Investor Sentiment, Institutional Ownership, and Informational Efficiency of Prices

Ufuk Güçbilmez, Martin Strieborny, Xiaoqi Yu

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Abstract

Investor sentiment influences both institutional decisions and stock market efficiency, challenging the conventional positive relation between institutional ownership (IO) and the informational efficiency of US stock prices. Using stock-level sentiment beta, we predict and confirm that while institutions generally enhance price efficiency, sentiment beta attenuates the IO-Efficiency relation, particularly in the latter half of the sample (1980Q1–2022Q2) and in pessimistic quarters with low investor sentiment. Our additional analysis shows that institutions underweight high-sentiment-beta stocks. Further decomposition reveals that only fundamental-driven IO enhances price efficiency, while sentiment-beta-driven IO has no significant effect. Our findings establish a direct link between sentiment beta, institutional ownership, and price efficiency, highlighting how sentiment moderates the IO-Efficiency relation and offering new insights into behavioral limits to arbitrage.

Keywords: Sentiment Beta, Institutional Investors, Informational Efficiency
JEL Codes: G14, G23, G40

1 Introduction

Institutional investors are widely regarded as sophisticated arbitrageurs whose informational advantages allow them to counteract mispricing and improve the informational efficiency of stock prices (Boehmer & Kelley, 2009; Cao et al., 2018). However, recent work by DeVault et al. (2019) challenges this view by proposing that investor sentiment itself reflects aggregate demand shocks driven by institutional trading. If investor sentiment proxies for institutional activity, the role of institutions in enhancing price efficiency may be overstated. This raises a critical question about the conditions under which institutional investors meaningfully contribute to price efficiency and whether sentiment weakens this relation.

Prior research has extensively examined the time-series relation between investor sentiment and either institutional behavior (Chen et al., 2021; Massa & Yadav, 2015) or market anomalies (Stambaugh et al., 2012, 2015). However, the cross-sectional impact of sentiment remains underexplored. This is important because stocks differ in their exposure to sentiment-driven noise, which may constrain institutions' ability to correct mispricing in certain stocks. Understanding how sentiment moderates the efficiency-enhancing role of institutional ownership is therefore crucial for evaluating the effectiveness of institutional arbitrage, especially in markets where sentiment distortions are both pervasive and unevenly distributed.

We examine this question using a sample of U.S. common stocks listed on NYSE, AMEX, and NASDAQ from 1980Q1 to 2022Q2. Our empirical framework employs three core constructs. First, we measure institutional ownership using quarterly 13F filings, which capture the aggregate holdings of institutional investors. Second, price (in)efficiency is measured using noise share, which quantifies the proportion of stock return variance driven by deviations from informationally efficient prices, following the decomposition methodology of Brogaard et al. (2022b). Third, we estimate sentiment beta for each stock by regressing its excess returns on changes in the Baker and Wurgler (2006) (BW) investor sentiment index, controlling for standard Fama-French risk factors (Fama & French, 1993) and liquidity factors (Pástor & Stambaugh, 2003). Sentiment beta captures cross-sectional differences in stocks' sensitivity to shifts in investor sentiment. Together, these measures allow us to test how sentiment-driven exposure moderates the efficiency-enhancing role of institutional ownership across a broad cross-section of stocks.

Our first hypothesis predicts sentiment beta should attenuate the relation between institutional ownership and price efficiency (henceforth referred to as IO-Efficiency relation), as increased sensitivity to investor sentiment heightens arbitrage risk to institutional investors. We start our empirical tests with portfolio sorting analysis. Stocks are sorted into 25 (5×5) portfolios based on sentiment beta ($|SBeta|$) and institutional ownership (IO) independently at quarter $q-1$, and for each portfolio, we report the average noise share at quarter q. First, the noise share of the high-IO portfolio is significantly lower than that of the low-IO portfolio, which echoes the findings of Boehmer and Kelley (2009) and Cao et al. (2018). Second and most importantly, the gap of average noise share between low- and high-IO portfolios significantly attenuates as sentiment beta increases, marking a 43% reduction from 12.4% in the low- to 7.09% in the high-sentiment-beta portfolio[1]. We also conduct the dependent sorting to better investigate the IO-Efficiency relation conditioning on sentiment beta, which gives a similar result. Our results suggest that the efficiency-enhancing effect of institutional investors significantly attenuates for stocks with higher exposure to the investor sentiment variation.

