuation frameworks may justify them. The aim is to establish a conceptual framework to assess whether similar mechanisms are present in the current AI boom.

2.1 The Dot-Com Bubble: Stylized Facts and Key Explanations

The dot-com bubble of the late 1990s represents one of the most extensively studied episodes of asset price inflation, offering a benchmark for analysing whether the contemporary technological boom of artificial intelligence exhibit similar characteristics.

Ofek and Richardson (2002) investigate the run up towards how Internet firms became 6 per cent of the United States public equity during February and represented 19 per cent of daily trading volume while having aggregate negative earnings. They conclude that this was driven by market irrationality that could not be corrected due to limits to arbitrage, so it drove prices away from fundamentals. To make their case,

they develop 3 explanations: (1) the implication of traditional valuation metrics for Internet companies; (2) corporate events that broke the law of one price and rational incorporation of new information; and (3) the excess volatility of Internet stocks compared to the ‘old economy’.

Firstly, [Ofek and Richardson \(2002\)](#) find that in order to justify dot-com companies’ valuations, earning growth would have to range between 12 percent for 30 years and 40.6 percent for 10 years, which means that the required growth rates were from 50 to 100 percent higher than the highest 2 per cent of existing firms. These results held with a cost of capital of 0% and for the entire sector, not just the top players. Therefore, there is evidence that investors were being highly optimistic about the future growth of the technology.

Secondly, IPO’s first day, spin-offs and name changes represented corporate events that broke the rationality of markets with a weakening of the law of one price and information inefficiency. [Ofek and Richardson \(2002\)](#) documented that in the second quarter of 1999 through the first quarter of 2000 there were 400 IPOs, from which 70 percent corresponded to the Internet sector and raised over \$33 billion dollars. During such period, 146 IPOs doubled the stock price in the first day, phenomenon quite rare over the two prior decades. Since the first day of the IPO is when investors can get hold of the shares, these large first day increases are consistent with a shift towards an optimistic investor-base. Moreover, [Lamont and Thaler \(2003\)](#) document several cases of equity carve-outs in which identical or nearly identical cash flow claims were priced inconsistently in financial markets. The most prominent example is the 3Com/Palm case, where market prices implied that the non-Palm assets of 3Com had a negative value, an outcome that is economically implausible. These discrepancies persisted despite being widely recognized and publicized, suggesting that market inefficiencies were not immediately arbitrated away. Such evidence challenges the strong form of the efficient market hypothesis, as prices appear to deviate substantially from any reasonable estimate of fundamental value. Furthermore, [Cooper et al. \(2001\)](#) find that changing a company name to include dot-com, dot-net or the word Internet could create substantial abnormal returns even if there was not real change in the company’s activity. In a sample of 147 firms in the period from June 1998 to August 1999, these companies had a significant average of 53 percent returns over the 5 days surrounding the name change.

Thirdly, the argument on “excess” volatility that Internet stock prices showed compared to the ‘old economy’ explained by [Ofek and Richardson \(2002\)](#), is based on [Black \(1986\)](#) where the extra volatility is explained by noise trading: investors trade for apparent ‘new’ information when actually it is not. This is consistent with the investor’s base that the Internet sector had, where retail investors outnumbered institutional compared to other stocks ([Hand, 2000; Ofek and Richardson, 2002](#)) and these investors were inexperienced ([Barber and Odean, 2002](#)).

However, mispricing led by human behaviour can only survive if arbitrage is not exercised by rational investors. Ofek and Richardson (2002) document that this was indeed the case due to evidence of the downside risk of shorting Internet stocks due to high volatility compared to other sectors and put-call parity violations in the options market for Internet stocks versus non-Internet. Moreover, this was intensified by the fact that hedge funds were heavily invested in technology (Brunnermeier and Nagel, 2004). This is consistent with rational investors that prefer to ride bubbles because of the limitation to arbitrage but also the predictability of investor sentiment. This allowed them to benefit from the upturn and reduce positions at the right time, avoiding the downturn as much as possible.

Therefore, what drove the bubble to burst? Ofek and Richardson (2003) suggest that the expiration of many post-IPO lockup allowed inside selling. By June of 2000, \$300 billion in shares had been unlocked in a short period of time which meant a permanent increase of available shares in the marketplace removing substantial short-sell constraints. In addition, the authors show substantial evidence that such shares were sold by a significant number of insiders. They argue that diversification aside, insiders would only sell if they believed that the prices were above their beliefs, introducing to the stock market clientele a more pessimistic belief.

Taken together, the evidence suggests that the dot-com bubble was not solely the result of changes in fundamentals or rational expectations about future growth. Rather, it emerged from the interaction of overly optimistic beliefs, narrative-driven investing, and structural frictions that limited the ability of rational arbitrageurs to correct mispricing. The combination of extreme valuations, persistent violations of fundamental pricing relationships, and clear constraints on arbitrage provides a compelling case that asset prices during this period deviated significantly from underlying economic fundamentals. These stylized facts form a critical foundation for assessing whether similar mechanisms may be at work in more recent technological booms, including the rapid rise of artificial intelligence.

2.2 Investor Behaviour and Technology Bubbles

The investor behaviour behind technology bubbles can be understood as the interaction between human judgment, narratives, feedback mechanisms and limits to arbitrage. While the first section showed that the dot-com bubble involved valuations disconnected from fundamentals, this section explains why investors may collectively sustain such valuations even when some market participants understand that prices are too high.

Shiller (2002) argues that the concept of a “bubble” necessarily implies some less-than-rational component in investor behaviour. However, this does not mean that investors are simply foolish. Instead, the mistakes behind bubbles are subtle errors of judgment that can affect individuals, experts, analysts, trustees and

professional investors alike. In this sense, bubbles are not only caused by uninformed retail investors, but also by the amplification of common human weaknesses in environments of uncertainty. Shiller explains that the essence of a speculative bubble is a feedback pattern: price increases generate investor enthusiasm, enthusiasm increases demand and higher demand pushes prices even further upward. This mechanism is especially relevant in technology bubbles because new technologies create uncertainty about future growth (Pástor and Veronesi, 2009), making it difficult for investors to distinguish justified optimism from excessive extrapolation.

A key behavioural mechanism in this process is the tendency of investors to extrapolate recent returns. Shiller (2002) links this to the representativeness heuristic, originally developed by Tversky and Kahneman (1974), where individuals see familiar patterns in random or uncertain information. In financial markets, this can lead investors to interpret recent price increases as evidence of a continuing trend, even when they know that such trends should not necessarily persist. At the same time, conservatism bias means that investors update too slowly when new information contradicts their existing beliefs (Beach and Braun 1994). Barberis, Shleifer and Vishny (1998) formalize these ideas in a model of investor sentiment, showing that markets can both underreact to new information in the short run and overreact to a long sequence of good news in the long run. In their model, investors are overconfident and after a pattern of good performance they believe they need to act on it and treat the firm as it belongs to a special category of “growth” companies, leading to excessive valuations.

Another important mechanism is attention. Shiller (2002) argues that assets whose prices have recently increased attract public and professional attention. Investors are more likely to buy assets that they are already thinking about, and recent price increases make these assets more salient. In a survey of institutional investors, Shiller and Pound (1989) found that investors holding stocks that had recently risen sharply were less likely to say that their interest came from a systematic search and more likely to have had their attention attracted by past price increases. This suggests that even professional investors can be pulled into bubbles through attention rather than purely fundamental analysis.

Narratives reinforce this process. Shiller (2017) defines narrative economics as the study of how popular stories spread and affect economic decisions. In a bubble, rapid price increases raise the contagion rate of stories that justify those increases. In stock market bubbles, these stories often concern glamorous new technologies and the people or firms that created them. Such narratives make high valuations appear more reasonable because investors interpret prices through a broader story of transformation, disruption and future growth. This is highly relevant for technology bubbles because the narrative is usually not entirely false: the Internet did transform the economy, and AI may also do so. The problem is that a plausible technological story can be extended into unrealistic expectations about the profitability of listed firms.

This is where “new era” thinking becomes important. [Shiller \(2002\)](#) argues that major speculative bubbles are usually supported by a superficially plausible popular story, or “new-era theory”, which appears to have support from authoritative figures. The error that investors make is assuming that because many people repeat the story, someone must have verified the missing links in the argument. In reality, the popularity of the story may itself be evidence of the bubble. This is important because technology bubbles usually contain genuine innovation, but investors may jump from the true statement that the technology is important to the much stronger and less certain claim that current valuations are justified.

Herding and conformity also help explain why bubbles can involve experts. [Shiller \(2002\)](#) notes that asset allocation decisions are extremely complex and require judgments about the distant future, technological change and social evolution. Because no investor can fully master all these dimensions, professionals often rely on the judgments of others and on conventional wisdom. This creates consensus-driven behaviour, where deviating from the group becomes difficult. Fiduciary standards and institutional pressures may reinforce this, since professional investors often need to justify their decisions to committees or clients. As a result, even investors who privately doubt valuations, may continue to participate in the bubble because doing so appears prudent relative to the consensus.

However, behavioural explanations are incomplete without explaining why rational investors do not eliminate mispricing. [De Long, Shleifer, Summers and Waldmann \(1990\)](#) introduce the concept of noise trader risk. In their model, irrational investors affect prices because their beliefs are unpredictable. A rational arbitrageur who shorts an overpriced asset faces the risk that optimistic noise traders become even more optimistic, pushing the price further away from fundamentals before it eventually corrects. This risk limits arbitrage even when the arbitrageur is correct about fundamental value. Therefore, prices can diverge significantly from fundamentals even in the absence of fundamental risk.

This mechanism is crucial for technology bubbles because investor sentiment can strengthen before it collapses. A rational investor may correctly believe that a technology stock is overvalued, but shorting it too early can be very costly. If the price continues rising, the arbitrageur may face losses, margin pressure or client withdrawals. Therefore, it may be rational not to attack the bubble aggressively. This helps explain why mispricing can survive even in liquid markets with sophisticated investors.

[Abreu and Brunnermeier \(2003\)](#) extend this idea by showing that bubbles can persist even when rational arbitrageurs know that prices are too high and collectively have enough resources to correct the mispricing. Their model focuses on a synchronization problem. Rational arbitrageurs may want to ride the bubble while it continues to generate high returns, but each wants to exit before the crash. Since arbitrageurs do not know when others will sell, they fail to coordinate their exit strategies. This lack of synchronization allows the bubble to persist for a substantial period. The authors also show that news events can have a

disproportionate effect because they help investors coordinate their selling, turning a relatively small event into a trigger for a large price decline.

This theory fits the behaviour of hedge funds during the dot-com bubble. Brunnermeier and Nagel (2004) document that hedge funds did not act as a correcting force. Instead, they were heavily invested in technology stocks and appear to have ridden the bubble rather than shorting it. This does not necessarily mean they were unaware of the bubble. Rather, sophisticated investors may have believed that they could profit from the continuation of the boom and exit before the downturn. The authors argue that this evidence challenges the efficient market view that rational speculators always stabilize prices.

Finally, not all bubble-like patterns in technology stocks must be interpreted as irrational. Pástor and Veronesi (2009) develop a rational model in which technological revolutions naturally generate bubble-like stock price patterns. In their model, investors are uncertain about the productivity of a new technology and learn over time. Early in the process, uncertainty is mostly idiosyncratic, which can support high valuations. As adoption becomes more likely, the uncertainty becomes systematic, increasing discount rates and eventually pushing prices down. Therefore, stock prices may rise and later fall even under rational expectations. The authors find empirical support for this mechanism in both the railroad revolution and the Internet revolution.

This contribution is important because it shows that a technology bubble does not have to be purely irrational. Some part of high valuations may reflect genuine uncertainty about a transformative technology. However, this does not contradict behavioural explanations. Rather, it suggests that technology bubbles are most likely when rational uncertainty and behavioural amplification coexist. A new technology creates real uncertainty about future productivity, while investor sentiment, narratives, attention and limits to arbitrage can push prices beyond levels justified by fundamentals.

Therefore, the literature suggests that investor behaviour in technology bubbles is driven by several reinforcing mechanisms. Investors extrapolate past returns, overreact to repeated good news, become attached to persuasive narratives, follow the judgments of others and pay more attention to assets whose prices have already risen. At the same time, rational arbitrageurs may fail to correct mispricing because of noise trader risk, short horizons, coordination problems and the incentive to ride the bubble. Therefore, technology bubbles are not simply the result of irrational retail investors, nor are they always fully irrational. They emerge from the interaction between genuine technological uncertainty, human judgment, narrative contagion and limits to arbitrage. This framework is essential for analysing the AI boom, where a real technological transformation may again coexist with optimistic expectations, strong narratives and valuation risks.

2.3 Positioning of this Study

While the existing literature provides extensive evidence on the dynamics of the dot-com bubble, investor behaviour and the role of valuation narratives, it remains largely focused on historical episodes. In particular, most studies analyse bubbles *ex post*, once prices have already collapsed, and therefore provide limited insight into how such dynamics unfold in real time. At the same time, although recent work has begun to examine the rise of artificial intelligence, the empirical literature on the AI boom remains relatively scarce and fragmented.

This thesis contributes to the literature by analysing the ongoing AI boom through the lens developed in the previous sections. First, it examines whether the relationship between valuations and fundamentals exhibits patterns similar to those observed during the dot-com bubble, where traditional valuation metrics temporarily lost relevance. Second, it studies the behaviour of institutional investors, who are typically considered more rational market participants, in order to assess whether they act as a stabilizing force or instead contribute to the amplification of price dynamics.

By combining these two perspectives, the thesis provides a more comprehensive assessment of whether current market developments reflect a bubble-like process. The analysis focuses not only on price dynamics, but also on the underlying drivers of valuations and the portfolio decisions of institutional investors. This approach allows for a real-time evaluation of the AI boom, contributing to the literature by extending the study of technology bubbles beyond historical episodes and into a contemporary setting.

2.4 Excursus on Reference Paper: “Who Drove and Burst the Tech Bubble”

An important contribution to the empirical literature on asset price bubbles is provided by [Griffin, Harris, Shu, and Topaloglu \(2011\)](#), who revisit the dynamics of the dot-com episode with a focus on the respective roles of institutional and individual investors. Contrary to the widespread narrative attributing the late-1990s technology bubble primarily to retail “noise traders”, the authors document that institutional investors were the dominant buyers during the run-up phase and that it was their coordinated exit in March 2000, not a shift in retail sentiment, that triggered the collapse. This empirical result challenges the efficient market hypothesis view ([Fama, 1970](#)) where sophisticated investors should arbitrage away mispricing, and instead, supports models in which strategic behaviour and limits to arbitrage play a central role, consistent with [Abreu and Brunnermeier \(2003\)](#).

