Investor Sentiment, Institutional Ownership, and Informational Efficiency of Prices ☆

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Abstract

We show that a stock's sensitivity to investor sentiment, measured by sentiment beta, significantly weakens the positive relation between institutional ownership and price efficiency. This impact of sentiment beta is more pronounced following optimistic periods, among overpriced stocks, and for active institutional ownership, confirming that sentiment beta acts as a binding arbitrage friction. We further show that this risk operates through two channels. First, only the sentiment-beta-orthogonal component of institutional ownership improves price efficiency, while the sentiment-beta-driven component does not. Second, institutions reduce both their holdings and trading in low-sentiment-beta stocks when sentiment exposure rises, precisely where their trading is most effective at reducing noise. Together, these channels create a self-reinforcing dynamic in which rising sentiment beta increases arbitrage risk, institutions disengage, and affected stocks are left with less informed participation and lower price efficiency. Our results are robust to alternative measures of efficiency, sentiment, and institutional activity, empirical specifications, and tests for reverse causality.

Keywords: Sentiment beta, Institutional ownership, Price efficiency, Arbitrage asymmetry

JEL Codes: G12, G14, G23, G40

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1 Introduction

Institutional investors are widely regarded as sophisticated arbitrageurs whose informational advantages enable them to correct mispricing and enhance the informational efficiency of stock prices (Boehmer & Kelley, 2009; Cao et al., 2018)[1]. Underlying this claim, is an implicit assumption that institutional investors can effectively arbitrage mispricing regardless of the source of price distortion. However, investor sentiment generates persistent, non-fundamental demand shocks that are difficult and risky to trade against (Baker & Wurgler, 2006; DeLong et al., 1990; Shleifer & Vishny, 1997). If sentiment creates arbitrage risks that constrain even sophisticated investors, then the effectiveness of institutional ownership for price discovery may depend critically on a stock's exposure to sentiment.

A substantial body of research documents that investor sentiment has important effects on institutional decisions and asset prices (see, e.g., Baker & Wurgler, 2006; Massa & Yadav, 2015; Stambaugh et al., 2012), focusing mostly on *time-series* patterns. How the impact of institutional investors on price efficiency varies with sentiment exposure *across stocks* remains largely unexplored. This paper addresses this gap by examining how sentiment beta affects the well-established positive relation between institutional ownership and informational efficiency of stock price (henceforth referred to as IO–Efficiency relation). By providing direct evidence on whether and how sentiment beta conditions the price discovery role of institutional investors, this study contributes to both the literature on limits to arbitrage and the role of institutional investors in market efficiency.

We examine this question using a sample of U.S. common stocks listed on the NYSE, AMEX, and NASDAQ from 1980Q1 to 2023Q4. Our empirical analysis builds on three key variables. First, institutional ownership (IO) is measured from quarterly 13F filings, which capture the aggregate holdings of institutional investors. Second, price (in)efficiency is proxied by noise share ($NoiseShare$), defined as the proportion of return variance attributable to deviations from informationally efficient prices, following the decomposition methodology of Brogaard et al. (2022). Higher noise share hence indicates lower stock price efficiency. Third, following Glushkov (2006), sentiment beta ($SBeta$) is estimated from a regression of each stock's excess returns on changes in the Baker–Wurgler (BW) investor sentiment index (Baker & Wurgler, 2006), after controlling for standard risk and liquidity factors. Sentiment beta captures a stock's return sensitivity to changes in investor sentiment, and thus reflects the extent to which its return is driven by sentimental traders. Together, these mea-

[1] In this paper, "informational efficiency of prices" and "price efficiency" are used interchangeably. Both refer to the extent to which market prices incorporate available information.

sures allow us to test how sentiment-driven exposure affects the efficiency-enhancing role of institutional ownership across a broad cross-section of stocks.

Our core hypothesis predicts that sentiment beta weakens the IO–Efficiency relation. As a stock's sensitivity to investor sentiment increases, institutional investors face greater arbitrage risk, which limits their willingness and ability to correct mispricing and therefore reduces their efficiency-enhancing effect. We test this using both dependent double sorting and multivariate regressions with extensive controls. In the 5×5 portfolio sorting analysis, stocks are first sorted by beginning-of-quarter sentiment beta and then by beginning-of-quarter institutional ownership, with average noise share reported for each portfolio. The noise share gap between low- and high-IO portfolios significantly weakens as sentiment beta increases, marking a 44% reduction from 8.5% in the low- to 4.8% in the high-$SBeta$ quintile group.[2] The panel regression analysis, in which noise share is regressed on institutional ownership and stock characteristics separately within each sentiment beta quintile, reinforces this pattern. The coefficient on institutional ownership increases monotonically from -0.074 in the low-$SBeta$ group to -0.027 in the high-$SBeta$ group. Economically, a one-standard-deviation increase in institutional ownership reduces noise share by 2.07 percentage points for low $SBeta$ stocks, whereas the reduction is only 0.81 percentage points for high $SBeta$ stocks. In the pooled specification, which augments the baseline regression with $SBeta$ and the interaction term $IO \times SBeta$, the interaction coefficient is positive and highly significant, confirming that sentiment beta systematically weakens the IO–Efficiency relation. These findings are both qualitatively and quantitatively confirmed by Fama–MacBeth (FMB) regressions (Fama & MacBeth, 1973).

Establishing that sentiment beta weakens the IO–Efficiency relation raises a natural question about whether this effect reflects a genuine arbitrage risk or merely a spurious correlation. To distinguish between the two, we conduct a series of mechanism tests that exploit the well-documented asymmetric structure of arbitrage constraints (Stambaugh et al., 2012, 2015). If sentiment beta truly captures arbitrage risk, its attenuation impact on the IO–Efficiency relation should be more pronounced in the settings where constraints bind more tightly. We assess this along three dimensions. First, we compare optimistic versus pessimistic quarters, defined as quarters with above- and below-median abnormal sentiment respectively, where abnormal sentiment is computed as the quarterly sentiment

[2] The high (low) portfolio refers to the top (bottom) stock portfolio, a standard terminology in asset pricing. In our case, since we sort stocks into five portfolios based on institutional ownership or sentiment beta, the high-IO (low-IO) and high-sentiment-beta (low-sentiment-beta) portfolios correspond to the top (bottom) quintile.

level minus its average over the previous eight quarters.[3] We find that sentiment beta weakens the IO–Efficiency relation more strongly following optimistic quarters, consistent with sentiment-driven overpricing and short-sale constraints being most severe in high-sentiment environments (Stambaugh et al., 2015). Second, we examine the role of mispricing direction using the measure of Stambaugh et al. (2015). We show that sentiment beta weakens IO–Efficiency relation more strongly among overpriced stocks than underpriced ones. This is consistent with overpricing being the setting where arbitrage constraints bind most tightly, as correction requires costly short selling rather than straightforward purchases. Third, we classify institutions into active and passive investors using three complementary approaches. We find that sentiment beta weakens the IO–Efficiency relation more strongly for active ownership than passive ownership. This is consistent with active institutions being more exposed to noise trader risk and interim losses given their reliance on informed arbitrage (Gromb & Vayanos, 2010; Shleifer & Vishny, 1997), making their efficiency contribution more sensitive to sentiment-induced risks than that of passive institutions. Together, these findings confirm that sentiment beta operates as an arbitrage risk whose effects intensify where theory predicts constraints are most binding.

The above tests validate sentiment beta as a genuine arbitrage risk, but leave open the question of how institutions actually respond to it. We investigate this through two complementary analyses. First, we decompose institutional ownership into a sentiment beta driven component ($\widehat{IO}$) and a residual component orthogonal to sentiment beta ($IO^{\perp}$). We find that only $IO^{\perp}$ maintains a strong negative relation with noise share, while $\widehat{IO}$ is associated with higher noise share. This indicates that the efficiency-enhancing effect of institutional ownership comes entirely from the sentiment-beta-orthogonal part, while sentiment-beta-driven institutional demand does not improve efficiency and may even impair it. Second, we examine how institution investors response to changes in sentiment beta ($\Delta SBeta$), motivated by Boehmer and Kelley (2009)'s insight that trading is a key channel through which institutions improve efficiency. We find that, when a stock's sentiment beta further increases, institutions significantly reduce both their holdings and their trading in stocks with low baseline sentiment beta, where their trades are most effective at reducing noise. At the same time, they barely adjust their positions in stocks with already-high sentiment beta, where their impact is already limited. This pattern is consistent with rational risk management in the face of rising noise trader risk and heightened interim-loss risk (DeLong et al., 1990; Gromb & Vayanos, 2010). The consequence is a self-reinforcing dynamic in which rising sentiment beta increases arbitrage risk, institutions respond by reducing their engagement, and this

[3] The terms *optimistic* and *pessimistic* are used in place of high/low sentiment quarters to avoid confusion with high/low sentiment beta.

disengagement leaves noise trading uncorrected, further reducing price efficiency. Sentiment-driven mispricing may therefore be more persistent than the standard view of institutional arbitrage would suggest, not because institutions act irrationally, but because their rational responses collectively withdraw informed participation from precisely the stocks that need it most.

This study contributes to the literature in several ways. First, it advances research on the relation between institutional investors and price efficiency. Foundational studies established that institutional ownership improves informational efficiency (Boehmer & Kelley, 2009) and that active institutions such as hedge funds play a particularly strong role (Cao et al., 2018). Subsequent work reinforces this consensus, showing that sophisticated institutions improve the incorporation of firm-specific information into prices (Kacperczyk et al., 2021), substitute for public information providers when analyst coverage declines (Chen et al., 2020), and reduce mispricing at the market level (Kokkonen & Suominen, 2015). However, more recent evidence suggests that this effect is not uniform, as concentration of active ownership can in some cases reduce efficiency (Xiong et al., 2025). We contribute to this evolving literature by showing that sentiment beta systematically conditions the effectiveness of institutional ownership in improving price efficiency, rather than treating institutional ownership as a uniform force for price discovery.

Second, we contribute to the literature on investor sentiment and limits to arbitrage. Prior studies have defined and estimated sentiment beta (Baker & Wurgler, 2006, 2007; Glushkov, 2006), and examined how institutional sentiment exposure shapes portfolio strategies and fund performance (e.g., Chen et al., 2021; Massa & Yadav, 2015), focusing primarily on return implications. The limits to arbitrage literature, meanwhile, has identified frictions such as short sale constraints (Miller, 1977) and idiosyncratic volatility (Stambaugh et al., 2015), largely through their effects on return patterns and anomaly persistence. We contribute to both strands by showing that sentiment beta constitutes a distinct, stock level arbitrage friction whose effects manifest not in return predictability but in the impairment of institutional price discovery, a channel not previously documented.

Third, this study speaks to the ongoing debate about whether institutional investors are sentimental traders. Existing literature presents conflicting evidence, with some studies showing that institutions ride sentiment (e.g., Chen et al., 2021; DeVault et al., 2019) and herd during high-sentiment periods (Guo et al., 2024), while others find that they bet against sentiment (e.g., Gao et al., 2023). A common feature of these studies is that they focus on the return or performance implications of institutional sentiment exposure, leaving open the question of what these behaviors mean for price efficiency. We bridge this gap by shifting the focus from whether institutions trade on sentiment to whether such trading always improves efficiency, and show that it does not. Furthermore, we show that institutions selectively withdraw from trading in low-sentiment-beta stocks, where their trades are most effective at reducing noise, while barely adjusting in high-sentiment-beta stocks where their impact is already limited. This selective disengagement suggests that sentiment-induced frictions not only constrain arbitrage but also distort the allocation of institutional trading capacity, helping to explain why institutions often contribute less to price efficiency in stocks most prone to sentiment.

The rest of the paper proceeds as follows. Section 2 develops the hypotheses for the empirical tests. Section 3 describes the data, sample, and construction of the key variables. Section 4 presents the main results on how sentiment beta affects the IO—Efficiency relation. Section 5 explores the mechanisms through which this effect arises. Section 6 provides the robustness of the baseline results. Section 7 concludes.

2 Related Literature and Hypothesis Development

The efficient market hypothesis is justified by arguing that rational and sophisticated investors would arbitrage away any mispricing. In practice, institutional investors are the primary candidates for this role, as they are commonly viewed as sophisticated market participants with better information and stronger incentives to monitor firms (e.g., Chen et al., 2020). Thus, they are expected to help incorporate information about fundamentals into stock prices, and a higher degree of institutional ownership is therefore commonly associated with greater price efficiency (e.g., Boehmer & Kelley, 2009; Cao et al., 2018).

This view, however, rests on two assumptions that are difficult to sustain in practice, namely that institutional investors know the fundamental value of stocks and that arbitrage is riskless or carries low risk. Sentiment can generate non-fundamental demand shocks that move prices away from intrinsic value and can persist, particularly when mispricing is risky to trade against (Baker & Wurgler, 2006, 2007; Barberis et al., 1998; DeLong et al., 1990). These shocks introduce sentiment-induced arbitrage risk, in which prices may diverge further before converging, exposing arbitrageurs to interim losses and tightening funding and performance constraints (Shleifer & Vishny, 1997). Cross-sectionally, sentiment effects are stronger for stocks that are difficult to value and costly to arbitrage, where sparse or noisy information increases the scope for belief-driven pricing (Baker & Wurgler, 2006, 2007). Therefore, although institutional ownership is expected to improve price efficiency on average, its effectiveness should be weaker for stocks with greater exposure to investor sentiment.

Hypothesis 1: The IO–Efficiency relation is *weaker* for stocks with *higher* sentiment beta.

The arbitrage risk introduced by sentiment-driven mispricing is not uniform across conditions. In particular, arbitrage is asymmetric because correcting overpricing is generally more difficult than correcting underpricing due to short-sale impediments (Miller, 1977; Stambaugh et al., 2012, 2015), suggesting that the impact of sentiment beta on the IO–Efficiency relation should be more pronounced when these constraints bind more tightly. This perspective yields additional predictions about how the impact depends on the state of market sentiment, the direction of mispricing, and the type of institutional investor.

First, both the prevailing market sentiment state and the direction of mispricing determine how tightly arbitrage constraints bind. When sentiment is high, optimistic demand is more likely to push prices above fundamentals, while short-sale impediments and interim-loss risk make such overpricing particularly hard to correct (Stambaugh et al., 2015). Supporting evidence shows that these distortions are concentrated on the overpricing side following high-sentiment periods, as sentiment-driven investors tilt toward overvalued stocks (Antoniou et al., 2016) and pricing errors are driven primarily by overpricing components (Chen et al., 2025). Stambaugh et al. (2015) further show that the negative relation between idiosyncratic volatility and future returns arises primarily following high-sentiment periods and is driven by the overpricing leg, indicating that arbitrage constraints bind most tightly when short-side correction is required. Because high-sentiment-beta stocks are particularly prone to overpricing, the impact of sentiment beta on the IO–Efficiency relation should be most pronounced following high-sentiment quarters and for stocks that are overpriced rather than underpriced.

Hypothesis 2: The impact of sentiment beta on the IO–Efficiency relation is *more* pronounced following *high sentiment (optimistic)* quarters.

Hypothesis 3: The impact of sentiment beta on the IO–Efficiency relation is *more* pronounced for *overpriced* stocks.

Second, arbitrage asymmetry also exists at investor level, with some investors being more able or willing to conduct arbitrage (Stambaugh et al., 2015).[4] A key distinction within institutional investors is between active and passive institutions. Active institutions have stronger incentives and greater flexibility both to acquire information and to trade on mispricing, and it is through this information-driven trading that active ownership contributes to price efficiency (Crane et al., 2023; Grossman & Stiglitz, 1980; Kacperczyk et al., 2021). In contrast, passive institutions primarily follow rules-based strategies that track benchmarks, and their trading is less tied to valuation signals, contributing less to price discovery (Brogaard et al., 2019; Madhavan, 2014; Sammon, 2024).

At the same time, the effectiveness of active institutional ownership in improving price efficiency depends on the reliability of the fundamental information underlying their portfolio decisions. For high-sentiment-beta stocks, greater fundamental uncertainty and noise trader risk erode the information content of active ownership positions, reducing the extent to which active ownership concentration reflects genuine fundamental information and thus limiting its effectiveness in improving price efficiency (Gromb & Vayanos, 2010; Shleifer & Vishny, 1997). Passive ownership, whose efficiency contribution is less tied to valuation signals, should be correspondingly less sensitive to sentiment beta. Therefore, the impact of sentiment beta on the IO–Efficiency relation should be more pronounced for active institutional ownership.

Hypothesis 4: The impact of sentiment beta on the IO–Efficiency relation is *more* pronounced for ownership by *active institutional investors*.

3 Data

Our sample comprises US common stocks listed on NYSE/AMEX/NASDAQ exchanges, covering the period from 1980Q1 to 2023Q4.[5] We collect daily data on stock returns, trading volumes, and prices from the Center for Research in Security Prices (CRSP), accounting information from Compustat, and institutional holding from the Refinitiv 13F filings database. We collect investor sentiment index from Jeffrey Wurgler's website[6]. Short interest data is primarily sourced from Compustat, covering NYSE and AMEX stocks since January 1973

[4]In Stambaugh et al. (2015), investor-level arbitrage asymmetry mainly refers to differences in investors' ability or willingness to take short positions when conducting arbitrage activities. Here the term is used more broadly to describe heterogeneity in arbitrage capacity and incentives across investor types, with some investors more able or willing to arbitrage than others.

[5]Note that 13F institutional holding data became available starting in 1980.

[6]We are grateful to Jeffrey Wurgler for generously making investor sentiment index publicly available at https://pages.stern.nyu.edu/~jwurgler/.

and NASDAQ stocks from July 2003 onward. For NASDAQ stocks prior to July 2003, data is obtained from Bloomberg.

We follow literature and employ the following filter criteria: 1) the duplicated stock-day observations and observations with missing values of price, return or volume are removed (Brogaard et al., 2022); 2) the stock-quarter observations that have fewer than 20 valid days are moved to ensure a sufficient number of observations for VAR decomposition and the reliability of efficiency measure (Brogaard et al., 2022); 3) stock observations with quarter-end price lower than \$5 are removed to avoid microstructure noise (Amihud, 2002; Cao et al., 2018); 4) stock observations with fewer than 5 institutional investors are removed to ensure an adequate proxy for institutional ownership (DeVault et al., 2019; Gao et al., 2023). This procedure leaves 442,875 stock-quarter observations, and the average number of stocks per quarter is 2,516.