Next, we estimate the impact of sentiment beta on IO-Efficiency relation using Fama and MacBeth (1973) regression to address the concern that other factors may drive the findings from portfolio sorting. Informational efficiency has been documented to be closely related to short interest and liquidity conditions. On the one hand, short-selling positions are often involved in sophisticated arbitrageurs' activities (Chen et al., 2019), and short sellers are more informed (Boehmer et al., 2010), leading to that short interest improves the informational efficiency (Boehmer & Wu, 2013). On the other hand, higher liquidity indicates lower trading costs, facilitating institutions' arbitrage activities Shleifer and Vishny (1997), and hence contributing to the price efficiency. Thus, we estimate the impact of sentiment beta on IO-Efficiency in Fama and MacBeth (1973) regression. Specifically, we sort stocks based on sentiment beta into 5 groups, and estimate Fama and MacBeth (1973) regression of noise share on institutional ownership, controlling for short interest and liquidity, as well as several stock characteristics. We show that the coefficient on institutional ownership increases nearly monotonically across groups, from -6.24 in the low- to -2.58 in the high-sentiment-beta group. In addition, the difference in coefficient between the two groups, 3.74, is statistically significant at 1% level. This corroborates our findings in portfolio sorting analysis that sentiment beta attenuates the IO-Efficiency relation. Our results hold in panel regressions with stock and year-quarter fixed effects, which mitigate omitted variable bias by accounting for unobserved heterogeneity across stocks and time periods, reinforcing the

[1]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.

baseline findings. They also remain robust to alternative price efficiency measures and institutional ownership specifications.

Our sample period spans a 40-year window from 1980 to 2022, during which market conditions have evolved significantly. To examine how our main finding evolves over time, we conduct subsample analyses. As shown in Figure 1, institutional ownership increases significantly to dominate the market after 2000Q1. Given this notable change, we designate 2000Q1 as the cutoff point and divide the full sample into two periods, each covering an appropriate 20-year window. We show that the IO-Efficiency relation is generally stronger in the second half of the sample period, suggesting that the increasing presence of institutional investors has enhanced price efficiency over time. However, the impact of sentiment beta on this relation becomes more pronounced in the second half. Specifically, while the difference in coefficients between low- and high-sentiment-beta groups is smaller and less statistically significant in the first half, it is much larger and highly significant in the second half (see Panel C of Table 8). For high-sentiment-beta stocks, the IO-Efficiency relation remains relatively stable across both periods, indicating that the moderating effect of sentiment beta persists over time. These findings suggest that the growing dominance of institutional investors improves price efficiency overall, but sentiment beta continues to constrain their ability to correct sentiment-driven mispricing, with this effect becoming more evident in the later period.

[Insert Figure 1 around here]

Second, we divide the full sample into two based on the time series of BW investor sentiment. Specifically, optimistic (pessimistic) quarters are defined as quarters with beginning-of-quarter investor sentiment levels higher (lower) than the full-sample median[2]. We find that the IO-Efficiency relation is significantly weaker in optimistic quarters, consistent with the arbitrage asymmetry argument proposed by Stambaugh et al. (2015). When sentiment is optimistic, noise traders exhibit strongly positive demand, but they do not show a correspondingly strong negative demand when sentiment is pessimistic. This asymmetry results in widespread overpricing and heightened limits to arbitrage during optimistic periods. Consistent with this framework, we find that the IO-Efficiency relation weakens significantly in