The paper combines proprietary NASDAQ transaction data with Thomson Financial 13F filings to construct a detailed classification of investor types, distinguishing hedge funds, mutual funds and investment advisors from several categories of retail investors (this methodology is directly aligned with the empirical strategy adopted in [Section 4.2](#)). Crucially, the authors show that institutional trading was largely discretionary rather than mechanically driven by fund inflows, implying that the observed patterns reflect active

investment decisions. Institutions remained net buyers throughout most of the run-up, only reducing exposure shortly before the peak, and are even shown to have purchased clearly overpriced securities, evidence inconsistent with rational arbitrage. At the peak, institutions rapidly exited while retail investors, particularly discount brokerage clients, continued buying, a dynamic repeated at the level of individual stocks.

Taken together, this evidence has direct implications for the analysis of the current AI boom. It suggests that strong institutional participation should not be interpreted as a validation of fundamentals per se but may instead reflect strategic behaviour aimed at exploiting ongoing price dynamics. Accordingly, changes in institutional trading patterns, especially in large-cap stocks and by hedge funds, may provide early signals of a potential market reversal, a hypothesis that is explored in part of the empirical analysis of this thesis.

3. Descriptive Evidence: The AI Boom in Context

3.1 Identifying AI-Related Firms

The identification of AI-related firms follows a structured approach aimed at capturing both large, established technology companies and smaller firms more directly exposed to artificial intelligence. First, all companies integrated in the Nasdaq-100 were retrieved from the [WRDS CRSP Daily Stock database](#) as of 31 December 2025. These firms were then categorised at the industry level using the Bloomberg Industry Classification Standard. The focus was placed on the most relevant technology-related industries, namely E-Commerce Discretionary, Internet Media & Services, IT Services, Semiconductors, Software, Technology Hardware and Electrical Equipment, as these sectors are most closely linked to the development and deployment of AI technologies.

However, restricting the sample to Nasdaq-100 firms and industry classifications may overlook a set of companies that are actively involved in artificial intelligence but are either smaller in size or not fully captured by these categories. To address this limitation, the sample was expanded by including U.S. firms contained in thematic exchange-traded funds that explicitly target AI exposure. In particular, constituents of the [iShares Future AI & Tech ETF](#) and the [iShares AI Innovation Active ETF](#) were retrieved as of mid-January 2026. These ETFs are designed to track companies that are expected to benefit from advances in artificial intelligence and therefore provide a complementary mechanism to identify relevant firms beyond standard industry classifications. The complete list of firms included in the analysis is reported in [Table 1](#) in the [Appendix](#).

For further reference while reading this paper, the 126 companies from the AI universe described in this section are used for the Descriptive Evidence and for the institutional holdings analysis in [Section 4.2](#),

where the objective is to capture firms that are directly exposed to the AI investment theme. For this reason, the sample is deliberately more curated and relies on Nasdaq-100 technology classifications and AI-focused ETFs, which better identify the companies most visibly associated with the current boom. (This resulted in 58 companies for the Descriptive Evidence as while retrieving the data, some firms were lost). The regression analysis in [Section 4.1](#) uses a broader AI sample to ensure robustness and comparability to the dot-com results as the latter universe is identified with the methodology of [Griffin et al. \(2011\)](#).

3.2 Price Dynamics

This section compares the trajectory of equity prices across the dot-com run-up and the current AI boom. [Section 3.2.1](#) plots stock price indices for the dot-com universe (1996-Q1 to 1999-Q4) and the AI universe (2022-Q1 to 2025-Q4), each rebased to 100 in its starting quarter, so that the magnitude and shape of the two re-ratings can be read on the same axis.

3.2.1 AI Stock Index vs Dot-Com Company (rebased to 100)

[Figure 1](#) plots two chain-linked, equal-weighted price indices, one for each cohort, anchored at 100 in their respective Q1-Y1. For every firm-quarter, simple quarterly returns are computed from [Compustat](#) closing prices (*prccq*), averaged cross-sectionally with equal weights and chain-linked forward; stock splits are removed using the [Compustat](#) cumulative adjustment factor *ajexq*. The AI universe contains 58 firms and the dot-com universe contains 600 firms.

The main reading is consistent with the "boom but not bubble" framing of Marks ([Financial Times, December 9, 2025](#)). The AI cohort has clearly been re-priced (2.6x rise in four years), in what looks like a substantial bull move, but on a like-for-like, equal-weighted basis, it is roughly half the magnitude of the dot-com run-up over the same horizon, and crucially it lacks the dot-com terminal acceleration. There is no AI-side analogue to the 1999-Q4 quarter in which the median internet firm gained 50% in twelve weeks. Even granting that AI valuations are stretched relative to history ([Financial Times, December 30, 2025](#)) and that some behaviours are plainly speculative ([Financial Times, December 9, 2025](#)), the AI price trajectory itself has not yet exhibited the parabolic terminal phase that defined the late-1999 dot-com peak. On price-trajectory evidence alone, what 2022–2025 looks like is a strong re-rating led by an AI's transformational potential, similar, according to Gareth Campbell (economic historian at Queens University Belfast) to past technological invention ([Financial Times, December 30, 2025](#)).

3.3 Valuation Multiples and Firm Fundamentals

Following the price dynamics documented in [Section 3.2](#), this section moves beyond price levels and looks at valuation multiples and the firm-level fundamentals that underpin them. [Section 3.3.1](#) reports the three

headline valuation multiples (P/E, EV/Sales, Market-to-Book), and sections 3.3.2 to 3.3.5 turn to the four operating and balance-sheet fundamentals that drive those multiples: revenue growth, profitability, cash flows and leverage. Together, the seven figures provide the descriptive picture that motivates the formal cross-sectional regressions of [Section 5.1](#): are AI firms simply re-running the dot-com pattern of high multiples disconnected from operational performance or are they fundamentally different from dot-com firms at comparable points in time?

The exercise compares 16 quarters of dot-com data (1996Q1–1999Q4) against 16 quarters of AI data (2022Q1–2025Q4). The dot-com window deliberately captures the four years immediately preceding the March 2000 burst, that is, the "ride-up" phase before the crash, while the AI window captures the most recent four years available, given that the "boom" is still ongoing. For each variable in each quarter, a market-cap-weighted mean is computed across firms in the sample and plotted on a relative-quarter axis so that the two periods can be read side-by-side without calendar-time noise. All variables are winsorised at the 2.5th and 97.5th percentiles to limit the influence of extreme observations. Two data caveats apply throughout: i) the [Compustat financial ratio file](#) for the dot-com period begins in 1997 (with *qdate* aligning a small number of observations to 1996 quarters), so the very first quarters of the dot-com window are sparser than the rest; ii) the cash-flow series uses the change in cash and equivalents (*chechy*), which is reported quarterly but represents an annual flow.

3.3.1 P/E, EV/Sales, Market-to-Book

[Figures 2, 3 and 4](#) plot the market-cap-weighted mean P/E, P/S and Market-to-Book (P/BV) ratios for the two time-windows. The dot-com series exhibits the classic run-up pattern: multiples rise materially over the four years towards the 2000 peak, with P/S and P/BV more than doubling from their 1996 starting points. The AI series enters its window already at high levels and continues its upward trend.

On a level basis, AI multiples are at least as high as dot-com on every measure and substantially higher on Market-to-Book. The unweighted median P/BV in the AI window is 9.78, against 4.46 in the dot-com window. The median P/S is also higher in AI (24.64 versus 18.78), while the median P/E is broadly similar (35.11 versus 35.56). On a market-cap-weighted basis, the dot-com mean P/E (58.84) and P/S (42.05) are higher than the AI means (43.00 and 29.40 respectively), but the dot-com mean is heavily inflated by a long right tail of extreme valuations. One caveat applies to the P/E series specifically: a large share of dot-com firms reported negative net income during the run-up and the multiple is computed on positive-earnings observations only. As will be discussed in [Section 4.1](#), this means the dot-com P/E series under-represents the broader internet population and should be read with that limitation in mind.

The main reading which emerges from these charts is that the spread between dot-com mean and median multiples is much larger than for AI (on a market-cap-weighted basis). In the dot-com era the right tail of the valuation distribution was very fat, consistent with the cluster of internet firms that achieved implausibly high valuations on weak earnings (Ofek et al., 2002; Morris et al., 2012).

3.3.2 Revenue Growth

Figure 5 plots the market-cap-weighted year-on-year revenue growth (log-difference) for the two windows. The dot-com series sits visibly above the AI series throughout the 16-quarter comparison: dot-com firms grew faster than today's AI firms and grew faster on average over the entire run-up.

This is the one fundamental on which dot-com firms genuinely outperformed AI firms, but, on closer reading, the gap is a symptom of the dot-com bubble rather than a sign of dot-com strength. The late-1990s narrative explicitly turned on the idea that the internet would generate extraordinary, sustained revenue expansion, and Ofek and Richardson (2002) calculate that dot-com valuations could only be rationalised by assuming earnings growth in the 12 to 40 percent range sustained for between 10 and 30 years. Morris and Alam (2012) reach the same conclusion from the value-relevance angle: during the bubble, traditional accounting fundamentals lost explanatory power as valuations were driven by forward-looking growth expectations. The AI cross-section, with materially lower headline growth, does not fit that template and the regression evidence in Section 5.1 confirms the asymmetry. Revenue growth is the single fundamental that meaningfully predicts dot-com P/BV in the regression, while AI multiples are explained by a broader set of operating and balance-sheet variables.

3.3.3 Profitability

Figure 6 plots the market-cap-weighted operating margin (operating income after depreciation divided by quarterly revenue) for the two windows. AI firms exhibit a stable, materially positive operating margin throughout the 2022-2025 window, while dot-com firms move around or below zero through most of the 1996-1999 run-up.

Profitability is the cleanest descriptive contrast between the two periods. Ofek et al. (2002) document that the internet sector ran aggregate negative earnings throughout the late-1990s run-up, meaning valuations had no fundamental anchor in profitability. The AI companies of 2022–2025, by contrast, are sustainably profitable, a structural distinction that sets the current episode apart from the dot-com boom. Harding M. (Financial Times, December 29, 2025) frames the same point qualitatively, arguing that the AI episode is best thought of as a boom rather than a bubble precisely because the underlying transformation is showing up in measurable revenue and productivity terms. This descriptive observation is what makes the regression

evidence in [Section 5.1](#) unsurprising in retrospect. AI valuations can be statistically anchored to operating performance because that performance is real and persistent in the data, whereas dot-com valuations could not be similarly anchored because the operating performance was simply not there.

3.3.4 Cash Flows

[Figure 7](#) plots the market-cap-weighted change in cash and equivalents (*chechy*) per firm. As with operating margin, the AI series sits well above the dot-com series for essentially the entire window, showing how AI firms operate at a scale of cash flow that the typical dot-com firm did not reach in absolute terms.

The cash-flow gap mirrors and reinforces the profitability gap, since AI firms are not only generating margins, but they are also converting those margins into measurable cash. Whether current cash flows justify current valuations is a separate, harder question that [Section 5.1](#) takes up econometrically; the descriptive point of the present subsection is more elementary, namely that the cash backbone exists at all in 2022–2025 and largely did not in 1996–1999, when the typical internet firm depended on equity raises and venture capital to sustain operations rather than internal cash generation.

3.3.5 Leverage

[Figure 8](#) plots the market-cap-weighted leverage ratio for the two windows. AI firms operate with substantially more leverage than dot-com firms did at comparable points in their respective episodes.

The first reading that can be inferred by the chart is structural. The AI cross-section contains large, cash-generative incumbents, the so-called Magnificent Seven and adjacent firms, whose mature balance sheets can support meaningful debt, whereas the dot-com cross-section was overwhelmingly composed of recently listed, equity-financed start-ups whose access to debt markets was mechanically more limited. On this reading, higher AI leverage is a sign of corporate maturity and is consistent with the much higher cash-flow base documented in [Section 3.3.4](#). The second reading that can be inferred is more cautious: Angelo Moratti (founder and chairman of Angel Capital Management and president of L&B Capital SGR), in an interview with [Il Sole 24 Ore](#), 2 January 2026, argues that leverage is the central distinguishing feature of the current cycle. AI infrastructure investment in the most recent year has been "financed almost entirely with new debt, in the hundreds of billions of dollars," a financing pattern that he warns may itself be a source of systemic risk. Moratti also flags a structural shift in how technology booms are funded: where dot-com firms went public within six to eight years of founding and raised equity through the public market, AI firms today delay listing as long as possible and finance themselves through private debt, meaning the leverage observed on the public-firm balance sheets in [Figure 8](#) is, if anything, an understatement of the leverage embedded in the broader AI ecosystem. Both readings are visible in the descriptive evidence: AI

firms are more leveraged because they are more able to be and because more leverage is being directed at them. [Section 5.1](#) confirms that this difference is statistically a strong distinction between the two regimes (leverage is highly significant in the AI P/BV regression, with a coefficient of 0.972, and statistically zero in the dot-com regression) and is one of the main drivers of the Chow-test rejection of equal pricing rules across the two periods.

4. Data and Methodologies

This chapter develops the data and methodology for the two empirical exercises that follow. [Section 4.1](#) sets up a cross-sectional comparison of how firm fundamentals are priced into valuation multiples in the dot-com (1998–2000) and AI (2022–2025) eras, including the construction of the regression panels, the variables used and a Chow-style structural-break test of whether the two regimes share a common pricing rule. [Section 4.2](#) sets up a complementary, behavioural analysis of institutional investor activity around the AI boom, using quarterly 13F disclosures and a price-neutral decomposition of portfolio weight changes that separates active trading decisions from the mechanical effect of price drift.

The two exercises approach the central question of whether the AI episode is comparable to the dot-com bubble from two distinct angles: how the market prices fundamentals and how sophisticated investors position around the boom.

4.1 Exercise 1: How Do Fundamentals Behave?

This section assesses how much of the cross-sectional variation in firm valuation multiples is explained by firm-level fundamentals during the dot-com (1998–2000) and AI (2022–2025) periods, and whether the relationship between valuations and fundamentals is structurally similar across the two eras. The analysis rests on quarterly firm-level accounting data and standardised valuation ratios, and proceeds in two complementary steps: i) panel regression of log valuation multiples on a common set of firm fundamentals, estimated separately for each era and run on three alternative dependent variables (P/BV as primary specification, P/S and P/E as robustness checks); ii) Chow-style structural-break test that pools the two samples and assesses whether the slope coefficients differ across regimes. Together, these two steps speak directly to the central question of whether the dot-com and AI eras can be compared on the basis of the same relationship between fundamentals and valuation.

4.1.1 Dataset Description

The exercise involved the construction of two datasets following a two-period approach in order to compare the dot-com bubble and the recent AI boom. For the dot-com period, the sample selection closely followed

Griffin et al. (2011). Firms were identified using the [WRDS Compustat – Capital IQ Fundamentals Quarterly](#) over the period January 1996 to December 2000. Two filters were applied to isolate technology firms. First, only companies traded on the NASDAQ exchange were retained, corresponding to exchange code 14 in Compustat. Second, firms were required to have a SIC code beginning with 737, which corresponds to “Computer and Data Processing Services” that captures the core set of internet and software firms at the centre of the dot-com bubble.