3.1 Informational Efficiency of Stock Price

The primary measure of price (in)efficiency used in this paper is noise share ($NoiseShare$), proposed by Brogaard et al. (2022), capturing the relative importance of pricing error. They apply the idea of Hasbrouck (1993) by decomposing stock price into an efficient price component (m_d) and a pricing error term (s_d):[7]

$$p_d = m_d + s_d, \tag{1}$$

where m_d follows a random-walk process with drift μ and innovation w_d. w_d is further partitioned into three innovation components to capture market-wide information ($\theta_{r_m}\varepsilon_{r_m,d}$), firm-specific private information ($\theta_x\varepsilon_{x,d}$), and firm-specific public information ($\theta_r\varepsilon_{r,d}$). The stock return is thus

$$r_d = p_d - p_{d-1} = \mu + (\theta_{r_m}\varepsilon_{r_m,d} + \theta_x\varepsilon_{x,d} + \theta_r\varepsilon_{r,d}) + \Delta s_d. \tag{2}$$

The components in Equation 2 are estimated in a structural VAR system. $\varepsilon_{r_m,d}$, $\varepsilon_{x,d}$, $\varepsilon_{r,d}$ are innovation terms, while θ_{r_m}, θ_x, θ_r are long-run permanent effects of these innovations, inferred from cumulative impulse response function. Specifically, the input variables in VAR system include market return (CRSP value-weighted market return), signed dollar volume

[7]Note that the method of Hasbrouck (1993) can be applied to return data at different frequencies. While the general notation indexes time by t, we use d to denote daily observations. This distinction helps avoid confusion because our variables are constructed from data sampled at multiple frequencies.

(product of sign of daily return, closing price and volume), and stock return. The VAR is estimated using 5 lags, and the long-run effect is estimated as the cumulative return response at $d = 15$, as in Brogaard et al. (2022).

We perform the variance decomposition every stock-quarter using daily data. In Equation 2, Δs_d is the realized return that cannot be captured by the innovation of information. Its variance, σ_s^2, is referred to as noise ($Noise$). Taking the variance of innovations, we obtain contributions to the variation in efficient price by market information $\theta_{r_m}^2 \sigma_{\varepsilon_{r_m}}^2$, firm-specific private information $\theta_x^2 \sigma_{\varepsilon_x}^2$, and firm-specific public information $\theta_r^2 \sigma_{\varepsilon_r}^2$. Normalizing noise by all variance components, we obtain our noise share capturing the relative importance of pricing error:[8]

$$NoiseShare = \frac{\sigma_s^2}{\sigma_w^2 + \sigma_s^2} = \frac{\sigma_s^2}{\theta_{r_m}^2 \sigma_{\varepsilon_{r_m}}^2 + \theta_x^2 \sigma_{\varepsilon_x}^2 + \theta_r^2 \sigma_{\varepsilon_r}^2 + \sigma_s^2}. \tag{3}$$

The noise and noise share measures fall between semi-strong-form efficiency and strong-form efficiency categories since they incorporate public information and a portion of private information inferred from signed dollar volume. While noise and noise share rely on daily rather than intraday observations, they draw on more broadly available data than the pricing error variance (PEV) measure of Boehmer and Kelley (2009) and Cao et al. (2018), and are better suited to longer-horizon analyses of stock price informativeness. Furthermore, the inclusion of additional trading variables, namely market return and stock closing price, improves the precision of pricing error estimation, as documented by Hasbrouck (1993) and Cao et al. (2018).

Figure 1 displays the time series of the cross-sectional average noise share, presented in both simple average and weighted average forms, with the latter based on total return variance. The average noise share over the sample period is 33.7% (See Panel A of Table 1). The quarterly noise share exhibits a similar pattern to the yearly noise share constructed by Brogaard et al. (2022). The noise share was high in early 1990s, which Brogaard et al. (2022) argue is partially driven by collusive behavior of dealers. Since then, the noise share has gradually declined. Another pattern from quarterly noise share is that the noise share surges during market crashes. For example, noise share surged around the 1987 market crash, the 2008 global financial crisis, and the 2020 COVID-19 health crisis.

[Insert Figure 1 around here]

[8] We are grateful to Jonathan Brogaard, Thanh Huong Nguyen, Talis Putnins, and Eliza Wu for generously providing the code to decompose the variance components (Brogaard et al., 2022).

[Insert Table 1 around here]

For our robustness tests, we consider three alternative measures of price (in)efficiency widely used in the literature, namely price delay, return autocorrelation, and variance ratio. The first measure is price delay, proposed by Hou and Moskowitz (2005), which captures the delay with which a stock incorporates market-wide information, henceforth referred to as Hou-Moskowitz (HM) price delay. For each stock-quarter, we estimate the following time-series regressions of daily stock return on CRSP value-weighted market return:

$$r_d = \underbrace{\overbrace{\alpha + \beta R_{m,d}}^{\text{Reg 1, } R^2_{Constrained}} + \sum_{n=1}^{5} \delta_n R_{m,d-n}}_{\text{Reg 2, } R^2_{Unconstrained}} + \varepsilon_d, \tag{4}$$

where r_d is the daily stock return and $R_{m,d}$ is the market return on day d. If the stock price responds with a delay to market-wide information, some δ_n coefficients in unconstrained regression are expected to differ significantly from zero. In constrained regression, we constrain δ_n to be zero, assuming efficient response without delay. HM price delay measure is then constructed as

$$HM = 1 - \frac{R^2_{Constrained}}{R^2_{Unconstrained}}. \tag{5}$$

HM price delay measure thus gauges the extent to which return variation is explained by lagged market return. A higher HM measure indicates a stronger delay in individual stocks reflecting market-wide information and less informational efficiency.

Our second alternative price (in)efficiency measure is return autocorrelation. Fama (1970) suggest that an efficient stock price follows a random walk process. Consequently, we would expect that return is unpredictable and not serially correlated. However, empirical studies find that many stocks have autocorrelated returns (Avramov et al., 2006; Chordia et al., 2005; Sias & Starks, 1997, among others). For each stock-quarter, we compute the absolute value of the first-order autocorrelation of daily returns

$$AutoCorr = |\rho_{r_d, r_{d-1}}|, \tag{6}$$

where ρ is the first-order autocorrelation of daily return. A higher autocorrelation indicates higher predictability of return using past returns, more deviation from random-walk price, and hence lower price efficiency.

Our third measure of price (in)efficiency is the variance ratio, which tests whether a stock price follows a random walk process (Lo & MacKinlay, 1988). Under the random walk hypothesis, the variance of returns increases linearly with the length of the sampling interval. Following Boehmer and Kelley (2009) and Cao et al. (2018), we compute the variance ratio as

$$|1 - VR(1,5)| = \left|1 - \frac{\sigma_5^2}{5\sigma_1^2}\right|, \tag{7}$$

where σ_1^2 and σ_5^2 denote the return variance over 1-day and 5-day intervals, respectively. By construction, if the stock price follows a random walk, then $|1 - \mathrm{VR}(1,5)| = 0$, indicating perfect price efficiency. A higher value of the variance ratio implies greater deviation from the random walk benchmark and thus lower price efficiency.

3.2 Institutional Ownership

Institutional investors with at least \$100 million in assets under management must file Form 13F with the SEC, reporting long equity positions exceeding 10,000 shares or \$200,000 in market value. In each quarter, the shares held by institutions are first checked and adjusted for stock splits using CRSP cumulative factors to adjust shares (CFACHR), and then aggregated by report date across all institutions for each stock in the sample.[9] The institutional ownership (IO) is then constructed as aggregated shares held by institutional investors divided by the quarter-end number of shares outstanding reported by CRSP.[10] The mean and median institutional ownership are 53% and 56%, respectively, over the sample period from 1980Q1 to 2023Q4. It exhibits a strong upward trend, increasing from about 30% in the early 1980s to roughly 75% by the end of the sample (see Figure 2). This pattern reflects the growing dominance of institutional investors in the stock market, consistent with Gao et al. (2023).

[Insert Figure 2 around here]

[9] The file date is the date (FDATE) the institutions file with the SEC while the report date (RDATE) represents the date for which the holdings are valid. For 13F filing dataset, the file date and report date are the same in a large majority of the investment companies, however, there are cases of late reporting that lead to discrepancies between two dates.

[10] The number of shares outstanding for stocks reported by CRSP is used because CRSP dataset provides more reliable data for this variable. In the 13F filing on Refinitiv, there are cases of missing or outdated number of shares outstanding. In addition, for obviously abnormal levels of institutional ownership, the shares held by institutions are cross-checked with events like share split and adjusted using CRSP cumulative factors to adjust shares (CFACSHR).

3.3 Sentiment Beta

To measure investor sentiment, we employ two widely used indices. The first is the Baker–Wurgler (BW) sentiment index (Baker & Wurgler, 2006, 2007), constructed as the first principal component of five sentiment proxies, including close-end fund discount ($CEFD$), number of IPOs ($NIPO$), average first-day return of IPO ($RIPO$), the share of equity issues in total equity and debt issues (S_t), and dividend premium (P^{D-ND}).[11] The second is the University of Michigan Consumer Sentiment Index (UMCSI), a survey-based measure of consumer confidence.[12] We use the BW index as our primary measure to estimate sentiment beta, and the UMCSI as an alternative in robustness tests. To obtain quarterly sentiment, we take the average of monthly sentiment within each quarter. Panel C of Table 1 presents the statistics of quarterly sentiment and Figure 3 displays the time-series plot. The average quarterly BW sentiment over the sample period is 0.246, with a standard deviation of 0.713.

[Insert Figure 3 around here]

To measure the stock-level sentiment exposure, this study follows previous literature and employs sentiment beta (Baker & Wurgler, 2007; Chen et al., 2021; Glushkov, 2006; Massa & Yadav, 2015, among others). Specifically, following Glushkov (2006), the individual stock's sentiment beta is estimated by regressing monthly excess return on the sentiment change index while controlling for Fama–French 3 risk factors and liquidity innovation factor. For each quarter q, we estimate the following time-series regression using a 36-month rolling window spanning months $t-35$ to t. We roll the window forward every three months and require at least 24 return observations within each estimation window,

$$r_{it} = \alpha_0 + \beta^{SENT}\Delta SENT_t + \beta^{MKT}MKT_t + \beta^{SMB}SMB_t + \beta^{HML}HML_t + \beta^{LIQ}LIQ_t + \varepsilon_{it}. \quad (8)$$

Here, r_{it} denotes the excess return of stock i in month t. MKT, SMB, and HML are the Fama–French factors (Fama & French, 1993), and LIQ is the liquidity factor of Pástor and Stambaugh (2003). We follow Glushkov (2006) to include the liquidity factor because liquidity is an important determinant of expected returns and contributes to price efficiency by lowering arbitrage costs (Amihud, 2002; Boehmer & Kelley, 2009; Pástor & Stambaugh, 2003). $\Delta SENT_t$ denotes the sentiment change index. Rather than using simple changes

[11] NYSE turnover, once a component of the sentiment index, is excluded because the turnover ratio has become less informative with the growth of institutional high-frequency trading and the fragmentation of trading venues. The authors discuss this issue in detail in the accompanying sentiment index data file.

[12] We download UMCSI data from https://data.sca.isr.umich.edu/data-archive/mine.php.

in the sentiment level index, we construct this measure as the first principal component of changes in the five aforementioned sentiment proxy variables, consistent with prior studies. This construction mitigates measurement noise that may arise when transitioning from levels to changes.

β^{SENT} denotes the loading on changes in investor sentiment, representing the raw sentiment beta. To reduce statistical noise in the raw sentiment beta estimates, we apply the Bayes–Stein shrinkage approach of Glushkov (2006). The resulting shrunk sentiment beta is denoted by $SBeta$:

$$SBeta_{i,q} = \frac{\sigma^2_{\text{prior},q-1}}{\sigma^2_{\text{prior},q-1} + \sigma^2_{\beta,q}} \left|\beta_{i,q}\right| + \frac{\sigma^2_{\beta,q}}{\sigma^2_{\text{prior},q-1} + \sigma^2_{\beta,q}} \beta^{\text{prior}}_{q-1}, \tag{9}$$

where

$$\beta^{\text{prior}}_{q-1} = \frac{1}{N_{q-1}} \sum_{i=1}^{N} \left|\beta_{i,q-1}\right|, \sigma^2_{\text{prior},q-1} = \frac{1}{N_{q-1}} \sum_{i=1}^{N} \left(\left|\beta_{i,q-1}\right| - \beta^{\text{prior}}_{q-1}\right)^2. \tag{10}$$

Sentiment beta ($SBeta$) captures the sensitivity of stock returns to changes in investor sentiment, where larger values indicate stronger sentiment-driven return variation.[13] We use shrunk sentiment beta in most of our analyses; however, our results are both qualitatively and quantitatively similar if we use the absolute value of raw sentiment beta instead.

The average sentiment beta over the sample period is 0.024 (See Panel C of Table 1). To examine how sentiment beta relates to stock characteristics, we sort stocks into groups based on their sentiment beta. In each quarter, the stocks are sorted into 5 groups based on beginning-of-quarter sentiment beta. The group of stocks with the highest 20% (lowest 20%) sentiment beta is referred to as the High (Low) group. Within each group, stock characteristics are first averaged across stocks. Then, the time-series mean of these averages, together with the mean difference between the high and low groups, are reported in Table 2. Stocks with higher sentiment beta demonstrate a monotonic cross-sectional trend of having lower price, lower market capitalization, less assets, along with higher volatility and higher idiosyncratic risk. This is consistent with the findings of Baker and Wurgler (2006) and Glushkov (2006).

[Insert Table 2 around here]

[13] Unless otherwise noted, we use the term sentiment beta to refer to the shrinkage estimate $SBeta$ throughout the paper.

3.4 Control Variables

Short Interest Ratio (Sir). Short interest reflects the aggregate number of shares sold short but not yet covered, and is widely used as a proxy for arbitrageurs' positions (Hanson & Sunderam, 2014) and short selling activity, which contributes to stock price efficiency (Boehmer & Kelley, 2009; Boehmer & Wu, 2013; Cao et al., 2018). Short interest data are collected monthly by exchanges, capturing uncovered shares sold short on and before the 15th of each month, provided it falls on a business day. The short interest ratio is constructed by dividing the total monthly short interest by the total number of shares outstanding reported by CRSP. The mean and median short interest ratio over the sample period are 3.1% and 2.0%, respectively.

Illiquidity (Illiq). Higher liquidity is associated with higher efficiency due to lower price impact or price pressure from trading activities. We employ the illiquidity measure proposed by Amihud (2002). In each quarter, the individual stock's illiquidity is calculated as the average daily ratio of absolute stock return to dollar volume

$$ill_{iq} = \frac{1}{D_{iq}} \sum_{d=1}^{D_{iq}} \frac{|ret_{iqd}|}{prc_{iqd} \cdot vol_{iqd}} * 10^6, \tag{11}$$

where ret_{iqd}, prc_{iqd} and vol_{iqd} are daily return, closing price, and daily volume for stock i on trading day d of quarter q, and D_{iq} is the number of trading days for stock i in quarter q. The illiquidity can be interpreted as the price response to one-dollar trading volume, thus measuring the price impact. To match the quarterly data of noise share and institutional ownership, we average the daily illiquidity ratios of stocks over the quarter.

Volatility (retSD). The volatility can reflect the uncertainty of the fundamental value of a security. Stocks with higher volatility are more difficult to value (Baker & Wurgler, 2006; DeVault et al., 2019; Gao et al., 2023). Their efficient price levels are therefore harder to maintained, potentially leading to higher noise in price. The volatility here is measured by the standard deviation of daily returns within the quarter.

Firm characteristics. The included firm characteristics are stock price ($Price$), total assets ($Assets$), and book-to-market ratio (BM). The stock price is the quarter-end adjusted closing price. The total assets is the quarter-end book value of the assets. The book-to-market value is the ratio of the book value of equity to its market value.

4 The Impact of Sentiment Beta on IO–Efficiency Relation

4.1 Portfolio Sorting Analysis

To investigate the impact of sentiment beta on the IO–Efficiency relation, we first perform a dependent double sorting analysis, a nonparametric technique that allows examination of the IO–Efficiency relation while controlling for sentiment beta (Bali et al., 2016). At the end of each quarter $q-1$, stocks are first sorted into quintile portfolios based on their sentiment beta. Within each sentiment beta group, stocks are further sorted into quintiles according to their institutional ownership to generate 25 (5×5) portfolios. The low- (high-) $SBeta$ and IO portfolios comprise the bottom (top) quintile of stocks based on each variable, respectively. For each portfolio, we compute the average noise share in quarter q and report time-series averages of quarterly noise share, together with the average difference in noise share between high- and low-IO portfolios and between high- and low-$SBeta$ portfolios. Standard errors are corrected for autocorrelation using the Newey and West (1987) method with 5 lags.

We tabulate the results in Table 3. First, the differences in noise share between high-IO and low-IO for all 5 sentiment beta groups are significantly negative at 1% level, indicating that higher institutional ownership is significantly associated with lower noise share and hence higher stock price efficiency, consistent with Boehmer and Kelley (2009) and Cao et al. (2018). Second, the differences in noise share attenuate as sentiment beta increases. Within the low-$SBeta$ group, high-IO stocks display an 8.5% lower noise share than low-IO stocks. By contrast, this noise share gap is only 4.8% within the high-$SBeta$ group. The difference-in-differences between the two groups is 3.7% and significant at the 1% level, indicating that sentiment beta significantly undermines the impact of institutional ownership on price efficiency. These results provide support both for the conventional notion that higher institutional ownership leads to higher price efficiency, and for our main hypothesis that this relation is weaker for stocks with higher sentiment beta.

[Insert Table 3 around here]

Figure 4 presents a visual summary of the portfolio sorting result. Noise share is plotted across sentiment beta quintiles for stocks with low and high institutional ownership. The gap between the two groups is largest in the lowest sentiment beta quintile and narrows as sentiment beta increases. This pattern is consistent with our core finding. The positive impact of institutional ownership on price efficiency weakens as sentiment beta rises.

[Insert Figure 4 around here]

4.2 Firm-level Regression Analysis

The results from portfolio sorting analysis can be driven by factors such as liquidity, size, or short interest that have been documented to affect price efficiency. To address this concern, we conduct stock-level regression analysis which controls for lagged noise share and stock characteristics. Following the settings of Boehmer and Kelley (2009) and Cao et al. (2018), we estimate the following equation for overall sample as well as within each sentiment beta quintile portfolio:

$$NoiseShare_{i,q} = \alpha_0 + \beta_1 IO_{i,q-1} + \beta_2 NoiseShare_{i,q-1} + \sum_{k=3}^{6} \beta_k X_{i,q-1} + \beta_7 Illiq_{iq} + \epsilon_{i,q}, \quad (12)$$

where $NoiseShare_{i,q}$ is the noise share of stock i at the end of quarter q. $IO_{i,q-1}$ is the institutional ownership at the end of quarter $q-1$. $NoiseShare_{i,q-1}$ is the noise share at the end of quarter $q-1$, which is included to account for possible mean reversion of price efficiency. $X_{i,q-1}$ is a set of stock characteristics measured at the end of quarter $q-1$, including short interest ratio (Sir), quarter-end closing price ($lnPrice$), total assets ($lnAsset$), book-to-market ratio (BM), and return volatility ($retSD$). Liquidity is contemporaneously associated with price efficiency. Following Cao et al. (2018), we control for $Illiq_{i,q}$ to ensure the observed improvement in efficiency is not merely attributable to improved liquidity.[14] We estimate this model using both the panel regression and Fama-MacBeth (FMB) regression (Fama & MacBeth, 1973) models. For the panel regressions, standard errors are clustered within each firm, and the year-quarter fixed effects are included in all regressions. For FMB regressions, standard errors are corrected for autocorrelation using the Newey and West (1987) method.