[2] In this study, our focus is on the impact of sentiment beta, and we primarily use the terms high-(low-) sentiment-beta in the main text. To avoid potential confusion, we define quarters with beginning-of-quarter investor sentiment levels higher (lower) than the full-sample median as optimistic (pessimistic) quarters. This terminology aligns with the practices in prior literature, such as Antoniou et al. (2016). While the terms high and low sentiment are also commonly used in the literature, such as in Stambaugh et al. (2012, 2015) and Yu and Yuan (2011), we adopt optimistic and pessimistic sentiment to ensure greater clarity in distinguishing between sentiment beta and sentiment levels.

optimistic quarters, with the attenuation effect pervasive across all sentiment beta groups. Conversely, during pessimistic quarters, the cross-sectional role of sentiment beta becomes more salient, with high-sentiment-beta stocks exhibiting a disproportionately weaker IO-Efficiency relation compared to low-sentiment-beta stocks.

One observation from the first subsample analysis is the concurrent presence of a dominant institutional investor base and a stronger cross-sectional impact of sentiment in the second half of the sample (2000Q1 to 2022Q2). This raises concerns that institutional investors themselves may act as sentimental traders, potentially contaminating the IO-Efficiency relation. While most studies characterize institutional investors as arbitrageurs who counteract sentiment-driven mispricing (Barber & Odean, 2008; Kumar & Lee, 2006, among others), some evidence suggests that institutions may trade with sentiment. For example, Brunnermeier and Nagel (2004) and Chen et al. (2021) show that hedge funds sometimes time and ride sentiment, while DeVault et al. (2019) provides evidence of institutions acting as sentimental traders.

To address this concern, we further analyze how institutional investors in our sample react to sentiment beta and assess the implications for price efficiency. First, we find that institutions, on average, trade against sentiment beta, suggesting a contrarian approach. Next, we decompose institutional ownership into two components, a sentiment-beta-driven component and a residual component. The residual ownership captures institutional holding decisions based on fundamental stock characteristics beyond sentiment-related noise trader risk. We find that sentiment-beta-driven institutional ownership is not significantly associated with informational efficiency, whereas residual ownership is significantly and negatively related to price inefficiency. This indicates that institutional decisions based on fundamental factors, such as riskiness and size, meaningfully enhance price efficiency, reinforcing the role of institutions as arbitrageurs who detect and correct mispricing.

This study contributes to the literature in a number of ways. First, we contribute to the literature on the relation between institutional investors and price efficiency. Two most closely related studies are Boehmer and Kelley (2009) and Cao et al. (2018). Boehmer and Kelley (2009) examine institutional investors as a whole and show that institutional ownership is associated with improved informational efficiency, and Cao et al. (2018) focus on hedge funds and show that hedge fund ownership contributes more to informationally efficient prices than ownership of other types of institution. Our contribution is to document the impact of investor sentiment on this IO-Efficiency relation. Specifically, we show that IO-Efficiency is contingent on sentiment beta; that is, the efficiency-enhancing effect of institutional ownership attenuates as sentiment beta increases.

Second, we contribute to the literature on investor sentiment and its impact; specifically, we contribute to the literature on sentiment beta, which is constructed to capture the cross-sectional effect of sentiment on individual stocks. Prior studies have systematically defined sentiment beta (Baker & Wurgler, 2006, 2007), provided method to estimate it (Glushkov, 2006), investigated its influence on trading strategies and performances of institutional investors, for instance mutual fund (Massa & Yadav, 2015), and hedge fund(Chen et al., 2021). Our contribution is to explicitly study how institutional investors' interactions with sentiment affect market efficiency. Specifically, we show that while sentiment beta presents challenges for institutions in arbitrage, their holdings based on fundamental factors still contribute to price efficiency.