For the AI period, a comparable approach was adopted using the same data source, namely the [WRDS Compustat – Capital IQ Fundamentals Quarterly](#), over the period January 2020 to December 2025. However, because SIC codes are no longer systematically assigned to newer firms, industry classification was based on NAICS codes instead. Firms were first selected using NAICS code 51 (“Information”), which broadly captures companies involved in digital services and technology. In addition, firms classified under NAICS code 334414 (“Semiconductor and Related Device Manufacturing”) were included in order to capture hardware producers that play a central role in the development and deployment of artificial intelligence but would otherwise be excluded under a purely services-based classification.

For both periods, firm-level financial data was retrieved from two sources. The first is [WRDS Compustat – Capital IQ Fundamentals Quarterly](#), which provides accounting variables including total assets (*atq*), total liabilities (*ltq*), quarterly revenue (*revtq*), operating income before depreciation (*oibdpq*), operating income after depreciation (*oiadpq*), the firm identifier (*gvkey*), and the report date (*datadate*). The second is the [Compustat Financial Ratios database](#), which supplies standard valuation metrics such as the price-to-book ratio (*ptb*), the price-to-sales ratio (*ps*), and the income-based price-to-earnings ratio (*pe_inc*). Combining these two sources yields two comparable samples of technology-oriented firms, one covering the dot-com period (1996–2001) and one the AI period (2020–2025), for which both accounting fundamentals and valuation measures are jointly observed.

4.1.2 Data Preparation and Sample Construction

This section describes the sequential steps through which the raw firm-level fundamentals and valuation ratios are transformed into the final analytical panels used in the cross-sectional valuation regressions, the construction of the regime-specific master samples, and the specification of the regressions and the Chow-style structural-break test.

Below the steps took for the data preparation and sample construction:

1. The fundamentals files are filtered to retain only observations with valid, non-missing values for *gvkey* and *datadate*. Within each regime, observations are sorted by firm and date so that lagged variables, in particular year-on-year growth measures, can be constructed within firm. The monthly

financial ratios files are similarly cleaned: rows with missing variables are dropped, and any same-firm same-date duplicates are reduced to a single record by retaining the most recent observation.

2. The empirical analysis uses three valuation multiples as alternative measures of how the equity market prices each firm relative to its fundamentals. The primary dependent variable is the price-to-book ratio (P/BV), defined as the firm's market capitalisation divided by the book value of common equity. P/BV is selected as the primary specification because book value of equity is well-defined for virtually all going concerns, including firms with negative or near-zero profits. The first robustness specification uses the price-to-sales ratio (P/S), defined as the firm's market capitalisation divided by trailing revenue. The second robustness specification uses the income-based price-to-earnings ratio (P/E), defined as price per share divided by earnings per share. P/E is mechanically undefined for firms with non-positive earnings, a constraint that is particularly binding in the dot-com sample (Ofek and Richardson, 2003). All three dependent variables are entered in logs, as raw valuation multiples are strongly right skewed in the cross-section (Hand, 2001).
3. The same set of five firm-level controls is used across all three valuation specifications, so that the only methodological difference between the primary and the robustness regressions is the dependent variable. The five variables capture four distinct fundamental dimensions: profitability, the operating and balance-sheet scale of the firm, capital structure and revenue dynamics.
 - i. Operating margin is constructed as operating income after depreciation divided by quarterly revenue (*oiadpq* / *revtq*), with operating income before depreciation (*oibdpq*) used as a fallback when *oiadpq* is unavailable. Operating margin is the central profitability indicator in the regression, more profitable firms convert each unit of revenue into greater free cash flow, which translates mechanically into higher equilibrium valuation multiples.
 - ii. The natural logarithm of quarterly revenue (*log_rev*) controls for firm scale, since larger firms systematically differ from smaller firms in their valuation multiples due to differences in risk, information environment and market visibility. This follows standard practice of including a scale control to avoid conflating size-related variation with the coefficients on profitability and growth (Fama and French, 1992; Core et al., 2003).
 - iii. The natural logarithm of total assets (*log_atq*) captures the scale of capital deployed to generate that revenue. Asset scale is conceptually distinct from revenue scale, as two firms with the same revenue can carry very different asset bases, and asset-light versus asset-heavy business models tend to receive different multiples in the cross-section.

- iv. Leverage is constructed as the ratio of total liabilities to total assets (ltq / atq). Capital structure is a standard determinant of valuation in corporate finance since it affects the cost of equity capital through financial risk, and, in the presence of distress costs and tax shields, it can drive a wedge between book value and market value of equity. Including leverage ensures that the regression isolates the contribution of operating fundamentals from capital-structure effects.
 - v. Revenue growth is constructed as the year-on-year log-difference of quarterly revenue, computed within firm by taking the four-quarter difference of $\log_rev$. Revenue growth is the variable most directly tied to the central narrative of both bubbles under study. The elevated valuations observed in the late dot-com period and in the AI boom are commonly justified as the rational pricing of expected future growth, with observed growth serving as the most natural proxy. The log-difference specification is used in preference to a simple percentage change because it is more stable when the base-period revenue is small and because a log-difference of log revenue is the natural growth measure that pairs symmetrically with a log-level dependent variable.
4. Since the [WRDS Financial Ratios file](#) is reported at monthly frequency while the fundamentals are quarterly, the valuation ratios are collapsed to a single firm-quarter observation. For each firm and each calendar quarter, the valuation ratio retained is the value reported on the latest *public_date* falling within that quarter, with the corresponding number of monthly observations stored as a diagnostic. The collapsed firm-quarter ratio file is then merged into the quarterly fundamentals panel on the firm-quarter key, where the calendar quarter is derived from *datadate*. The merge is restricted to a many-to-one structure so that each fundamentals row receives at most one valuation observation, and match rates are reported in the regression diagnostics for each regime.
 5. Each merged panel is then restricted to the relevant estimation window, defined as 1998Q1–2000Q4, for the dot-com period (including the price-acceleration period emphasised in [Ofek and Richardson, \(2003\)](#) and as 2022Q1–2025Q4 for the AI period, beginning approximately one year before the November 2022 release of ChatGPT. From each restricted panel, the regime-specific master sample is then constructed by retaining only those firm-quarters for which all variables are simultaneously non-missing. Strictly positive values are imposed on the relevant valuation ratio, on quarterly revenue and on total assets, so that all log transformations are defined. To limit the influence of extreme observations on OLS estimates, all independent variables are winsorised at the 2.5th and 97.5th percentiles within each regime, given the well-known prevalence of outliers in valuation multiples and accounting ratios ([Morris et al., 2012](#)).

6. The empirical workhorse is a cross-sectional regression of the log valuation multiple on the five firm fundamentals, estimated separately for each regime. The fundamentals enter the model in a nested fashion across five specifications, each adding one control to the previous one:

$$(1) \log(Y_{i,t}) = \alpha + \beta_1 op_margin_{i,t} + \gamma_t + \varepsilon_{i,t}$$

$$(2) \log(Y_{i,t}) = \alpha + \beta_1 op_margin_{i,t} + \beta_2 \log_rev_{i,t} + \gamma_t + \varepsilon_{i,t}$$

$$(3) \log(Y_{i,t}) = \alpha + \beta_1 op_margin_{i,t} + \beta_2 \log_rev_{i,t} + \beta_3 \log_atq_{i,t} + \gamma_t + \varepsilon_{i,t}$$

$$(4) \log(Y_{i,t}) = \alpha + \beta_1 op_margin_{i,t} + \beta_2 \log_rev_{i,t} + \beta_3 \log_atq_{i,t} + \beta_4 leverage_{i,t} + \gamma_t + \varepsilon_{i,t}$$

$$(5) \log(Y_{i,t}) = \alpha + \beta_1 op_margin_{i,t} + \beta_2 \log_rev_{i,t} + \beta_3 \log_atq_{i,t} + \beta_4 leverage_{i,t} + \beta_5 rev_growth_{i,t} + \gamma_t + \varepsilon_{i,t}$$

where $Y_{i,t}$ is the valuation ratio for firm i in quarter t , γ_t is a quarter fixed effect (a full set of calendar-quarter dummies estimated within regime) and $\varepsilon_{i,t}$ is the residual. Standard errors are clustered at the firm level to account for serial correlation in firm residuals across quarters. Each specification is estimated twice for each regime, once with quarter fixed effects and once without, so that the role of within-quarter cross-sectional pricing of fundamentals can be separated from the role of common time-series valuation drift. Specification (1) provides the baseline cross-sectional relationship between profitability and valuation; (2) and (3) add the two scale controls; (4) introduces capital structure; and (5) adds revenue growth, which is the most demanding specification in data terms because the year-on-year log-difference requires four prior quarters of revenue and so mechanically truncates the first four quarters of each estimation window. Regression results for the primary P/BV specification are reported in [Table 2](#) and [Table 3](#), with the no-fixed-effects counterparts in [Table 4](#) and [Table 5](#). The corresponding tables for the P/S and P/E robustness specifications are in the [Appendix](#).

7. The final methodological step assesses whether the relationship between valuation multiples and fundamentals is statistically the same across the dot-com and AI regimes. The two regime-specific master samples are stacked into a single pooled panel, and an indicator variable, AI_regime , is created equal to one for AI observations and zero for dot-com observations. For each of the five nested specifications, the model: (6) $\log(Y_{i,t}) = \alpha + \beta_1 X_{i,t} + \delta AI_regime_i + \theta (AI_regime_i \cdot X_{i,t}) + \gamma_t + \varepsilon_{i,t}$ is estimated on the pooled panel, where $X_{i,t}$ is the corresponding vector of fundamentals and $(AI_regime_i \cdot X_{i,t})$ is the vector of regime–fundamentals interactions. The intercept shift δ captures any difference in baseline log valuation between the two periods, while the vector θ captures, variable by variable, the difference in slope coefficients. The Chow-style joint test corresponds to the null hypothesis $H_0: \theta = 0$ (i.e. that the AI regime exhibits the same fundamentals-to-valuation slopes as the dot-com regime). The null is tested using a Wald statistic that imposes the joint zero restriction on

θ , with standard errors clustered at the firm level. The test is run twice for each specification, with and without quarter fixed effects, mirroring the design of the regime-specific regressions. Test results for the primary P/BV specification are reported in [Table 14](#) and [Table 15](#), with the P/S and P/E counterparts referenced in the [Appendix](#).

4.2 Exercise 2: What Are Rationale Investors Doing?

This section investigates the portfolio behaviour of institutional investors with respect to AI stocks over the period spanning the AI boom. The analysis rests on mandatory quarterly disclosure data, which allows us to track, at a granular level, how different categories of rational investors adjusted their exposure to AI companies over time. The core methodological contribution is a price-neutral decomposition of portfolio weight changes, which separates the passive mechanical effect of price appreciation from deliberate active trading decisions.

4.2.1 Dataset Description

The backbone of the analysis is the [Thomson Reuters institutional holdings database](#), drawn from mandatory 13F filings submitted to the U.S. Securities and Exchange Commission. Under Section 13(f) of the Securities Exchange Act of 1934, all institutional investment managers exercising discretion over more than \$100 million in qualifying securities are required to disclose their equity holdings on a quarterly basis, within 45 days of each quarter-end. Each filing reports, for every position held, the manager identifier, manager name, institution type code, the report date, the CUSIP of the security, the number of shares held, and the price per share at the reporting date. The raw dataset, covering the period from the first quarter of 2015 through the second quarter of 2025, comprises 57,957,953 manager-security-quarter observations, spanning 11,465 unique institutional filers and 37,506 distinct securities identified by CUSIP.

The institutional type code reported in the 13F filing classifies filers into five broad categories: banks and trust companies (typecode 1), insurance companies (typecode 2), investment companies and mutual funds (typecode 3), pension funds and other corporate entities (typecode 4), and independent investment advisors (typecode 5). This classification is fundamental to the group-level analysis conducted in this exercise, as the investment mandate, return objectives and trading behaviour vary substantially across these categories.

To compute the buy-and-hold benchmark weights that underpin the price-neutral decomposition, monthly stock price data are sourced from the [Center for Research in Security Prices](#). Specifically, monthly closing prices are extracted and aligned to quarter-end months (March, June, September, and December) by taking the median price within each quarter-end month for each security, identified by an eight-digit CUSIP prefix. These CRSP prices serve as the external price source to compute quarterly holding period returns for each

security, independently of the prices reported in the 13F filing itself, thereby ensuring that the passive appreciation component of portfolio weight changes is estimated on a consistent and verifiable basis.

4.2.2 Data Preparation and Sample Construction

This section describes the sequential steps through which the raw 13F observations are transformed into the final analytical panel, including the cleaning procedures, the institutional classification scheme, the identification of hedge funds and the construction of the price-neutral weight decomposition.

- i. Raw data cleaning and aggregation: the raw 13F records are first filtered to retain only observations with valid, non-missing values for the manager identifier, report date, CUSIP, number of shares and price per share, with the additional requirement that both shares held and price are strictly positive. Positions are then aggregated to the manager-security-quarter level by summing the market value (defined as shares multiplied by reported price) across all records sharing the same manager, report date and CUSIP. This produces a clean position-level panel, referred to as the holdings base, in which each row represents the total dollar market value of a given security held by a given institution at a given quarter-end. Securities with missing or empty CUSIPs, or with non-positive aggregated market values, are excluded. The resulting holdings base contains observations for 11,465 distinct managers across 42 quarterly reporting dates.
- ii. Manager dimension and type classification: for each manager identifier, a single institutional profile comprising the most frequently reported manager name and type code across all reporting periods is constructed and stored in a manager dimension table, ensuring that minor variations in name spelling or type code across filings do not generate spurious multiple entries for the same institution. Managers are then assigned to one of six investment groups (Banks, Insurance Companies, Mutual Funds, Independent Investment Advisors, Hedge Funds and Others) following the standard 13F type code classification used in the literature ([Griffin et al., 2011](#)) with a dedicated procedure to identify hedge funds described below.
- iii. Hedge fund identification: the identification of hedge funds from 13F data is non-trivial, as the SEC disclosure framework does not provide a dedicated typecode for hedge funds. These entities most commonly file under typecode 5 (independent investment advisors), but most type-5 filers are not hedge funds. Following an approach in the spirit of [Griffin and Xu \(2009\)](#), hedge funds are identified using a name-based heuristic applied within the typecode 5 universe. Specifically, a filer is classified as a hedge fund if it: (i) holds typecode 5; (ii) does not contain in its name any term associated with non-hedge-fund investment vehicles (e.g. private equity, venture capital, real estate, wealth advisory or ETFs); and (iii) either contains at least one strong hedge-fund-specific keyword in its name (such as hedge, long short, macro) or contains at least two organizational form keywords commonly associated with hedge

fund structures (such as capital, partners, management, fund, trading, or LP). This procedure identifies 1,157 unique hedge fund managers out of the 11,465 total filers in the sample.