The coefficients of interest are β_1, and the difference in β_1 between regressions of high- and low-$SBeta$ groups $\beta_1^{HighSBeta} - \beta_1^{LowSBeta}$. β_1 is expected to be negative since institutional investors improve the price efficiency in general, while our Hypothesis 1 predicts a significantly positive difference ($\beta_1^{HighSBeta} > \beta_1^{LowSBeta}$), as high sentiment beta weakens the IO–Efficiency relation.

[14]Note that including lagged illiquidity $Illiq_{i,q-1}$ gives the quantitatively similar result.

In Table 4, we report results of the panel regressions and FMB regressions in Panels A and B, respectively. Column (1) presents the results for the full sample as a benchmark, while Column (2) through (6) present the results progressing from the lowest to the highest sentiment beta group. First, consistent with Boehmer and Kelley (2009) and Cao et al. (2018), the overall relation between institutional ownership and noise share is negative across all sentiment beta groups. Second, and of primary interest, from Column (2) to (6) the β_1 coefficients increase monotonically from -0.074 to -0.027. This pattern indicates that the negative relation between institutional ownership and noise share weakens as sentiment beta increases. In terms of economic significance, in the low-$SBeta$ group a one-standard-deviation increase in institutional ownership reduces noise share by 2.07 percentage points, In the high–$SBeta$ group the reduction is only 0.81 percentage points.[15] This suggests that the efficiency-enhancing effect of institutional ownership more than halves as sentiment beta moves from the lowest to the highest group. The FMB regressions also yield consistent results, confirming that the impact of sentiment beta on the IO–Efficiency relation is not driven by the choice of estimation method.

[Insert Table 4 around here]

The regressions estimated separately within each sentiment beta quintile allow us to qualitatively conclude that sentiment beta weakens the IO–Efficiency relation. To examine quantitatively the incremental effect of sentiment on the IO–Efficiency relation revealed in the above analysis, we include the interaction term of sentiment beta and institutional ownership in the regression. Specifically, we estimate the following equation:

$$\begin{aligned} NoiseShare_{i,q} =& \alpha_0 + \beta_1 IO_{i,q-1} + \beta_2 SBeta_{i,q-1} + \beta_3 (IO \times SBeta)_{i,q-1} \\ & + \beta_4 NoiseShare_{i,q-1} + \sum_{k=5}^{8} \beta_k X_{i,q-1} + \beta_9 Illiq_{i,q} + \epsilon_{i,q}, \end{aligned} \tag{13}$$

where $SBeta$ and $IO \times SBeta$ are two additional variables, with β_1 and β_3 being the coefficients of interest. We expect β_1 to be negative and β_3 to be positive, consistent with that sentiment beta attenuates the negative IO–Efficiency relation.

We report results in the Column (7) of Table 4. Both β_1 and β_3 have the expected signs and are statistically significant at the 1% level, corroborating the above evidence that

[15] The standard deviations of institutional ownership are 0.28 and 0.30 for low- and high-sentiment beta groups of stock, so one SD increase in IO is associated with $0.074 * 0.28 = 2.07\%$ ($0.027 * 0.30 = 0.81\%$) for low- (high-) sentiment beta stocks.

sentiment beta weakens the IO–Efficiency relation. The marginal effect of institutional ownership is conditional on sentiment beta and is given by $-0.069 + 0.540 \times SBeta$. As $SBeta$ rises from 0.019 (the mean in the low–$SBeta$ group) to 0.033 (the mean in the high-$SBeta$ group), the effect of institutional ownership on noise share moves from -0.059 to -0.051, marking a 12.87% reduction in magnitude. Again, the FMB estimates confirm this pattern, suggesting that the results are robust to alternative estimation techniques.

We note that the coefficient for the direct effect of $SBeta$ is negative in Column (7), indicating that stocks with higher sentiment beta are more efficiently priced on average. While a positive direct effect might seem more intuitive, this finding admits a coherent interpretation. High-$SBeta$ stocks share features of hard-to-value firms where valuation uncertainty is high, and Kumar (2009) shows that such stocks simultaneously attract more intensive informed trading as sophisticated investors exploit amplified behavioral biases. Consistent with this, Brogaard et al. (2022) documents that hard-to-value stocks carry a lower noise share but higher private information share, suggesting that the informed trading channel can dominate and suppress overall noise even where sentiment-driven distortions are present. Importantly, our central prediction concerns the interaction term β_3, which captures how sentiment exposure weakens the marginal contribution of institutional ownership to price efficiency, and it is through this channel that sentiment beta exerts its primary influence on the IO–Efficiency relation.

So far, our results confirm the findings of Boehmer and Kelley (2009) and Cao et al. (2018), connecting higher institutional ownership with smaller pricing errors and greater price efficiency. However, sentiment beta weakens this relation. These results hold across both the subsample and pooled interaction specifications, nd are confirmed by both panel and FMB regressions. These findings underscore the role of sentiment beta in shaping the IO–Efficiency relation.

5 Mechanism Analysis

5.1 Validating the Limits-to-Arbitrage Mechanism

Our baseline results show that sentiment beta weakens the IO–Efficiency relation, consistent with the hypothesis that sentiment-induced arbitrage risk limits institutions' ability to correct mispricing. This finding is suggestive, but it does not fully establish sentiment beta as a genuine arbitrage friction. Stronger evidence would come from showing that its impact is more pronounced in settings where arbitrage constraints bind more tightly. We exploit the well-documented asymmetry in arbitrage constraints to test this prediction. Arbitrage asymmetry refers to the idea that overpricing is harder to correct than underpricing due to short-sale impediments (Stambaugh et al., 2015). Prior evidence shows that mispricing and anomaly returns are indeed concentrated on the short side and that overpricing corrects more slowly (Avramov et al., 2013; Stambaugh et al., 2012).

We test this prediction by exploiting variation in arbitrage constraints across three dimensions. First, we contrast optimistic and pessimistic quarters, as optimistic market conditions are associated with more pervasive sentiment-driven overpricing and tighter limits to arbitrage (Stambaugh et al., 2015). Second, we examine the direction of mispricing directly by contrasting overpriced and underpriced stocks, where arbitrage asymmetry implies that constraints bind more severely on the overpricing side. Third, we distinguish between active and passive institutional ownership as a proxy for arbitrage capacity. Active institutions engage in informed, discretionary trading premised on costly information acquisition (Crane et al., 2023; Grossman & Stiglitz, 1980; Kacperczyk et al., 2021), whereas passive institutions largely follow benchmark-tracking strategies (Brogaard et al., 2019; Madhavan, 2014; Sammon, 2024). If sentiment beta genuinely captures arbitrage risk, its impact on the IO–Efficiency relation should be most pronounced following high-sentiment periods, among overpriced stocks, and in the presence of active ownership. These three settings are where arbitrage constraints are most binding and where the capacity for sentiment-correcting arbitrage can be directly tested.

5.1.1 Investor Sentiment: Pessimistic versus Optimistic Quarters

Hypothesis 2 predicts that the impact of sentiment beta on IO–Efficiency relation is stronger following optimistic quarters with high sentiment levels. To test this hypothesis, we first conduct a portfolio sorting analysis, similar to that in Table 3, separately for optimistic and pessimistic quarters. Specifically, we define optimistic (pessimistic) quarters as those in which the abnormal sentiment level is above (below) the sample median. The abnormal sentiment level is computed as the difference between the quarterly sentiment level and its average over the previous eight quarters. This classification shares the same conceptual logic as Antoniou et al. (2013), in that both employ a backward-looking moving average to detrend the sentiment series and identify regimes relative to recent history rather than the full-sample distribution.[16] Moreover, because the benchmark is constructed solely using information available up to quarter q, this method avoids look-ahead bias and reflects the actual information set available to investors at the time. We then perform double sorting within both optimistic and pessimistic periods, followed by computing the high-minus-low portfolio differences across the two sentiment regimes.

We report portfolio sorting results in Panel A of Table 5. The middle three IO groups are omitted for brevity. Sentiment beta weakens the IO–Efficiency relation following both optimistic and pessimistic quarters, with high-minus-low $SBeta$ spreads of 4.2% and 3.2%, respectively, both significant at the 1% level. Consistent with our hypothesis, the impact of sentiment beta is more pronounced following optimistic quarters, with the spread being 0.9% larger than that following pessimistic quarters. This difference, however, does not reach conventional levels of statistical significance, and the sorting analysis alone does not provide conclusive evidence of a sentiment-regime-dependent pattern. The limited power of the double-sorting approach, which does not control for firm-level characteristics that vary systematically across sentiment regimes, likely contributes to this imprecision.

[Insert Table 5 around here]

We then conduct regression analysis and report results in Panel B of Table 5. Columns (1) and (2) replicate the baseline regression from Column (7) of Table 4, estimated separately for pessimistic and optimistic subsamples. The coefficient on $IO \times SBeta$ is 0.278 following pessimistic quarters and 0.868 following optimistic quarters, significant at the 10% and 1% levels, respectively. The substantially larger coefficient following optimistic quarters is consistent with our prediction that sentiment beta has stronger impact when sentiment-driven overpricing is more prevalent. Column (3) formally tests this difference using a triple interaction model on the full sample. The baseline interaction $IO \times SBeta$ is positive at 0.196 but not significant, reflecting the average effect pooled across sentiment regimes. The more informative estimate is the triple interaction $High \times IO \times SBeta$, where $High$ is a dummy variable equal to one for optimistic quarters. The coefficient is positive and highly significant, indicating that the role of sentiment beta on the IO–Efficiency relation is concentrated following optimistic quarters. Column (4) corroborates this finding by replacing the dummy with the continuous sentiment index $SENT$. The triple interaction $SENT \times IO \times SBeta$

[16] The two approaches differs in implementation. Antoniou et al. (2013) construct a weighted three-month rolling average of the residual sentiment index, assigning weights of 3, 2, and 1 to months t, $t-1$, and $t-2$, respectively. Our approach instead computes abnormal sentiment as the deviation of the quarterly level from its eight-quarter trailing mean. Despite these implementation differences, both measures capture sentiment relative to recent norms rather than absolute levels.

is again positive and statistically significant, suggesting that as sentiment becomes more optimistic, sentiment beta exerts a stronger impact on the IO–Efficiency relation.[17]

Taken together, these results provide support to the argument that sentiment-driven distortions are more pronounced following high-sentiment environments, where limits to arbitrage are more binding.

5.1.2 Mispricing Factor: Underpricing versus Overpricing

Investor sentiment is a time-series measure that captures the overall market mood, with high sentiment corresponding to periods when stocks are more likely to be overpriced. To more directly assess stock-level mispricing, we adopt the mispricing measure developed by Stambaugh et al. (2015). This *Mispricing* measure is constructed by averaging a stock's percentile rankings across 11 well-established anomalies (e.g., net stock issues, accruals, momentum), producing a composite mispricing score that ranges from 0 to 100. According to this measure, the stocks with the highest values of mispricing are the most "overpriced," and those with the lowest values are the most "underpriced." By aggregating across multiple anomalies, this approach reduces idiosyncratic noise and more accurately captures relative mispricing in the cross-section. The mispricing measure for individual stocks is available from July 1965 to December 2016, and we retrieve this data from Robert Stambaugh's personal website.[18]

Hypothesis 3 predicts that sentiment beta has more pronounced impact on the IO–Efficiency relation among overpriced stocks. To test this, we perform both portfolio sorting and regression analyses. Specifically, we first sort stocks into two groups based on their beginning-of-quarter mispricing scores, and then within each group conduct the same double-sorting procedure as in Table 3. We report portfolio sorting results in Panel A of Table 6. The Middle three IO groups are omitted for brevity. The high-minus-low $SBeta$ spread is 5.8% among overpriced stocks and 2.6% among underpriced stocks, both significant at the 1% level. The difference between two is 3.2% and statistically significant, indicating that sentiment beta more strongly weakens the IO–Efficiency relation among overpriced stocks, consistent with our hypothesis.

[Insert Table 6 around here]

[17]Note that the direct impact of $High$ and $SENT$ are not reported in the regression output, as they vary only over time and not across firms within a given quarter and hence are fully absorbed by time fixed effects.

[18]We are grateful to Robert Stambaugh for making the mispricing measure for individual stocks publicly available at https://finance.wharton.upenn.edu/∼stambaug/.

Examining the last three columns of Panel A clarifies the role of institutional ownership and provides additional support for the arbitrage asymmetry interpretation. In the Low IO subsample, overpriced stocks are generally noisier than underpriced stocks, as shown by the mostly positive noise share difference between overpriced and underpriced stocks in the Low IO column. In contrast, in the High IO subsample, this difference is close to zero and often slightly negative, indicating that when institutional ownership is high, overpriced stocks are not noisier than underpriced stocks. This asymmetric pattern is consistent with the view that overpricing, rather than underpricing, is the side where institutional engagement matters most. Because short-sale constraints prevent full arbitrage correction on the overpricing side in ways they do not on the underpricing side (Miller, 1977; Stambaugh et al., 2015), overpriced stocks remain more persistently mispriced and thus present greater scope for informed institutional trading to improve efficiency. At the same time, the fact that this improvement is not uniformly large across all sentiment beta groups is consistent with the interpretation that institutions rationally engage in arbitrage but face higher sentiment-related arbitrage risk and tighter limits to arbitrage in sentiment-sensitive stocks.

Panel B of Table 6 presents regression results that further support our main findings. We augment the baseline regression by including $MISP$ and its interactions with IO and $SBeta$, where $MISP = |Mispricing - 50|$ measures the magnitude of mispricing. To examine whether the impact of sentiment beta varies with the direction of mispricing, we then split the sample into underpriced and overpriced stocks based on whether the $Mispricing$ is below or above 50. Column (1) reports results for the full sample with non-missing mispricing data, while Columns (2) and (3) report results for the underpriced and overpriced subsamples, respectively. In Column (1), the coefficient on the triple interaction term $MISP \times IO \times SBeta$ is positive but insignificant, suggesting that the role of mispricing is not evident when overpriced and underpriced stocks are pooled together. However, when the sample is split by mispricing status, a clear asymmetry emerges. The triple interaction term is positive at 0.017 but statistically insignificant in the underpricing subsample. However, it is positive, equal to 0.031, and becomes significant at the 5% level in the overpricing subsample. This confirms that the impact of sentiment beta on the IO–Efficiency relation is particularly pronounced among overpriced stocks.

Overall, the results support the arbitrage asymmetry mechanism by showing that the attenuating effect of sentiment beta on the IO–Efficiency relation is significantly stronger among overpriced stocks, where mispricing is harder to correct. The efficiency gains from institutional ownership are most evident in overpriced stocks, but this corrective effect weakens progressively with sentiment beta, consistent with limits to arbitrage.

5.1.3 Active versus Passive Institutional Ownership

Aggregate institutional ownership conceals substantial heterogeneity. The key distinction relevant for informational efficiency is between active and passive institutions. These two groups of investors differ in how they acquire and process information and how their trading contributes to price discovery. Active institutions are more likely to engage in arbitrage by acquiring and processing private information (Bushee, 2001; Grossman & Stiglitz, 1980; Kacperczyk et al., 2021). Passive institutions typically follow benchmark-oriented strategies and engage in little, if any, arbitrage activity (e.g., Sammon, 2024). As active institutions engage more directly in trading against mispricing, they are more exposed to sentiment-driven price movements and the associated interim-loss risk as well. Consequently, active ownership is generally more effective in reducing noise share, but its contribution to price efficiency is more weakened by sentiment beta than that of passive ownership.

We follow Kacperczyk et al. (2021) and Agarwal et al. (2013, 2024) in defining active versus passive investors using three alternative approaches. First, following Ferreira and Matos (2008) and Kacperczyk et al. (2021), and based on Bushee (2001)'s type classification, investment companies (INV) and independent investment advisors (IIA) are classified as active investors, while banks (BNK), insurance companies (INS), and others are considered more benchmark-driven (Classification I). Second, under Bushee (2001)'s modal classification, transient (TRA) and dedicated (DED) institutions are considered active, as both groups are characterised by higher turnover or concentrated holdings, whereas quasi-indexers (QIX) largely adopt passive, index-tracking strategies (Classification II). Third, following Agarwal et al. (2013, 2024) and Cao et al. (2018), hedge funds are identified as active investors, as they rely heavily on private information and arbitrage strategies, in contrast to other 13F institutions whose positions are often tied to benchmarks or longer-term mandates (Classification III).

These three classifications separate active from passive investors with different approaches, which leads to clear predictions, and they complement each other. Classification I is most reliable for identifying passive ownership, because identified passive institutions (e.g., banks) are more likely to be benchmark-driven and less likely to engage in arbitrage. However, its active group (IIA and INV) is broad, and not all investors in these types should be viewed as active arbitrageurs. Classifications II and III are closer to arbitrage activity, because transient/dedicated institutions and hedge funds are more likely to trade on information and against mispricing. At the same time, the remaining groups in these schemes may not be purely passive, since quasi-indexers can still trade around benchmarks and non-hedge-fund institutions may also engage in active trading (Kacperczyk et al., 2021). Thus, we expect sentiment beta to have a stronger impact on active ownership under Classifications II and III, and little impact (insignificant positive or even negative) on passive ownership under Classification I.

We repeat the baseline interaction regression of Column (7) of Table 4, which includes $IO \times SBeta$ as the key term, separately for active and passive ownership, and then including both in the same specification. This allows us to compare how the interaction with $SBeta$ differs across active and passive institutions. The results are presented in Table 7, in which Panel A presents the regression result and Panel B presents the Wald tests of coefficient differences.

[Insert Table 7 around here]

First, we find consistent evidence across the three classifications that active ownership is more negatively related to noise share. In other words, active investors are more effective at reducing noise in stock prices, which is consistent with our prediction based on their investment style and their greater reliance on information acquisition and processing. For example, under Classification I, the coefficient on active IO is −0.092, while that on passive IO is only −0.072. In Column (3), where both active and passive IO are included in the same regression, the difference becomes clearer. The coefficient on passive IO is −0.022, which is significantly smaller in magnitude than the coefficient on active IO (−0.088). The difference is −0.067 and is statistically significant at the 1% level. Regarding economic significance, a 1 percentage-point increase in active IO is associated with a 0.088 percentage-point decrease in noise share, whereas the same increase in passive IO reduces noise share by only 0.022 percentage points, implying that the effect of active IO is four times as large. Though the difference between active and passive IOs is smaller under Classifications II and III, active IO remains the more effective contributor to reducing noise share. This evidence is consistent with the findings in Cao et al. (2018) and Kacperczyk et al. (2021), among others.

Second, regarding the interactions with sentiment beta, we find that the efficiency-enhancing effect of active ownership declines more strongly than that of passive ownership as sentiment exposure increases. Under Classification I, the interaction term for active institutional ownership is large and highly significant, with a coefficient of 0.863 in the regression estimated separately and 0.908 when both ownership types are included in the same specification. In contrast, the corresponding coefficient for passive institutional ownership is small and statistically insignificant. Panel B further corroborates this distinction, indicating that the interaction effect of active ownership is significantly stronger than that of passive ownership. The difference between the two amounts to 1.268 and is significant at the 1% level. This pattern is consistent with the idea that active investors, who rely more heavily on arbitrage and informed trading, are particularly sensitive to noise trader risk induced by sentiment beta. The results for Classifications II and III show a similar but smaller gap. The interaction terms for active IO remain economically larger than those for passive IO, and the differences tested in Panel B, equal to 0.993 and 0.978 respectively, are again highly significant. Overall, these findings indicate that active ownership across all three classifications is more susceptible to the impact of sentiment beta on the IO–Efficiency relation.