Third, this study speaks to the literature on whether institutional investors are sentimental traders. DeVault et al. (2019) argue institutional investors are sentimental traders based on evidence of a positive relation between institutions' net buying of risky stocks, i.e., stocks with high return volatility, and contemporaneous change in investor sentiment. Gao et al. (2023) challenge their view by arguing sentiment level better reflects the mispricing and showing institutions reduce their risky holdings following the high sentiment period, suggesting institutions trade against sentiment. Though the two studies differ in focus and methodology, both rely on return volatility to infer institutions' sentimental demand. However, increased volatility may also signify greater informativeness (Dávila & Parlatore, 2023), so institutions' interactions with volatility possibly reflect trading based on their private information, rather than sentimental demand. Our contribution is to provide more direct evidence on institutional reaction to sentiment. Specifically, we show that institutional investors tend to trade against sentiment in that they reduce their holdings of stocks with higher exposure to sentiment, as captured by sentiment beta.

The rest of the paper proceeds as follows. Section 2 reviews the literature and develops the hypotheses for empirical tests. Section 3 introduces and describes data, sample, and the construction of key variables. Section 4 presents the main result of the impact of sentiment beta on the IO-Efficiency relation, as well as the robustness check. Section 5 examines the implication of arbitrage asymmetry in our context. Section 6 further examines how institutional investors react to sentiment and the impact of their reactions on price efficiency. Section 7 concludes our findings.

2 Related Literature and Hypothesis Development

The efficient market hypothesis is justified by arguing that rational and sophisticated investors would arbitrage away any mispricing (Akbas et al., 2016). In practice, institutional investors are generally regarded as sophisticated investors who make informed decisions and are able to exploit the mispricing (Shleifer & Vishny, 1997). Thus, in general, we expect a positive relation between institutional ownership and price efficiency, as their participation in particular stocks incorporates information about the fundamental value into the stock price. This perspective rests on the assumptions that institutional investors know the fundamental value of the stocks, and that the arbitrage activities are riskless or carry low risk. These two assumptions usually do not hold in the financial market, especially when considering the impact of investor sentiment. Cross-sectionally, stocks that are hard to value, such as young and small stocks, also tend to be more sensitive to investor sentiment where the valuations are more subject to behavioral biases due to sparse information available. As a result, they are more driven by sentimental traders and make themselves difficult to arbitrage, introducing noise trader risk for sophisticated arbitrageurs (Baker & Wurgler, 2006, 2007; Barberis et al., 1998; DeLong et al., 1990). Upon facing both fundamental risk and noise trader risk, institutional investors' impact might be undermined by investor sentiment. Therefore, while institutional ownership generally contributes to stock price efficiency, the strength and consistency of this relation are contingent upon the extent to which stock is affected by sentiment.

Hypothesis 1: The efficiency-enhancing effects of institutional ownership on stock price should significantly *weaken* if the stock price is *more sensitive* to investor sentiment.

Investor sentiment influences the stock market by driving prices across numerous stocks in the same direction (Baker & Wurgler, 2006; Stambaugh et al., 2012). During optimistic (pessimistic) quarters, when investor sentiment is above (below) the sample median, excessive optimism (pessimism) leads to overpricing (underpricing) beyond efficient levels. However, overpricing is more persistent and harder to correct than underpricing due to short-sale impediments (Miller, 1977; Stambaugh et al., 2015; Yu & Yuan, 2011). Many institutional investors are restricted from short selling, and even those who can often hesitate due to the risk of prolonged price increases, requiring additional capital and exposing them to potential forced liquidation (Stambaugh et al., 2012). While reducing long positions can contribute to price adjustments, its effectiveness in correcting sentiment-driven overpricing is limited compared to short selling, particularly in markets with significant short-sale constraints.

As a result, mispricing persists more during optimistic sentiment periods, and institutional ownership plays a weaker role in improving price efficiency, as sentiment-driven distortions dominate. Additionally, market-wide sentiment effects dampen differences between high- and low-sentiment beta stocks, making their contrast less significant.

Conversely, following pessimistic sentiment periods, differences in sentiment sensitivity among stocks (sentiment beta) become more pronounced. With weaker market-wide sentiment effects, stocks with high sentiment beta remain highly responsive to even small sentiment shifts, while low-sentiment-beta stocks remain relatively stable. Since overall sentiment plays a smaller role, stock-level differences in sentiment beta become the dominant driver of variation in price efficiency, leading to a clearer distinction between high- and low-sentiment-beta groups.