Within the hedge fund group, a further distinction is made between standard hedge funds and trading-intensive hedge funds, motivated by the empirical observation that hedge funds vary substantially in their portfolio turnover and, therefore, in their capacity to actively respond to investment themes such as the AI boom. For each hedge fund manager, the median quarterly portfolio turnover (defined as the sum of gross purchases and sales divided by beginning-of-quarter portfolio market value, winsorized at the 99th percentile to mitigate the influence of reporting anomalies) is computed over the full sample period. Managers whose median turnover exceeds the 80th percentile of the turnover distribution across all hedge funds are classified as trading-intensive. This yields a sub-group of 234 high-turnover hedge fund managers, labelled HF (trading-intensive), which are analysed separately throughout the remaining of the exercise.

To ensure that the turnover calculation correctly reflects each manager's actual investment decisions, consecutive reporting periods are matched using each manager's own filing calendar, rather than assuming a fixed three-month gap between successive reports. For each manager, the actual next filing date is identified using a forward-looking lag within that manager's own reporting sequence. This prevents the systematic exclusion of positions held by managers whose quarterly filing dates do not fall precisely on calendar quarter-end dates, which would otherwise introduce a downward bias in measured turnover for a non-trivial fraction of the sample.

- iv. AI stock universe and CUSIP mapping: The set of AI companies that defines the portfolio theme of interest is constructed from a curated list of publicly traded firms identified as AI-related, as described in [Section 3.1](#). These companies are matched to the 13F holdings base via ticker symbols. Since the 13F data do not provide a canonical CUSIP-to-ticker mapping, the mapping is constructed empirically by identifying, for each CUSIP, the ticker most frequently associated with it across all reporting periods in the raw data. The final matched universe comprises 126 unique CUSIPs corresponding to AI companies present in the 13F filing universe, reflecting the fact that several firms trade under multiple share classes and are therefore represented by more than one CUSIP.
- v. Price-neutral weight decomposition: the central analytical object in this exercise is the price-neutral decomposition of portfolio weight changes, which isolates the active trading component of changes in AI portfolio weights from the passive component attributable to differential price appreciation. For each manager and each quarter, the actual AI portfolio weight is defined as:

$$(7) \ w_{i,t}^{actual} = \frac{\sum_{s \in \mathcal{A}} MV_{i,s,t}}{\sum_s MV_{i,s,t}}$$

where $\mathcal{A}$ denotes the set of AI companies, $MV_{i,s,t}$ is the market value of security s in manager i 's portfolio at quarter t , and the denominator sums over all securities in the portfolio.

The counterfactual buy-and-hold weight is then constructed as the portfolio weight that would have prevailed at the end of quarter t had the manager held the exact same positions as at the end of quarter $t - 1$ and allowed prices to evolve according to observed CRSP returns. Formally, for each position held at $t - 1$, the buy-and-hold market value at t is computed as:

$$(8) \quad MV_{i,s,t}^{BH} = MV_{i,s,t-1} \times \frac{P_{s,t}^{CRSP}}{P_{s,t-1}^{CRSP}}$$

where $P_{s,t}^{CRSP}$ denotes the CRSP closing price of security s at quarter-end t . The buy-and-hold AI weight is then:

$$(9) \quad w_{i,t}^{BH} = \frac{\sum_{s \in \mathcal{A}} MV_{i,s,t}^{BH}}{\hat{V}_{i,t}^{BH}}$$

where the denominator $\hat{V}_{i,t}^{BH} = V_{i,t}^{BH} / \rho_{i,t}$ is the buy-and-hold total portfolio value scaled upward by the inverse of the CRSP coverage ratio $\rho_{i,t}$. This correction addresses the denominator inconsistency that would otherwise arise from the fact that CRSP prices are available only for a subset of the securities held: since w^{actual} is computed over the full portfolio (including securities not covered by CRSP), w^{BH} must be scaled to the same universe to ensure comparability. Only manager-quarter pairs with a coverage ratio $\rho_{i,t} \geq 95\%$ (meaning that at least 95% of the prior-quarter portfolio value can be matched to CRSP prices) are retained in the decomposition sample. The trading component is then:

$$(10) \quad \Delta w_{i,t} = w_{i,t}^{actual} - w_{i,t}^{BH}$$

A positive value of $\Delta w_{i,t}$ indicates that the manager actively increased AI exposure beyond what passive price drift would have produced (i.e., net buying of AI stocks) while a negative value signals active reduction of AI exposure. Group-level trading components are computed as the cross-sectional mean of $\Delta w_{i,t}$ within each investor group and quarter, and then cumulatively summed over time to produce the cumulative trading component series presented in the figures.

4.2.3 Final Panel Description

After applying the CRSP coverage filter ($\rho_{i,t} \geq 95\%$) and requiring that both the actual and buy-and-hold AI portfolio weights be computable for a given manager-quarter, the final decomposition panel comprises 162,934 manager-quarter observations, covering 10,461 unique institutional managers across 38 quarterly reporting dates, spanning from the first quarter of 2016 through the second quarter of 2025. The starting point of the decomposition panel is one quarter later than the raw data (Q1 2015), since the buy-and-hold benchmark requires a full prior-quarter holding to be observable.

Table 20 reports the distribution of manager-quarter observations and unique managers across the six investor groups. Pension funds represent the largest group by both observation count and number of distinct managers (5,949 managers), reflecting the high number of corporate and public pension plans required to file under Section 13(f). The Others category (comprising type-5 filers not classified as hedge funds, as well as managers with missing or unclassifiable type codes) is the second largest group, with 2,770 unique managers. The hedge fund groups together account for 1,026 unique managers, of which 831 are standard hedge funds and 195 are classified as trading-intensive based on their median portfolio turnover. Mutual funds account for 514 managers, while banks (160) and insurance companies (42) represent the smallest groups by manager count.

The portfolio size distribution across the sample is highly right-skewed, as is typical of institutional investor databases. The average portfolio market value across all manager-quarter observations is approximately \$5.9 billion, while the median is substantially lower at \$352.8 million, indicating that a small number of very large institutions (primarily large mutual fund families and pension plans) account for a disproportionate share of total assets under management. On average, each manager holds positions in approximately 255 distinct securities per quarter.

The CRSP coverage ratio averages 95.5% across the decomposition sample, confirming that the buy-and-hold benchmark captures most of the portfolio value subject to the decomposition, and that the denominator correction described in Section 4.2.2 is operating on a relatively small residual. Cases with coverage below the 95% threshold are excluded, ensuring that the estimated trading components are not contaminated by imprecise buy-and-hold benchmarks.

5. Empirical Results

This chapter reports the results of the two empirical exercises whose methodology was developed in Section 4. Section 5.1 presents the cross-sectional regression and Chow-test evidence: AI-era valuations appear to be statistically anchored to firm fundamentals whereas dot-com-era valuations are not, and the Chow test seems to confirm that the two regimes follow structurally different pricing rules. Section 5.2 presents the institutional-ownership evidence: hedge funds and trading-intensive hedge funds appear to be the principal active accumulators of AI exposure, similarly to the role they played in the dot-com episode (Griffin et al., 2011). Taken together, the two sets of results push back against a literal "history repeating itself" reading of the AI episode while highlighting behavioural parallels at the institutional level that warrant a rational-bubble-riding interpretation.

5.1 Empirical Results I: How Do Fundamentals Behave?

This section reports the empirical results of the regression and structural break tests. The primary specification regresses $\log(P/BV)$ on a nested set of profitability, scale, capital-structure and growth controls; $\log(P/S)$ and $\log(P/E)$ are reported as robustness checks. A pooled Chow-style interaction test then tries to assess whether the slope coefficients on those fundamentals differ statistically across the two regimes. [Section 5.1.1](#) presents the regime-specific results and the Chow-style test and closes on the thesis-level reading: the AI cross-section is statistically anchored to fundamentals in a way that the dot-com cross-section was not, and the two regimes appear to be statistically distinguishable once the regression controls for the dimensions of firm heterogeneity that mattered most in each period.

5.1.1 Cross-Sectional Comparison of Firm Fundamentals

The most informative side-by-side comparison comes from specification (4) of the primary P/BV regression, which includes operating margin, log revenue, log assets and leverage, that is, the four fundamentals that do not require a four-quarter lag and are therefore estimated on the full master sample. In the AI panel (2022-2025), all four controls enter the regression with coefficients that are highly significant at the 1% level: operating margin is -0.028 (0.008), log revenue 0.242 (0.066), log assets -0.161 (0.062), and leverage 0.972 (0.218). The signs together describe a coherent pricing story: among AI firms, larger revenue scale and higher leverage are rewarded with higher P/BV multiples, while asset-heavy business models are penalised, consistent with an investor preference for asset-light, growth-oriented technology firms. In the dot-com panel (1998–2000) and in the same specification, none of the four fundamentals reaches conventional statistical significance (operating margin is -0.024 (0.050), log revenue 0.006 (0.094), log assets 0.098 (0.091) and leverage 0.362 (0.260)). The point estimates are too noisy to be statistically distinguished from zero. Full results are reported in [Table 2](#) and [Table 3](#).

The asymmetry survives the inclusion of revenue growth in specification (5), the most fully specified model. For AI, the same four controls remain significant at the 5% level or better, alongside a revenue growth coefficient of 0.513 (significant at 1%). For dot-com, only operating margin (0.151, 5%), leverage (0.714, 5%) and revenue growth (0.658, 1%) reach significance, while the two scale controls remain insignificant. The pattern is also robust to dropping the quarter fixed effects: in [Table 4](#) and [Table 5](#), the AI coefficients retain their sign and significance from specification (3) onward, while the dot-com regressors remain mostly insignificant outside specification (5). The reading of the primary regression is therefore clear: AI-era valuations appear to be statistically anchored to a meaningful subset of firm fundamentals, whereas dot-com-era valuations seem not; except via revenue growth itself, the single variable around which the late-1990s pricing narrative explicitly turned.

The robustness checks add texture without overturning the core finding. The P/S results in [Table 6](#) and [Table 7](#) show fundamentals significant at the 1% level in both regimes ([Table 8](#) and [Table 9](#) for P/S no quarter fixed effects), which is the natural consequence of regressing a sales-based ratio on size variables that are themselves a function of sales. The price-to-earnings results in [Table 10](#) and [Table 11](#) are weaker in both regimes, with most fundamentals insignificant outside specification (5). As pointed out in [Section 4.1](#), dot-com P/E results should be read as describing the profitable subset of dot-com firms rather than the broader internet population (revert to [Table 12](#) and [Table 13](#) for P/E no quarter fixed effects results).

The Chow-style structural-break test prove whether the slope coefficients on fundamentals are statistically different across the two periods. The null hypothesis is that the AI slopes equal the dot-com slopes (that fundamentals are priced the same way in both regimes). Rejecting the null implies that the two periods cannot be treated as a single pricing regime, and that direct cross-era comparisons of valuation multiples must account for a structurally different fundamentals-to-valuation mapping. Failing to reject the null implies that the two regimes are statistically indistinguishable on the dimensions tested.

For the primary P/BV specification reported in [Table 14](#) and [Table 15](#), the test fails to reject the null in specifications (1) and (2), where the only fundamentals included are operating margin and log revenue. It rejects at the 5% level or better in specifications (3) through (5), once log assets, leverage and revenue growth are added (the pattern is robust to dropping the quarter fixed effects). The substantive reading is that the dot-com and AI regimes appear to price profitability and the simplest revenue-scale measure similarly enough that the test cannot distinguish them, but they seem to price the size-and-leverage profile of firms in structurally different ways. This coincides with the regime-specific regressions: the AI cross-section discriminates among firms on log assets and leverage; the dot-com cross-section does not. The Chow test confirms that the two pricing schemes are statistically distinct.

The Chow results on the robustness specifications offer two further observations. For P/S, in [Table 16](#), the test rejects equality of slopes at very high confidence levels in specifications (1) through (4) but fails to reject in specification (5), the model that includes revenue growth. Adding revenue growth therefore absorbs the regime difference for sales-based multiples: once year-on-year growth is held constant, the two regimes price the cross-section of P/S similarly (revert to [Table 17](#) and [Table 19](#) for the P/S and P/E Chow-style pooled interaction test without QFE, and to [Table 18](#) for the P/E Chow-style pooled interaction test with QFE).

Two findings stand out from the exercise: i) AI-era cross-sectional valuations appear to be statistically explained by firm fundamentals; ii) the relationship between fundamentals and valuations seems to differ structurally from the dot-com era. Taken together, these two findings caution against a literal "history

repeats itself" reading of the AI episode. The market in 1998-2000 priced dot-com firms in a way that the regression cannot recover from observable fundamentals, the market in 2022-2025 appears to price AI firms in a way that it largely can. The question on whether AI multiples are excessive in absolute terms, the regression does not directly answer. What it does answer is that, conditional on fundamentals, the AI cross-section seems more anchored than the dot-com cross-section was, and that the two regimes appear not to be statistically interchangeable. Evidence of high AI valuations cannot therefore be transposed mechanically into evidence of a dot-com-style bubble, the two episodes operate on different valuation mechanics and a richer characterisation of whether AI is in a bubble must look beyond cross-sectional fundamentals alone.

5.2 Empirical Results II: What Are Rationale Investors Doing?

This section examines the institutional composition of AI equity ownership and analyses the behavioural dynamics underlying changes in that ownership. The price-neutral decomposition introduced in [Section 4.2.2](#) partitions each investor group's quarterly change in AI portfolio weight into an active trading component and a passive price component reflecting valuation drift alone. [Section 5.2.1](#) documents the cross-sectional structure of AI exposure as of the full sample (2016Q1-2025Q1) and assesses which groups have built their AI positions primarily through active rebalancing. [Section 5.2.2](#) focuses on the timing of that trading activity around the 2023 AI price acceleration and draws comparisons to the institutional behaviour documented during the dot-com episode by [Griffin et al.](#) Throughout, the results are interpreted in the context of the rational bubble-riding framework of [Abreu and Brunnermeier \(2003\)](#).

5.2.1 Changes in Institutional Ownership

We begin by examining how AI exposure is distributed across institutional investors and how this exposure has been accumulated over time. [Table 20](#) reports the distribution of reporting managers across investor groups, but while this is informative for understanding the composition of the dataset, it does not identify which groups are driving the evolution of AI exposure. To address this, [Table 21](#) decomposes the total change in mean AI portfolio weight from the first to the last quarterly observation into its trading and price components, each expressed as a share of the absolute total change. This decomposition provides a direct measure of whether exposure increases reflect active portfolio decisions or passive valuation effects.