5.2 Institutional Disengagement and Its Efficiency Consequences

5.2.1 Decomposing Institutional Ownership by Sentiment Exposure

Our tests in the previous section (Section 5.1) demonstrate that sentiment beta weakens the IO–Efficiency relation most strongly where arbitrage constraints are tightest, i.e. following high-sentiment periods, among overpriced stocks, and for active institutional ownership. Having established that sentiment beta operates as a genuine arbitrage friction, we now assess how this friction manifests in the composition and dynamics of institutional investment in sentiment-prone stocks.

Specifically, we test whether aggregate institutional ownership comprises heterogeneous components with distinct effects on price efficiency. Prior research provides evidence that institutional ownership is systematically related to stocks' sentiment exposure. Massa and Yadav (2015) and Chen et al. (2021) show that mutual fund and hedge fund performance varies with sentiment beta exposure, indicating that institutional ownership contains a sentiment-related component.

If sentiment beta acts as an arbitrage friction, the portion of IO that is systematically related to sentiment beta should contribute differently to efficiency than the sentiment-beta-orthogonal component. The sentiment-beta-driven component may reflect institutions' exposure to sentiment movements or constrained arbitrage capacity in sentiment-prone stocks. To the extent that this component is not rooted in fundamental information about firm cash flows and risks, it is unlikely to improve informational efficiency. By contrast, the sentiment-beta-orthogonal component more likely reflects institutions' discretionary investment based on fundamental analysis, and is therefore expected to have a stronger negative association with noise share.

We follow the decomposition approach of Nagel (2005) and Boehmer and Kelley (2009). The former regresses institutional ownership on firm size to partial out size-related variation, while the latter regresses it on liquidity to alleviate liquidity-driven effects. Specifically, we decompose institutional ownership in each quarter t by estimating the following cross-sectional regression:

$$\text{logit}\,(IO_{i,q}) = \log\left(\frac{IO_{i,q}}{1-IO_{i,q}}\right) = \alpha + \beta SBeta_{i,q-1} + \varepsilon_{i,q}, \tag{14}$$

where $\text{logit}\,(IO_{i,q})$ is the logit transformation of institutional ownership, following Nagel (2005) to improve the regression's specification. We obtain sentiment beta-driven institutional ownership as $\widehat{IO} = \hat{\alpha} + \hat{\beta} SBeta_{i,q-1}$, and residual institutional ownership, $IO^{\perp}$. On average, across all quarters, we obtain the following relationship:[19]

$$\text{logit}(IO_{i,q}) = \underset{(4.27)}{0.8167} - \underset{(-5.46)}{24.2439}\ SBeta_{i,q-1} + \varepsilon_{i,q}. \tag{15}$$

This average relation between logit institutional ownership and sentiment beta indicates that, overall, institutions underweight stocks with higher sentiment beta, consistent with Glushkov (2006).

We then regress noise share on these two components, both separately and jointly, to examine whether their contributions to price efficiency differ as predicted. The results is reported in Table 8. Column (1) establishes a benchmark by regressing noise share on overall *logitIO*, comparable to Column (1) of Table 4. Columns (2) and (3) then examine the residual and sentiment-beta-driven components separately, while Column (4) includes both simultaneously to directly compare their contributions to price efficiency.

[Insert Table 8 around here]

The results show that $IO^{\perp}$ maintains a statistically significant negative association with noise share across specifications, consistent with our conjecture that this component more likely reflects informed institutional trading that is not driven by sentiment exposure and therefore enhances price efficiency. In contrast, $\widehat{IO}$ exhibits a significantly positive coefficient, suggesting that institutions' sentiment beta-driven positions are associated with higher noise share, potentially due to uninformed or sentiment-driven demand (e.g., DeVault et al., 2019). When both components are included in Column (4), the opposing signs remain and

[19] T statistics, computed based on Newey and West (1987) adjusted standard error, are presented in parentheses

both coefficients are statistically significant, confirming that the two components exert fundamentally different effects on price efficiency.

Overall, this decomposition analysis complements our baseline findings by demonstrating that the attenuation of the IO–Efficiency relation by sentiment beta stems from the fact that the sentiment-beta-driven component of institutional ownership does not enhance price efficiency and may even impair it. In contrast, the residual component, orthogonal to sentiment exposure, continues to improve efficiency. These results reinforce the notion that aggregate institutional ownership conceals heterogeneous effects, with only the informed portion contributing to price discovery. The decomposition thus underscores the importance of disentangling the underlying drivers of institutional demand when evaluating its role in price efficiency.

5.2.2 Dynamic Institutional Response to Changes in Sentiment Beta

The decomposition analysis establishes that only sentiment-beta-orthogonal institutional ownership improves price efficiency, but leaves open the question of how this cross-sectional pattern emerges dynamically. We now examine whether institutions actively adjust their holdings and their trading activities in response to changes in sentiment beta.

Institutional responses could operate through two distinct channels, both of which would contribute to the weaker IO–Efficiency relation. On the one hand, institutions may reduce their engagement with stocks whose sentiment exposure increases, recognizing rising sentiment beta as a deteriorating arbitrage condition characterized by increased noise trader risk (DeLong et al., 1990) and tighter limits to arbitrage (Shleifer & Vishny, 1997). Such withdrawal would leave high-sentiment-beta stocks with persistently lower institutional participation, directly contributing to the weaker IO–Efficiency relation.

On the other hand, institutions may increase their positions in stocks with rising sentiment beta, either to exploit predictable sentiment-driven price movements (e.g., Chen et al., 2021; Massa & Yadav, 2015) or due to their own sentimental demand (e.g., Brunnermeier & Nagel, 2004; DeVault et al., 2019; Griffin et al., 2011). As our decomposition demonstrates, sentiment-beta-driven ownership does not improve price efficiency. Therefore, if institutions tilt toward stocks with rising sentiment exposure, the composition of institutional ownership in these stocks shifts away from information-based investment and toward sentiment-related positions, leading to a weaker IO–Efficiency relation.

We investigate which channel operates by estimating following panel regressions:

$$Y_{i,q} = \alpha_0 + \beta_1 \Delta SBeta_{i,q-1} + \gamma Y_{i,q-1} + \theta X_{i,q-1} + \varepsilon_{i,q}, \tag{16}$$

where the dependent variable $Y_{i,q}$ is either $\Delta IO_{i,q}$ or $Trade_{i,q}$. $\Delta IO_{i,q}$ is the quarterly change in institutional ownership, and $Trade_{i,q}$ is the sum of absolute buys and sells scaled by shares outstanding. $\Delta SBeta_{i,q-1}$ captures changes in sentiment exposure. We estimate these regressions separately within quintiles of beginning-of-quarter sentiment beta to test whether institutional responses vary with baseline sentiment exposure. The control variables include changes in stock characteristics specified in the baseline regression. All regressions include year-quarter fixed effects, and standard errors are clustered at the firm level.

We report the results in Table 9. Panel A examines changes in institutional ownership in response to changes in sentiment beta. Column (1) shows that, on average across all stocks, there is no significant relation between changes in IO and changes in sentiment beta. However, this aggregate result masks substantial cross-sectional heterogeneity. Columns (2)-(6) reveal that institutional responses vary systematically with baseline sentiment exposure. In low-sentiment-beta stocks (Column 2), institutions reduce ownership when sentiment beta increases, with a statistically significant coefficient of -0.249. This negative response weakens monotonically across sentiment beta groups and becomes statistically insignificant for stocks with already-high sentiment exposure (Columns 5-6).

[Insert Table 9 around here]

Panel B presents analogous results for institutional trading activity. The trading patterns mirror the results for ownership changes. Institutions significantly reduce trading when sentiment beta rises in low-sentiment-beta stocks, with a significant coefficient of -0.414. However, this response attenuates and becomes insignificant in high-sentiment-beta stocks. These findings are consistent with the withdrawal mechanism. When sentiment exposure increases in low-sentiment-beta stocks, where arbitrage was previously more feasible, institutions actively disengage by reducing both their positions and trading activity. In contrast, when sentiment beta increases in already-sentiment-prone stocks, institutions make minimal adjustments, having already limited their exposure to these stocks where arbitrage constraints are most binding.

This asymmetric response provides crucial insight into the dynamic process underlying our cross-sectional results. The stocks where institutions withdraw most strongly, i.e. low-sentiment-beta stocks, are precisely those where our baseline analysis shows institutions are most effective at reducing noise share. Conversely, high-sentiment-beta stocks, where institutions barely adjust to further increases in sentiment exposure, are those where institutional ownership has the weakest efficiency-enhancing effect. This suggests that as sentiment beta rises in a stock, institutional withdrawal reduces the informed participation that would otherwise improve efficiency, actively generating the weaker IO–Efficiency relation observed in high-sentiment-beta stocks.

The evidence of institutional withdrawal indicates that institutions recognize rising sentiment exposure as arbitrage risk and respond by reducing their capital allocation to affected stocks, consistent with rational risk management facing sentiment-induced noise trader risk (DeLong et al., 1990) and heightened interim-loss risk (Gromb & Vayanos, 2010). Importantly, institutions reduce both their holdings and trading activity simultaneously. This joint reduction amplifies the efficiency consequences, leaving high-sentiment-beta stocks with less informed capital and less informational trading, both of which are needed to reduce noise and improve price efficiency.

Overall, we establish that sentiment beta shapes the IO–Efficiency relation through both compositional and dynamic channels. The decomposition analysis shows that only sentiment-orthogonal ownership improves efficiency, while the dynamic analysis demonstrates that institutions actively withdraw when sentiment exposure increases, particularly from low-sentiment-beta stocks where their presence would be most valuable. Together, these channels create a self-reinforcing pattern where high sentiment beta constrains institutional arbitrage, institutions respond by withdrawing, and this withdrawal leaves noise trading uncorrected, further reducing informational efficiency.

6 Robustness Tests

6.1 Alternative Measures of Institutional Activity

Our baseline analysis estimates the model in levels, consistent with Boehmer and Kelley (2009). By contrast, Cao et al. (2018) estimate the model in first differences to eliminate unobservable heterogeneity across stocks. As a robustness check, we re-estimate our baseline model with first-differenced variables. Specifically, we regress the change in noise share on the lagged change in institutional ownership, and report the results in Panel A of Table 10. Across sentiment beta groups, shown in Columns (2)–(6), the coefficient on ΔIO increases nearly monotonically from –0.062 in the low $SBeta$ group to –0.027 in the high $SBeta$ group, becoming statistically insignificant in the latter. In Column (7), the interaction between ΔIO and $SBeta$ is positive (1.50) and significant at the 5% level, confirming the impact of sentiment beta.

[Insert Table 10 around here]

In addition to changes in institutional ownership, it is also informative to examine institutional trading activity. Trades, defined as the sum of absolute buys and sells, capture portfolio adjustments even when net ownership changes are small, and therefore provide a complementary perspective on the role of institutions in shaping price efficiency. Boehmer and Kelley (2009) also provide evidence that trading plays an important role in improving price efficiency beyond holdings. Panel B of Table 10 reports the corresponding results from the level regression of noise share on trades. On average, a one percentage point increase in institutional trades is associated with a 0.177 percentage point decrease in noise share, whereas a one percentage point increase in institutional ownership is associated with only a 0.054 percentage point decrease. Because the two variables have different standard deviations, a simple one percentage point increase is not directly comparable. When scaled by their respective variations, a one standard deviation increase in trades (ownership) corresponds to a 1.24 (1.57) percentage point decrease in noise share, suggesting that both play similarly important roles in improving price efficiency. The level of sentiment beta also weakens the efficacy of institutional trades, as shown by the monotonically increasing (less negative) coefficient from low- to high-$SBeta$ groups. The highly significant coefficient on the interaction term in Column (7) further reinforces this result. Economically, as sentiment beta rises from 0.019 (the mean in the low-sentiment-beta group) to 0.033 (the mean in the high-sentiment-beta group), the effect of institutional trades on noise share changes from –0.197 to –0.165, representing a 16.21% reduction in magnitude.

Overall, the robustness analyses using both first-differenced ownership and institutional trades confirm that our baseline result is not sensitive to model specification or measurement choice. Whether institutional activity is captured by net ownership changes or by trading intensity, sentiment beta consistently weakens the efficiency-enhancing effect of institutions. This reinforces our central finding that institutional investors contribute to price efficiency, but their influence is attenuated in stocks more exposed to sentiment.

6.2 Alternative Sentiment Index

To alleviate concerns that our findings are sensitive to the choice of sentiment index, we re-estimate sentiment beta using changes in UMCSI and replicate the baseline analyses. The results are reported in Table 11. In Panel A, the coefficient on institutional ownership increases monotonically from -0.072 in the low $SBeta\_UMCSI$ group to -0.026 in the high $SBeta\_UMCSI$ group. In the interaction specification, the coefficient on $IO \times SBeta\_UMCSI$ is positive at 0.310, significant at the 10% level. The FMB regression in panel B corroborates both patterns. Overall, the results suggest our finding is robust to the choice of underlying sentiment index.

[Insert Table 11 around here]

6.3 Alternative Price Efficiency Measures

To examine whether our baseline findings are sensitive to the choice of price efficiency measure, we replicate the baseline analyses using three widely employed alternatives: return autocorrelation, variance ratio, and HM price delay (e.g., Boehmer & Kelley, 2009; Cao et al., 2018). Results are reported in Table 12, with Panels A to C presenting portfolio sorting and Panel D presenting panel and FMB regression results.

[Insert Table 12 around here]

The variance ratio produces the most consistent support across all three tests. In the portfolio sorting analysis, the noise share gap between high- and low-IO portfolios narrows significantly from -0.096 in the low-sentiment-beta group to -0.043 in the high-sentiment-beta group, with a difference-in-differences of 0.052 significant at the 1% level. The panel regression interaction coefficient between IO and $SBeta$ is 0.447, significant at the 1% level, and the FMB regression corroborates this finding. This stronger consistency is expected, as variance ratio and noise share both measure deviations from random walk pricing and therefore capture a closely related dimension of informational efficiency (Boehmer & Kelley, 2009; Lo & MacKinlay, 1988).

Return autocorrelation and HM price delay show supportive but less uniform patterns. For return autocorrelation, the attenuation of the IO–Efficiency relation by sentiment beta is significant in the portfolio sorting and panel regression but not in the FMB regression.

For HM price delay, this pattern holds only in the panel regression. This variation across measures is informative. Return autocorrelation captures short-term return predictability that partly reflects microstructure noise and liquidity effects unrelated to sentiment-driven mispricing (Chordia et al., 2005), reducing its sensitivity to the friction we study. HM price delay measures how quickly stocks incorporate market-wide information (Hou & Moskowitz, 2005), a dimension of efficiency that institutional ownership improves largely independent of sentiment exposure. Since sentiment beta operates as a firm-specific friction that impairs stock-level pricing error correction rather than the speed of market-wide information transmission, its moderating effect on the IO–Efficiency relation is less likely to manifest through this measure.

Overall, the pattern of results across measures is broadly consistent with our baseline finding that IO–Efficiency relation is weaker for high sentiment beta stocks, with the degree of support varying in a manner that aligns with the conceptual focus of each measure.

6.4 Positive versus Negative Sentiment Beta

A natural question is whether the effect of sentiment beta differs between stocks with positive and negative sentiment exposure. Prior studies show that the direction of sentiment beta matters for institutional trading strategies and returns. Massa and Yadav (2015) and Chen et al. (2021) show that mutual funds and hedge funds adopt heterogeneous strategies based on their sentiment beta exposure, with contrarian and momentum strategies yielding different performance implications. In those contexts, the sign of sentiment beta is economically meaningful because it determines the nature of the strategy and the direction of mispricing.

However, our focus is on price efficiency rather than returns. From an efficiency standpoint, what matters is the extent to which a stock's price is driven by non-fundamental sentiment fluctuations, which is determined by the magnitude of sentiment exposure regardless of its direction. A stock with a large positive sentiment beta and one with a large negative sentiment beta both attract greater sentiment-induced noise and pose greater arbitrage risk, making it harder for institutional investors to correct pricing errors in either case. We therefore expect the attenuation of the IO–Efficiency relation to be driven by the magnitude rather than the direction of sentiment beta.

We replicate baseline panel regression for subsamples of positive and negative raw sentiment beta (*sbeta*) respectively. Note that we use *sbeta* to split sample but still use $SBeta$ in the regression to capture magnitude. We report the results in Table 13. The coefficient on IO increases monotonically in both subsamples, rising from -0.071 (-0.077) in the low $SBeta$ group to -0.026 (-0.028) in the high $SBeta$ group for negative (positive) subsample. In the interaction specification, the coefficients on the interaction $IO \times SBeta$ are positive and statistically significant in both subsamples. In the Internet Appendix, we also replicate the single sorting analysis in Table 2 and double sorting analysis in Table 3, and find similar patterns across both subsamples.

[Insert Table 13 around here]

Taken together, these results confirm that the attenuation of the IO–Efficiency relation by sentiment beta is not sensitive to the sign of raw sentiment beta, and that it is the magnitude rather than the direction of sentiment exposure that drives our baseline finding.

6.5 Test for Reverse Causality

As a further test, we examine whether institutional investors tend to invest more in stocks that have recently improved in price efficiency, and whether this preference varies with sentiment beta. Following Boehmer and Kelley (2009) and Cao et al. (2018), we regress changes in institutional ownership on one-quarter-lagged changes in each efficiency measure, estimated separately within five sentiment beta groups. As reported in Table 14, the slope estimates are uniformly small and statistically indistinguishable from zero across all groups and measures, with the sole exception of a weakly negative coefficient on ΔHM in the high $SBeta$ group. Importantly, there is no systematic pattern across sentiment beta groups that would suggest institutions differentially chase efficiency improvements in high- versus low-$SBeta$ stocks. The evidence thus provides little support for the view that reverse causality drives either the IO–Efficiency relation or its moderation by sentiment beta.

[Insert Table 14 around here]

7 Conclusion

This study provides novel evidence on the conditional role of institutional investors in promoting informational price efficiency. While confirming the well-established IO–Efficiency relation, i.e. positive relation between institutional ownership and efficiency (Boehmer &

Kelley, 2009; Cao et al., 2018, among others), we show that a stock's sensitivity to investor sentiment, captured by its sentiment beta, significantly weakens this relation in an economically meaningful and robust way. We validate sentiment beta as a genuine arbitrage friction, showing that its moderating effect is strongest where limits-to-arbitrage theory predicts constraints to bind most tightly. We further show that this friction operates through both the composition and dynamics of institutional investment. Only the sentiment-orthogonal component of institutional ownership improves efficiency, while the sentiment-driven component does not. Moreover, institutions actively reduce their holdings and trading in stocks with rising sentiment exposure, leaving those stocks with less informed participation and therefore lower price efficiency.