Hypothesis 2: The weakening impact of sentiment beta on the IO-Efficiency relation is *more pronounced* following *pessimistic* sentiment periods.

The attenuation effect of sentiment beta on the IO-Efficiency relation can be explained by two non-mutually exclusive mechanisms related to institutional trading behavior. First, even if institutional investors recognize mispricing and adjust their holdings in response to sentiment-driven distortions, their arbitrage efforts may be insufficient to counteract noise trader risk. In this case, institutions allocate less ownership to high-sentiment-beta stocks, potentially limiting their exposure to persistent mispricing. However, this reduced participation simultaneously weakens their capacity to correct prices (DeLong et al., 1990; Edelen et al., 2016). For example, Massa and Yadav (2015) show that institutional selling of overvalued, sentiment-sensitive stocks fails to fully reverse price distortions due to sustained retail investor demand.

Second, institutions may themselves contribute to sentiment-driven mispricing by riding with prevailing sentiment. If institutions increase holdings in high-sentiment-beta stocks to exploit short-term trends, their trading amplifies—rather than corrects—noise trader effects, rendering their ownership ineffective in promoting price efficiency (Brunnermeier & Nagel, 2004; Chen et al., 2021). Whether institutions ultimately act as arbitrageurs or trend-followers remains an open question, but either behavior would rationalize the weakened IO-Efficiency relation.

Hypothesis 3a: Institutional ownership is *lower* in stocks with higher sentiment beta, suggesting that institutions adjust their holdings to limit exposure to sentiment-driven mispricing.

Hypothesis 3b: Institutional ownership is *higher* in stocks with higher sentiment beta, suggesting that institutions adjust their holdings in ways that reinforce sentiment-driven mispricing.

Investor sentiment can be regarded as the difference between the beliefs of sentiment-driven traders and correct efficient beliefs conditional on available information (DeLong et al., 1990; Stambaugh et al., 2015). Motivated by this, it is plausible to assume that the overall institutional ownership of a stock consists of both a sentiment-driven component and a component based on fundamental information at the institutions' hands. The information-based ownership, further referred to as discretionary ownership, reflects institutional investors' informational advantage and professional capacity to incorporate fundamental information into stock prices. It is expected that discretionary ownership should contribute to improving price efficiency.

Hypothesis 4: The discretionary information-based institutional ownership maintains its function of improving price efficiency, while sentiment-beta-driven ownership has no significant impacts.

3 Data and Variables

3.1 Data and Sample

Our sample comprises US common stocks listed on NYSE/AMEX/NASDAQ exchanges, covering the periods 1980Q1 to 2022Q2[3]. 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[4]. Short interest data is primarily sourced from Compustat, covering NYSE and AMEX stocks since January 1973 and NASDAQ stocks from July 2003 onward. For NASDAQ stocks prior to July 2003, data is obtained from Bloomberg.

We follow literature and employ below filter criteria: 1) the duplicated stock-day observations and observations with missing values of price, return or volume are removed (Brogaard

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

[4]We thank Jeffrey Wurgler generously making investor sentiment index publicly available at https://pages.stern.nyu.edu/ jwurgler/.

et al., 2022b); 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., 2022b); 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 425,114 stock-quarter observations, and the average number of stocks per quarter is 2,500.

3.2 Key Variables

3.2.1 Informational Efficiency of Stock Price

The primary measure of price (in)efficiency used in this paper is $NoiseShare$, proposed by Brogaard et al. (2022b), capturing the relative importance of pricing error. They inherit the idea of Hasbrouck (1993) by decomposing stock price into an efficient price component (m_t) and a pricing error term (s_t),

$$p_t = m_t + s_t \tag{1}$$

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

$$r_t = p_t - p_{t-1} = \mu + (\theta_{r_m}\varepsilon_{r_m,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t}) + \Delta s_t \tag{2}$$

The components in Equation 2 are estimated in a structural VAR system. $\varepsilon_{r_m,t}$, $\varepsilon_{x,t}$, $\varepsilon_{r,t}$ are innovation terms, while θ_{r_m}, θ_x, θ_r are long-run permanent effects of these innovations, inferred from cumulative impulse response. Specifically, the input variables in VAR system include market return (CRSP value-weighted market return), signed dollar volume (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 $t = 15$.

