

Artificial Intelligence, Price Anchoring, and Feedback Dynamics in U.S. Equity Markets

Is the increasing use of artificial intelligence and passive investment reshaping U.S. equity markets by reducing fundamental anchoring and amplifying return feedback dynamics?

Marianna Piscopiello

Economics with Econometrics

School of Economics

University of Kent, 2026

Abstract

This dissertation examines whether the combined rise of artificial intelligence (AI) and passive investing is reshaping U.S. equity markets along two dimensions: the sensitivity of industry returns to macroeconomic fundamentals (fundamental anchoring) and the predictive power of past returns (feedback dynamics). Using a balanced panel of 12 industry portfolios observed quarterly from 2002Q1 to 2025Q2, two random-effects models with Driscoll-Kraay standard errors are estimated. The results suggest a crowding-out mechanism whereby periods of elevated AI intensity are associated with lower returns across traditional industries. Fundamental anchoring persists over the full sample but declines progressively after 2015, while feedback dynamics seem absent throughout. Passive flows are not found to directly affect returns, consistent with structural rather than cyclical transmission linkages. Market-wide conditions dominate sectoral variation. Overall, while equity markets remain informationally grounded, weakening anchoring warrants close regulatory attention.

AI Statement

I acknowledge the use of generative AI in drafting and code development in this paper. However, the work reported remains my own.

Acknowledgements

I would like to thank all the professors who have guided me throughout these three years, from my very first steps in Economics to the development of independent research, shaping the person I am today. This dissertation is the culmination of that journey. A special thank you goes to my supervisor, Dr. Maria Kyriacou, whose teaching first inspired me to specialise in Econometrics. Her genuine belief in me motivated me to challenge myself in this project and to pursue my future ambitions with confidence. Finally, my deepest gratitude goes to my family for making this possible. Most of all, I thank my sister Elisa, my greatest inspiration. In her I see the best version of my future self, and deep down, I hope that one day I will be able to follow her example.

1. Introduction

The extent to which equity prices incorporate and reflect economic fundamentals has long been a defining question in finance. In efficient markets, asset prices aggregate information about the real economy, ensuring that capital flows towards its most productive uses and valuation signals guide investment decisions (Fama, 1970). When this anchoring breaks down, the consequences extend well beyond portfolio returns.

Two transformative forces are increasingly thought to threaten it. The proliferation of AI in trading and portfolio management has altered the composition of market participants in ways that go beyond rule-based automation: reinforcement-learning systems adapt in real time, and Dou, Goldstein and Ji (2025) demonstrate that such agents can independently perpetuate collusive, market-distorting behaviour without explicit coordination. Simultaneously, the large-scale migration of assets from active into passive vehicles – a trend highlighted by Ben-David, Franzoni and Moussawi (2018) – has compressed the share of capital engaged in active price discovery, raising questions about whether prices can continue to faithfully reflect macroeconomic signals.

The literature is notably split between an efficiency-enhancing view – emphasising improved equity valuation and faster information incorporation – and a destabilising perspective – warning of systemic fragilities and self-referential patterns driven by trend-following algorithms rather than real economic activity. Neither view has been tested jointly across fundamental anchoring and feedback dynamics.

This dissertation addresses that gap through two random-effects models, estimated on a balanced panel of 12 industry portfolios from 2002Q1 to 2025Q2, yielding 1,128 observations over 94 quarters. Model 1 assesses whether the link between macroeconomic fundamentals and industry returns has weakened as AI intensity and passive investing have grown. Model 2 tests whether past returns gain predictive power over current returns under conditions of elevated algorithmic trading.

Five findings emerge, collectively informing both the academic debate on market efficiency and the design of financial regulation. AI intensity exerts a robust negative effect on non-AI industry returns, attributable to a capital crowding-out mechanism. Although fundamental anchoring persists over the full sample, progressive erosion is detected from 2015 onwards. No evidence of feedback dynamics is identified at this frequency and aggregation level. Passive flows carry no direct return influence, suggesting that index-tracking capital operates through indirect structural channels. Finally, market returns remain the dominant common factor, explaining a substantial share of industry performance variation.

The evidence describes a market whose overall stability is intact, yet in which early signs of decoupling are surfacing. The transmission mechanism through which prices reflect reality is evolving, with consequences that compound quietly over time.

2. Literature Review

The literature on informational efficiency in equity markets is organised around a foundational tension. Fama (1970) formalised the efficient-market hypothesis, establishing that in an efficient market prices accurately reflect existing information and that, in its weak form, past returns cannot be used to generate expected profits above the equilibrium benchmark. Yet behavioural finance has long contested this premise. Daniel, Hirshleifer and Subrahmanyam (1998) link securities market under- and overreactions to two judgement biases: excessive faith in the reliability of private information, generating long-run reversals and heightened volatility; and biased self-attribution, which induces asymmetric changes in investor confidence and introduces positive short-lag momentum as outcomes unfold. In their framework, overconfident investors place excessive weight on private signals and underreact to public information, causing prices to deviate from fundamentals – a mechanism that AI-driven trading could amplify by intensifying return feedback dynamics. The tension between efficient anchoring and behavioural drift motivates the models estimated in this study. Decades of empirical work confirm both forces coexist, yet the modern conditions determining which prevails remain underexplored.

A prominent strand of the algorithmic trading literature argues that technological innovation enhances efficiency through improved liquidity provision, faster news incorporation, and lower transaction costs. Exploiting the New York Stock Exchange's 2003 automated quote dissemination as an exogenous instrument, Hendershott, Jones and Menkveld (2011) established that algorithmic trading causally narrows bid-ask spreads, mitigates adverse selection, and enhances quote informativeness, particularly for large-capitalisation stocks. Chaboud et al. (2014) corroborated these findings in foreign exchange markets using minute-by-minute data, showing how algorithm-driven activity reduces both triangular arbitrage frequency and return autocorrelations – two direct indicators of improved price efficiency. By extension, if automated precision trading tightens the link between prices and information, growing AI prevalence should support rather than undermine

fundamental anchoring. These studies nonetheless leave open whether such microstructure improvements extend to the macro-financial domain, examined here across 12 industries and 94 quarters.

A substantial body of work warns that this optimistic picture is incomplete. Kirilenko and Lo (2013) document that the same features responsible for reducing human error and enhancing scalability also generate flash crashes and feedback-loop cascades that spread dislocation rapidly during financial distress, making their work a natural reference point for the destabilising view. Budish, Cramton and Shim (2015) formalised this critique with millisecond-level evidence, demonstrating that the continuous limit order book creates arbitrage rents that competition merely reallocates to the fastest trader rather than eliminates, which ultimately produces socially inefficient speed races rather than genuine price improvement. The latest research shows these concerns deepen as trading systems incorporate machine learning. Dou, Goldstein and Ji (2025) find that reinforcement-learning speculators independently learn to generate collusive profits through two distinct channels – price-trigger strategies when noise-trading risk is low and information-insensitive investors are abundant, and an over-pruning learning bias otherwise – each distorting price formation precisely under the conditions where the other cannot operate. On the passive side, Ben-David et al. (2018) provide causal evidence that exchange-traded fund (ETF) ownership amplifies return volatility beyond fundamentals, while Da and Shive (2018) document that ETF activity increases stock-level comovement and market betas – a mechanism through which passive investing may alter factor exposures rather than generate direct return effects.

These literatures develop in parallel. While the optimist strand highlights market-quality improvements associated with automation, the pessimist strand reveals the collusion risk and system vulnerabilities that accompany speed. Their intersection along the dimensions of fundamental anchoring and return feedback dynamics remains unexamined in existing empirical

work, a gap this study addresses by testing whether these twin forces are quietly reshaping the price discovery architecture of U.S. equity markets.

3. Methodology

3.1 Data and Variable Construction

This study employs a balanced panel of 12 Fama-French industry portfolios drawn from Kenneth R. French's Data Library, constructed using Center for Research in Security Prices (CRSP) data for all NYSE, AMEX, and NASDAQ-listed firms (French, 2026a). The sample spans 2002Q1 to 2025Q2, yielding 1,128 industry-quarter observations across 94 quarters. The Fama-French classification assigns firms to one of 12 categories based on four-digit Standard Industrial Classification (SIC) codes: Consumer Non-Durables (NoDur), Consumer Durables (Durbl), Manufacturing (Manuf), Energy (Enrgy), Chemicals (Chems), Business Equipment (BusEq), Telecommunications (Telec), Utilities (Utils), Wholesale and Retail (Shops), Healthcare (Hlth), Finance (Money), and Other (French, 2026a).