The results reveal substantial heterogeneity across investor types. Hedge Funds (broadly defined) derive 80.9% of their total AI weight increase from the trading component, with only 19.1% attributable to passive price appreciation. Pension funds show an almost identical trading share of 80.9%, followed by Banks at 69.1% and Insurance companies at 58.6%. Mutual Funds stand in sharp contrast, as active trading contributes just 4.5% of their AI weight change, with the remaining 95.5% reflecting passive price

appreciation of pre-existing AI holdings. For trading-intensive hedge funds and Insurance companies, the decomposition reveals a further structural feature, the price component is negative (-3.4 and -6.0 percentage points respectively). This does not imply that these groups sold AI positions (net buying and selling is captured entirely by the trading component, which is positive for both). Rather, a negative price component means that, holding their prior-quarter portfolios fixed, AI stocks underperformed the rest of their holdings on a price basis over the sample. Two mechanisms seem to drive this: i) both groups entered the key drawdown and rotation quarters with above-average AI weights, amplifying the dilution when AI corrected; ii) their non-AI holdings rallied precisely in those quarters, as trading-intensive hedge funds held large positions in non-AI growth names that fell less than AI during selloffs, while Insurance portfolios were tilted toward defensives and pharmaceuticals that actively appreciated during risk-off rotations. As a result, passive drift was working against the AI weight for these groups, and the observed increase in their headline AI exposure is entirely attributable to active accumulation that more than offset the negative drift, consistent with countercyclical position-building rather than passive participation in the AI rally.

By looking at [Figure 9](#), which plots the cumulative trading component for each investor group over time, it's possible to notice a clear distinction across investor groups, however three distinct patterns should be pointed out:

1. For Mutual Funds, the cumulative trading component remains close to zero throughout the sample, ending at 0.8 percentage points. Their AI exposure has therefore been generated almost entirely through holding appreciating assets rather than through active reallocation, which aligns with the predominantly index-tracking and flow-constrained nature of their mandates.
2. Pension funds seem to exhibit a gradual and monotonic increase in their cumulative trading component, rising from near zero in 2016 to 5.6 percentage points by 2025 Q1, with no pronounced inflection points. This pattern is consistent with slow-moving, mandate-driven rebalancing toward a long-term growth theme.
3. Trading-intensive hedge funds display a markedly different trajectory, characterized by early and elevated trading activity and a more variable path over time (Note that the classification relies on post-2022 sector definitions applied retrospectively, positions held in 2016–2017 in firms such as NVIDIA or cloud infrastructure providers likely reflected broader semiconductor or enterprise software strategies rather than an explicit AI thesis).

5.2.2 Trading Behaviour around AI Price Peaks

Having analysed which investor groups seem to be responsible for actively increasing AI exposure, the analysis now turns to the timing of this activity, with particular focus on the 2023 AI price acceleration. This period, marked by the rapid commercialisation of large language models and a sharp revision in expectations regarding AI monetisation, provides a natural setting to assess whether institutional behaviour is consistent with rational bubble-riding.

The timing of accumulation by Hedge Funds trading-intensive managers appears to be sharply concentrated around this window. Their quarterly trading component surged to 3.42pp in Q2 2023 and 3.45pp in Q3 2023, the two largest consecutive quarterly contributions for this group in the entire nine-year sample. The cumulative trading component peaked at 13.2pp in Q3 2023 before falling by 2.67pp in Q4 2023, a partial reversal that coincided with the first peak in public enthusiasm for AI and is suggestive of deliberate position adjustment around a perceived price peak. Broadly defined Hedge Funds, by contrast, display a smoother profile, with the cumulative trading component rising from 6.8pp at the start of 2023 to 8.1pp by mid-2024.

These institutional dynamics invite direct comparison with [Griffin et al. \(2011\)](#), who show that institutions made 63.6% of active technology stock purchases during the dot-com bubble, with hedge funds identified as "the most aggressive investors" in the sector. Their findings support the [Abreu and Brunnermeier \(2003\)](#) synchronisation failure model, in which sophisticated investors actively build positions while prices are inflating rather than correcting the overvaluation. The parallels with the AI boom are notable, in both episodes hedge funds, especially trading-intensive ones, appear to strongly contribute to active accumulation, while broader investor categories seem to play a more limited active role.

However, two divergences from the dot-com episode nonetheless merit emphasis. First, the Q4 2023 partial reduction in Hedge Funds trading-intensive positions does not constitute coordinated selling, the cumulative trading component remained in positive territory and accumulation resumed in 2024 (+2.76pp in Q2 2024 and a further +1.72pp in Q4 2024). In the absence of a sustained, broad-based reduction in positions, the synchronisation mechanism required for a market correction under [Abreu and Brunnermeier \(2003\)](#) seems not observable in the data. Second, the behaviour of mutual funds differs sharply between the two episodes. [Griffin et al. \(2011\)](#) document that mutual funds were active buyers during the dot-com boom, exhibiting momentum-following behaviour alongside hedge funds, whereas our decomposition finds that mutual funds derive 95.5% of their AI weight change from price appreciation. The mutual fund channel that amplified dot-com technology buying appears to be absent or substantially attenuated in the current AI boom.

It is worth noting that contemporary commentary captures this interpretive ambiguity directly. Harding R. (Financial Times, December 29, 2025) argues that the AI market is "best thought of as a boom rather than a bubble," given that the underlying transformation is materialising in measurable revenue and productivity terms. Howard M. (Financial Times, December 9, 2025) warns that "bubbles are what happen when enthusiasm reaches irrational proportions" and that the pace of AI capital commitment carries speculative characteristics regardless of underlying value. The institutional evidence assembled here does not resolve this debate. What it appears to establish is that the behavioural fingerprint of the AI boom is sufficiently similar to the dot-com episode to make rational bubble-riding models a useful interpretive lens, though institutional positioning alone cannot characterise the current episode as a bubble in the technical sense, a question that ultimately depends on whether elevated valuations remain anchored in fundamentals.

5.3 Limitations

Several limitations of this study merit acknowledgement before turning to the conclusions. The most fundamental is that the AI episode remains unfinished given that the boom is still currently ongoing. The empirical analysis necessarily captures only a partial arc of a phenomenon whose ultimate trajectory, whether correction, consolidation or continued expansion, cannot yet be observed. This is a constraint that limits the comparability with the dot-com evidence in Griffin et al. (2011), where the full cycle from accumulation through collapse was available. A second limitation concerns the institutional holdings data since 13F filings require disclosure only of long equity positions, meaning that short positions, derivatives and synthetic exposures are entirely absent from the dataset. This means that the measured AI portfolio weights reflect gross long exposure rather than net economic interest and may therefore overstate the directional conviction of certain investor groups, particularly trading-intensive hedge funds whose strategies often involve substantial offsetting short books. Third, the identification of AI-related firms inevitably involves a degree of judgment, as neither SIC codes nor NAICS classifications map cleanly onto the AI ecosystem. The reliance on industry filters and ETF constituent lists introduces a degree of subjectivity into the sample construction that means that the results are sensitive to the boundary drawn around the AI universe and may not generalise uniformly across alternative classification schemes.

6. Conclusion

This paper set out to assess whether the current AI boom exhibits characteristics like the dot-com bubble of the late 1990s, or whether it reflects a fundamentally different market dynamic, approached from two complementary angles, namely the relationship between firm valuations and fundamentals and the behaviour of institutional investors.

Viewed against the dot-com bubble, the current AI boom does not appear to be a similar, as the two episodes are constructed differently. The clearest signal comes from the regression analysis, where valuation multiples during the dot-com period were only weakly related to observable firm characteristics, whereas in the AI period they remain closely anchored to underlying economic performance, a finding confirmed by the structural-break tests. The institutional evidence points in the same direction, although with some echoes of the past, since hedge funds and other active institutional investors appear associated with active accumulation of AI-related equities in a manner consistent with rational bubble-riding models. Yet, unlike the dot-com period, there is no clear evidence of the broad-based momentum buying across investor categories that characterised the late 1990s run-up. Taken together, the two exercises suggest that, while certain investor behaviours rhyme with the past, the underlying architecture of the current cycle is built on different foundations.

Those foundations become even clearer when the analysis is set against the current state of the market. The pace of price appreciation alone distinguishes the two cycles, as the NASDAQ more than tripled from late 1998 to March 2000, whereas it has risen approximately 100 percent over the past three years, a much slower and more controlled trajectory that lacks the parabolic terminal acceleration that defined the dot-com peak. The composition of the boom differs along similar lines, since the late 1990s were characterised by hundreds of smaller, equity-financed internet firms with negative earnings and limited operating history, while the current cycle is anchored around a much smaller number of very large incumbents, a difference in concentration that is also visible in the IPO market, where 1999 saw more than 500 offerings, a dynamic largely absent today. The underlying commercial reality of the technology reinforces this contrast further, as AI is being adopted not only as a product but as the foundation of an entire business stack encompassing semiconductors, chips and the broader infrastructure on which deployment depends, with that infrastructure already operating at significant scale and generating real earnings. A contrast with the internet era in which the commercial realisation of the technology's promise largely remained ahead of it.

Taken together, the regression evidence, the institutional behaviour analysis and the broader structural comparison consistently indicate that the current episode does not resemble a dot-com-style bubble. More broadly, the findings suggest that technological booms should not be evaluated solely through the lens of past episodes, as each cycle reflects a specific combination of technological innovation, market structure and investor behaviour that may not map cleanly onto prior ones. Whether the AI boom carries risks of a different nature, including the possibility of overvaluation relative to intrinsic value, is a question the paper does not resolve and one that future research should address as the cycle continues to develop.

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Declaration on the Use of Artificial Intelligence Tools

Generative artificial intelligence tools were used during the preparation of this manuscript to assist with language refinement, editing, and organizational suggestions. The authors independently verified all arguments, references, data descriptions, and interpretations presented in the paper and assume full responsibility for the final content.

Appendix

Exercise 1 – Outputs

Figures

Figure 1

Rebased equal-weighted stock price comparison, dot-com (1996-1999) vs AI (2022-2025)

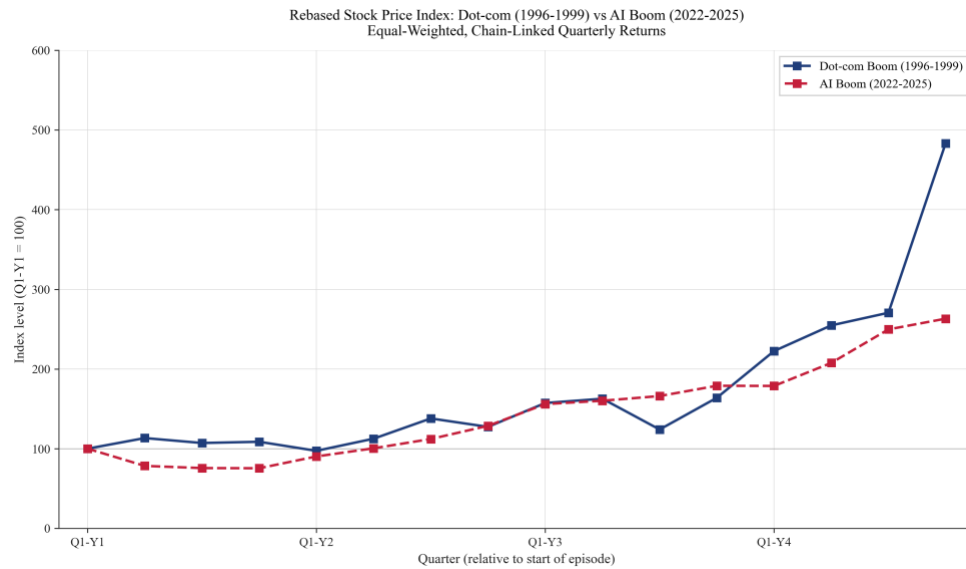


Figure 2

Market-cap-weighted P/E comparison, dot-com (1996-1999) vs AI (2022-2025)

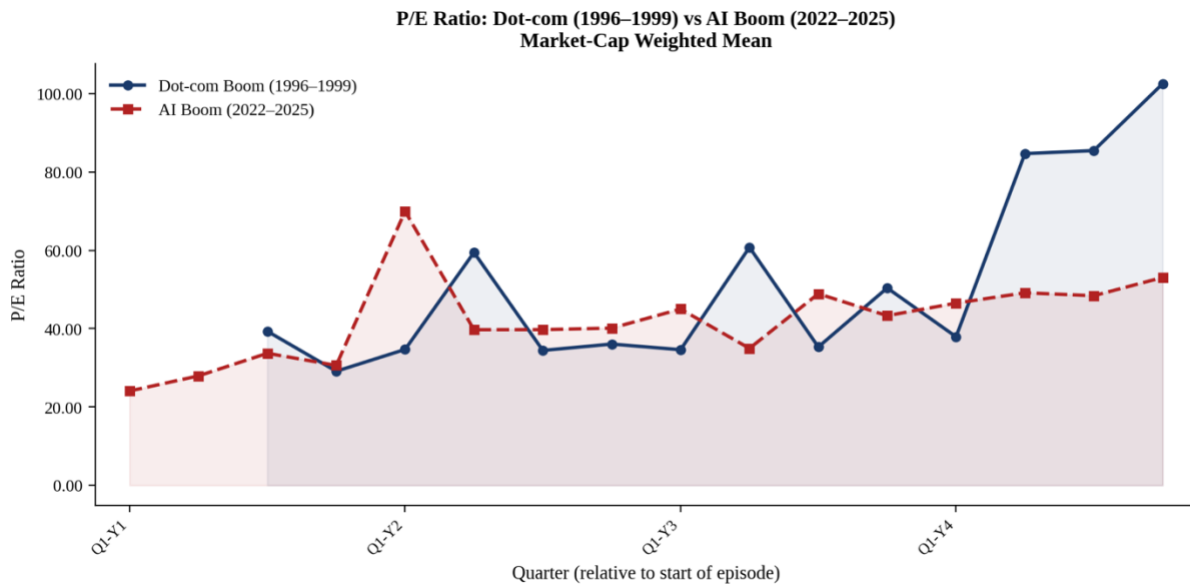


Figure 3

Market-cap-weighted P/S comparison, dot-com (1996-1999) vs AI (2022-2025)