In our study, we perform the variance decomposition every stock-quarter using daily data. Then, in Equation 2, Δs_t 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 have contributions of 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 $\theta_r^2 \sigma_{\varepsilon_r}^2$, to the variation in efficient price. Normalizing $Noise$ by all variance components, we obtain our noise share capturing the relative importance of pricing error. More detailed estimation procedure can be found in Appendix and Brogaard et al. (2022b)[5].

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

The noise and noise share measures fall between semistrong-form efficiency and strong-form efficiency categories since they incorporate public information and a portion of private information inferred from signed dollar volume. Though noise and noise share, compared to pricing error variance (PEV) employed by Boehmer and Kelley (2009) and Cao et al. (2018) who use intraday data, rely on lower-frequency daily observations, they leverage more broadly available data and enable longer-horizon examinations of changes in the information characteristics in stock prices. Moreover, the inclusion of additional trading variables, market return and stock closing price, strengthens the estimation of pricing error, as discussed by Hasbrouck (1993) and Cao et al. (2018).

Figure 3 plots 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 34.71% (See Panel A of Table 1). The quarterly noise share exhibits a similar pattern to the yearly noise share constructed by Brogaard et al. (2022b). The noise share is obviously high in early 1990s, Brogaard et al. (2022b) discuss this 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 COVID-19 breakout.

[Insert Table 1 around here]

[Insert Figure 3 around here]

We also consider two alternative widely used price (in)efficiency measures, Hou and Moskowitz (2005)'s price delay (henceforth referred to as HM Price Delay), and return

[5] We thank Prof. Jonathan Brogaard, Dr. Thanh Huong Nguyen, Prof. Talis Putnins, and Prof. Eliza Wu for generously providing the code to decompose the variance components (Brogaard et al., 2022a, 2022b).

autocorrelation. HM price delay measure is proposed by Hou and Moskowitz (2005) and widely used in literature (Boehmer & Kelley, 2009; Cao et al., 2018; Cao et al., 2023, among others). It captures the delay with which a stock responds to market-wide information. For each stock-quarter, we estimate the following time series regression of daily stock return on CRSP value-weighted market return,

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

where r_d is the daily stock return, $R_{m,d}$ is the market return on day d. We should expect at least some coefficients δ in unconstrained regression, the one that includes 5 lagged market returns, to be significantly different from zero, if the stock price response in a delay to market-wide information. In constrained regression, we constrain δ to be zero. Our HM price delay measure is then constructed as,

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

Thus, HM price delay measure 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 an efficient stock price follows a random walk process, as such we should expect that return is unpredictable and is not serially correlated. However, empirical studies find 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.

3.2.2 Institutional Ownership

The institutional investors who manage a portfolio that has a value of $100 million or more are obliged to file Form 13F, on which their long-equity positions that are greater than 10,000 shares or $200,000 in market value are reported, with the SEC. 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[6]. The institutional ownership is then constructed as aggregated shares held by institutional investors divided by the quarter-end number of shares outstanding reported by CRSP[7]. The detailed construction process is described in the Appendix.

Over the sample period from 1980Q1 to 2022Q2, institutional ownership significantly increased from around 30% to 70%, indicating the growing influence and dominance of institutional investors in the stock market (See Figure 1). The average and median institutional ownership are 49% and 51% respectively, and the average number of institutional investors is 128.

3.2.3 Investor Sentiment and Sentiment Beta

The BW investor sentiment index (Baker & Wurgler, 2006, 2007) is employed. It is 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})[8]. To have quarterly sentiment, we take the average of monthly sentiment within each quarter. Panel C of Table 1 reports the statistics of quarterly sentiment and Figure 2 presents the time-series plot. The average quarterly sentiment over the sample period is 0.23, with a

[6]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.