Our findings carry broad implications for how we understand the limits of institutional arbitrage. The standard view treats institutional ownership as a relatively uniform force for efficiency. Our results indicate that its effectiveness is deeply conditional on the sentiment environment surrounding individual stocks. This conditionality also has practical relevance for investors, as sentiment beta represents a tractable indicator of where institutional arbitrage is most constrained. For regulators, our results suggest that policies easing short-selling constraints could disproportionately improve price efficiency in high-sentiment-beta stocks, where arbitrage is most impeded and mispricing most persistent. More broadly, the documented institutional withdrawal suggests that sentiment-driven frictions are actively reinforced by the rational responses of sophisticated investors, pointing to a more persistent form of market inefficiency than previously recognized.

Despite these findings, some limitations offer avenues for future research. While we employ extensive controls and fixed effects, establishing a purely causal link between sentiment beta, institutional decisions, and efficiency remains challenging given their inherent simultaneity. Our sample also precedes the recent rise of generative AI, which has likely transformed how information is produced, disseminated, and processed in financial markets, potentially altering the dynamics of sentiment and arbitrage (Bertomeu et al., 2025). Future work could exploit exogenous shocks to sentiment or arbitrage constraints to strengthen causal inference, and explore whether these technological forces have further complicated the interplay between institutional investors and market efficiency.

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Tables

Table 1: Descriptive Statistics

This table reports descriptive statistics for the sample variables, all of which are constructed at the quarterly level, covering the period from 1980Q1 to 2023Q4. It reports the time-series means of the cross-section mean, median, and standard deviation for all variables, except for the level ($SENT$) and change ($\Delta SENT$) of the investor sentiment index, whose statistics are directly calculated based on the time series data. Panel A reports the price efficiency measures. $NoiseShare$ is share of variance attributable to $Noise$, following Brogaard et al. (2022). $AutoCorr$ is the absolute value of the first-order autocorrelation of daily stock return, computed as $|\rho_{r_d,r_{d-1}}|$, following Chordia et al. (2005). HM is the delay of stock price responses to market-wide information, following Hou and Moskowitz (2005). $|1 - VR(1,5)|$ is the variance ratio, where $VR(1,5)$ is the ratio of the variance of 5-day returns to the variance of 1-day returns, each normalized by the corresponding period length. Panel B reports the institutional holdings and tradings. IO is the ratio of shares held by 13F institutions to total quarter-end shares outstanding. HF is the ratio of the shares held by the hedge funds, identified following Agarwal et al. (2013, 2024), to total shares outstanding. $Active$ and $Passive$ are shares held by active and passive investors, scaled by total shares outstanding, respectively. $Active1/Passive1$ classify investors by reported type, whereas $Active2/Passive2$ classify by modal, following classification scheme of Bushee (2001). $SENT$ and $\Delta SENT$ are the quarterly average of the monthly Baker and Wurgler (2006) sentiment index and the change in the quarterly sentiment index, respectively. $sbeta$ denotes the original sentiment beta, estimated as the loading on the change in sentiment under the Fama–French three-factor model using a 36-month rolling window. $SBeta$ is the Bayesian–Stein shrunk sentiment beta, a weighted average of sentiment beta and shrinkage target derived from prior information, following Glushkov (2006). $SBeta\_UMCSI$ is the Bayesian–Stein shrunk sentiment beta estimated using University of Michigan Consumer Sentiment Index. Panel D reports the stock characteristics. $Illiq$ is the Amihud (2002) illiquidity measure. Sir is the ratio of quarter-end aggregate share held short to total shares outstanding. $retSD$ is the quarterly standard deviation of daily stock return. $Price$ is the quarter-end adjusted closing price. $lnME$ and $lnAsset$ are the natural logarithms of quarter-end market capitalization and book value of assets, respectively. BM is the ratio of the book to market value of equity. $Mispricing$ is the quarterly average of monthly mispricing introduced by Stambaugh and Yuan (2017). All continuous variables are winsorized at 2.5% and 97.5% within each quarter.

	N	Mean	Median	Std	Min	p25	p75	Max
Panel A: Price Efficiency Measures								
$NoiseShare$	442,875	0.337	0.304	0.147	0.131	0.226	0.419	0.721
AR	442,875	0.137	0.115	0.102	0.005	0.054	0.199	0.394
HM	442,869	0.421	0.390	0.251	0.054	0.217	0.600	0.936
$\|1 - VR(1,5)\|$	442,875	0.265	0.236	0.183	0.011	0.114	0.388	0.694
Panel B: Institutional Holdings and Tradings								
IO	442,875	0.529	0.556	0.224	0.066	0.376	0.704	0.874
HF	396,739	0.100	0.086	0.064	0.010	0.054	0.133	0.281
$Active1$	442,875	0.357	0.365	0.163	0.033	0.243	0.475	0.763
$Passive1$	442,875	0.148	0.144	0.085	0.008	0.079	0.210	0.405
$Active2$	436,657	0.135	0.118	0.090	0.008	0.065	0.189	0.484
$Passive2$	436,657	0.384	0.396	0.178	0.043	0.254	0.519	0.707
ΔIO	442,875	0.004	0.002	0.027	-0.060	-0.009	0.016	0.077
$Trade$	442,875	0.086	0.075	0.059	0.005	0.039	0.121	0.241
Panel C: BW Quarterly Sentimnent and Sentiment Beta								
$SENT$	176	0.246	0.101	0.713	-0.941	-0.270	0.665	2.629
$\Delta SENT$	176	0.025	0.075	1.022	-4.185	-0.510	0.495	3.414
$SBeta$	442,875	0.024	0.022	0.007	0.017	0.019	0.027	0.046
$SBeta\_UMCSI$	441,284	0.020	0.018	0.005	0.014	0.016	0.022	0.037
$sbeta$	442,875	0.000	0.000	0.027	-0.062	-0.015	0.015	0.065
Panel D: Other Firm Characteristics								
$Illiq$	441,902	0.214	0.038	0.423	0.000	0.006	0.190	1.998
Sir	308,997	0.031	0.020	0.032	0.002	0.010	0.040	0.142
$retSD$	442,875	0.026	0.024	0.012	0.010	0.017	0.032	0.060
$Price$	442,875	29.771	20.104	31.022	2.811	10.831	36.188	156.581
$lnME$	442,875	6.475	6.252	1.481	4.383	5.257	7.452	9.966
$lnAsset$	426,828	6.828	6.682	1.740	3.625	5.539	8.012	10.708
BM	398,847	0.646	0.576	0.392	0.094	0.343	0.871	1.732
$Mispricing$	345,118	49.492	48.943	12.659	13.504	40.510	57.971	90.751

Table 2: Stock Characteristics: Sorted on Sentiment Beta

This table reports the average price efficiencies, institutional holdings and trading, and stock characteristics within each of the 5 sentiment beta-sorted portfolios, first determining the means within each portfolio for each quarter and then averaging means across quarters, covering the sample period from 1980Q2 to 2023Q4. Sentiment beta portfolios are constructed by sorting stocks on lagged Bayesian-Stein shrunk sentiment beta $SBeta$, with each accounting for 20% of all stocks. The mean difference between high- and low-sentiment beta portfolios is reported, along with its T-statistics, which is computed based on Newey and West (1987) standard errors with 5 lags, in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Varaibles	Low $SBeta$	2	3	4	High $SBeta$	High-Minus-Low	
						Mean	T-stat
$SBeta$	0.019	0.020	0.022	0.025	0.033	0.014***	(14.47)
Panel A: Price [In]efficiency Measures							
$NoiseShare$	0.342	0.341	0.338	0.334	0.328	-0.014***	(-6.23)
AR	0.137	0.138	0.137	0.136	0.132	-0.006***	(-4.41)
HM	0.395	0.401	0.407	0.420	0.447	0.052***	(6.98)
$VR(1,5)$	0.268	0.267	0.267	0.264	0.255	-0.013***	(-5.36)
$Noise\_SD$	0.016	0.017	0.018	0.019	0.024	0.007***	(14.84)
$PrivateInfo\_SD$	0.014	0.014	0.015	0.017	0.021	0.008***	(17.28)
$PublicInfo\_SD$	0.013	0.013	0.014	0.015	0.019	0.006***	(15.80)
$MktInfo\_SD$	0.011	0.011	0.011	0.012	0.014	0.004***	(11.04)
Panel B: Institutional Holdings and Tradings							
IO	0.544	0.546	0.548	0.549	0.507	-0.037***	(-6.64)
HF	0.094	0.096	0.099	0.105	0.110	0.016***	(6.50)
$Active1$	0.357	0.360	0.366	0.375	0.358	0.001	(0.29)
$Passive1$	0.164	0.162	0.158	0.151	0.126	-0.038***	(-17.84)
$Active2$	0.127	0.129	0.134	0.141	0.150	0.022***	(6.55)
$Passive2$	0.406	0.405	0.402	0.396	0.344	-0.062***	(-15.32)
ΔIO	0.003	0.003	0.003	0.004	0.006	0.003***	(8.02)
$Trade$	0.083	0.085	0.087	0.091	0.092	0.008***	(3.86)
Panel C: Other Firm Characteristics							
$Illiq$	0.171	0.174	0.189	0.205	0.226	0.055**	(2.34)
Sir	0.027	0.028	0.029	0.033	0.043	0.016***	(8.25)
$retSD$	0.022	0.023	0.024	0.026	0.033	0.011***	(15.04)
$Price$	32.538	32.346	31.229	29.583	25.423	-7.116***	(-4.16)
$lnME$	6.840	6.801	6.668	6.453	5.987	-0.854***	(-23.97)
$lnAsset$	7.324	7.264	7.088	6.779	6.074	-1.250***	(-20.59)
BM	0.663	0.658	0.652	0.641	0.594	-0.069***	(-5.38)
$Mispricing$	48.187	48.289	48.737	49.583	52.145	3.958***	(14.26)

Table 3: Double Sorting Analysis: IO-Efficiency Relation Conditional on Sentiment Beta

This table reports the average noise share for 25 portfolios constructed by dependent double sorting on sentiment beta ($SBeta$) and institutional ownership (IO), covering the sample period from 1980Q2 to 2023Q4. Stocks are first sorted into five portfolios by beginning-of-quarter $SBeta_{i,q-1}$; within each sentiment beta portfolio stocks are sorted again based on beginning-of-quarter $IO_{i,q-1}$. The mean differences between high and low portfolios are reported, along with their T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Low IO	2	3	4	High IO	HML	All Stocks
Low $SBeta$	0.393	0.353	0.334	0.321	0.309	-0.085***	0.342
						(-9.20)	
2	0.391	0.352	0.333	0.320	0.310	-0.081***	0.341
						(-8.49)	
3	0.386	0.347	0.330	0.318	0.310	-0.076***	0.338
						(-7.91)	
4	0.374	0.343	0.327	0.317	0.308	-0.067***	0.334
						(-7.83)	
High $SBeta$	0.355	0.336	0.326	0.317	0.308	-0.048***	0.328
						(-8.60)	
HML	-0.038***	-0.016***	-0.008***	-0.004	-0.001	0.037***	-0.014***
	(-6.96)	(-5.36)	(-3.34)	(-1.45)	(-0.64)	(6.99)	(-6.21)
All Stocks	0.380	0.346	0.330	0.319	0.309	-0.071***	0.337
						(-8.59)	

Table 4: Baseline Regression: IO-Efficiency Relation Conditional on Sentiment Beta

This table reports estimates from regressions of noise share on one-quarter lagged institutional ownership, sentiment beta, and other control variables, covering the sample period from 1980Q2 to 2023Q4. Panel A presents for panel regression with year-quarter fixed effects. T-statistics, computed based on standard error clustered at the firm level, are reported in parentheses. Panel B presents for Fama-MacBeth regression. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are presented in parentheses. Column (1) reports estimates for the full sample as a benchmark. Columns (2)–(6) report estimates within quintiles of beginning-of-quarter $SBeta$ from Low to High. Column (7) returns to the full sample and includes $SBeta$ and the interaction $IO \times SBeta$ to quantify the incremental impact of sentiment beta. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Sentiment Beta Group					All (w/ interactions)
		Low $SBeta$	2	3	4	High $SBeta$	
Panel A: Panel Regression							
$IO_{i,q-1}$	-0.054***	-0.074***	-0.062***	-0.051***	-0.045***	-0.027***	-0.069***
	(-26.16)	(-20.25)	(-17.72)	(-15.07)	(-13.53)	(-8.32)	(-19.78)
$SBeta_{i,q-1}$							-0.814***
							(-10.29)
$IO \times SBeta$							0.540***
							(5.54)
$NoiseShare_{i,q-1}$	0.060***	0.064***	0.061***	0.068***	0.047***	0.044***	0.059***
	(24.54)	(13.52)	(13.48)	(14.25)	(9.40)	(8.17)	(24.28)
$Illiq_{i,q}$	0.020***	0.015***	0.021***	0.019***	0.016***	0.025***	0.019***
	(10.67)	(3.67)	(7.27)	(5.21)	(6.90)	(7.80)	(10.56)
$Sir_{i,q-1}$	-0.104***	-0.073***	-0.114***	-0.114***	-0.110***	-0.086***	-0.100***
	(-13.10)	(-3.98)	(-6.67)	(-6.84)	(-7.45)	(-6.46)	(-12.66)
$lnPrice_{i,q-1}$	0.002***	0.003***	0.003***	0.002***	0.001	-0.001	0.002***
	(4.16)	(3.40)	(4.03)	(3.03)	(1.52)	(-0.68)	(4.01)
$lnAsset_{i,q-1}$	0.001*	0.000	0.000	-0.000	-0.001	-0.001	0.000
	(1.87)	(0.39)	(0.15)	(-0.21)	(-1.32)	(-1.25)	(1.06)
$lnBM_{i,q-1}$	0.005***	0.006***	0.005***	0.004***	0.005***	0.003***	0.004***
	(8.61)	(5.74)	(5.42)	(4.05)	(5.08)	(3.38)	(8.18)
$retSD_{i,q-1}$	-0.039	-0.286***	-0.154**	0.017	0.127*	0.425***	0.067*
	(-1.05)	(-3.82)	(-2.06)	(0.24)	(1.83)	(6.83)	(1.80)
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
N	278,520	58,725	58,167	57,122	54,842	49,664	278,520
adj. R^2	0.061	0.074	0.072	0.060	0.056	0.052	0.061
Panel B: FMB Regression							
$IO_{i,q-1}$	-0.045***	-0.063***	-0.056***	-0.041***	-0.030***	-0.021***	-0.070***
	(-10.19)	(-8.76)	(-8.95)	(-7.43)	(-6.01)	(-4.60)	(-7.18)
$SBeta_{i,q-1}$							-1.025***
							(-5.16)
$IO \times SBeta$							**0.755****
							(2.08)
$NoiseShare_{i,q-1}$	0.052***	0.053***	0.051***	0.059***	0.040***	0.039***	0.051***
	(9.60)	(8.26)	(8.47)	(9.86)	(6.59)	(4.92)	(9.62)
$Illiq_{i,q}$	0.478***	0.508***	0.473***	0.504***	0.498***	0.444***	0.468***
	(4.59)	(4.58)	(4.41)	(3.99)	(4.48)	(4.40)	(4.64)
$Sir_{i,q-1}$	-0.124***	-0.053	-0.121**	-0.212***	-0.194***	-0.100**	-0.116***
	(-4.41)	(-0.79)	(-2.37)	(-3.38)	(-3.14)	(-2.48)	(-4.27)
$lnPrice_{i,q-1}$	0.002***	0.003***	0.004***	0.002**	0.001*	0.001	0.002***
	(5.56)	(3.57)	(4.30)	(2.17)	(1.92)	(0.96)	(5.40)
$lnAsset_{i,q-1}$	0.002***	0.002**	0.001	0.001	0.001*	0.001*	0.001***
	(3.57)	(2.18)	(1.55)	(0.84)	(1.71)	(1.77)	(3.13)
$lnBM_{i,q-1}$	0.004***	0.004***	0.004***	0.003**	0.004***	0.003**	0.004***
	(3.97)	(3.25)	(2.81)	(2.44)	(2.92)	(2.30)	(3.80)
$retSD_{i,q-1}$	-0.111	-0.500***	-0.429***	-0.185	0.198	0.582***	-0.004
	(-0.83)	(-3.22)	(-2.72)	(-1.22)	(1.09)	(3.81)	(-0.03)
N	278,520	58,725	58,167	57,122	54,842	49,664	278,520
adj. R^2	0.040	0.052	0.045	0.040	0.036	0.040	0.041

Table 5: The Role of Investor Sentiment Levels

This table examines how sentiment beta's impact on IO-Efficiency relation varies across period of high (optimistic) and low (pessimistic) investor sentiment, covering the sample period from 1980Q2 to 2023Q4. Specifically, optimistic (pessimistic) quarters are defined as those in which the abnormal sentiment level, calculated as the current quarter's sentiment minus its average over the past eight quarters, is above (below) the sample median. Panel A presents double-sorting portfolio analysis, similar to Table 3, but conducted separately for optimistic and pessimistic quarters and the middle three IO groups are omitted for brevity. The final three columns report the difference in portfolio means between optimistic and pessimistic periods. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are reported in parentheses. Panel B reports panel regressions of noise share on lagged IO, $SBeta$, their interaction, and control variables. Regressions are estimated separately for pessimistic (Column 1) and optimistic (Column 2) quarters. Columns (3) and (4) report interaction models using the full sample, where IO and $SBeta$ are interacted with either a pessimistic-quarter dummy ($High_{q-1}$) or the continuous sentiment index ($SENT_{q-1}$). All regressions include year–quarter fixed effects. T-statistics, based on robust standard errors clustered at the firm level, are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Double Sorting: Optimistic v.s. Pessimistic Sentiment Quarters

	Optimistic: High Sentiment			Pessimistic: Low Sentiment			High–Low (Sentiment)		
	Low IO	High IO	HML	Low IO	High IO	HML	Low IO	High IO	HML
Low SBeta	0.393	0.310	-0.083***	0.393	0.307	-0.086***	0.000	0.003	0.003
			(-8.31)			(-7.72)	(0.00)	(0.63)	(0.25)
2	0.392	0.312	-0.080***	0.390	0.307	-0.083***	0.002	0.005	0.003
			(-7.39)			(-7.38)	(0.17)	(1.09)	(0.24)
3	0.384	0.311	-0.073***	0.388	0.309	-0.080***	-0.004	0.002	0.006
			(-7.21)			(-6.43)	(-0.30)	(0.51)	(0.54)
4	0.369	0.308	-0.061***	0.380	0.307	-0.073***	-0.011	0.001	0.011
			(-7.43)			(-6.23)	(-0.84)	(0.12)	(1.05)
High SBeta	0.350	0.308	-0.042***	0.361	0.307	-0.054***	-0.011	0.001	0.012
			(-6.54)			(-8.06)	(-1.15)	(0.14)	(1.62)
HML	-0.044***	-0.002	0.042***	-0.032***	0.000	0.032***	-0.011	-0.002	0.009
	(-6.68)	(-0.92)	(7.00)	(-5.05)	(0.01)	(4.93)	(-1.64)	(-0.69)	(1.41)
All	0.378	0.310	-0.068***	0.383	0.308	-0.075***	-0.005	0.002	0.007
			(-7.69)			(-7.25)	(-0.40)	(0.54)	(0.72)