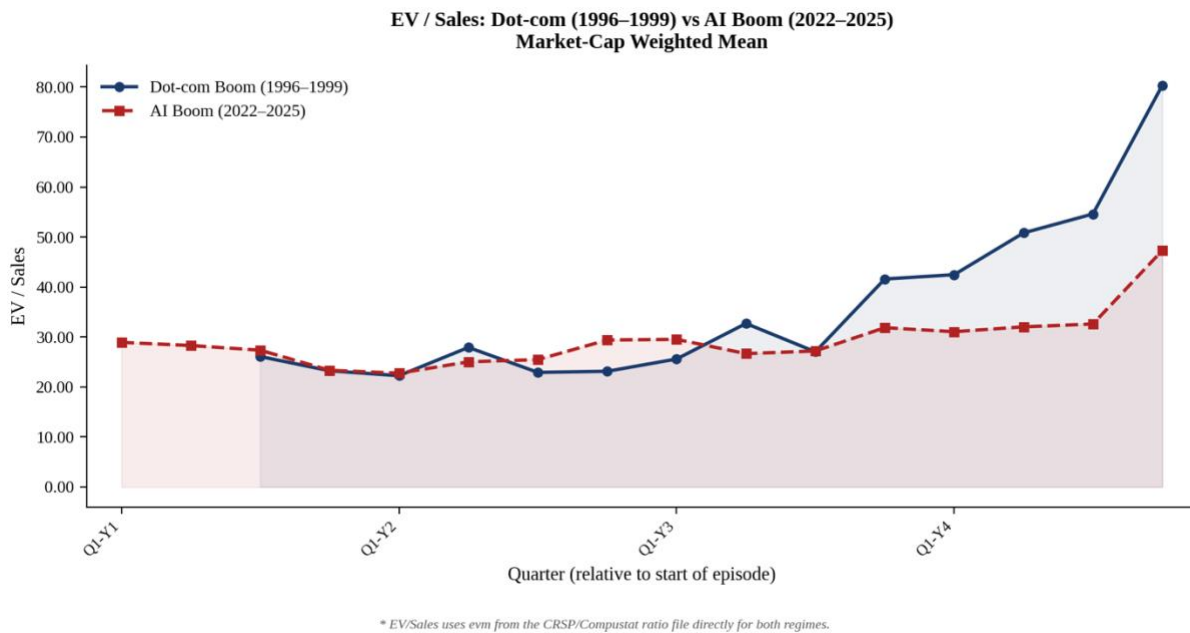


Figure 4

Market-cap-weighted P/BV comparison, dot-com (1996-1999) vs AI (2022-2025)

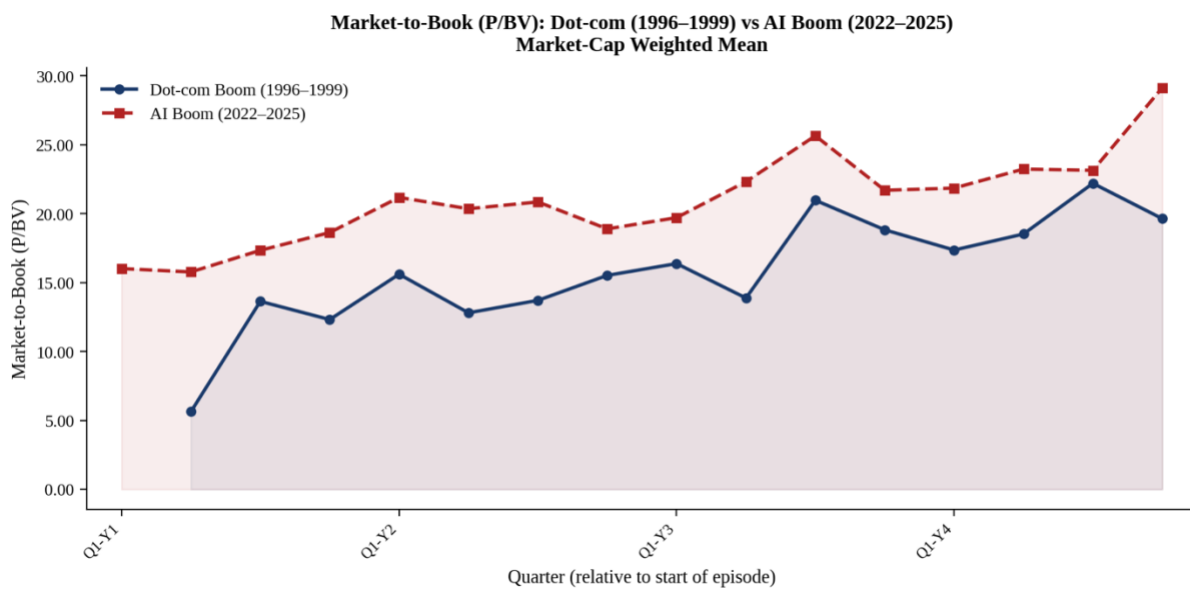


Figure 5

Market-cap-weighted year-on-year revenue growth comparison (log-difference), dot-com (1996-1999) vs AI (2022-2025)

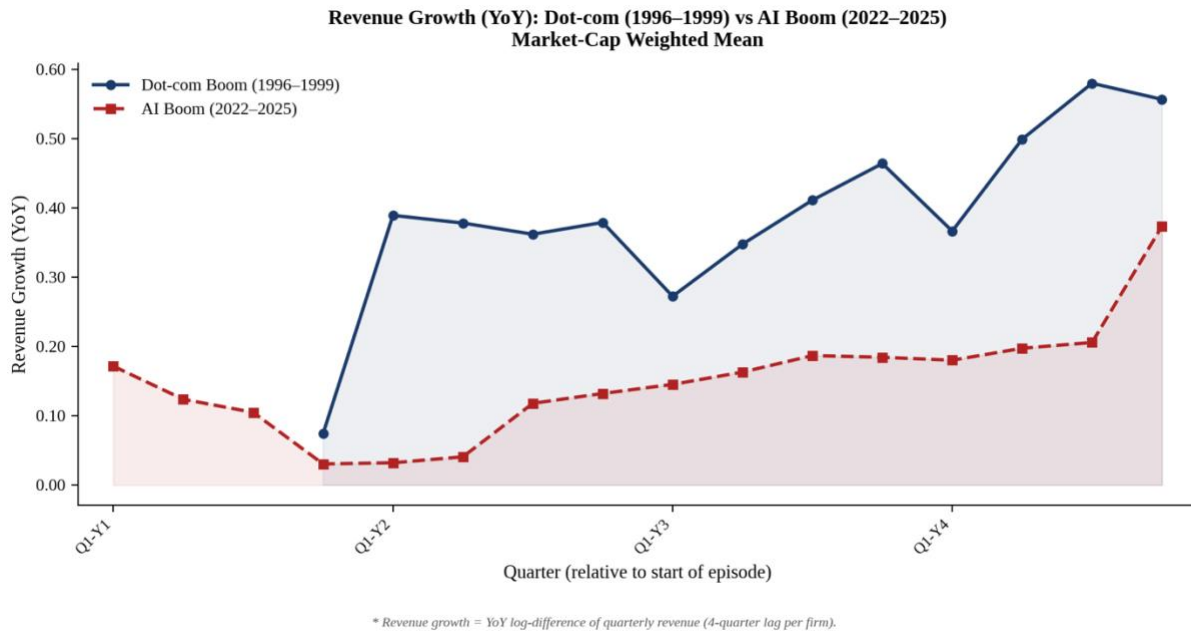


Figure 6

Market-cap-weighted operating margin comparison, dot-com (1996-1999) vs AI (2022-2025)

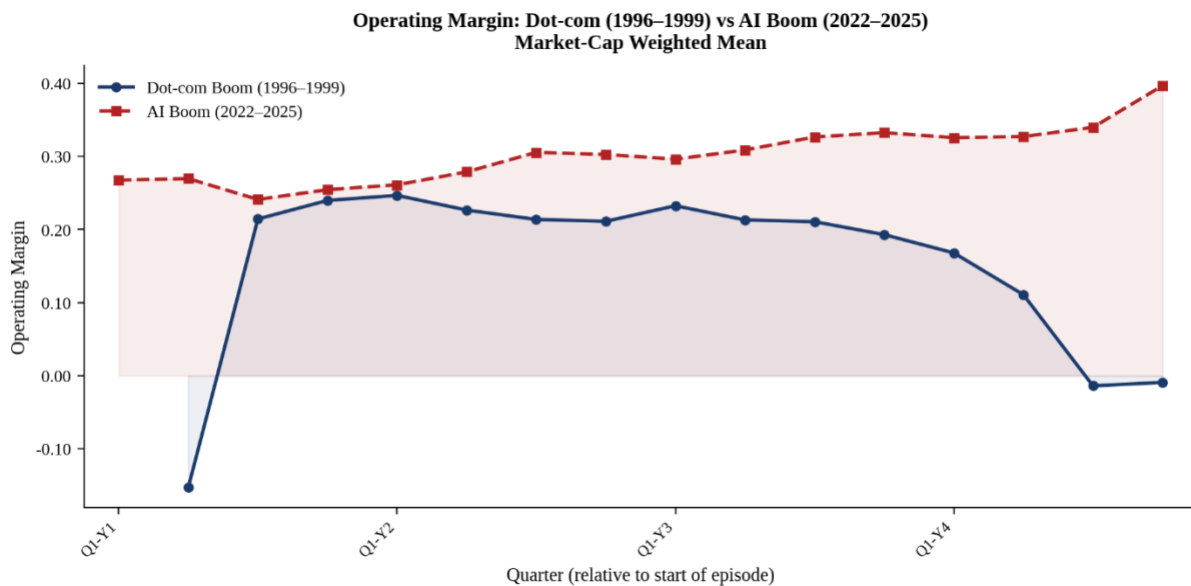


Figure 7

Market-cap-weighted change in cash and equivalents (annual flow, reported quarterly), dot-com (1996-1999) vs AI (2022-2025)

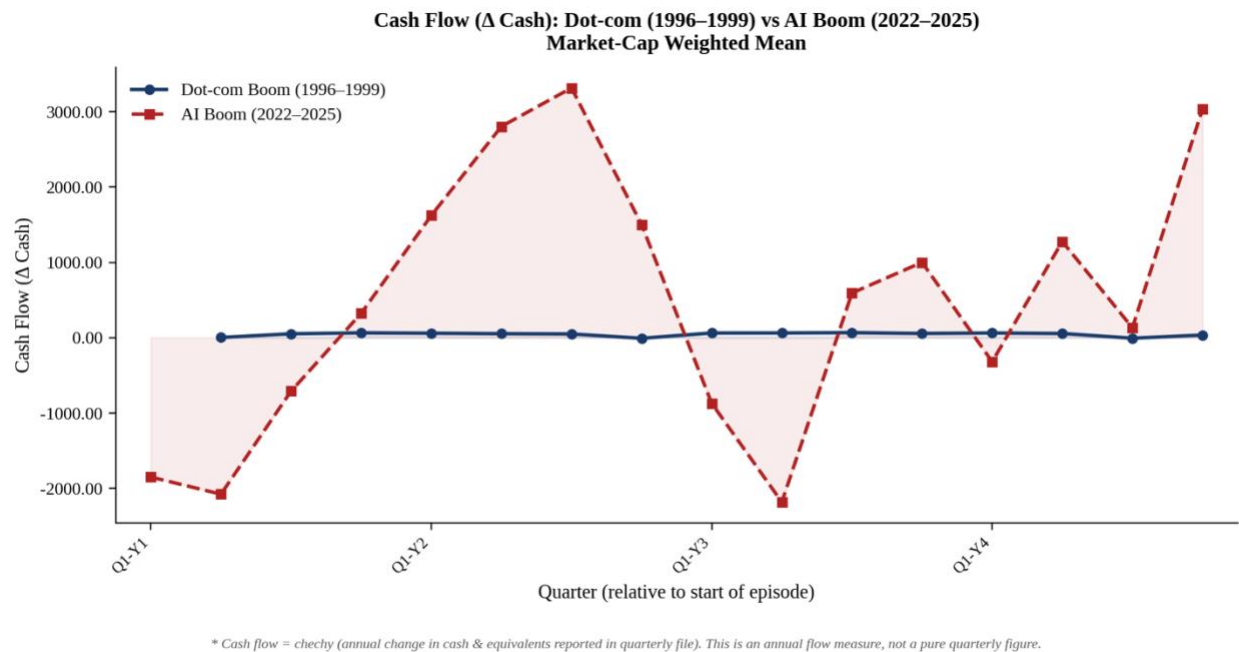
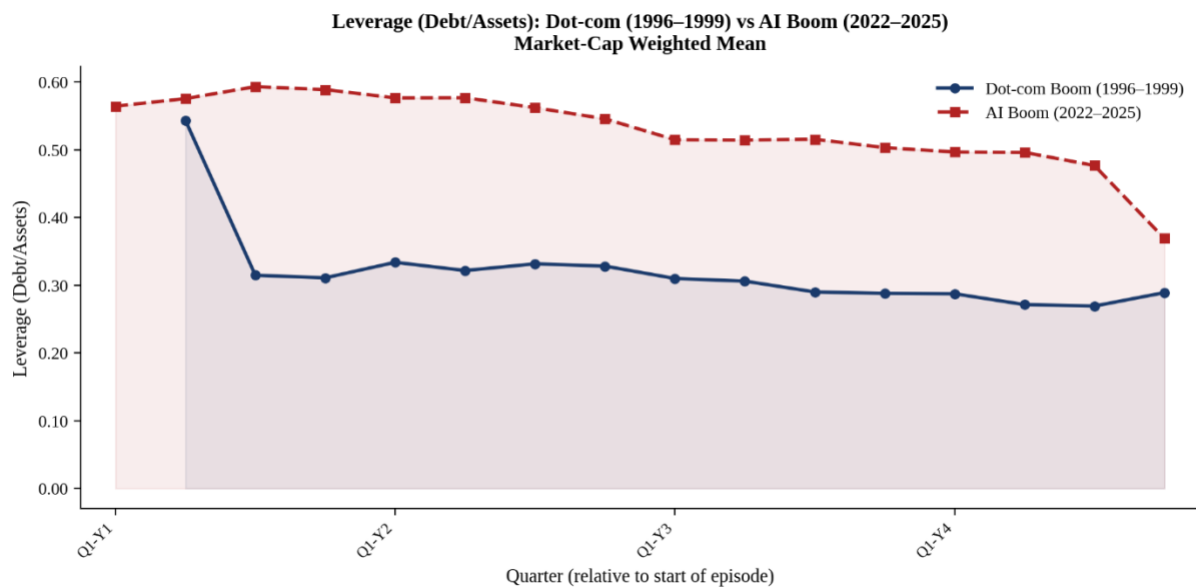


Figure 8

Market-cap-weighted leverage ratio, dot-com (1996-1999) vs AI (2022-2025)



Tables

Table 1

AI-related firms identified for Descriptive Evidence and Institutional Holding Analysis