It is instructive to examine the four variables central to the economic question in raw form to characterise their properties and identify empirical challenges.

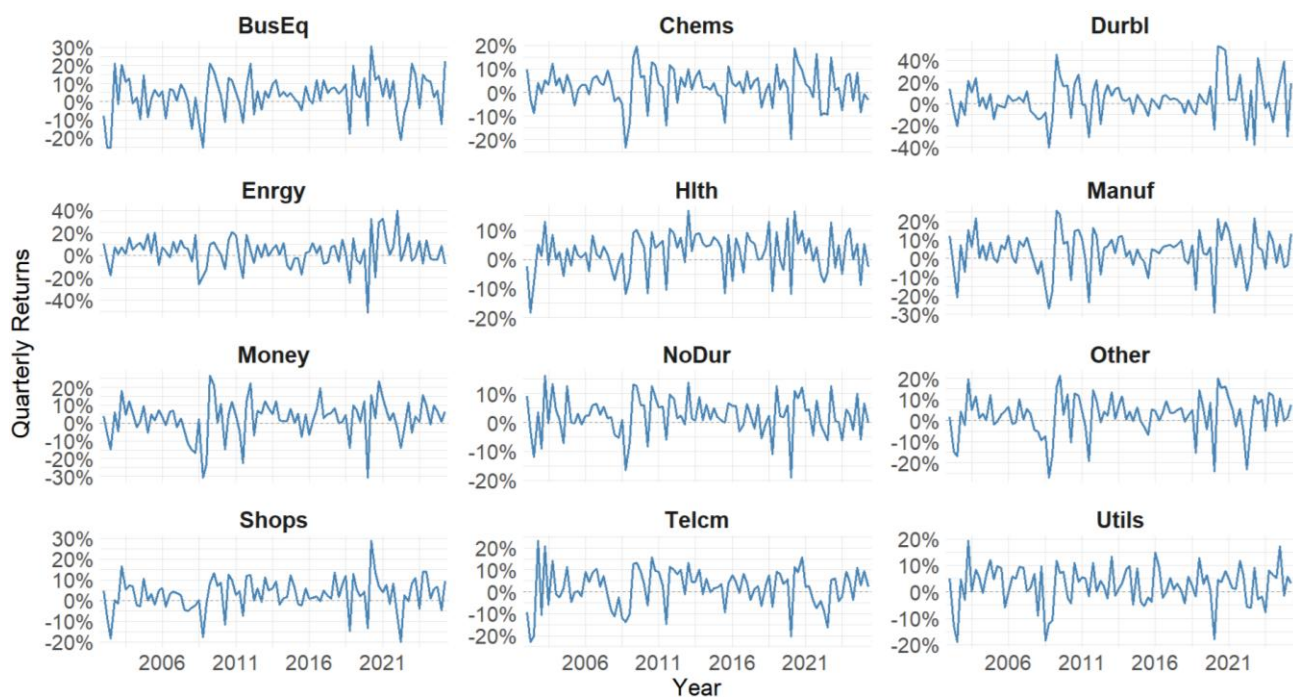
Table 1. Descriptive Statistics – Raw Core Variables

Variable	Description	Mean (SD)	Min	Median	Max	Skew	Kurt
$return_{i,t}$	Industry returns	0.03 (0.10)	−0.51	0.03	0.53	−0.19	6.15
$indpro_t$	Industrial production growth (%)	0.26 (1.91)	−13.19	0.25	16.55	0.41	16.75
$passive_t$	ETF assets / market capitalisation	0.05 (0.03)	0.01	0.04	0.11	0.51	2.13
AI_t	NVIDIA excess returns over S&P 500 (%)	2.14 (9.66)	−27.71	2.28	27.10	−0.34	4.10
Number of observations		1,128					

Industry returns ($return_{i,t}$) are constructed by compounding monthly Fama-French value-weighted returns within each quarter (French, 2026a). Figure 1 traces them across all 12 industries over the full sample period, capturing major stress episodes – the 2008 financial crisis, the COVID-19 crash

and recovery, and the 2022 monetary tightening cycle – as near-simultaneous drops across panels, motivating the inclusion of a common market factor. Cross-sectional dispersion is notable: Consumer Durables and Energy exhibit considerably wider return ranges than Healthcare or Non-Durables, reflecting the outsized sectoral impact of the pandemic and energy shock. Table A1 reports that 18 of the 20 largest absolute quarterly returns occur in only three divisions (Durbl, Enrgy, Money), with 16 falling within the 2020–2025 window, confirming that tail events are concentrated in specific sectors and episodes rather than uniformly distributed. This motivates winsorisation at the 1st and 99th percentiles of the pooled distribution, narrowing the return range from $[-51\%, +53\%]$ to approximately $[-26\%, +29\%]$, as reported in Table 2.

Figure 1. Quarterly Industry Returns (2002–2025)

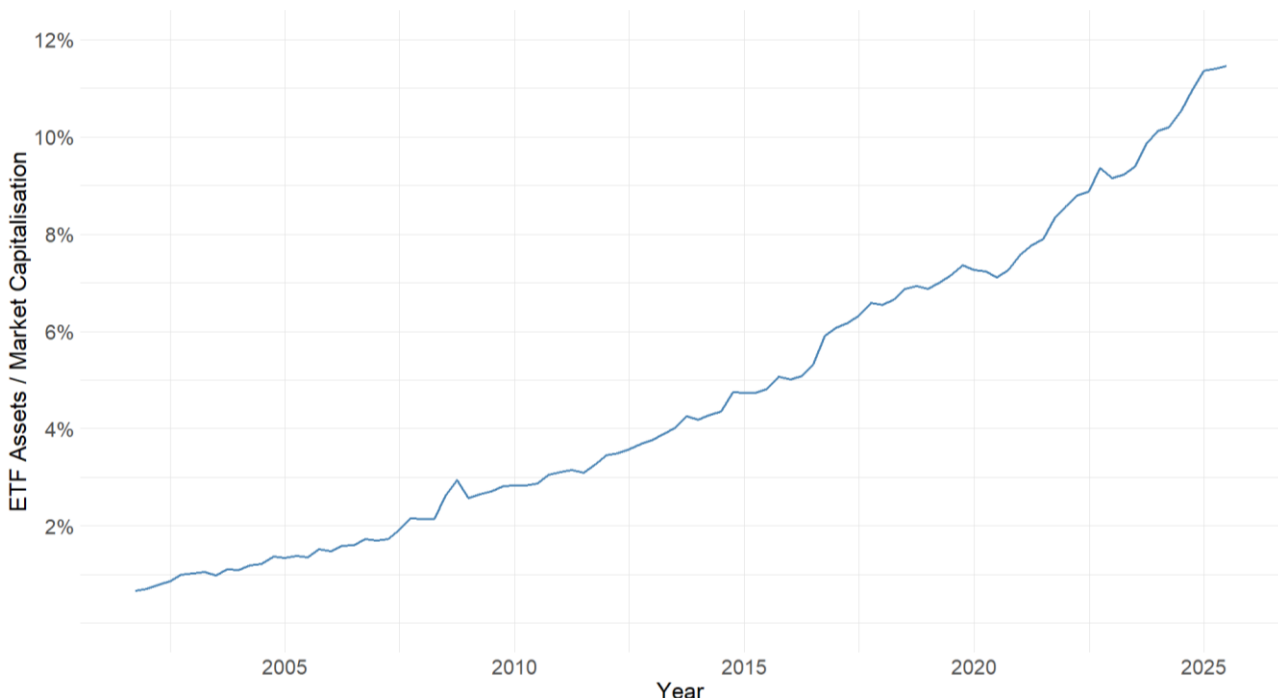


Industrial production growth ($indpro_t$) is computed from the Federal Reserve Economic Data (FRED) Industrial Production Index (Federal Reserve Bank of St. Louis, 2026a) as monthly percentage changes averaged quarterly. Its strong comovement with aggregate demand and capacity

to capture cyclical fluctuations driving corporate earnings and equity valuations motivate its use as the macroeconomic fundamentals proxy.