Panel B: Regression Analysis: Optimistic v.s. Pessimistic Sentiment Quarters

	(1)	(2)	(3)	(4)
	Sentiment Period Group		Interaction Models	
	Pessimistic	Optimistic	$High_{q-1}$ interactions	$SENT_{q-1}$ interactions
$IO_{i,q-1}$	-0.062***	-0.077***	-0.058***	-0.071***
	(-14.70)	(-16.70)	(-14.11)	(-19.93)
$SBeta_{i,q-1}$	-0.610***	-1.052***	-0.491***	-0.879***
	(-6.10)	(-9.32)	(-4.98)	(-10.83)
$IO \times SBeta$	0.278*	0.868***	0.196	0.646***
	(2.26)	(6.11)	(1.60)	(6.36)
$High \times IO$			-0.022***	
			(-4.16)	
$High \times SBeta$			-0.696***	
			(-5.05)	
$High \times IO \times SBeta$			0.764***	
			(4.31)	
$SENT \times IO$				-0.018***
				(-4.30)
$SENT \times SBeta$				-0.540***
				(-4.18)
$SENT \times IO \times SBeta$				0.851***
				(5.02)
Controls	Yes	Yes	Yes	Yes
FE	Quarter	Quarter	Quarter	Quarter
N	129,262	149,258	278,520	278,520
adj. R^2	0.062	0.061	0.061	0.061

Table 6: The Role of Mispricing

This table examines how sentiment beta's impact on IO-Efficiency relation varies across mispricing conditions, covering the sample period from 1980Q2 to 2016Q4, during which the mispricing measure is available. Panel A presents a triple-sorting portfolio analysis. In each quarter, stocks are first sorted based on Stambaugh et al. (2015)'s mispricing measure ($Mispricing$), into overpricing and underpricing subsamples. Within each mispricing group, the same double-sorting procedure as in Table 3 is conducted. The middle three IO groups are omitted for brevity, and the final three columns report the difference in portfolio means between overpricing and underpricing stocks. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are reported in parentheses. Panel B reports panel regressions of noise share on lagged IO, $SBeta$, $MISP$, their interactions, and controls, estimated for the full sample (Column 1), the underpricing subsample (Column 2), and the overpricing subsample (Column 3). $MISP$ is calculated as $|Mispricing - 50|$. All regressions include year–quarter fixed effects. T-statistics, based on robust standard errors clustered at the firm level, are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Double Sorting: Underpricing v.s. Overpricing Stocks

	Underpricing			Overpricing			Overpricing-Underpricing		
	Low IO	High IO	HML	Low IO	High IO	HML	Low IO	High IO	HML
Low SBeta	0.383	0.313	-0.070***	0.402	0.307	-0.095***	0.019***	-0.006**	-0.026***
			(-9.87)			(-10.66)	(4.15)	(-2.25)	(-5.15)
2	0.381	0.313	-0.067***	0.396	0.307	-0.089***	0.015***	-0.006**	-0.021***
			(-9.16)			(-10.25)	(3.37)	(-2.32)	(-3.90)
3	0.379	0.311	-0.068***	0.390	0.307	-0.083***	0.011**	-0.004*	-0.015***
			(-9.65)			(-9.18)	(2.15)	(-1.84)	(-2.67)
4	0.368	0.310	-0.057***	0.375	0.305	-0.070***	0.007*	-0.005**	-0.013***
			(-7.92)			(-8.29)	(1.75)	(-2.23)	(-2.71)
High SBeta	0.351	0.307	-0.044***	0.344	0.307	-0.037***	-0.006*	0.000	0.007
			(-6.60)			(-7.78)	(-1.94)	(0.07)	(1.27)
HML	-0.032***	-0.006**	0.026***	-0.057***	0.001	0.058***	-0.026***	0.007	0.032***
	(-6.48)	(-2.41)	(5.43)	(-9.89)	(0.19)	(8.53)	(-5.17)	(1.48)	(4.72)
All	0.372	0.311	-0.061***	0.382	0.307	-0.075***	0.009***	-0.004***	-0.013***
			(-9.39)			(-10.00)	(2.95)	(-2.59)	(-4.07)

Panel B: Regression Analysis: Underpricing v.s. Overpricing Stocks

	(1) Overall	(2) Underpricing Sample	(3) Overpricing Sample
$IO_{i,q-1}$	-0.074***	-0.076***	-0.072***
	(-13.88)	(-10.19)	(-10.06)
$SBeta_{i,q-1}$	-1.000***	-0.876***	-1.047***
	(-7.44)	(-4.37)	(-5.92)
$MISP_{i,q-1}$	-0.000	-0.000	0.000
	(-0.89)	(-1.19)	(0.74)
$IO \times SBeta$	0.585***	0.565**	0.501**
	(3.27)	(2.13)	(2.11)
$MISP \times IO$	-0.000	0.001**	-0.001***
	(-0.28)	(1.99)	(-2.87)
$MISP \times SBeta$	-0.002	-0.019	-0.003
	(-0.28)	(-1.36)	(-0.30)
$MISP \times IO \times SBeta$	0.012	0.017	0.031**
	(0.99)	(0.85)	(2.01)
Controls	Yes	Yes	Yes
FE	Quarter	Quarter	Quarter
N	216,083	120,757	95,326
adj. R^2	0.057	0.054	0.064

Table 7: Active versus Passive Institutional Ownership

This table reports estimates from panel regressions, similar to Column (7) of Table 4, replacing total institutional ownership with its decomposition into active and passive ownerships. Institutional investors are classified into active and passive categories based on three alternative classification schemes (I–III), following Kacperczyk et al. (2021) and Agarwal et al. (2013, 2024). Panel A reports the regression. Columns (1)–(3), (4)–(6), and (7)–(9) present results for Classifications I, II, and III, respectively, with specifications for active ownership only, passive ownership only, and both. All regressions include year–quarter fixed effects. T-statistics, based on robust standard errors clustered at the firm level, are reported in parentheses. Panel B reports Wald test results comparing the coefficients on active and passive ownership, as well as the difference in their interaction effects with sentiment beta. F-statistics from the tests of linear restrictions are reported in square brackets. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Classification I			Classification II			Classification III		
	Active	Passive	Both	Active	Passive	Both	Active	Passive	Both
Panel A: Panel Regressions of Noise Share on Active / Passive Ownership, and Sentiment Beta									
$ActiveIO_{i,q-1}$ (a)	-0.092***		-0.088***	-0.146***		-0.111***	-0.141***		-0.093***
	(-21.30)		(-19.57)	(-18.64)		(-14.62)	(-11.92)		(-8.23)
$PassiveIO_{i,q-1}$ (b)		-0.079***	-0.021**		-0.072***	-0.055***		-0.078***	-0.071***
		(-9.39)	(-2.50)		(-16.76)	(-12.94)		(-17.85)	(-16.59)
$SBeta_{i,q-1}$	-0.876***	-0.398***	-0.855***	-0.702***	-0.747***	-0.831***	-0.745***	-0.810***	-0.986***
	(-12.02)	(-6.97)	(-11.35)	(-11.56)	(-10.76)	(-10.72)	(-11.34)	(-10.15)	(-10.95)
$ActiveIO \times SBeta$ (c)	0.863***		0.908***	1.723***		1.279***	2.306***		1.551***
	(7.23)		(7.07)	(7.61)		(5.65)	(7.77)		(5.35)
$PassiveIO \times SBeta$ (d)		-0.403	-0.359		0.525***	0.286**		0.670***	0.573***
		(-1.48)	(-1.24)		(4.42)	(2.40)		(5.33)	(4.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
N	278,520	278,520	278,520	275,043	275,043	275,043	234,448	234,448	234,448
adj. R^2	0.062	0.057	0.062	0.059	0.060	0.062	0.052	0.056	0.057
Panel B: Test the Difference									
(a) - (b)			-0.067***			-0.056***			-0.022*
			[38.46]			[37.02]			[3.14]
(c) - (d)			1.268***			0.993***			0.978***
			[12.47]			[13.16]			[9.05]

Table 8: Decomposing IO: Noise Share Regressions on Sentiment Beta–Driven and Residual IOs

This table reports estimates from panel regressions of noise share on sentiment beta-driven IO and residual IO. Specifically, in each quarter, logit transformed institutional ownership (IO) is regressed on one-quarter lagged sentiment beta ($SBeta$). The fitted values from this regression define the sentiment beta-driven component of IO, while the residuals capture the orthogonal, information-based component. Column (1) reports for raw logit IO as a benchmark, comparable to Column (1) in Table 4. Column (2) and (3) report for residual IO and sentiment beta-driven IO, respectively, and Column (4) includes both. T-statistics, computed based on robust standard errors clustered at the firm level, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$logitIO_{i,q-1}$	-0.004***			
	(-19.55)			
$IO^{\perp}$		-0.004***		-0.004***
		(-19.64)		(-19.61)
$\widehat{IO}$			0.006***	0.004**
			(2.65)	(2.01)
$NoiseShare_{i,q-1}$	0.065***	0.065***	0.068***	0.065***
	(25.65)	(25.64)	(26.07)	(25.63)
$Illiq_{i,q}$	0.022***	0.022***	0.023***	0.022***
	(11.34)	(11.35)	(11.69)	(11.36)
$Sir_{i,q-1}$	-0.099***	-0.099***	-0.182***	-0.099***
	(-11.80)	(-11.72)	(-23.44)	(-11.75)
$lnPrice_{i,q-1}$	0.001***	0.001***	0.001*	0.001***
	(2.96)	(2.98)	(1.73)	(2.98)
$lnAsset_{i,q-1}$	-0.000	-0.000	-0.001***	-0.000
	(-1.44)	(-1.50)	(-2.86)	(-1.59)
$lnBM_{i,q-1}$	0.009***	0.009***	0.010***	0.009***
	(9.50)	(9.48)	(9.99)	(9.46)
$retSD_{i,q-1}$	-0.048	-0.038	0.047	-0.026
	(-1.24)	(-0.99)	(1.21)	(-0.67)
FE	Quarter	Quarter	Quarter	Quarter
N	278,520	278,520	278,520	278,520
adj. R^2	0.057	0.057	0.054	0.057

Table 9: Institutional Responses to Change in Sentiment Beta

This table reports the analysis of institutional responses to changes in sentiment beta. Panel A reports estimates from a panel regression of the change in institutional ownership ($\Delta IO_{i,q}$) on the change in sentiment beta ($\Delta SBeta_{i,q-1}$) and other control variables. Panel B reports estimates from a panel regression of institutional trading ($Trade_{i,q}$), defined as the sum of shares bought and sold scaled by total shares outstanding, on the change in sentiment beta ($\Delta SBeta_{i,q-1}$) and other control variables. Control variables include the lagged dependent variable, $\Delta Illiq_{i,q-1}$, $\Delta Sir_{i,q-1}$, $\Delta lnPrice_{i,q-1}$, $\Delta lnAsset_{i,q-1}$, $\Delta lnBM_{i,q-1}$, and $\Delta retSD_{i,q-1}$, and all specifications include quarter fixed effects. Column (1) reports results for the full sample, while Columns (2)–(6) report results for sentiment beta groups from low to high. T-statistics, based on robust standard errors clustered at the firm level, are reported in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Institutional Ownership Adjustment to Changes in Sentiment Beta (DepVar is $\Delta IO_{i,q}$)

	All	Sentiment Beta Group				
		Low $\|SBeta\|$	2	3	4	High $\|SBeta\|$
$\Delta SBeta_{i,q-1}$	0.006	-0.249***	-0.114***	-0.103***	0.002	-0.011
	(0.46)	(-5.47)	(-2.76)	(-2.88)	(0.05)	(-0.42)
$\Delta IO_{i,q-1}$	0.059***	0.048***	0.057***	0.059***	0.050***	0.065***
	(19.44)	(7.34)	(9.08)	(9.58)	(8.10)	(10.51)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
N	265,045	56,489	55,882	54,660	52,114	45,900
adj. R^2	0.047	0.053	0.050	0.045	0.047	0.048

Panel B: Institutional Trading Adjustment to Changes in Sentiment Beta (DepVar is $Trade_{i,q}$)

	All	Sentiment Beta Group				
		Low $\|SBeta\|$	2	3	4	High $\|SBeta\|$
$\Delta SBeta_{i,q-1}$	-0.014	-0.414***	-0.205***	0.019	0.050	-0.070*
	(-0.70)	(-6.22)	(-3.44)	(0.37)	(1.12)	(-1.95)
$Trade_{i,q-1}$	0.741***	0.752***	0.745***	0.739***	0.732***	0.725***
	(250.21)	(168.27)	(167.60)	(168.20)	(164.47)	(154.06)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
N	265,045	56,489	55,882	54,660	52,114	45,900
adj. R^2	0.627	0.629	0.620	0.618	0.620	0.637

Table 10: Robustness Analysis using First Differenced Regression

This table replicates the baseline regression using change in institutional ownership and trades. Column structure and regression settings follow Table 4. Panel A reports results for the regression of change in noise share ($\Delta NOiseShare$) on changes in institutional ownership (ΔIO), and Panel B reports results for the regression of noise share on institutional trades ($Trade$), where $Trade$ is defined as the sum of absolute buys and sells. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Sentiment Beta Group					
		Low $\lvert SBeta\rvert$	2	3	4	High $\lvert SBeta\rvert$	
Panel A: Regression of Change in Noise Share on Change in Institutional Ownerships							
$\Delta IO_{i,q-1}$	-0.053***	-0.062***	-0.052**	-0.059***	-0.041**	-0.027	-0.090***
	(-5.70)	(-2.83)	(-2.43)	(-2.87)	(-2.11)	(-1.46)	(-4.54)
$NoiseShare_{i,q-1}$	-0.926***	-0.917***	-0.922***	-0.918***	-0.942***	-0.944***	-0.927***
	(-335.21)	(-178.67)	(-190.58)	(-180.76)	(-177.31)	(-160.81)	(-337.73)
$\Delta Illiq_{i,q}$	0.019***	0.018***	0.026***	0.020***	0.018***	0.015***	0.019***
	(7.28)	(3.34)	(4.34)	(2.83)	(3.88)	(4.09)	(7.26)
$\Delta Sir_{i,q-1}$	-0.005	0.080*	-0.045	-0.013	-0.041	0.011	-0.008
	(-0.30)	(1.89)	(-1.09)	(-0.31)	(-1.10)	(0.34)	(-0.48)
$\Delta lnPrice_{i,q-1}$	0.004***	0.008*	0.010**	0.008**	0.006*	-0.003	0.004***
	(2.69)	(1.90)	(2.51)	(2.10)	(1.90)	(-1.27)	(2.68)
$\Delta lnAsset_{i,q-1}$	-0.016***	-0.016***	-0.018***	-0.014**	-0.023***	-0.008*	-0.015***
	(-6.54)	(-2.72)	(-3.14)	(-2.25)	(-4.21)	(-1.88)	(-6.23)
$\Delta lnBM_{i,q-1}$	-0.007***	-0.009**	-0.006	-0.002	-0.006*	-0.010***	-0.007***
	(-3.87)	(-2.10)	(-1.42)	(-0.61)	(-1.65)	(-3.24)	(-4.07)
$\Delta retSD_{i,q-1}$	0.286***	0.317***	0.307***	0.388***	0.267***	0.168**	0.279***
	(7.97)	(3.41)	(3.29)	(4.50)	(3.36)	(2.47)	(7.78)
$SBeta_{i,q-1}$							-0.477***
							(-11.59)
$\Delta IO_{i,q-1} \times SBeta_{i,q-1}$							1.500**
							(2.43)
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
N	265,042	56,489	55,880	54,660	52,113	45,900	265,042
adj. R^2	0.481	0.480	0.485	0.479	0.488	0.480	0.481
Panel B: Regression of Level of Noise Share on Institutional Trades							
$Trade_{i,q-1}$	-0.177***	-0.232***	-0.193***	-0.176***	-0.155***	-0.098***	-0.240***
	(-28.52)	(-18.34)	(-16.30)	(-15.53)	(-14.01)	(-9.62)	(-21.48)
$NoiseShare_{i,q-1}$	0.059***	0.064***	0.061***	0.065***	0.045***	0.042***	0.058***
	(23.92)	(13.44)	(13.38)	(13.74)	(8.95)	(7.89)	(23.68)
$Illiq_{i,q}$	0.020***	0.017***	0.022***	0.019***	0.016***	0.025***	0.020***
	(10.92)	(3.85)	(7.66)	(5.27)	(7.08)	(7.82)	(10.82)
$Sir_{i,q-1}$	-0.092***	-0.063***	-0.109***	-0.101***	-0.098***	-0.079***	-0.090***
	(-11.92)	(-3.47)	(-6.30)	(-6.00)	(-6.57)	(-5.84)	(-11.66)
$lnPrice_{i,q-1}$	0.001***	0.002**	0.002***	0.002**	0.001	-0.001	0.001**
	(2.65)	(2.23)	(2.85)	(2.13)	(0.85)	(-1.09)	(2.43)
$lnAsset_{i,q-1}$	0.001**	0.000	0.000	0.000	-0.000	-0.000	0.000
	(2.40)	(0.51)	(0.24)	(0.29)	(-0.43)	(-0.45)	(1.59)
$lnBM_{i,q-1}$	0.006***	0.011***	0.009***	0.005***	0.006***	0.002	0.006***
	(6.72)	(5.85)	(5.32)	(3.15)	(3.88)	(1.35)	(6.45)
$retSD_{i,q-1}$	0.179***	-0.051	0.051	0.222***	0.314***	0.547***	0.276***
	(4.73)	(-0.66)	(0.66)	(2.97)	(4.46)	(8.81)	(7.17)
$SBeta_{i,q-1}$							-0.679***
							(-12.00)
$Trade_{i,q-1} \times SBeta_{i,q-1}$							2.278***
							(7.36)
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
N	278,520	58,725	58,167	57,122	54,842	49,664	278,520
adj. R^2	0.060	0.070	0.069	0.060	0.056	0.052	0.060