Company	BICS_Level_3_Industry_Name	Index / ETF
ACCENTURE PLC CLASS A	IT Services	iShares Future AI & Tech
Adobe Inc	Software	Nasdaq 100
Advanced Micro Devices Inc	Semiconductors	Nasdaq 100
Airbnb Inc	Internet Media & Services	Nasdaq 100
Alphabet Inc	Internet Media & Services	Nasdaq 100
Alphabet Inc	Internet Media & Services	Nasdaq 100
Amazon.com Inc	E-Commerce Discretionary	Nasdaq 100
Analog Devices Inc	Semiconductors	Nasdaq 100
Apple Inc	Technology Hardware	Nasdaq 100
Applied Materials Inc	Semiconductors	Nasdaq 100
ARISTA NETWORKS INC	Technology Hardware	iShares AI Innovation Active
ARM Holdings PLC	Semiconductors	Nasdaq 100
ASML Holding NV	Semiconductors	Nasdaq 100
Atlassian Corp	Software	Nasdaq 100
Autodesk Inc	Software	Nasdaq 100
BLOOM ENERGY CLASS A CORP	Electrical Equipment	iShares Future AI & Tech
Booking Holdings Inc	Internet Media & Services	Nasdaq 100
Broadcom Inc	Semiconductors	Nasdaq 100
Cadence Design Systems Inc	Software	Nasdaq 100
CELESTICA INC	Technology Hardware	iShares AI Innovation Active
Cisco Systems Inc	Technology Hardware	Nasdaq 100
CLOUDFLARE INC CLASS A	Software	iShares AI Innovation Active
Cognizant Technology Solutions Corp	IT Services	Nasdaq 100
CrowdStrike Holdings Inc	Software	Nasdaq 100
Datadog Inc	Software	Nasdaq 100
DoorDash Inc	Internet Media & Services	Nasdaq 100
Fortinet Inc	Software	Nasdaq 100
Intel Corp	Semiconductors	Nasdaq 100
INTERNATIONAL BUSINESS MACHINES CO	IT Services	iShares Future AI & Tech
Intuit Inc	Software	Nasdaq 100
KLA Corp	Semiconductors	Nasdaq 100
Lam Research Corp	Semiconductors	Nasdaq 100
Marvell Technology Inc	Semiconductors	Nasdaq 100
MercadoLibre Inc	E-Commerce Discretionary	Nasdaq 100
Meta Platforms Inc	Internet Media & Services	Nasdaq 100
Microchip Technology Inc	Semiconductors	Nasdaq 100
Micron Technology Inc	Semiconductors	Nasdaq 100
Microsoft Corp	Software	Nasdaq 100

Company	BICS_Level_3_Industry_Name	Index / ETF
Monolithic Power Systems Inc	Semiconductors	Nasdaq 100
NVIDIA Corp	Semiconductors	Nasdaq 100
NXP Semiconductors NV	Semiconductors	Nasdaq 100
ONTO INNOVATION INC	Semiconductors	iShares Future AI & Tech
ORACLE CORP	Software	iShares AI Innovation Active
Palantir Technologies Inc	Software	Nasdaq 100
Palo Alto Networks Inc	Software	Nasdaq 100
PDD Holdings Inc	E-Commerce Discretionary	Nasdaq 100
QUALCOMM Inc	Semiconductors	Nasdaq 100
Roper Technologies Inc	Software	Nasdaq 100
RUBRIK INC CLASS A	Software	iShares AI Innovation Active
Seagate Technology Holdings PLC	Technology Hardware	Nasdaq 100
Shopify Inc	Software	Nasdaq 100
SNOWFLAKE INC	Software	iShares AI Innovation Active
Strategy Inc	Software	Nasdaq 100
Synopsys Inc	Software	Nasdaq 100
Texas Instruments Inc	Semiconductors	Nasdaq 100
VERTIV HOLDINGS CLASS A	Electrical Equipment	iShares AI Innovation Active
Western Digital Corp	Technology Hardware	Nasdaq 100
Workday Inc	Software	Nasdaq 100
Zscaler Inc	Software	Nasdaq 100

Table 2

P/BV specification matrix, Dot-com (1998–2000), with QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	0.002 (0.032)	-0.051 (0.036)	-0.031 (0.050)	-0.024 (0.050)	0.151** (0.060)
Log(Revenue)		0.103*** (0.034)	0.049 (0.083)	0.006 (0.094)	-0.086 (0.104)
Log(Assets)			0.059 (0.081)	0.098 (0.091)	0.101 (0.101)
Leverage				0.362 (0.260)	0.714** (0.292)
Revenue growth¹					0.658*** (0.078)
QFE	Yes	Yes	Yes	Yes	Yes
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	2872	2872	2872	2872	2009
Firms	378	378	378	378	352
R²	0.109	0.123	0.124	0.128	0.251
Adj. R²	0.105	0.119	0.120	0.123	0.246

Table 3

P/BV specification matrix, AI (2022–2025), with QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	0.009* (0.006)	-0.012 (0.007)	-0.032*** (0.008)	-0.028*** (0.008)	-0.025** (0.010)
Log(Revenue)		0.099*** (0.026)	0.310*** (0.068)	0.242*** (0.066)	0.211*** (0.069)
Log(Assets)			-0.212*** (0.065)	-0.161*** (0.062)	-0.133** (0.065)
Leverage				0.972*** (0.218)	0.909*** (0.227)
Revenue growth¹					0.513*** (0.100)
QFE	Yes	Yes	Yes	Yes	Yes
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	4873	4873	4873	4873	3546
Firms	388	388	388	388	367
R²	0.014	0.046	0.062	0.101	0.104
Adj. R²	0.011	0.043	0.058	0.098	0.100

¹ Year-over-Year log difference

Table 4

P/BV specification matrix, Dot-com (1998–2000), no QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	0.016 (0.033)	-0.029 (0.036)	-0.005 (0.054)	0.002 (0.054)	0.193*** (0.063)
Log(Revenue)		0.090*** (0.033)	0.032 (0.083)	-0.014 (0.094)	-0.104 (0.104)
Log(Assets)			0.062 (0.079)	0.104 (0.090)	0.101 (0.100)
Leverage				0.373 (0.259)	0.734** (0.291)
Revenue growth¹					0.689*** (0.081)
QFE	No	No	No	No	No
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	2872	2872	2872	2872	2009
Firms	378	378	378	378	352
R²	0.000	0.012	0.013	0.017	0.132
Adj. R²	0.000	0.011	0.012	0.015	0.130

Table 5

P/BV specification matrix, AI (2022–2025), no QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	0.009 (0.006)	-0.012* (0.007)	-0.032*** (0.008)	-0.029*** (0.008)	-0.025*** (0.010)
Log(Revenue)		0.100*** (0.026)	0.310*** (0.068)	0.243*** (0.066)	0.213*** (0.069)
Log(Assets)			-0.212*** (0.065)	-0.161*** (0.063)	-0.134** (0.065)
Leverage				0.964*** (0.219)	0.906*** (0.227)
Revenue growth¹					0.525*** (0.100)
QFE	No	No	No	No	No
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	4873	4873	4873	4873	3546
Firms	388	388	388	388	367
R²	0.003	0.035	0.051	0.090	0.101
Adj. R²	0.002	0.035	0.050	0.089	0.100

Table 6

P/S specification matrix, Dot-com (1998–2000), with QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	-0.487*** (0.033)	-0.515*** (0.039)	-0.175*** (0.064)	-0.210*** (0.063)	0.060 (0.058)
Log(Revenue)		0.057 (0.046)	-0.905*** (0.098)	-0.700*** (0.098)	-0.765*** (0.089)
Log(Assets)			1.045*** (0.095)	0.852*** (0.098)	0.797*** (0.088)
Leverage				-1.653*** (0.276)	-1.053*** (0.267)
Revenue growth¹					1.208*** (0.075)
QFE	Yes	Yes	Yes	Yes	Yes
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	2922	2922	2922	2922	2049
Firms	383	383	383	383	357
R²	0.251	0.253	0.421	0.458	0.647
Adj. R²	0.248	0.250	0.418	0.455	0.645

Table 7

P/S specification matrix, AI (2022–2025), with QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	-0.124*** (0.007)	-0.146*** (0.009)	-0.057*** (0.012)	-0.068*** (0.011)	-0.076*** (0.012)
Log(Revenue)		0.081*** (0.028)	-0.639*** (0.071)	-0.519*** (0.074)	-0.546*** (0.070)
Log(Assets)			0.716*** (0.064)	0.610*** (0.067)	0.644*** (0.065)
Leverage				-0.912*** (0.187)	-0.890*** (0.189)
Revenue growth¹					1.127*** (0.095)
QFE	Yes	Yes	Yes	Yes	Yes
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	5229	5229	5229	5229	3862
Firms	402	402	402	402	383
R²	0.189	0.202	0.314	0.352	0.425
Adj. R²	0.186	0.199	0.311	0.349	0.423

Table 8

P/S specification matrix, Dot-com (1998–2000), no QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	-0.502*** (0.032)	-0.528*** (0.037)	-0.155** (0.066)	-0.190*** (0.065)	0.092 (0.061)
Log(Revenue)		0.055 (0.046)	-0.927*** (0.098)	-0.719*** (0.098)	-0.785*** (0.089)
Log(Assets)			1.057*** (0.094)	0.861*** (0.097)	0.802*** (0.089)
Leverage				-1.645*** (0.273)	-1.049*** (0.265)
Revenue growth¹					1.229*** (0.077)
QFE	No	No	No	No	No
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	2922	2922	2922	2922	2049
Firms	383	383	383	383	357
R²	0.192	0.194	0.377	0.413	0.602
Adj. R²	0.191	0.193	0.376	0.412	0.601

Table 9

P/S specification matrix, AI (2022–2025), no QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	-0.123*** (0.007)	-0.146*** (0.009)	-0.057*** (0.012)	-0.068*** (0.011)	-0.077*** (0.012)
Log(Revenue)		0.082*** (0.028)	-0.641*** (0.071)	-0.521*** (0.074)	-0.543*** (0.070)
Log(Assets)			0.719*** (0.064)	0.612*** (0.067)	0.642*** (0.065)
Leverage				-0.914*** (0.187)	-0.889*** (0.189)
Revenue growth¹					1.131*** (0.095)
QFE	No	No	No	No	No
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	5229	5229	5229	5229	3862
Firms	402	402	402	402	383
R²	0.179	0.192	0.306	0.344	0.423
Adj. R²	0.179	0.192	0.305	0.343	0.422

Table 10

P/E specification matrix, Dot-com (1998–2000), with QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	-0.013 (0.369)	-0.000 (0.380)	-0.006 (0.372)	-0.077 (0.364)	-1.338*** (0.412)
Log(Revenue)		-0.007 (0.050)	-0.210* (0.113)	-0.133 (0.104)	-0.235** (0.110)
Log(Assets)			0.230** (0.113)	0.187* (0.105)	0.253** (0.115)
Leverage				-0.929*** (0.358)	-0.634 (0.413)
Revenue growth¹					2.095*** (0.249)
QFE	Yes	Yes	Yes	Yes	Yes
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	1408	1408	1408	1408	927
Firms	210	210	210	210	187
R²	0.041	0.041	0.053	0.067	0.264
Adj. R²	0.033	0.032	0.044	0.057	0.253

Table 11

P/E specification matrix, AI (2022–2025), with QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	-0.304 (0.289)	-0.178 (0.338)	-0.173 (0.342)	-0.119 (0.336)	-0.134 (0.373)
Log(Revenue)		-0.028 (0.031)	-0.038 (0.101)	0.004 (0.105)	0.023 (0.108)
Log(Assets)			0.009 (0.093)	-0.022 (0.094)	-0.021 (0.098)
Leverage				-0.441** (0.198)	-0.587*** (0.205)
Revenue growth¹					0.883*** (0.312)
QFE	Yes	Yes	Yes	Yes	Yes
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	2170	2170	2170	2170	1608
Firms	239	239	239	239	218
R²	0.016	0.018	0.018	0.031	0.056
Adj. R²	0.008	0.010	0.010	0.023	0.046

Table 12

P/E specification matrix, Dot-com (1998–2000), no QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	-0.101 (0.354)	-0.080 (0.362)	-0.055 (0.357)	-0.121 (0.350)	-1.432*** (0.411)
Log(Revenue)		-0.012 (0.049)	-0.226** (0.114)	-0.150 (0.105)	-0.258** (0.112)
Log(Assets)			0.240** (0.114)	0.198* (0.106)	0.279** (0.115)
Leverage				-0.902** (0.359)	-0.671 (0.419)
Revenue growth¹					2.030*** (0.250)
QFE	No	No	No	No	No
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	1408	1408	1408	1408	927
Firms	210	210	210	210	187
R²	0.000	0.000	0.014	0.027	0.219
Adj. R²	-0.001	-0.001	0.011	0.024	0.215

Table 13

P/E specification matrix, AI (2022–2025), no QFE

Variables / Regressions	(1)	(2)	(3)	(4)	(5)
Operating margin	-0.338 (0.287)	-0.211 (0.336)	-0.208 (0.340)	-0.152 (0.334)	-0.142 (0.371)
Log(Revenue)		-0.028 (0.031)	-0.036 (0.100)	0.005 (0.103)	0.020 (0.108)
Log(Assets)			0.008 (0.092)	-0.024 (0.093)	-0.018 (0.097)
Leverage				-0.448** (0.197)	-0.586*** (0.204)
Revenue growth¹					0.872*** (0.298)
QFE	No	No	No	No	No
Standard errors	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm	Clustered by firm
N	2170	2170	2170	2170	1608
Firms	239	239	239	239	218
R²	0.003	0.005	0.005	0.019	0.050
Adj. R²	0.003	0.004	0.004	0.017	0.047

Table 14

Chow-style pooled interaction test WITH QFE, P/BV regression

Regression	N	Firms	Quarters	R2	Adj R2	Wald stat	p-value	Conclusion
Regression 1	7745	712	28	0.0701	0.0667	0.048147	0.826320	No significant difference
Regression 2	7745	712	28	0.0960	0.0922	1.379496	0.501703	No significant difference
Regression 3	7745	712	28	0.1063	0.1025	11.139764	0.010994	Different across regimes
Regression 4	7745	712	28	0.1338	0.1297	18.488199	0.000990	Different across regimes
Regression 5	5555	670	21	0.1718	0.1673	12.706192	0.026293	Different across regimes

Table 15

Chow-style pooled interaction test WITHOUT QFE, P/BV regression

Regression	N	Firms	Quarters	R2	Adj R2	Wald stat	p-value	Conclusion
Regression 1	7745	712	28	0.0287	0.0283	0.045258	0.831531	No significant difference
Regression 2	7745	712	28	0.0538	0.0535	0.431695	0.805858	No significant difference
Regression 3	7745	712	28	0.0644	0.0636	10.160054	0.017253	Different across regimes
Regression 4	7745	712	28	0.0914	0.0903	17.384575	0.001627	Different across regimes
Regression 5	5555	670	21	0.1311	0.1294	16.360536	0.005887	Different across regimes

Table 16

Chow-style pooled interaction test WITH QFE, P/S regression

Regression	N	Firms	Quarters	R2	Adj R2	Wald stat	p-value	Conclusion
Regression 1	8151	730	28	0.2225	0.2197	112.242257	3.162123e-26	Different across regimes
Regression 2	8151	730	28	0.2314	0.2284	122.012260	3.201654e-27	Different across regimes
Regression 3	8151	730	28	0.3627	0.3601	31.249302	7.532606e-07	Different across regimes
Regression 4	8151	730	28	0.3997	0.3971	38.603596	8.411436e-08	Different across regimes
Regression 5	5911	690	21	0.5226	0.5202	8.004907	1.559654e-01	No significant difference