[7]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).

[8]The NYSE turnover, used to be one proxy in sentiment index, has been dropped since turnover ratio does not mean as once it did given the explosion of institutional high-frequency trading and the migration of trading to a variety of venue. The authors discuss the issue, and the details can be found in the downloaded sentiment index Excel file.

standard deviation of 0.05.

[Insert Figure 2 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, each 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. In quarter q, for stocks with at least 30 return observations over the 36-month period covering month $t-35$ to month t, we roll the window forward every 3 months and perform the following time-series regression,

$$r_{it} = \alpha_0 + \beta^{SENT}\Delta SENT_t + \beta^{MKT} MKT_t + \beta^{SMB} SMB_t + \beta^{HML} HML_t + \beta^{LIQ} LIQ_t + \varepsilon_{it} \quad (7)$$

where r_{it} is the excess return of stock i in month t, MKT, SMB, and HML are Fama-French factors (Fama & French, 1993), LIQ is the Pástor and Stambaugh (2003) liquidity factor. The liquidity factor is included for two reasons. First, Pástor and Stambaugh (2003) document that liquidity is an important factor in pricing common stocks as stocks with higher sensitivity to aggregate liquidity are expected to have high returns in the cross-section. Second, liquidity contributes to price efficiency, as stocks with higher liquidity impose lower costs on arbitragers (Amihud, 2002; Boehmer & Kelley, 2009). To assess the impact of sentiment on the relation of institutional ownership and price efficiency, it is imperative to control for the impact of liquidity when estimating sentiment beta. $\Delta SENT_t$ is the sentiment change index, instead of simply taking the changes in sentiment level index, we construct it as the first principal component of the changes in five aforementioned sentiment proxy variables, align with the prior practices (Baker & Wurgler, 2007; Chen et al., 2021; Glushkov, 2006; Massa & Yadav, 2015). The primary reason for doing so is the noisiness in the proxy variable can vary when transitioning from levels to changes.

β^{SENT} is sentiment beta, henceforth referred to as $SBeta$. To reduce the statistical noise in the sentiment beta measure, following Glushkov (2006), the Bayes-Stein adjustment procedure is conducted to shrink the sentiment beta measure by incorporating prior knowledge, denoted as $|SBeta|$.

$$|SBeta|_q = \frac{\sigma^2_{\text{prior},q-1}}{\sigma^2_{\text{prior},q-1} + \sigma^2_{\beta,q}} |\beta_{i,q}| + \frac{\sigma^2_{\beta,q}}{\sigma^2_{\text{prior},q-1} + \sigma^2_{\beta,q}} \beta^{\text{prior}}_{q-1} \quad (8)$$

where,

$$\beta_{q-1}^{\text{prior}} = \frac{1}{N_{q-1}} \sum_{i=1}^{N} |\beta_{i,q-1}| \, , \sigma_{\text{prior},q-1}^{2} = \frac{1}{N_{q-1}} \sum_{i=1}^{N} \left(|\beta_{i,q-1}| - \beta_{q-1}^{\text{prior}} \right)^{2} \tag{9}$$

Sentiment beta, $SBeta$, measures the sensitivity of stock return to change in investor sentiment or the extent to which the stock return is driven by investor sentiment. The price of the stock with positive (negative) sentiment beta is more driven by momentum (contrarian) sentimental traders (Glushkov, 2006). The greater the magnitude of the sentiment beta of a stock, the more significant the impact of sentiment on its price and return, which is captured by the shrinkage estimate of sentiment beta, $|SBeta|$. Since most of the analysis will be conducted on shrinkage sentiment beta, $|SBeta|$, we will use terms *sentiment beta* and *shrinkage sentiment beta* interchangeably henceforth. Where it requires original sentiment beta ($SBeta$), we will use the term *original sentiment beta*. In addition, for the results' readability, we multiply sentiment beta by 100.