Table 11: IO-Efficiency Relation Conditional on UMCSI-based Sentiment Beta

This table replicates the baseline regressions by replacing sentiment beta ($SBeta$), which is estimated from the Baker and Wurgler (2006) sentiment index, with an alternative sentiment beta ($SBeta\_UMCSI$), which is estimated from the University of Michigan Consumer Sentiment Index ($UMCSI$). Panel A presents for panel regression with year-quarter fixed effects. T-statistics, computed based on standard error clustered at the firm level, are reported in parentheses. Panel B presents for Fama-MacBeth regression. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are presented in parentheses. Column (1) reports estimates for the full sample as a benchmark. Columns (2)–(6) report estimates within quintiles of beginning-of-quarter $SBeta$ from Low to High. Column (7) returns to the full sample and includes $SBeta$ and the interaction $IO \times SBeta$ to quantify the incremental impact of sentiment beta. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Sentiment Beta Group					All (w/ interactions)
		Low $SBeta$	2	3	4	High $SBeta$	
Panel A: Panel Regression							
$IO_{i,q-1}$	-0.054***	-0.070***	-0.064***	-0.053***	-0.046***	-0.026***	-0.060***
	(-25.92)	(-19.58)	(-18.26)	(-15.35)	(-14.05)	(-7.93)	(-15.02)
$SBeta_{i,q-1}$							-0.656***
							(-5.51)
$IO \times SBeta$							**0.310***
							(1.81)
$NoiseShare_{i,q-1}$	0.060***	0.068***	0.069***	0.059***	0.045***	0.048***	0.060***
	(24.53)	(14.87)	(14.99)	(12.27)	(9.27)	(8.57)	(24.31)
$Illiq_{i,q}$	0.019***	0.015***	0.018***	0.018***	0.019***	0.024***	0.019***
	(10.54)	(4.47)	(5.61)	(5.08)	(6.35)	(8.25)	(10.49)
$Sir_{i,q-1}$	-0.106***	-0.078***	-0.106***	-0.088***	-0.123***	-0.104***	-0.102***
	(-13.47)	(-4.20)	(-6.12)	(-5.22)	(-8.33)	(-8.02)	(-12.86)
$lnPrice_{i,q-1}$	0.002***	0.002***	0.003***	0.002**	0.001	0.000	0.002***
	(3.75)	(2.82)	(3.49)	(2.29)	(1.57)	(0.17)	(3.53)
$lnAsset_{i,q-1}$	0.001*	0.001	0.001	-0.000	-0.001	-0.001**	0.000
	(1.93)	(1.55)	(1.63)	(-1.01)	(-1.12)	(-2.17)	(1.23)
$lnBM_{i,q-1}$	0.007***	0.008***	0.008***	0.006***	0.008***	0.006***	0.007***
	(7.72)	(4.79)	(4.65)	(3.49)	(4.78)	(3.30)	(7.51)
$retSD_{i,q-1}$	-0.063*	-0.325***	-0.158**	-0.013	0.122*	0.317***	0.004
	(-1.69)	(-4.26)	(-2.11)	(-0.18)	(1.88)	(4.69)	(0.10)
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
N	278,520	57,930	57,727	56,950	55,171	49,899	277,677
adj. R^2	0.061	0.071	0.069	0.061	0.058	0.051	0.061
Panel B: FMB Regression							
$IO_{i,q-1}$	-0.045***	-0.057***	-0.052***	-0.040***	-0.041***	-0.022***	-0.062***
	(-10.19)	(-8.54)	(-8.99)	(-7.42)	(-8.48)	(-4.76)	(-7.98)
$SBeta_{i,q-1}$							-1.219***
							(-3.62)
$IO \times SBeta$							**1.117*****
							(2.63)
$NoiseShare_{i,q-1}$	0.052***	0.053***	0.059***	0.051***	0.040***	0.049***	0.052***
	(9.60)	(8.73)	(8.11)	(7.47)	(5.58)	(6.10)	(9.63)
$Illiq_{i,q}$	0.478***	0.529***	0.460***	0.567***	0.416***	0.496***	0.476***
	(4.59)	(4.52)	(4.44)	(4.37)	(4.29)	(4.23)	(4.61)
$Sir_{i,q-1}$	-0.124***	-0.082	-0.133*	-0.115*	-0.200***	-0.053	-0.113***
	(-4.41)	(-1.46)	(-1.74)	(-1.83)	(-3.68)	(-1.06)	(-4.14)
$lnPrice_{i,q-1}$	0.002***	0.002***	0.003***	0.002**	0.002**	0.002**	0.002***
	(5.56)	(3.14)	(3.53)	(2.58)	(2.51)	(2.02)	(5.62)
$lnAsset_{i,q-1}$	0.002***	0.002***	0.002**	0.001	0.001	0.001**	0.001***
	(3.57)	(2.73)	(2.50)	(1.02)	(1.19)	(2.23)	(3.21)
$lnBM_{i,q-1}$	0.004***	0.003**	0.005***	0.003**	0.004***	0.003**	0.004***
	(3.97)	(2.13)	(2.87)	(2.30)	(3.86)	(2.36)	(3.77)
$retSD_{i,q-1}$	-0.111	-0.725***	-0.280	-0.151	0.106	0.433***	-0.045
	(-0.83)	(-3.90)	(-1.53)	(-0.87)	(0.88)	(2.92)	(-0.35)
N	278,520	57,930	57,727	56,950	55,171	49,899	277,677
adj. R^2	0.040	0.050	0.048	0.041	0.038	0.044	0.041

Table 12: Robustness Analysis using Alternative Price Efficiency Measures

This table replicates the baseline analyses in Table 3 and Table 4 by replacing noise share with three alternative measures of price efficiency. Panels A, B, and C report dependent double sorting results for return autocorrelation (AR), variance ratio ($|1-VR(1,5)|$), and HM price delay (HM), respectively. For brevity, the three middle sentiment beta groups are omitted. The mean differences between high and low portfolios are reported, along with their T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, in parentheses. Panel D presents the regression results, both panel regression and FMB regression specifications. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Low IO	2	3	4	High IO	HML	All Stocks
Panel A: Autocorrelation, AR							
Low $SBeta$	0.173	0.145	0.132	0.123	0.120	-0.052***	0.139
						(-7.20)	
High $SBeta$	0.144	0.135	0.128	0.122	0.119	-0.025***	0.130
						(-6.28)	
HML	-0.028***	-0.009***	-0.004***	-0.001	-0.001	0.027***	-0.009***
	(-6.55)	(-6.01)	(-2.86)	(-0.65)	(-1.28)	(6.63)	(-6.17)
All Stocks	0.165	0.143	0.132	0.123	0.120	-0.045***	0.136
						(-6.84)	
Panel B: Variance Ratio, $\lvert 1-VR(1,5)\rvert$							
Low $SBeta$	0.331	0.281	0.259	0.243	0.235	-0.096***	0.270
						(-8.73)	
High $SBeta$	0.277	0.261	0.249	0.240	0.234	-0.043***	0.252
						(-6.55)	
HML	-0.054***	-0.020***	-0.010***	-0.003	-0.002	0.052***	-0.018***
	(-8.17)	(-6.86)	(-3.86)	(-1.28)	(-0.73)	(8.57)	(-7.05)
All Stocks	0.314	0.276	0.257	0.243	0.235	-0.079***	0.265
						(-7.94)	
Panel C: HM Price Delay, HM							
Low $SBeta$	0.501	0.429	0.386	0.349	0.331	-0.170***	0.399
						(-7.32)	
High $SBeta$	0.518	0.471	0.432	0.397	0.368	-0.151***	0.437
						(-11.15)	
HML	0.017	0.041***	0.046***	0.048***	0.037***	0.019	0.038***
	(1.28)	(3.91)	(5.66)	(6.91)	(4.83)	(1.54)	(4.89)
All Stocks	0.509	0.446	0.405	0.368	0.345	-0.165***	0.415
						(-8.30)	

Panel D: Regression Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel Regression			FMB Regression		
DepVar is	HM	AR	$\lvert 1-VR(1,5)\rvert$	HM	AR	$\lvert 1-VR(1,5)\rvert$
$IO_{i,q-1}$	-0.121***	-0.019***	-0.056***	-0.118***	-0.020***	-0.057***
	(-17.98)	(-9.09)	(-13.60)	(-5.00)	(-4.12)	(-5.91)
$SBeta_{i,q-1}$	-0.148	-0.134***	-0.712***	0.579	-0.268**	-1.074***
	(-1.05)	(-2.58)	(-7.53)	(1.35)	(-2.13)	(-3.60)
$IO_{i,q-1} \times SBeta_{i,q-1}$	1.295***	-0.027	0.447***	1.045	0.215	1.414**
	(7.17)	(-0.43)	(3.78)	(1.51)	(0.99)	(2.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Quarter	Quarter	Quarter	/	/	/
N	278,520	278,520	278,520	278,520	278,520	278,520
adj. R^2	0.394	0.054	0.034	0.235	0.027	0.033

Table 13: IO-Efficiency Relation: Positive versus Negative Original Sentiment Beta Subsamples

This table replicates the baseline panel regression presented in Table 4. Panel A reports for negative sentiment beta subsample, while Panel B reports for positive subsample. Columns (2)–(6) report estimates within quintiles of beginning-of-quarter $SBeta$ from Low to High. Column (7) returns to the full sample and includes $SBeta$ and the interaction $IO \times SBeta$ to quantify the incremental impact of sentiment beta. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Sentiment Beta Group					All (w/ interactions)
		Low $SBeta$	2	3	4	High $SBeta$	
Panel A: Negative Subsample							
$IO_{i,q-1}$	-0.054***	-0.071***	-0.064***	-0.055***	-0.039***	-0.026***	-0.069***
	(-21.33)	(-15.15)	(-13.47)	(-12.18)	(-8.72)	(-5.80)	(-15.67)
$SBeta_{i,q-1}$							-0.847***
							(-7.97)
$IO \times SBeta$							**0.580*****
							(4.44)
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	140,694	29,364	29,218	28,998	28,129	24,985	140,694
adj. R^2	0.059	0.071	0.073	0.060	0.051	0.049	0.060
Panel B: Positive Subsample							
$IO_{i,q-1}$	-0.053***	-0.077***	-0.060***	-0.046***	-0.048***	-0.028***	-0.068***
	(-21.14)	(-15.74)	(-13.33)	(-10.11)	(-10.41)	(-6.10)	(-14.80)
$SBeta_{i,q-1}$							-0.827***
							(-7.51)
$IO \times SBeta$							**0.538*****
							(3.91)
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	137,826	29,361	28,949	28,124	26,713	24,679	137,826
adj. R^2	0.064	0.076	0.071	0.064	0.064	0.058	0.064

Table 14: Test for Reverse Causality

This table reports the slope estimates from the univariate regression of change in institutional ownership on one-quarter lagged change in price efficiency. Each row corresponds to a separate specification using one alternative measure of price efficiency. The regressions are estimated with year-quarter fixed effects. T-statistics, computed based on standard error clustered at the firm level, are reported in parentheses. All regression slopes are multiplied by 100 for ease of exposition. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
			Sentiment Beta Group		
	Low $SBeta$	2	3	4	High $SBeta$
$\Delta NoiseShare$	0.001	0.008	-0.033	-0.023	-0.026
	(0.01)	(0.16)	(-0.68)	(-0.46)	(-0.47)
ΔAR	0.032	0.027	-0.071	-0.038	-0.055
	(0.48)	(0.40)	(-1.02)	(-0.53)	(-0.69)
$\Delta\lvert 1 - VR(1,5)\rvert$	0.059	-0.005	-0.050	0.024	-0.059
	(1.59)	(-0.14)	(-1.24)	(0.57)	(-1.31)
ΔHM	-0.034	-0.031	-0.020	0.012	-0.058*
	(-1.02)	(-0.92)	(-0.59)	(0.36)	(-1.66)

Figures

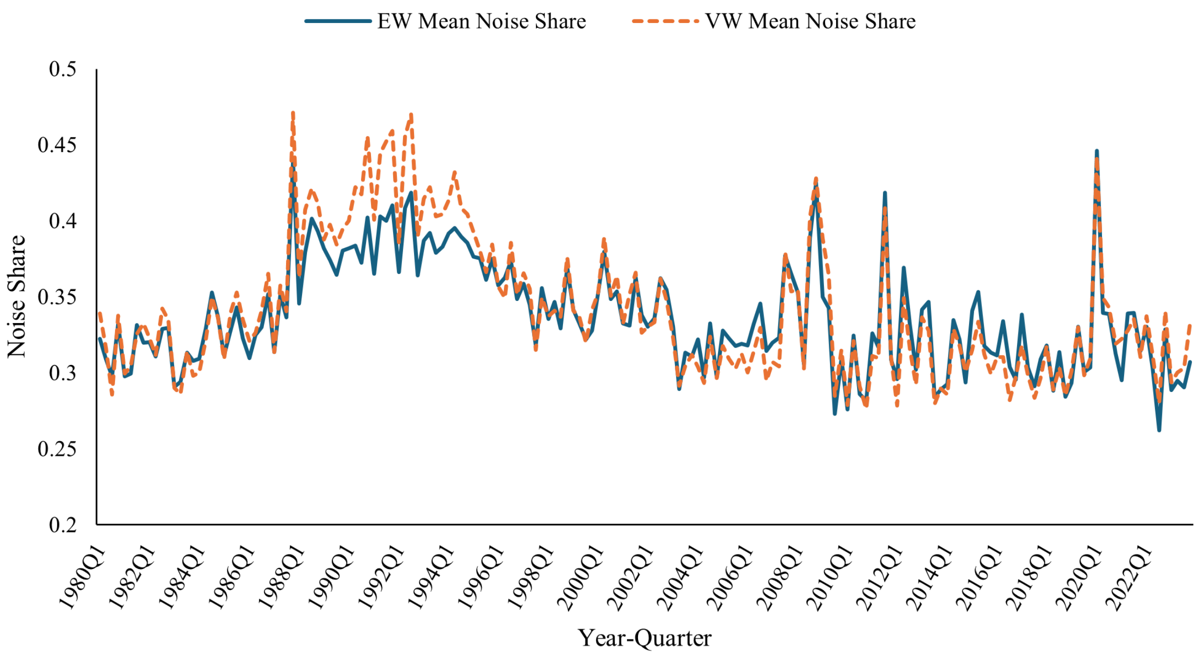

Figure 1: The Time Series Means of Cross-Sectional Average Noise Share

This graph displays the quarterly average levels of noise share, plotting both equal-weighted and variance-weighted averages.

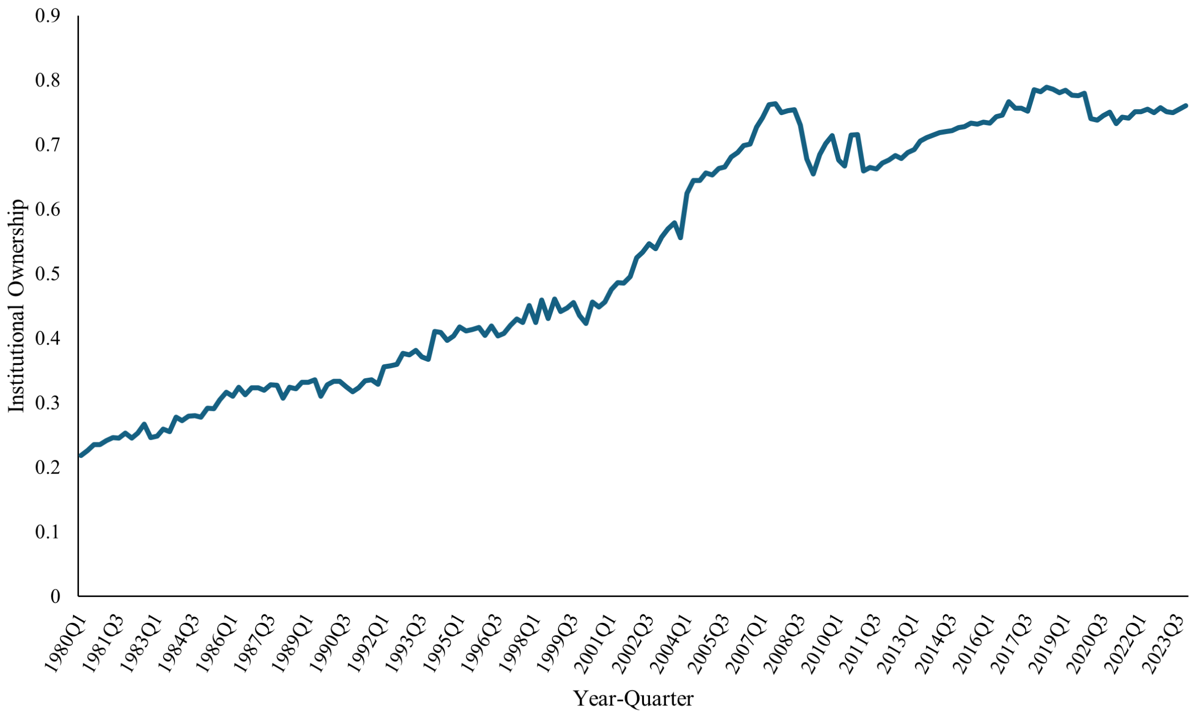

Figure 2: The Time Series of Institutional Ownership

This graph plots the time-series trend in equal-weighted average levels of institutional ownership for sample stocks, covering the period from 1980Q1 to 2023Q4. Institutional ownership is defined as the fraction of shares held by 13F institutional investors to total shares outstanding.

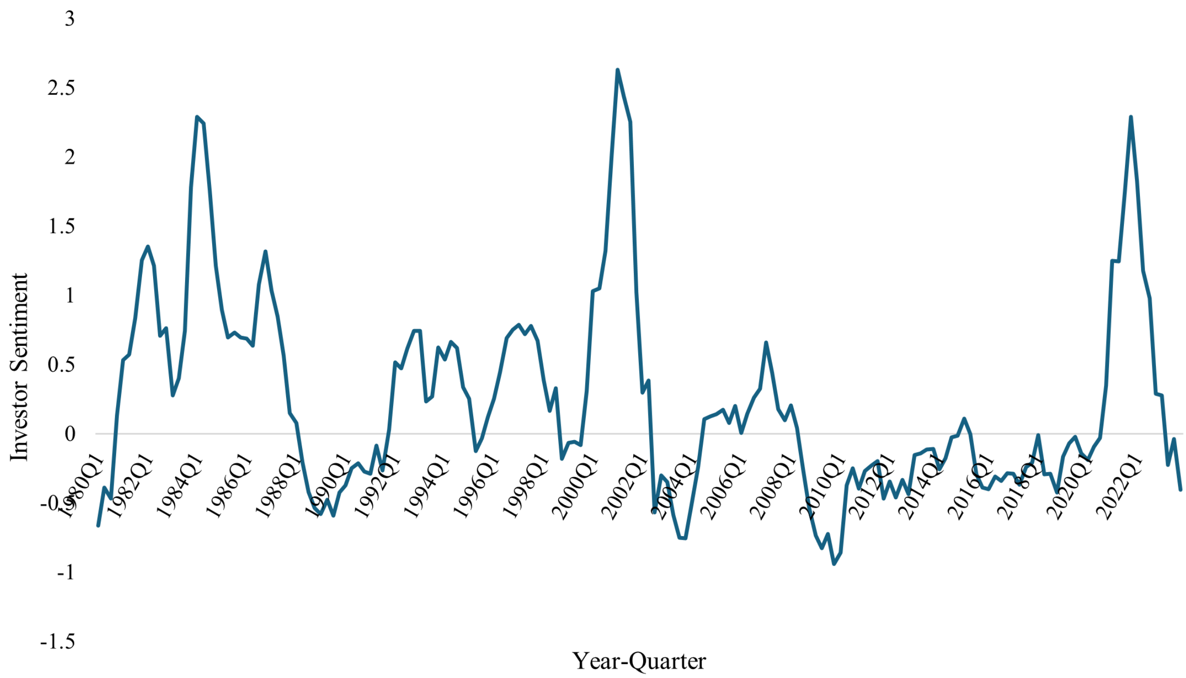

Figure 3: The Quarterly Investor Sentiment Index

This graph plots the time-series of quarterly Baker and Wurgler (2006, 2007) investor sentiment. The original BW investor sentiment index is a standardized monthly series, with mean of 0 and standard deviation of 1. The quarterly investor sentiment is calculated as the average of monthly sentiment level within the quarter.