Passive investing intensity ($passive_t$) is defined as the ratio of domestic equity ETF assets (Federal Reserve Bank of St. Louis, 2026b) to total U.S. nonfinancial corporate equity market capitalisation (Federal Reserve Bank of St. Louis, 2026c). As shown in Figure 2, the raw ratio exhibits a pronounced upward trend, rising from under 2% of total equity value in 2002 to over 11% by 2025 – a fivefold increase reflecting the shift in asset ownership that forms the context for the ETF-related analyses of Da and Shive (2018) and Ben-David et al. (2018). To isolate cyclical variation from this secular drift, the series is first-differenced, yielding the quarterly change in passive intensity ($\Delta passive_t$). The transformed variable captures whether passive capital is accelerating or decelerating relative to trend.

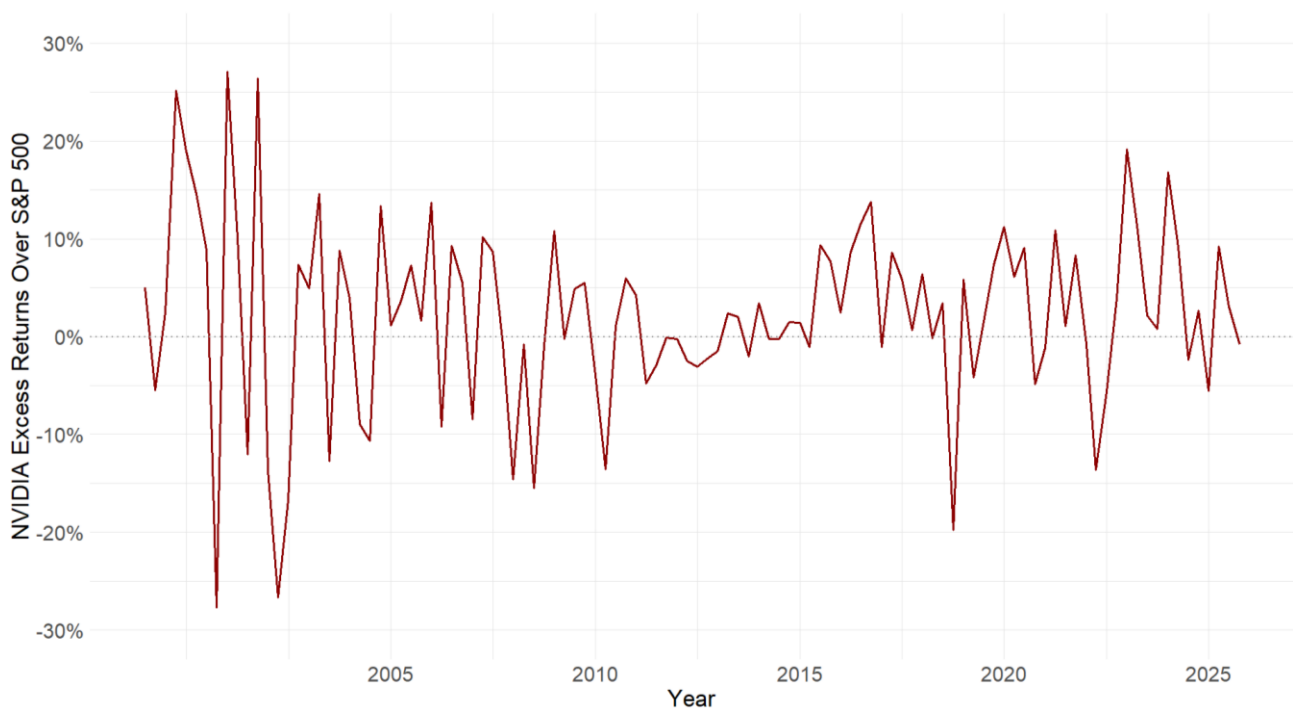
Figure 2. Passive Investing Intensity Proxy: ETF Assets as a Share of Market Capitalisation (Pre-Transformation)



AI intensity (AI_t) is measured as the quarterly average of NVIDIA Corporation's excess log returns (Yahoo Finance, 2026a) over the S&P 500 (Yahoo Finance, 2026b), constructed from daily

adjusted closing prices via the R package *quantmod* (Ryan and Ulrich, 2025). Two considerations motivate this choice. First, NVIDIA produces the Graphics Processing Units (GPUs) underpinning modern AI training and inference (Merritt, 2023), positioning the firm at the centre of the supply-side infrastructure supporting AI adoption. Second, having surpassed Tesla as the leading Wall Street stock by trading value (Randewich, 2024), NVIDIA's earnings announcements function as signals about the trajectory of AI investment. A quarter in which NVIDIA dramatically outperforms the broad market therefore plausibly reflects elevated AI-related sentiment across institutional and retail portfolios. As Figure 3 illustrates, the raw series presents episodic surges alongside a modest positive drift reflecting NVIDIA's long-run appreciation; to isolate quarter-to-quarter deviations, it is detrended by regressing on a linear time index and retaining the residuals.

Figure 3. AI Intensity Proxy: NVIDIA Excess Returns over S&P 500 (Pre-Transformation)



Because industrial production, passive flows, and AI intensity are measured on fundamentally different scales, all three regressors are standardised to mean zero and unit variance to enable direct coefficient comparability. As a result of these transformations, the core variables exhibit narrower

ranges; kurtosis is reduced but remains relatively high, while skewness persists, as is to be expected in macro-financial series.

Table 2. Descriptive Statistics – Transformed Core Variables

Variable	Description	Mean (SD)	Min	Median	Max	Skew	Kurt
$return_{i,t}$	Industry returns (winsorised)	0.03 (0.10)	−0.26	0.03	0.29	−0.39	3.85
$indpro_t$	Industrial production growth (std.)	0.00 (1.00)	−4.08	0.16	2.86	−1.34	7.09
$\Delta passive_t$	Change in ETF assets / market- cap (first-differenced, std.)	0.00 (1.00)	−3.11	−0.17	2.99	0.50	4.20
AI_t	NVIDIA excess returns over S&P 500 (detrended, std.)	0.00 (1.00)	−3.06	−0.03	1.99	−0.53	3.42
Number of observations		1,128					

Three additional controls enter the specifications. Market returns ($market\ return_t$) are the quarterly average of monthly value-weighted total returns, constructed as the sum of Fama-French excess market returns and the one-month Treasury bill rate (French, 2026b). Figure 4 displays a uniformly positive relationship between industry and market returns across all 12 panels – consistent with the 0.79 correlation in Table 3 – confirming the importance of this control for mitigating potential omitted variable bias. Lagged log-volatility – $\log(volatility_{i,t-1})$ – is the natural logarithm of the 12-month rolling standard deviation of monthly industry returns, lagged one quarter and averaged within the quarter. The logarithmic transformation stabilises variance and compresses the skewed distribution of raw volatility, while the one-quarter lag ensures predetermination relative to current returns. This control captures time-varying risk – visible in Figure 1 as the changing amplitude of return swings around crisis episodes – whose omission would otherwise bias coefficients on other regressors. Lagged returns ($return_{i,t-1}$) – the one-quarter lag of industry returns – enter exclusively in Model 2 to test the feedback dynamics hypothesis and are left unwinsorised to preserve the full return distribution for the predictability assessment.

Figure 4. Industry Returns Against Market Returns (2002–2025)



Note: Each panel plots quarterly winsorised industry returns against market returns for one of the 12 industries over the full sample period. Each point represents one quarter. The fitted line corresponds to the OLS regression, with the shaded band denoting the 95% confidence interval.

Table A2 reports descriptive statistics for all transformed variables. Jarque-Bera statistics reject normality ($p < 0.001$) in all series – a common feature of financial data that does not compromise inference given the large sample size ($N = 1,128$), which ensures asymptotic normality of OLS estimates under standard assumptions (Wooldridge, 2020), and the distributional robustness of Driscoll-Kraay standard errors to heteroskedasticity, serial correlation, and cross-sectional dependence (Driscoll and Kraay, 1998). Augmented Dickey-Fuller (ADF) tests reject unit roots for macro regressors at the 5% level (Table A3), ruling out spurious correlation from non-stationary series.