Table 17

Chow-style pooled interaction test WHITOUT QFE, P/S regression

Regression	N	Firms	Quarters	R2	Adj R2	Wald stat	p-value	Conclusion
Regression 1	8151	730	28	0.1944	0.1941	135.216310	2.960890e-31	Different across regimes
Regression 2	8151	730	28	0.2035	0.2030	145.585089	2.435564e-32	Different across regimes
Regression 3	8151	730	28	0.3413	0.3407	31.684807	6.098275e-07	Different across regimes
Regression 4	8151	730	28	0.3783	0.3776	38.548360	8.635218e-08	Different across regimes
Regression 5	5911	690	21	0.5044	0.5035	10.817556	5.511975e-02	No significant difference

Table 18

Chow-style pooled interaction test WHIT QFE, P/E regression

Regression	N	Firms	Quarters	R2	Adj R2	Wald stat	p-value	Conclusion
Regression 1	3578	418	28	0.0268	0.0189	0.382289	0.536381	No significant difference
Regression 2	3578	418	28	0.0281	0.0196	0.393058	0.821578	No significant difference
Regression 3	3578	418	28	0.0332	0.0242	2.953012	0.398927	No significant difference
Regression 4	3578	418	28	0.0468	0.0374	4.428409	0.351121	No significant difference
Regression 5	2535	380	21	0.1474	0.1372	13.785244	0.017033	Different across regimes

Table 19

Chow-style pooled interaction test WHITOUT QFE, P/E regression

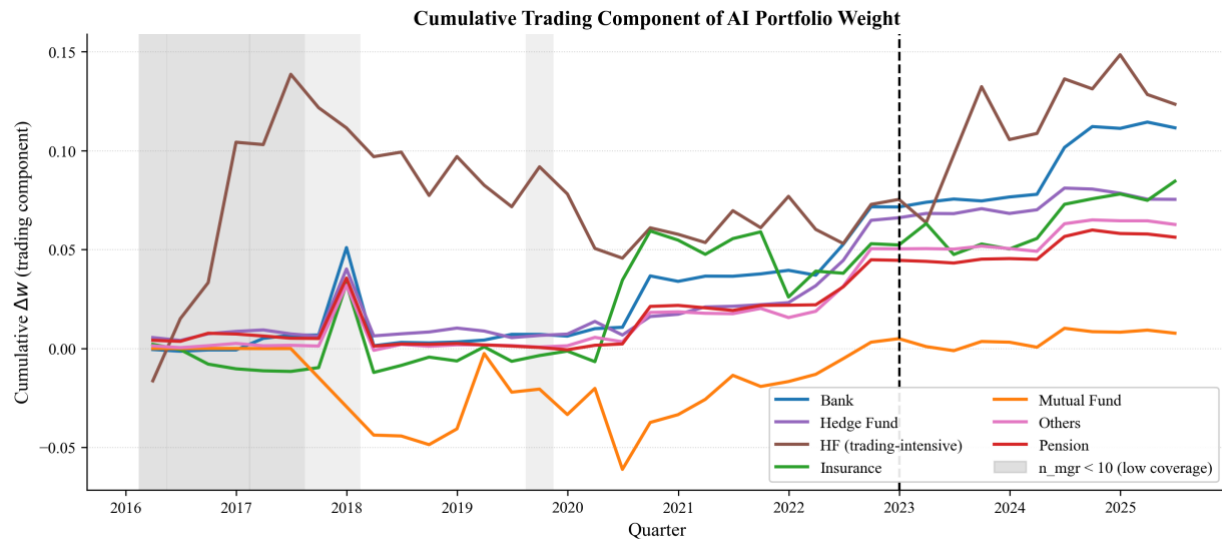
Regression	N	Firms	Quarters	R2	Adj R2	Wald stat	p-value	Conclusion
Regression 1	3578	418	28	0.0019	0.0010	0.269609	0.603594	No significant difference
Regression 2	3578	418	28	0.0033	0.0019	0.228636	0.891974	No significant difference
Regression 3	3578	418	28	0.0090	0.0070	3.048873	0.384151	No significant difference
Regression 4	3578	418	28	0.0225	0.0200	4.375364	0.357583	No significant difference
Regression 5	2535	380	21	0.1251	0.1213	14.204707	0.014360	Different across regimes

Exercise 2 – Outputs

Figures

Figure 9

Cumulative trading component of AI portfolio weight over time (2016-2025)



Tables

Table 20

Group manager counts

Investor Group	# Managers
Pension	5949
Others	2770
Hedge Fund	831
Mutual Fund	514
HF (trading-intensive)	195
Bank	160
Insurance	42

Table 21

Decomposition of trading vs price. We decomposed the total change in each investor group's AI portfolio weight over the sample period into two components: the active trading component, which captures the portion attributable to deliberate buying and selling of AI stocks, and the passive price-drift component, which captures the portion that would have occurred even without any trading, simply due to AI stocks

appreciating faster than the rest of the portfolio. The final two columns express each component as a share of total absolute movement and sum to 100% by construction.

Investor group	Total change in AI weight	Active trading component	Passive price component	Share due to trading (%)	Share due to price-drift (%)
Bank	0.1616	0.1114	0.0499	69.0528	30.9471
Hedge Fund	0.0895	0.0753	0.0178	80.8657	19.1342
HF (trading-intensive)	0.0895	0.1234	-0.0338	78.4799	21.5200
Insurance	0.0248	0.0844	-0.0596	58.6384	41.3615
Mutual Fund	0.1710	0.0077	0.1633	4.5061	95.4938
Others	0.0949	0.0626	0.0323	65.9430	34.0569
Pension	0.0697	0.0562	0.0135	80.6328	19.3671

Summary Statistics

Table 22

Summary statistics for the cross-sectional valuation regression sample. Dot-com window: 1998Q1-2000Q4. AI window: 2022Q1-2025Q4. All variables are winsorised at the 2.5% and 97.5% percentiles within each regime, matching the regression sample.

Variable	Dot-com window (1998-2000)							
	N	Mean	SD	p25	Median	p75	Min	Max
Price-to-sales (P/S)	2,922	15.52	35.35	1.43	3.18	9.91	0.32	181.38
Price-to-book (P/B)	2,872	7.53	9.14	1.98	4.06	8.70	0.59	42.09
Price-to-earnings (P/E)	1,408	70.01	28.58	3.11	629.58	1,408	70.01	28.58
Operating margin	6,071	-0.61	1.58	-0.53	-0.03	0.10	-7.76	0.30
Revenue (USD mn, quarterly)	6,071	37.89	64.11	5.86	13.83	35.68	0.52	310.93
Total assets (USD mn)	6,071	195.90	342.28	32.50	73.22	183.23	4.55	1,732.25
Leverage (Liab. / Assets)	6,071	0.36	0.24	0.18	0.30	0.48	0.05	1.11
Revenue growth (YoY log-diff)	4,074	0.45	0.66	0.04	0.31	0.74	-0.75	2.32

Variable	AI window (2022-2025)							
	N	Mean	SD	p25	Median	p75	Min	Max
Price-to-sales (P/S)	5,229	8.65	19.78	1.06	3.08	7.67	0.14	115.65
Price-to-book (P/B)	4,873	5.75	7.85	1.29	2.81	6.38	0.26	37.86
Price-to-earnings (P/E)	2,170	57.43	31.62	2.79	283.78	2,170	57.43	31.62
Operating margin	7,230	-1.35	5.51	-0.30	-0.01	0.13	-31.97	0.40
Revenue (USD mn, quarterly)	7,230	651.94	1,655.84	19.54	105.30	389.95	0.14	8,943.48
Total assets (USD mn)	7,230	5,481.87	13,294.54	134.84	767.09	3,261.65	6.15	67,592.65
Leverage (Liab. / Assets)	7,230	0.53	0.34	0.29	0.47	0.71	0.07	1.60
Revenue growth (YoY log-diff)	5,242	0.07	0.41	-0.06	0.06	0.19	-1.10	1.41

Table 23

Summary statistics for the 13F portfolio decomposition sample, computed at the manager-quarter level over the full sample window (2015Q1-2025Q2). Portfolio market value is in USD billions; turnover is winsorised at the 99th percentile as in the main analysis. The bottom panel reports the same statistics by manager group.

Coverage	Variable	N	Mean	SD	p25	Median	p75	Min	Max
ALL MANAGERS	Portfolio market value (USD bn)	226,702	5.89	72.68	0.16	0.35	1.10	0.00	6,146
	Number of equity positions	226,702	254.87	547.27	33.00	90.00	214.00	1.00	9,050
	Top-10 portfolio share	226,702	0.56	0.27	0.34	0.51	0.78	0.02	1.00
	Portfolio turnover (winsorised)	214,834	0.30	0.23	0.14	0.22	0.38	0.00	1.15
	AI portfolio weight (actual)	162,934	0.08	0.11	0.01	0.05	0.11	0.00	1.00
	AI portfolio weight (buy-and-hold)	162,934	0.08	0.11	0.01	0.05	0.11	0.00	1.00
	Active AI tilt (actual - BH)	162,934	0.00	0.04	0.00	0.00	0.00	-1.00	1.00
BANK	Portfolio market value (USD bn)	4,290	36.82	173.35	0.30	0.90	4.61	0.00	2,663
	Number of equity positions	4,290	798.45	1,223.07	135.00	325.00	803.00	1.00	7,282
	Top-10 portfolio share	4,290	0.38	0.19	0.25	0.33	0.46	0.10	1.00
	Portfolio turnover (winsorised)	4,114	0.21	0.16	0.12	0.17	0.25	0.01	1.15
	AI portfolio weight (actual)	3,452	0.09	0.06	0.05	0.08	0.12	0.00	0.38
	AI portfolio weight (buy-and-hold)	3,452	0.09	0.06	0.05	0.08	0.11	0.00	0.45
	Active AI tilt (actual - BH)	3,452	0.00	0.02	0.00	0.00	0.00	-0.23	0.17
HEDGE FUND	Portfolio market value (USD bn)	22,629	5.22	26.16	0.18	0.45	1.64	0.00	625
	Number of equity positions	22,629	181.55	427.20	16.00	42.00	125.00	1.00	4,425
	Top-10 portfolio share	22,629	0.63	0.28	0.38	0.6147	0.92	0.04	1.00
	Portfolio turnover (winsorised)	21,660	0.33	0.20	0.18	0.29	0.44	0.00	1.15
	AI portfolio weight (actual)	13,521	0.11	0.13	0.01	0.08	0.15	0.00	1.00
	AI portfolio weight (buy-and-hold)	13,521	0.11	0.13	0.01	0.08	0.15	0.00	1.00
	Active AI tilt (actual - BH)	13,521	0.00	0.05	-0.0	0.00	0.01	-1.00	1.00
HF (TRADING-INTENSIVE)	Portfolio market value (USD bn)	4,202	1.86	4.63	0.15	0.49	1.43	0.00	53.50
	Number of equity positions	4,202	287.97	472.63	23.00	61.00	360.00	1.00	3,763
	Top-10 portfolio share	4,202	0.53	0.32	0.24	0.51	0.82	0.03	1.00
	Portfolio turnover (winsorised)	3,931	0.77	0.20	0.64	0.77	0.90	0.00	1.15
	AI portfolio weight (actual)	2,161	0.12	0.15	0.02	0.09	0.15	0.00	1.00
	AI portfolio weight (buy-and-hold)	2,161	0.12	0.15	0.02	0.09	0.15	0.00	1.00
	Active AI tilt (actual - BH)	2,161	0.00	0.11	-0.02	0.00	0.02	-1.00	1.00
INSURANCE	Portfolio market value (USD bn)	995	22.91	53.50	0.17	0.68	7.18	0.00	327.93
	Number of equity positions	995	676.90	1,129.70	20.00	107.00	515.50	1.00	4,452
	Top-10 portfolio share	995	0.58	0.31	0.28	0.58	0.89	0.10	1.00
	Portfolio turnover (winsorised)	948	0.27	0.22	0.13	0.19	0.34	0.01	1.15
	AI portfolio weight (actual)	743	0.09	0.09	0.00	0.08	0.15	0.00	0.62
	AI portfolio weight (buy-and-hold)	743	0.09	0.09	0.00	0.08	0.14	0.00	0.61
	Active AI tilt (actual - BH)	743	0.00	0.02	0.00	0.00	0.00	-0.19	0.20

Coverage	Variable	N	Mean	SD	p25	Median	p75	Min	Max
MUTUAL FUND	Portfolio market value (USD bn)	6,124	2.12	13.14	0.13	0.21	0.49	0.00	183.81
	Number of equity positions	6,124	169.33	397.06	21.00	61.00	145.00	1.00	3,951
	Top-10 portfolio share	6,124	0.63	0.26	0.42	0.61	0.88	0.06	1.00
	Portfolio turnover (winsorised)	5,586	0.30	0.22	0.14	0.23	0.39	0.01	1.15
	AI portfolio weight (actual)	4,895	0.10	0.13	0.01	0.05	0.14	0.00	1.00
	AI portfolio weight (buy-and-hold)	4,895	0.10	0.13	0.01	0.05	0.14	0.00	1.00
	Active AI tilt (actual - BH)	4,895	0.00	0.04	0.00	0.00	0.00	-0.54	0.41
OTHERS	Portfolio market value (USD bn)	78,303	9.05	109.48	0.19	0.51	1.86	0.00	6,146
	Number of equity positions	78,303	284.17	613.44	25.00	80.00	230.00	1.00	6,360
	Top-10 portfolio share	78,303	0.57	0.28	0.32	0.51	0.83	0.02	1.00
	Portfolio turnover (winsorised)	74,864	0.32	0.24	0.15	0.24	0.41	0.00	1.15
	AI portfolio weight (actual)	51,124	0.09	0.11	0.01	0.07	0.13	0.00	1.00
	AI portfolio weight (buy-and-hold)	51,124	0.09	0.12	0.01	0.07	0.13	0.00	1.00
	Active AI tilt (actual - BH)	51,124	0.00	0.05	0.00	0.00	0.00	-1.00	1.00
PENSION	Portfolio market value (USD bn)	110,159	2.79	30.73	0.15	0.28	0.69	0.00	1,738
	Number of equity positions	110,159	227.61	456.45	49.00	101.00	210.00	1.00	9,050
	Top-10 portfolio share	110,159	0.55	0.25	0.34	0.50	0.74	0.03	1.00
	Portfolio turnover (winsorised)	103,731	0.26	0.21	0.13	0.19	0.31	0.00	1.15
	AI portfolio weight (actual)	87,038	0.07	0.10	0.01	0.04	0.09	0.00	1.00
	AI portfolio weight (buy-and-hold)	87,038	0.07	0.10	0.01	0.04	0.09	0.00	1.00
	Active AI tilt (actual - BH)	87,038	0.00	0.04	0.00	0.00	0.00	-1.00	1.00