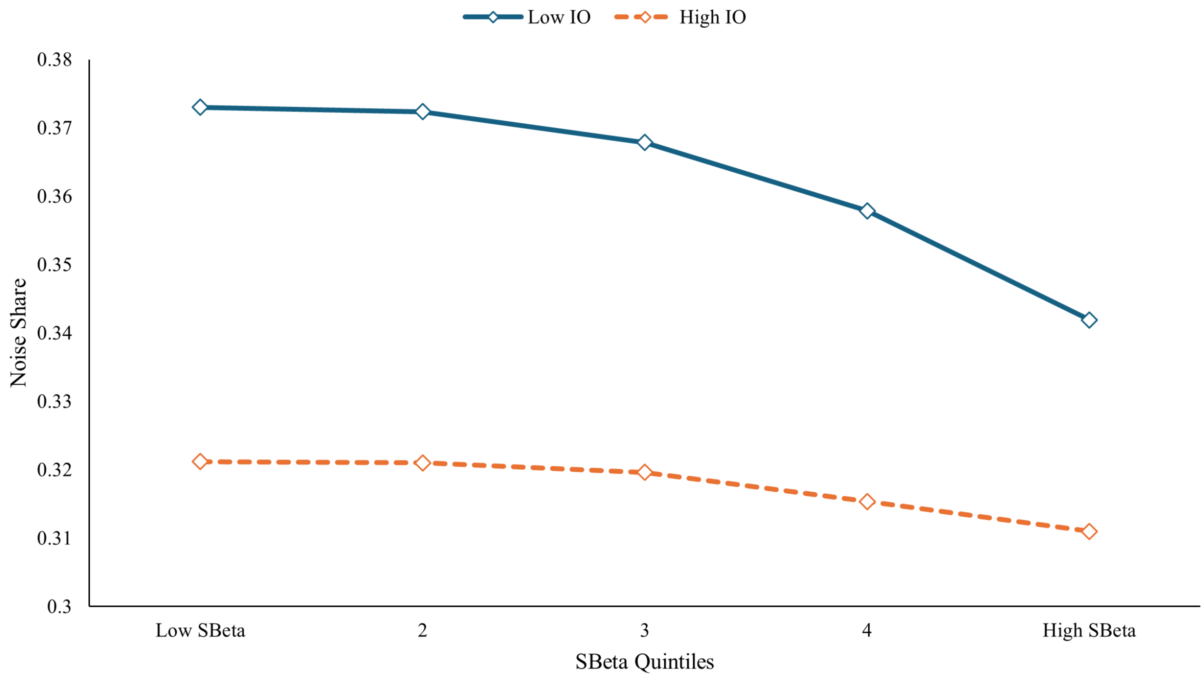

Figure 4: Mean Noise Shares of High and Low Institutional Ownership

This graph plots the mean noise share for high-IO and low-IO stocks, sorted by sentiment beta. High (low) IO is defined as institutional ownership above (below) the cross-sectional median in each quarter.

Internet Appendix

I Analysis on Positive versus Negative Sentiment Beta

In this Appendix, we investigate whether the impact of sentiment beta on the IO–Efficiency relation differs between stocks with positive and negative original sentiment betas. The sample is split by the sign of the original sentiment beta ($sbeta$). Stocks with positive (negative) $sbeta$ suggest that their prices and returns are more influenced by momentum (contrarian) sentiment traders. A larger absolute value of $sbeta$ indicates greater sensitivity to changes in investor sentiment, but the direction of the effect differs between positive and negative beta stocks. Original sentiment beta ($sbeta$) is used only to partition the sample, while all sorting and regression tests continue to use the shrunk sentiment beta ($SBeta$) to rank stocks by sentiment exposure within each subsample.

First, we replicate the analysis in Table 2 for subsamples with positive and negative original sentiment betas. Table IA.1 reports the means of key variables for the negative $sbeta$ subsample, while Table IA.2 reports the corresponding results for the positive $sbeta$ subsample.

Table IA.3 replicates the portfolio sorting analysis in Table 3 for the two subsamples. Panel A and Panel B report results for stocks with negative and positive original sentiment beta, respectively. Within the negative (positive) subsample, higher $SBeta$ groups correspond to more negative (more positive) sentiment betas. We observe a similar pattern across the two subsamples. As the magnitude of sentiment beta increases, the IO–Efficiency relation weakens. The difference in differences estimates are 0.031 and 0.042, respectively, and both are statistically significant at the 1% level. Figure IA.1 replicates Figure 4 by replacing the shrunk sentiment beta ($SBeta$) with the original sentiment beta ($sbeta$) and sorting stocks into 10 groups based on $sbeta$. The figure shows that higher institutional ownership is associated with lower noise share, but this relation is weaker at both ends of the sentiment beta distribution.

Table IA.4 replicates the baseline regression analysis for stocks with negative and positive sentiment betas, respectively. The results are both quantitatively and qualitatively similar to the baseline specification for both subsamples. For the interaction specification, the estimated coefficient on $SBeta \times IO$ is 0.580 and 0.538 for the two subsamples, respectively, both of which are comparable to the baseline estimate of 0.540. These results strengthen the conclusion that, for the IO–Efficiency relation, the magnitude of sentiment beta matters

Table IA.1: Stock Characteristics: Sorted on Sentiment Beta (Negative Subsample)

This table replicates Table 2 by using subsample of stocks with negative original sentiment beta (*sbeta*). The mean difference between high- and low-sentiment beta portfolios is reported, along with its T-statistics, which is computed based on Newey and West (1987) standard errors with 5 lags, in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Variables	Low $SBeta$	2	3	4	High $SBeta$	High-Minus-Low Mean	High-Minus-Low T-stat
$sbeta$	-0.002	-0.007	-0.013	-0.022	-0.041	-0.039***	(-13.75)
$SBeta$	0.019	0.020	0.022	0.025	0.033	0.014***	(13.80)
Panel A: Price [In]efficiency Measures							
$NoiseShare$	0.341	0.341	0.336	0.330	0.326	-0.015***	(-6.87)
AR	0.137	0.137	0.136	0.134	0.130	-0.007***	(-4.68)
HM	0.394	0.402	0.406	0.416	0.442	0.048***	(5.93)
$VR(1,5)$	0.267	0.267	0.266	0.261	0.254	-0.013***	(-5.74)
$PrivateInfoShare$	0.253	0.255	0.259	0.268	0.288	0.036***	(11.45)
$PublicInfoShare$	0.231	0.232	0.234	0.234	0.231	-0.000	(-0.08)
$MktInfoShare$	0.170	0.167	0.166	0.162	0.151	-0.019***	(-4.95)
$NoiseSD$	0.016	0.017	0.017	0.019	0.023	0.007***	(18.29)
$PrivateInfoSD$	0.014	0.014	0.015	0.017	0.021	0.007***	(17.81)
$PublicInfoSD$	0.013	0.013	0.014	0.015	0.018	0.005***	(18.95)
$MktInfoSD$	0.011	0.011	0.011	0.012	0.014	0.003***	(14.60)
Panel B: Institutional Holdings and Tradings							
IO	0.544	0.543	0.550	0.556	0.522	-0.022***	(-4.09)
HF	0.094	0.095	0.099	0.105	0.111	0.017***	(6.43)
$Active1$	0.356	0.358	0.367	0.378	0.367	0.011***	(2.76)
$Passive1$	0.164	0.162	0.159	0.154	0.130	-0.034***	(-19.55)
$Active2$	0.127	0.129	0.134	0.143	0.152	0.025***	(7.91)
$Passive2$	0.405	0.404	0.404	0.402	0.356	-0.050***	(-13.68)
ΔIO	0.003	0.003	0.003	0.004	0.006	0.003***	(6.79)
$Trade$	0.083	0.084	0.087	0.092	0.094	0.010***	(5.08)
Panel C: Other Firm Characteristics							
$Illiq$	0.165	0.169	0.175	0.182	0.200	0.035*	(1.85)
Sir	0.026	0.028	0.030	0.033	0.043	0.017***	(7.93)
$retSD$	0.022	0.023	0.024	0.026	0.032	0.010***	(18.14)
$Price$	32.507	32.126	31.283	29.335	24.520	-7.986***	(-4.47)
$lnME$	6.842	6.788	6.676	6.499	6.059	-0.783***	(-20.45)
$lnAsset$	7.329	7.248	7.093	6.813	6.178	-1.151***	(-20.26)
BM	0.664	0.660	0.653	0.631	0.594	-0.069***	(-3.62)
$Leverage$	0.229	0.231	0.230	0.231	0.235	0.006	(1.13)
$Mispricing$	48.128	48.287	48.693	49.439	51.564	3.436***	(8.24)

Table IA.2: Stock Characteristics: Sorted on Sentiment Beta (Positive Subsample)

This table replicates Table 2 by using subsample of stocks with positive original sentiment beta (*sbeta*). The mean difference between high- and low-sentiment beta portfolios is reported, along with its T-statistics, which is computed based on Newey and West (1987) standard errors with 5 lags, in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Variables	Low $SBeta$	2	3	4	High $SBeta$	High-Minus-Low Mean	High-Minus-Low T-stat
sbeta	0.002	0.007	0.013	0.022	0.043	0.040***	(15.07)
$SBeta$	0.019	0.020	0.022	0.025	0.033	0.014***	(14.53)
Panel A: Price [In]efficiency Measures							
$NoiseShare$	0.343	0.341	0.340	0.337	0.331	-0.012***	(-4.68)
AR	0.138	0.138	0.139	0.138	0.134	-0.004***	(-3.18)
HM	0.396	0.400	0.407	0.422	0.451	0.055***	(7.25)
$VR(1,5)$	0.269	0.267	0.268	0.266	0.257	-0.012***	(-4.25)
$PrivateInfoShare$	0.252	0.252	0.257	0.264	0.284	0.032***	(9.31)
$PublicInfoShare$	0.230	0.231	0.231	0.232	0.231	0.000	(0.17)
$MktInfoShare$	0.170	0.170	0.166	0.162	0.150	-0.019***	(-5.15)
$NoiseSD$	0.016	0.017	0.018	0.020	0.024	0.008***	(12.37)
$PrivateInfoSD$	0.014	0.014	0.015	0.017	0.022	0.008***	(15.33)
$PublicInfoSD$	0.013	0.013	0.014	0.015	0.019	0.006***	(13.29)
$MktInfoSD$	0.011	0.011	0.011	0.012	0.015	0.004***	(8.87)
Panel B: Institutional Holdings and Tradings							
IO	0.545	0.548	0.547	0.542	0.490	-0.055***	(-7.15)
HF	0.094	0.096	0.099	0.105	0.108	0.014***	(5.38)
$Active1$	0.358	0.361	0.365	0.371	0.347	-0.010*	(-1.94)
$Passive1$	0.164	0.163	0.158	0.148	0.121	-0.043***	(-13.87)
$Active2$	0.128	0.130	0.134	0.141	0.146	0.018***	(4.48)
$Passive2$	0.406	0.407	0.401	0.390	0.332	-0.075***	(-12.96)
ΔIO	0.003	0.003	0.003	0.004	0.006	0.003***	(7.19)
$Trade$	0.084	0.085	0.087	0.090	0.089	0.005**	(2.13)
Panel C: Other Firm Characteristics							
$Illiq$	0.176	0.181	0.203	0.228	0.250	0.074***	(2.66)
Sir	0.027	0.027	0.029	0.033	0.042	0.015***	(7.73)
$retSD$	0.022	0.023	0.024	0.027	0.034	0.011***	(12.43)
$Price$	32.554	32.517	31.267	29.968	26.281	-6.273***	(-3.57)
$lnME$	6.840	6.805	6.664	6.405	5.914	-0.926***	(-22.98)
$lnAsset$	7.323	7.266	7.069	6.718	5.986	-1.337***	(-17.82)
BM	0.661	0.655	0.649	0.645	0.595	-0.066***	(-4.77)
$Leverage$	0.230	0.228	0.228	0.228	0.233	0.003	(0.58)
$Mispricing$	48.214	48.323	48.828	49.869	52.860	4.646***	(8.02)

Table IA.3: Double Sorting Analysis: IO-Efficiency Relation Conditional on Sentiment Beta

This table replicates the portfolio sorting analysis in Table 3. Panel A reports results for stocks with negative original sentiment beta (*sbeta*), and Panel B reports results for stocks with positive original sentiment beta. The mean differences between high and low portfolios are reported, along with their T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Low *IO*	2	3	4	High *IO*	HML	All Stocks
Panel A: Negative Original Sentiment Beta ($sbeta_{i,q-1} < 0$) ***Subsample***							
Low *SBeta*	0.390	0.352	0.334	0.320	0.310	-0.080***	0.341
						(-9.09)	
2	0.390	0.351	0.332	0.320	0.310	-0.080***	0.341
						(-8.43)	
3	0.382	0.346	0.329	0.318	0.307	-0.075***	0.336
						(-9.83)	
4	0.368	0.337	0.323	0.314	0.310	-0.058***	0.330
						(-7.65)	
High *SBeta*	0.355	0.334	0.321	0.314	0.306	-0.049***	0.326
						(-8.28)	
HML	-0.035***	-0.018***	-0.012***	-0.006**	-0.004*	0.031***	-0.015***
	(-6.22)	(-5.79)	(-4.92)	(-2.26)	(-1.83)	(6.02)	(-6.85)
All Stocks	0.377	0.344	0.328	0.317	0.309	-0.068***	0.335
						(-9.04)	
Panel A: Positive Original Sentiment Beta ($sbeta_{i,q-1} \geq 0$) ***Subsample***							
Low *SBeta*	0.395	0.355	0.335	0.321	0.308	-0.086***	0.343
						(-8.57)	
2	0.391	0.352	0.335	0.320	0.309	-0.082***	0.341
						(-7.72)	
3	0.387	0.350	0.332	0.320	0.313	-0.074***	0.340
						(-6.75)	
4	0.376	0.349	0.332	0.320	0.307	-0.069***	0.337
						(-6.82)	
High *SBeta*	0.354	0.340	0.329	0.321	0.310	-0.044***	0.331
						(-7.71)	
HML	-0.040***	-0.015***	-0.006**	-0.000	0.002	0.042***	-0.012***
	(-6.38)	(-4.30)	(-2.12)	(-0.05)	(0.67)	(6.34)	(-4.65)
All Stocks	0.381	0.349	0.333	0.321	0.310	-0.071***	0.339
						(-7.76)	

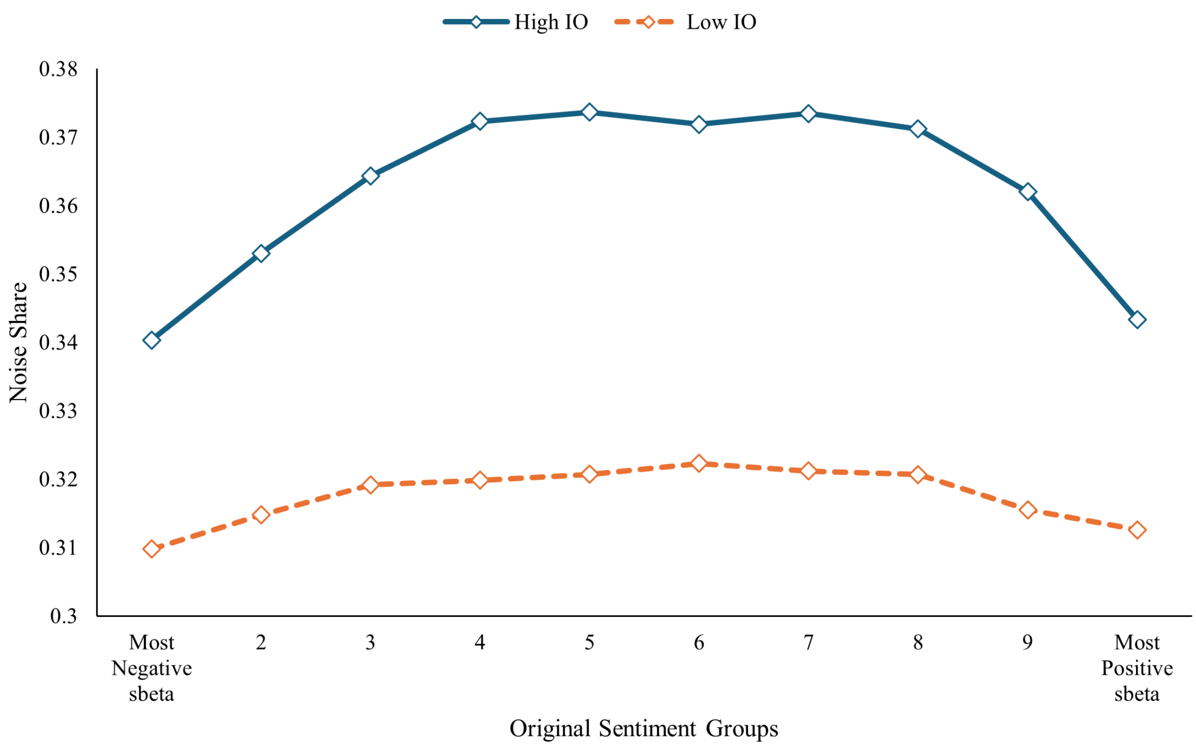

Figure IA.1: Mean Noise Shares of High and Low Institutional Ownership

This graph plots the mean noise share for high-IO and low-IO stocks, sorted by original sentiment beta (*sbeta*). High (low) IO is defined as institutional ownership above (below) the cross-sectional median in each quarter.

more than its direction.

Table IA.4: Baseline Regression: IO-Efficiency Relation Conditional on Sentiment Beta

This table replicates the baseline panel regression presented in Table 4. Panel A reports for negative sentiment beta subsample, while Panel B reports for positive subsample. Columns (2)–(6) report estimates within quintiles of beginning-of-quarter $SBeta$ from Low to High. Column (7) returns to the full sample and includes $SBeta$ and the interaction $IO \times SBeta$ to quantify the incremental impact of sentiment beta. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Sentiment Beta Group					All (w/ interactions)
		Low $SBeta$	2	3	4	High $SBeta$	
Panel A: Negative Subsample							
$IO_{i,q-1}$	-0.054***	-0.071***	-0.064***	-0.055***	-0.039***	-0.026***	-0.069***
	(-21.33)	(-15.15)	(-13.47)	(-12.18)	(-8.72)	(-5.80)	(-15.67)
$SBeta_{i,q-1}$							-0.847***
							(-7.97)
$IO \times SBeta$							**0.580*****
							(4.44)
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	140,694	29,364	29,218	28,998	28,129	24,985	140,694
adj. R^2	0.059	0.071	0.073	0.060	0.051	0.049	0.060
Panel B: Positive Subsample							
$IO_{i,q-1}$	-0.053***	-0.077***	-0.060***	-0.046***	-0.048***	-0.028***	-0.068***
	(-21.14)	(-15.74)	(-13.33)	(-10.11)	(-10.41)	(-6.10)	(-14.80)
$SBeta_{i,q-1}$							-0.827***
							(-7.51)
$IO \times SBeta$							**0.538*****
							(3.91)
FE	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	137,826	29,361	28,949	28,124	26,713	24,679	137,826
adj. R^2	0.064	0.076	0.071	0.064	0.064	0.058	0.064