Pairwise correlations are presented in Table 3. All are modest, the largest being the 0.79 correlation between industry and market returns. The near-zero correlation between AI intensity and industrial production confirms that NVIDIA's excess returns fluctuate independently of the broad business

cycle, supporting separate identification within the same regression. The mild negative association between AI intensity and passive flows (−0.13) may reflect quarters in which AI-driven sentiment surges coincide with market-wide volatility that temporarily dampens ETF inflows.

Table 3. Correlation matrix

	$return_{i,t}$	$indpro_t$	$\Delta passive_t$	AI_t	$market\ return_t$	$\log(volatility_{i,t-1})$	$return_{i,t-1}$
$return_{i,t}$	1.00	0.19	0.11	0.32	0.79	0.12	0.01
$indpro_t$	0.19	1.00	−0.03	0.00	0.21	0.01	0.41
$\Delta passive_t$	0.11	−0.03	1.00	−0.13	0.11	0.02	0.01
AI_t	0.32	0.00	−0.13	1.00	0.47	0.01	−0.03
$market\ return_t$	0.79	0.21	0.11	0.47	1.00	0.11	0.01
$\log(volatility_{i,t-1})$	0.12	0.01	0.02	0.01	0.11	1.00	0.11
$return_{i,t-1}$	0.01	0.41	0.01	−0.03	0.01	0.11	1.00

3.2 Model Specifications

Two random-effects models are estimated, each addressing a distinct dimension of the research question. The index i denotes an industry portfolio and t a calendar quarter. The terms μ_i and v_i represent industry-specific random effects in Models 1 and 2, respectively. The error term $\epsilon_{i,t}$ is assumed independently and identically distributed with zero mean and constant variance, conditional on the regressors.

Model 1: Price-Fundamental Link. This model tests whether the relationship between macroeconomic fundamentals and industry returns has weakened as AI intensity and passive investing have grown:

$$Return_{i,t} = \alpha + \mu_i + \beta_1 indpro_t + \beta_2 \Delta passive_t + \beta_3 AI_t + \beta_4 (indpro_t \times \Delta passive_t) + \beta_5 (indpro_t \times AI_t) + \beta_6 \log(volatility_{i,t-1}) + \beta_7 market\ return_t + \epsilon_{i,t}$$

A joint F-test of the interaction terms β_4 and β_5 fails to reject the null of no moderating influence ($\chi^2 = 1.029$, $p = 0.598$). The preferred restricted specification retains direct effects only:

$$Return_{i,t} = \alpha + \mu_i + \beta_1 indpro_t + \beta_2 \Delta passive_t + \beta_3 AI_t + \beta_4 \log(volatility_{i,t-1}) + \beta_5 market\ return_t + \epsilon_{i,t}$$

Model 2: Feedback Dynamics. This model tests whether passive flows and AI intensity amplify return autocorrelation:

$$\begin{aligned} \text{Return}_{i,t} = & \alpha + v_i + \gamma_1 \text{return}_{i,t-1} + \gamma_2 \Delta \text{passive}_t + \gamma_3 \text{AI}_t + \gamma_4 (\text{return}_{i,t-1} \times \Delta \text{passive}_t) \\ & + \gamma_5 (\text{return}_{i,t-1} \times \text{AI}_t) + \gamma_6 \log(\text{volatility}_{i,t-1}) + \gamma_7 \text{market return}_t + \gamma_8 \text{indpro}_t \\ & + \epsilon_{i,t} \end{aligned}$$

Joint insignificance of γ_4 and γ_5 ($\chi^2 = 2.133$, $p = 0.344$) again justifies the restricted form:

$$\begin{aligned} \text{Return}_{i,t} = & \alpha + v_i + \gamma_1 \text{return}_{i,t-1} + \gamma_2 \Delta \text{passive}_t + \gamma_3 \text{AI}_t + \gamma_4 \log(\text{volatility}_{i,t-1}) \\ & + \gamma_5 \text{market return}_t + \gamma_6 \text{indpro}_t + \epsilon_{i,t} \end{aligned}$$

Standard errors are estimated using the Driscoll-Kraay correction with a four-quarter lag window – chosen to match the quarterly frequency of the data and capture dependence structures extending up to one year – providing robustness to both cross-sectional and temporal correlation in residuals.

Hausman tests fail to reject the null of random-effects consistency for all four specifications (Table A4; p-values ranging from 0.870 to 0.984). Random effects are also conceptually appropriate: the 12 Fama-French industries may be regarded as a draw from a broader population of sector groupings, and the primary regressors of interest vary only across quarters, meaning fixed-effects estimation would absorb all between-industry variation without materially reducing endogeneity concerns. Both restricted models are jointly significant at the 0.1% level. Pesaran tests yield z-statistics of -1.275 (Model 1) and -1.224 (Model 2) – both insignificant ($p > 0.20$), suggesting no cross-sectional dependence – and all variance inflation factors (VIFs) lie below 1.5, well within conventional thresholds, indicating that multicollinearity does not distort estimates (Table A5).

4. Results

4.1 Main Estimates

Tables 4 and 5 present the estimation results for the adopted restricted specifications. Five findings emerge with clarity.

Table 4. Model 1 – Restricted Specification Results

Variable	Coefficient	Standard Error	P-value
Intercept	0.0193	0.0178	0.276
$indpro_t$	0.0021**	0.0010	0.030
$\Delta passive_t$	0.0017	0.0014	0.242
AI_t	-0.0048***	0.0014	<0.001
$\log(volatility_{i,t-1})$	0.0056	0.0056	0.316
$market\ return_t$	2.7996***	0.0581	<0.001

Note: * denotes significance at 10% level, ** at the 5% level, and *** at the 1% level. The model is jointly significant at the 0.1% level ($\chi^2 = 3070.6$, $p < 0.001$).

Table 5. Model 2 – Restricted Specification Results

Variable	Coefficient	Standard Error	P-value
Intercept	0.0213	0.0182	0.241
$return_{i,t-1}$	-0.0173	0.0287	0.547
$\Delta passive_t$	0.0017	0.0015	0.238
AI_t	-0.0048***	0.0014	<0.001
$\log(volatility_{i,t-1})$	0.0061	0.0057	0.288
$market\ return_t$	2.7931***	0.0659	<0.001
$indpro_t$	0.0029*	0.0017	0.081

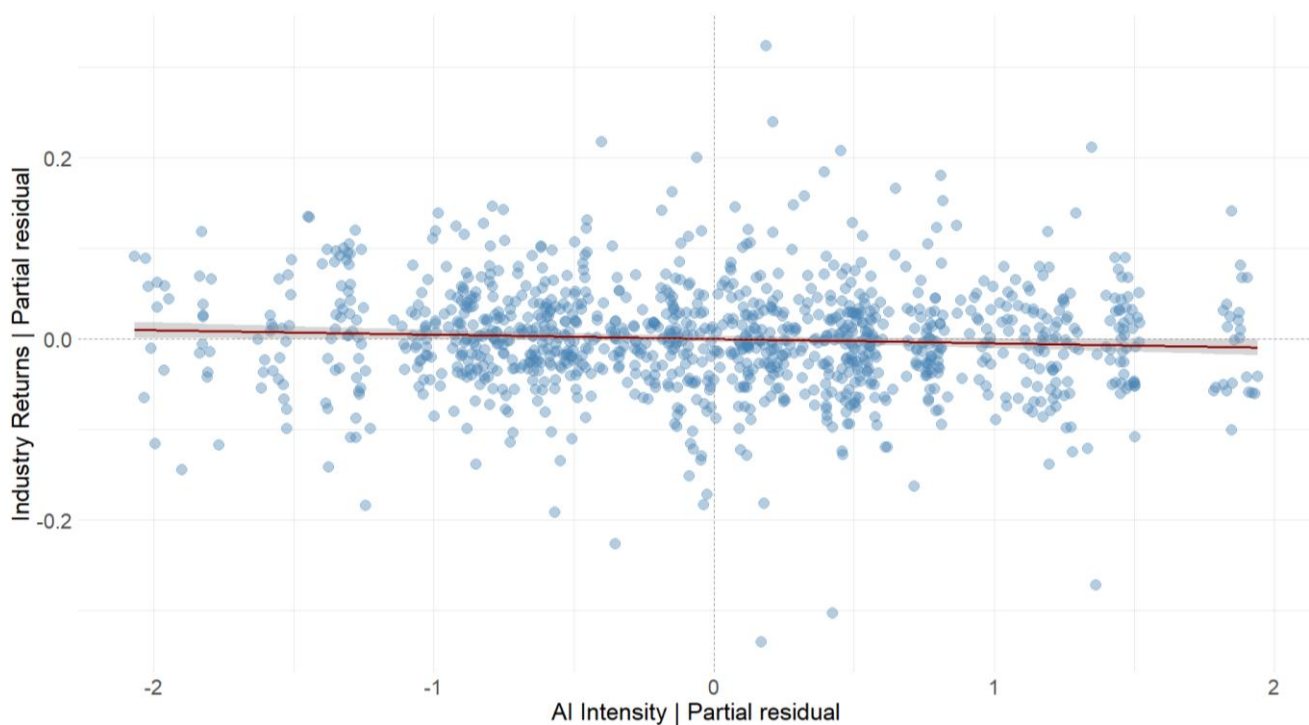
Note: * denotes significance at 10% level, ** at the 5% level, and *** at the 1% level. The model is jointly significant at the 0.1% level ($\chi^2 = 3195.5$, $p < 0.001$).

AI intensity exerts a negative and highly significant effect on industry returns. In both models, a one-standard-deviation positive shock to AI intensity is associated with a 0.48 percentage point reduction in quarterly industry returns (Model 1: $\hat{\beta}_3 = -0.0048$, $p < 0.001$; Model 2: $\hat{\gamma}_3 = -0.0048$, $p < 0.001$). To appreciate the magnitude: a two-standard-deviation increase – comparable to the NVIDIA-driven sentiment surge of early 2023, when the firm posted quarterly excess returns of

approximately 20% over the S&P 500 (Figure 3) – subtracts roughly one full percentage point from an average industry's quarterly returns.

This finding can be interpreted as a capital crowding-out effect: quarters in which AI-related equities dramatically outperform the broad market coincide with portfolio rotations towards that segment, drawing funds away from others. This reallocation operates through two complementary channels. Active managers increase explicit AI-themed allocations; simultaneously, passive investors become more heavily exposed to such stocks as their growing market values raise their share in capitalisation-weighted indices. The interpretation resonates with Danielsson and Uthemann's (2025) emphasis on AI's capacity to synchronise investment decisions and amplify capital flows towards prevailing market narratives. Figure 5 confirms the relationship after removing the influence of controls: a statistically significant downward slope between AI intensity and industry returns persists across the full panel.

Figure 5. AI Intensity and Industry Returns: Conditional Relationship

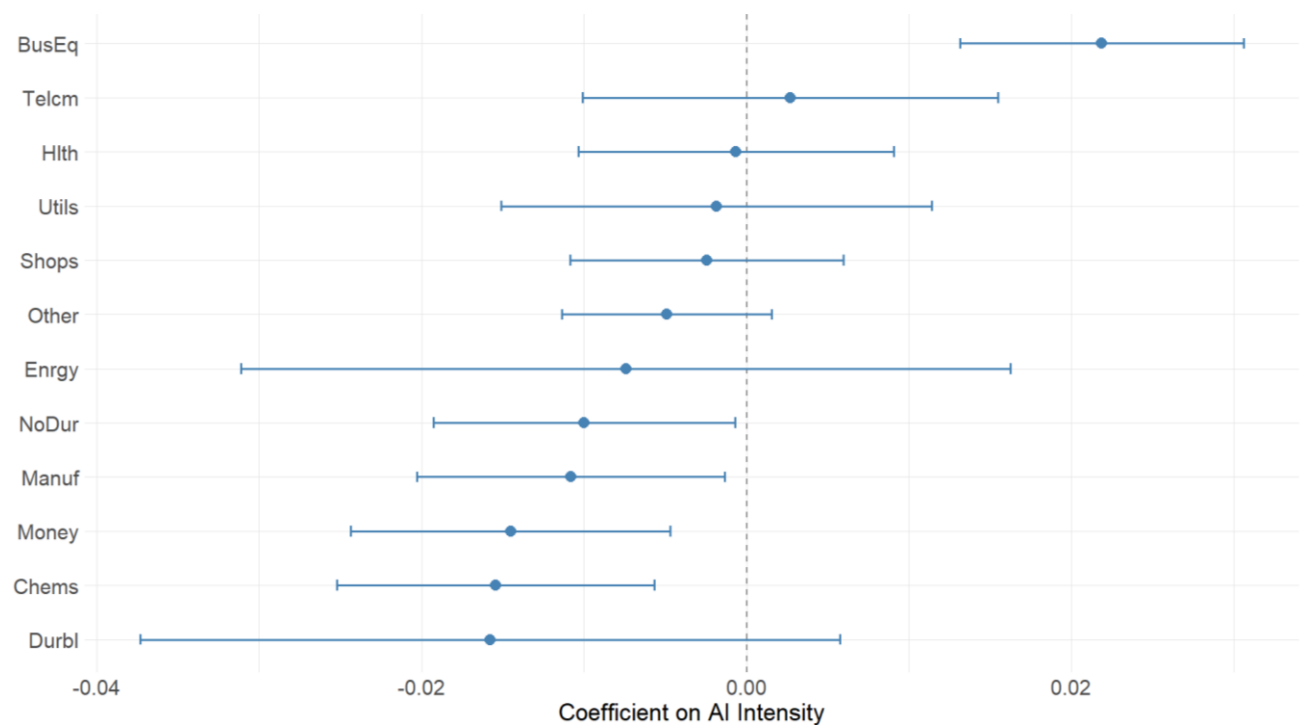


Note: The figure plots partial residuals from Model 1 expressed in decimal form, isolating the conditional relationship between AI intensity and industry returns after removing the influence of industrial production growth, passive investing flows, lagged log-

volatility, and market returns. Each point represents one industry-quarter observation. The fitted OLS line has slope -0.0048 ($p < 0.001$), matching $\hat{\beta}_3$.

The cross-industry heterogeneity in Figure 6 is economically insightful. Estimating sector-specific AI coefficients reveals that 10 of 12 segments carry negative point estimates. Durables, Chemicals, and Financials exhibit the most pronounced negative values, whereas Business Equipment and Telecommunications display positive estimates in line with their status as direct complements to AI infrastructure. Crucially, this visual evidence supports the hypothesis that AI operates as a sectoral redistributive force, diverting returns from non-AI divisions and suppressing their performance.

Figure 6. AI Crowding-Out Effect by Industry



Note: Industry-specific AI coefficients from Model 1 are estimated by OLS on each industry's time series separately. Horizontal lines denote 95% confidence intervals. This approach does not apply Driscoll-Kraay or random effects corrections, which require a panel structure; the figure is intended to illustrate cross-sectional heterogeneity in the crowding-out mechanism rather than to support formal inference.

Fundamentals continue to anchor industry returns. Industrial production growth is a positive and significant predictor in Model 1 ($\hat{\beta}_1 = 0.0021$, $p = 0.030$): a one-standard-deviation improvement corresponds to a 0.21 percentage point increase in a typical industry's quarterly returns. Replicated in Model 2 ($\hat{\gamma}_6 = 0.0029$, $p = 0.081$), this finding confirms that the information content of macroeconomic conditions is not yet lost. Markets retain a meaningful real-economy link even as

technology expands, supporting Fama's (1970) efficient-market hypothesis and the evidence of improved price discovery associated with algorithmic trading reported by Hendershott et al. (2011) and Chaboud et al. (2014). A generalised fundamental-decoupling narrative finds no validation over the full sample.

Passive investing flows have no significant direct effect. The coefficient on $\Delta \text{passive}_t$ is positive but statistically insignificant in both specifications (Model 1: $\hat{\beta}_2 = 0.0017$, $p = 0.242$; Model 2: $\hat{\gamma}_2 = 0.0017$, $p = 0.238$). This is itself an economically meaningful result. It does not imply the irrelevance of passive investing intensity – Ben-David et al. (2018) and Da and Shive (2018) document measurable effects on stock volatility, comovement, and beta amplification – but rather that direct transmission from quarterly flow changes to industry returns is undetectable at this frequency and aggregation level. The influence of passive capital on equity markets is more plausibly structural than cyclical: as passive ownership accumulates, it systematically alters factor exposures and amplifies cross-sectional correlation while compressing liquidity during stress episodes, operating continuously in the background rather than through discrete quarterly return shifts. This distinction carries direct regulatory implications, discussed in Section 4.3.

No evidence of return feedback dynamics. The lagged return coefficient in Model 2 is small, negative, and statistically indistinguishable from zero ($\hat{\gamma}_1 = -0.0173$, $p = 0.547$). There is no momentum – the tendency for positive returns to persist – and no reversal, whereby past winners subsequently underperform. An industry's return in one quarter carries no information about the next, after controlling for common factors. This constitutes a direct test of Daniel et al.'s (1998) prediction that overconfidence-driven dynamics, accompanied by biased self-attribution, should generate positive short-lag autocorrelations. The absence of any such pattern at the quarterly industry-portfolio level suggests that broad sector aggregates do not appear to exhibit the serial predictability that the market fragility hypothesis associates with an environment increasingly populated by trend-following algorithms.

Market returns are the dominant common factor. The market return coefficient is large (approximately 2.80), highly significant ($p < 0.001$), and stable in both models. The strong correlation in Table 3 and the uniformly positive slopes in Figure 4 indicate that systematic market-wide forces explain the vast majority of industry-level return variation. This resonates with Fama's (1970) framework: if security valuations capture available information, common macroeconomic shocks should constitute the primary source of fluctuations across industries, with the market factor acting as the main transmission channel for the absorption of economic news into prices.

4.2 Robustness

Four sets of robustness checks confirm the stability of these results and provide further detail on the temporal evolution of the relationships tested.

Standard errors. Table A6 compares Driscoll-Kraay and conventional standard errors. The correction is conservative for the intercept (ratio 1.41–1.43), lagged returns (1.54), and lagged log-volatility (1.40–1.42), where cross-sectional and temporal dependence have the greatest impact. Estimated uncertainty is smaller for AI intensity (0.66–0.69) and industrial production (0.54–0.84), indicating that accounting for dependence sharpens inference for these variables. The AI coefficient remains significant at the 0.1% level under both approaches, implying the central finding is not driven by the choice of standard error correction.

Parsimonious models. Excluding all statistically insignificant regressors leaves core estimates essentially unchanged: the AI coefficient moves from -0.0048 to -0.0053 , and the market return coefficient from roughly 2.80 to 2.83 (Table A7). The industrial production coefficient in Model 1 remains stable (0.0021 versus 0.0020), while in Model 2 it becomes marginally more significant ($p = 0.030$ versus 0.081) once noise from insignificant regressors is removed. The decision to retain such variables in the main specifications is grounded in the methodology and purpose of this study. Specifically, $\Delta passive_t$ is central to the research question and kept for theoretical consistency;

$return_{i,t-1}$ directly tests the feedback dynamics hypothesis – the conclusion of no momentum or reversal is economically informative and would be unassessable if lagged returns were excluded; $\log(volatility_{i,t-1})$ serves as a standard control for time-varying risk whose inclusion helps prevent omitted variable bias. These results are indicative of robust inference relative to specification choice.

Rolling window regressions. The upper panel of Figure 7 tracks the industrial production coefficient from Model 1 estimated over successive 24-quarter windows, a length that balances statistical precision with sensitivity to medium-run changes. The coefficient strengthens progressively during the early post-crisis period (approximately 2008–2014), peaking around 2015Q2 – a phase in which real-economy fundamentals were the dominant driver of equity valuations. From 2015 onwards, it declines persistently, crossing zero and turning negative in the post-COVID era.

Two mutually reinforcing developments underlie this pattern. The mid-2010s brought the first wave of AI commercialisation, alongside the passive investing acceleration visible in the steepening slope of Figure 2 from 2015 onwards; the post-COVID period, characterised by unprecedented monetary policy intervention and the generative AI boom of 2023–2024, severed the traditional relationship between industrial cycles and stock prices. The gradual nature of this decoupling resonates with Brynjolfsson, Rock and Syverson’s (2017) characterisation of AI as a general-purpose technology whose macroeconomic impact materialises only after extensive complementary innovation, organisational restructuring, and new skill formation – processes that historically evolve across decades before manifesting as measurable shifts in aggregate productivity. By the same logic, the erosion of fundamental anchoring may not be instantaneous but rather a slow-moving secular transition.

The lower panel of Figure 7 plots the rolling coefficient on lagged returns from Model 2, fluctuating around zero throughout the full sample. A slight negative drift appears between approximately 2021

and 2023 – potentially reflecting mild mean reversion during the COVID recovery – but never achieves significance. This flat trajectory supports the view that return feedback dynamics did not emerge as a structural feature of the sample period, either before or after the technological expansion.

Split-sample analysis. Table 6 formalises the regime shift suggested by the rolling evidence, using 2015Q2 as the breakpoint – the window-end date at which the anchoring coefficient peaks before its sustained decline. In Model 1, the industrial production coefficient falls from 0.0025 (pre-2015Q2) to -0.0004 (post-2015Q2), a difference of -0.0029 that is marginally significant at the 10% level ($p = 0.086$). While this does not constitute evidence of a sharp discrete break, it is consistent with progressive erosion and provides modest but meaningful support for the weakening price informativeness anticipated by Dou et al. (2025). In Model 2, the lagged return coefficient moves from 0.0124 to -0.0620 across the same split, but the difference is statistically insignificant ($p = 0.195$), confirming the absence of feedback loops in both sub-periods.

Table 6. Split-Sample Analysis – Parameter Estimates Before and After 2015Q2

Model	Period	Coefficient	Standard Error	P-value
Model 1 (Fundamental Anchoring)	Pre-2015Q2	0.0025	0.0012	—
Model 1 (Fundamental Anchoring)	Post-2015Q2	-0.0004	0.0012	—
Model 1 (Fundamental Anchoring)	Difference	-0.0029	0.0017	0.086
Model 2 (Feedback Dynamics)	Pre-2015Q2	0.0124	0.0248	—
Model 2 (Feedback Dynamics)	Post-2015Q2	-0.0620	0.0517	—
Model 2 (Feedback Dynamics)	Difference	-0.0743	0.0573	0.195

Together, these robustness results describe a financial setting in which the real-economy signal, though persistent, is being gradually displaced by AI-driven capital rotation, while self-referential dynamics remain absent – a combination more in line with Fama’s (1970) efficient-market characterisation than with the decoupling narrative, but that nonetheless registers an early warning of deteriorating fundamental anchoring.

Figure 7. Fundamental Anchoring and Return Feedback Persistence Over Time



Note: Each plot illustrates the coefficient estimate from a random-effects regression with Driscoll-Kraay standard errors, fitted over successive 24-quarter rolling windows. The shaded band represents the 95% confidence interval. The dotted red line is a LOESS smoother tracing the underlying trend. The vertical dashed line marks the breakpoint adopted in the split-sample analysis (2015Q2).

4.3 Discussion, Policy Implications, and Limitations

The analysis supports the view of a U.S. equity environment in which fundamentals remain anchored in aggregate, yet that anchoring is under pressure. The detected deterioration appears progressive and concentrated in the later years of the sample, compatible with Brynjolfsson, Rock and Syverson's (2017) general-purpose technology narrative. Viewed through their framework, the 2020s may represent a transitional phase in which AI's consequences on the equity landscape gradually displace macro signals – with the full implications for price informativeness still partially latent, obscured by adjustment costs and the slow development of complementary assets that unfold over extended periods (Brynjolfsson et al., 2017). If AI's effects materialise with long and variable lags, monitoring their ongoing footprint on market dynamics becomes especially important for guiding forward-looking regulatory design.

The most immediate concern is sectoral concentration, threatening the allocative efficiency of equity markets: when AI sentiment surges, capital systematically exits non-AI industries, potentially amplifying downturns in those sectors and generating broader fragility if the AI theme reverses sharply. While not yet a systemic risk, this pattern warrants sustained monitoring and further inquiry into whether AI-intensive trading necessitates updated volatility controls or limits on portfolio concentration. The absence of feedback loops and the insignificant direct effect of passive flows together suggest that momentum-based circuit breakers designed to limit fast, trend-following algorithmic trading are not an urgent priority at the quarterly industry frequency; existing stability mechanisms appear adequate at this horizon. Regulatory focus should instead target the indirect channels through which passive investing reshapes markets: the gradual convergence of risk exposures across industries, amplified comovement that erodes diversification benefits, and the potential for acute liquidity losses during large-scale redemption episodes. Addressing these vulnerabilities would require targeted instruments, including enhanced transparency on ETF

holdings, stress-testing frameworks for large outflows, and regular assessments of sectoral passive ownership concentration.

Several limitations are worth noting. NVIDIA's excess returns blend AI-related sentiment with firm-specific idiosyncratic components and do not directly capture automated activity volume or AI adoption penetration. A more precise proxy might aggregate patent filings, AI investment announcements, or institutional transaction data. Similarly, the ETF-flow proxy cannot distinguish between fund types or ownership compositions by sector, potentially obscuring heterogeneous passive effects. Causality presents a further challenge. The crowding-out hypothesis assumes AI sentiment drives capital away from other segments, but the reverse could also hold: weak non-AI sector performance mechanically raises NVIDIA's relative returns. Addressing this would require an instrument for AI intensity that is correlated with AI sentiment but unrelated to the unobserved drivers of traditional industry returns. However, such an instrument is difficult to find given the breadth of interconnected macroeconomic forces. Its absence is an acknowledged limitation, and the crowding-out interpretation is best viewed as the most plausible account of the observed pattern rather than a causal claim. Additionally, quarterly data may be too broad to detect the high-frequency dynamics that algorithmic trading can generate, discussed by Kirilenko and Lo (2013) and examined at millisecond resolution by Budish et al. (2015); the lack of such dynamics at this horizon does not preclude their presence at shorter ones. Finally, industry-level aggregation necessarily masks substantial within-sector heterogeneity, a dimension only partially addressed through panel analysis.

5. Conclusion

The empirical evidence reveals a nuanced picture of contemporary U.S. equity markets, neither fully supporting the optimistic vision of AI-enhanced efficiency, nor validating the pessimistic prediction of destabilising feedback loops.

Five findings stand out. First, AI intensity exerts a robust negative effect on quarterly industry returns, acting as a sectoral redistributive force that diverts capital from non-AI segments during sentiment spikes – consistent with Danielsson and Uthemann’s (2025) prediction of intensified procyclical, synchronised capital behaviour – without directly severing the informational relationship between prices and economic activity. Second, fundamental anchoring persists over the full 2002–2025 period but is weakening. Industrial production growth retains its role as a positive and significant predictor of industry returns, although rolling-window and split-sample analyses reveal a sustained deterioration from 2015Q2 that intensifies in the post-COVID era. Third, no evidence of feedback dynamics emerges: the lagged-return coefficient fails to attain statistical significance throughout the sample and across both sub-periods, providing no support for the market-fragility hypothesis and aligning instead with informationally efficient pricing. Fourth, passive investing flows exert no direct effect on returns, suggesting their influence operates through indirect structural channels – factor exposure, amplified comovement, and liquidity transformation – in line with the microstructure mechanisms identified by Ben-David et al. (2018) and Da and Shive (2018). Fifth, aggregate market returns remain the dominant driver of industry variation, a pattern that neither AI sentiment nor passive growth has yet materially altered.

For policymakers, the gradual weakening of fundamental anchoring demands the most attention. Regulatory priorities should emphasise indirect passive channels and sectoral concentration risk over momentum-based circuit breakers, and be informed by granular data on algorithmic order flow, ETF ownership composition, and passive-driven changes in systematic exposures.

A natural extension would estimate a conditional factor model in which industry factor loadings vary over time as functions of lagged state variables. Ferson and Schadt (1996) show that conditional sensitivities can be modelled as linear functions of public information, allowing risk exposure to evolve with changing market conditions. This framework is particularly relevant in light of the null direct effect of passive investing intensity found here: Da and Shive (2018) document that ETF activity reshapes market betas at the stock level, suggesting passive flows may alter industries' sensitivity to the market factor rather than generate a uniform return shift. Further research could employ high-frequency data to detect shorter-horizon feedback dynamics, alongside sharper AI and passive investing proxies to minimise idiosyncratic noise. Finally, extending the panel to a cross-country setting would help establish whether the crowding-out pattern and anchoring decline are U.S.-specific phenomena or symptoms of a broader systemic transformation in the global equity landscape.

While overall enduring efficiency offers some reassurance against fragility narratives, the crowding-out mechanism identifies a new channel of capital misallocation. Coupled with the post-2015 deterioration in fundamental anchoring, the evidence is consistent with an evolving market in which AI-driven capital rotation is quietly displacing macroeconomic signals from equity prices. Ultimately, the architecture is shifting – gradually, persistently, and in a direction that demands sustained attention from researchers, investors, and regulators. Whether the 2020s represent a transitional decade towards structurally looser anchoring is perhaps the most critical question these findings raise, and the one future research is best placed to answer.

6. Bibliography

- Ben-David, I., Franzoni, F. and Moussawi, R. (2018) ‘Do ETFs increase volatility?’, *The Journal of Finance*, 73(6), pp. 2471–2535. Available at: <https://doi.org/10.1111/jofi.12727>
- Brynjolfsson, E., Rock, D. and Syverson, C. (2017) ‘Artificial intelligence and the modern productivity paradox: a clash of expectations and statistics’. NBER Working Paper No. 24001. Cambridge, MA: National Bureau of Economic Research. Available at: <https://doi.org/10.3386/w24001>
- Budish, E., Cramton, P. and Shim, J. (2015) ‘The high-frequency trading arms race: frequent batch auctions as a market design response’, *The Quarterly Journal of Economics*, 130(4), pp. 1547–1621. Available at: <https://doi.org/10.1093/qje/qjv027>
- Chaboud, A.P., Chiquoine, B., Hjalmarsson, E. and Vega, C. (2014) ‘Rise of the machines: algorithmic trading in the foreign exchange market’, *The Journal of Finance*, 69(5), pp. 2045–2084. Available at: <https://doi.org/10.1111/jofi.12186>
- Da, Z. and Shive, S. (2018) ‘Exchange traded funds and asset return correlations’, *European Financial Management*, 24(1), pp. 136–168. Available at: <https://doi.org/10.1111/eufm.12137>
- Daniel, K., Hirshleifer, D. and Subrahmanyam, A. (1998) ‘Investor psychology and security market under- and overreactions’, *The Journal of Finance*, 53(6), pp. 1839–1885. Available at: <https://doi.org/10.1111/0022-1082.00077>
- Danielsson, J. and Uthemann, A. (2025) ‘Artificial intelligence and financial crises’. SRC Discussion Paper No. 133. London: Systemic Risk Centre, The London School of Economics and Political Science. Available at: https://www.fmg.ac.uk/sites/default/files/2025-09/DP935_133.pdf (Accessed: 6 February 2026).

Dou, W.W., Goldstein, I. and Ji, Y. (2025) ‘AI-powered trading, algorithmic collusion, and price efficiency’. NBER Working Paper No. 34054. Cambridge, MA: National Bureau of Economic Research. Available at: <https://doi.org/10.3386/w34054>

Driscoll, J.C. and Kraay, A.C. (1998) ‘Consistent covariance matrix estimation with spatially dependent panel data’, *The Review of Economics and Statistics*, 80(4), pp. 549–560. Available at: <https://www.jstor.org/stable/2646837>

Fama, E.F. (1970) ‘Efficient capital markets: a review of theory and empirical work’, *The Journal of Finance*, 25(2), pp. 383–417. Available at: <https://doi.org/10.2307/2325486>

Federal Reserve Bank of St. Louis (2026a) *INDPRO: Industrial Production: Total Index* [dataset]. Federal Reserve Economic Data (FRED). Available at: <https://fred.stlouisfed.org/series/INDPRO> (Accessed: 24 February 2026).

Federal Reserve Bank of St. Louis (2026b) *BOGZ1FL564091600Q: Exchange-Traded Funds; Total Financial Assets in Domestic Equity Funds, Level* [dataset]. Federal Reserve Economic Data (FRED). Available at: <https://fred.stlouisfed.org/series/BOGZ1FL564091600Q> (Accessed: 25 February 2026).

Federal Reserve Bank of St. Louis (2026c) *NCBEILQ027S: Nonfinancial Corporate Business; Corporate Equities; Liability, Level* [dataset]. Federal Reserve Economic Data (FRED). Available at: <https://fred.stlouisfed.org/series/NCBEILQ027S> (Accessed: 25 February 2026).

Ferson, W.E. and Schadt, R.W. (1996) ‘Measuring fund strategy and performance in changing economic conditions’, *The Journal of Finance*, 51(2), pp. 425–461. Available at: <https://doi.org/10.1111/j.1540-6261.1996.tb02690.x>

- French, K.R. (2026a) *12 Industry Portfolios* [dataset]. Fama-French Data Library. Available at: https://mba.tuck.dartmouth.edu/pages/faculty/Ken.French/data_library.html (Accessed: 24 February 2026).
- French, K.R. (2026b) *Fama/French 3 Factors* [dataset]. Fama-French Data Library. Available at: https://mba.tuck.dartmouth.edu/pages/faculty/Ken.French/data_library.html (Accessed: 3 March 2026).
- Hendershott, T., Jones, C.M. and Menkveld, A.J. (2011) ‘Does algorithmic trading improve liquidity?’, *The Journal of Finance*, 66(1), pp. 1–33. Available at: <https://doi.org/10.1111/j.1540-6261.2010.01624.x>
- Kirilenko, A.A. and Lo, A.W. (2013) ‘Moore’s Law versus Murphy’s Law: algorithmic trading and its discontents’, *Journal of Economic Perspectives*, 27(2), pp. 51–72. Available at: <https://doi.org/10.1257/jep.27.2.51>
- Merritt, R. (2023) ‘Why GPUs are great for AI’, *NVIDIA Blog*, 4 December. Available at: <https://blogs.nvidia.com/blog/why-gpus-are-great-for-ai/> (Accessed: 30 May 2026).
- Randewich, N. (2024) ‘Nvidia dethrones Tesla as Wall Street's most traded stock’, *Reuters*, 20 February. Available at: <https://www.reuters.com/technology/nvidia-dethrones-tesla-wall-streets-most-traded-stock-2024-02-20/> (Accessed: 30 May 2026).
- Ryan, J.A. and Ulrich, J.M. (2025) *quantmod: Quantitative Financial Modelling Framework*. R package version 0.4.28. Available at: <https://CRAN.R-project.org/package=quantmod> (Accessed: 15 April 2026).
- Wooldridge, J.M. (2020) *Introductory econometrics: a modern approach*. 7th edn. Boston, MA: Cengage Learning.

Yahoo Finance (2026a) *NVIDIA Corporation (NVDA) daily adjusted closing prices* [dataset].

Available at: <https://finance.yahoo.com> (Accessed: 15 April 2026).

Yahoo Finance (2026b) *S&P 500 Index (^GSPC) daily adjusted closing prices* [dataset]. Available at: <https://finance.yahoo.com> (Accessed: 15 April 2026).

7. Appendix

Table A1. Largest Absolute Quarterly Industry Returns (Pre-Winsorisation)

Industry	Date	Returns (%)
Durbl	2020-04-01	53.4
Durbl	2020-07-01	52.2
Enrgy	2020-01-01	−51.2
Durbl	2020-10-01	49.5
Durbl	2009-04-01	45.8
Durbl	2023-01-01	42.3
Durbl	2008-10-01	−40.6
Enrgy	2022-01-01	39.7
Durbl	2024-10-01	39.5
Durbl	2022-10-01	−38.3
Durbl	2022-04-01	−33.4
Enrgy	2021-01-01	32.8
Enrgy	2020-04-01	32.5
Durbl	2011-07-01	−31.2
BusEq	2020-04-01	30.7
Money	2008-10-01	−30.5
Money	2020-01-01	−30.5
Durbl	2025-01-01	−30.2
Enrgy	2020-10-01	29.8
Manuf	2020-01-01	−29.2

Note: The table reports the 20 largest quarterly industry returns by absolute magnitude prior to transformation. Extreme observations are concentrated during periods of market stress and motivate the use of mild winsorisation at the 1st and 99th percentiles of the pooled distribution.

Table A2. Descriptive Statistics – All variables (Transformed)

Variable	Description	Mean (SD)	Min	Median	Max	Skew	Kurt	J-B
$return_{i,t}$	Industry returns	0.03 (0.10)	-0.26	0.03	0.29	-0.39	3.85	63.35
$indpro_t$	Industrial production growth	0.00 (1.00)	-4.08	0.16	2.86	-1.34	7.09	1123.12
$\Delta passive_t$	Change in ETF assets / market capitalisation	0.00 (1.00)	-3.11	-0.17	2.99	0.50	4.20	115.44
AI_t	NVIDIA excess returns over S&P 500	0.00 (1.00)	-3.06	-0.03	1.99	-0.53	3.42	61.87
$market\ return_t$	Value-weighted market returns	0.01 (0.03)	-0.08	0.01	0.07	-0.89	4.04	201.33
$\log(volatility_{i,t-1})$	Lagged log-volatility	-3.10 (0.44)	-4.44	-3.13	-1.64	0.37	3.41	33.08
$return_{i,t-1}$	Lagged industry returns	0.03 (0.10)	-0.51	0.04	0.53	-0.19	6.14	469.29
Number of observations		1,128						

Note: The dependent variable $return_{i,t}$ and the additional controls – $market\ return_t$, $\log(volatility_{i,t-1})$, and $return_{i,t-1}$ – are left unstandardised to preserve their natural units, as they are already on economically interpretable scales (percentage returns and log-volatility). Jarque-Bera statistics are added relative to Tables 1 and 2 and are discussed in the main text.

Table A3. Augmented Dickey-Fuller Stationarity Test

Variable	ADF Statistic	P-value	Stationarity (5% level)
$indpro_t$	-3.963	0.014	Yes
$\Delta passive_t$	-4.141	0.010	Yes
AI_t	-4.897	0.010	Yes

Note: The ADF tests are reported only for variables that could plausibly contain a unit root (industrial production, passive flows, and AI intensity). Financial returns are generally stationary and fluctuate around a stable mean, while volatility measures are typically stationary and mean reverting.

Table A4. Hausman Test (Random Effects versus Fixed Effects)

Model	Chi-square	df	P-value	Preferred Specification
Model 1 (Full)	1.449	7	0.984	Random Effects
Model 2 (Full)	2.427	8	0.965	Random Effects
Model 1 (Restricted)	1.409	5	0.923	Random Effects
Model 2 (Restricted)	2.491	6	0.870	Random Effects

Table A5. Variance Inflation Factor – Restricted Models

Variable	Model 1 VIF	Model 2 VIF
$indpro_t$	1.068	1.292
$\Delta passive_t$	1.060	1.061
AI_t	1.357	1.358
$\log(volatility_{i,t-1})$	1.016	1.032
$market\ return_t$	1.435	1.447
$return_{i,t-1}$	—	1.226

Table A6. Comparison of Standard Errors – Conventional versus Driscoll-Kraay

Model	Variable	Conventional SE	Driscoll-Kraay SE	Ratio
Model 1	Intercept	0.0125	0.0178	1.41
Model 1	$indpro_t$	0.0018	0.0010	0.54
Model 1	$\Delta passive_t$	0.0018	0.0014	0.79
Model 1	AI_t	0.0021	0.0014	0.69
Model 1	$\log(volatility_{i,t-1})$	0.0040	0.0056	1.40
Model 1	$market\ return_t$	0.0755	0.0581	0.77
Model 2	Intercept	0.0127	0.0182	1.43
Model 2	$return_{i,t-1}$	0.0187	0.0287	1.54
Model 2	$\Delta passive_t$	0.0018	0.0015	0.81
Model 2	AI_t	0.0021	0.0014	0.66
Model 2	$\log(volatility_{i,t-1})$	0.0040	0.0057	1.42
Model 2	$market\ return_t$	0.0758	0.0659	0.87
Model 2	$indpro_t$	0.0020	0.0017	0.84

Table A7. Comparison of Model Specifications – Main versus Parsimonious

Variable	Model	Main Specification		Parsimonious Specification	
		Coefficient	P-value	Coefficient	P-value
$indpro_t$	Model 1	0.0021**	0.030	0.0020**	0.030
AI_t	Model 1	−0.0048***	<0.001	−0.0053***	<0.001
$market\ return_t$	Model 1	2.7996***	<0.001	2.8263***	<0.001
$indpro_t$	Model 2	0.0029*	0.081	0.0020**	0.030
AI_t	Model 2	−0.0048***	<0.001	−0.0053***	<0.001
$market\ return_t$	Model 2	2.7931***	<0.001	2.8263***	<0.001