The average sentiment beta over the sample period is 2.41 (See Panel C of Table 1). Stocks with high sentiment beta are those more affected by sentiment and tend to have smaller sizes and higher risks (i.e., return volatility). Table 2 reports the price efficiency, institutional ownership, and firm characteristics for groups of stock sorted based on 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. Stocks with higher sentiment beta demonstrate a monotonic trend of having smaller values in terms of price, market capitalization, or 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]

3.2.4 Control Variables

Short Interest Ratio (SIR). The short interest of any individual stock is the aggregate uncovered shares sold short on and before the 15th of each month (if it is a business day) and the exchanges collect this information monthly. The short interest can reflect arbitrageurs' positions (Hanson & Sunderam, 2014) and the short selling activities can contribute to the stock price efficiency (Boehmer & Kelley, 2009; Boehmer & Wu, 2013; Cao et al., 2018). The short interest ratio is calculated by dividing the total monthly number of short interests by the total number of shares reported by CRSP. The average short interest ratio is 2.7%. It increased significantly from less than 1% in 1980Q1, peaking at 7.4% in 2008Q2. Subsequently, it declines and stabilizes at a level of around 4.5% (See Figure 1).

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

$$ill_{ij} = \frac{1}{D_{ij}} \sum_{d=1}^{D_{ij}} \frac{|ret_{ijd}|}{prc_{ijd} \cdot vol_{ijd}} * 10^6 \tag{10}$$

where D_ij is the number of trading days for stock i in quarter j, ret_{ijd},prc_{ijd} and vol_{ijd} are daily return, closing price, and daily volume for stock i on trading day d of quarter j. It can be interpreted as the price response to one-dollar trading volume and hence measure the price impact. To match the quarterly data of noise share and institutional ownership, the daily illiquidity ratios of stocks are averaged over the quarter.

Volatility (SD). The volatility can reflect the uncertainty of the fundamental value of a security, stocks with higher volatility is harder to value (Baker & Wurgler, 2006; DeVault et al., 2019; Gao et al., 2023) and hence their efficient levels of price are 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, market capitalization, total assets, and book-to-market ratios. The stock price is the quarter-end adjusted closing price. The market capitalization is calculated using quarter-end price and shares outstanding. The total asset is the quarter-end book value of the asset. The book-to-market value is the ratio of the book value of equity to its market value. Panel D of Table 1 reports the statistics for control variables. Our sample stocks have an average price of $24.50, an average asset size of $4.94 billion, and an average BM ratio of 0.66.

4 Empirical Results: The Impact of Sentiment Beta

4.1 Portfolio Sorting Analysis

To investigate the impact of sentiment beta on the relation between institutional ownership and noise share, we first perform the portfolio-sorting analysis. Portfolio-sorting analysis is a straightforward and nonparametric technique to examine the cross-sectional relation between two or more variables (Bali et al., 2016). At the end of each quarter $q-1$, stocks are independently sorted into quintile portfolios based on their sentiment beta and institutional ownership to generate 25 (5×5) portfolios. The low- (high-) sentiment beta and institutional ownership portfolios comprise the bottom (top) quintile of stocks based on sentiment beta and institutional ownership, respectively. We compute the average noise share in each quarter q for each of 25 the portfolios. We report the time-series averages of quarterly noise share for each of the 25 portfolios and the average difference in noise share between high- and low-institutional-ownership portfolios as well as between high- and low-sentiment-beta portfolios. The standard errors in all estimations are corrected for autocorrelation using the Newey and West (1987) method.

Panel A of Table 3 reports the independent portfolio sorting results. 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. Second, the differences in noise share attenuate as sentiment beta increases. For the low-sentiment-beta group, high-IO stocks display a 12.4% lower noise share than low-IO stocks, while this noise share gap declines to 7.1% for the high-sentiment-beta group. In addition, the difference-in-differences of low- and high-sentiment-beta groups is 5.32%, significant at 1% level, indicating that sentiment significantly undermines the impact of institutional ownership on price efficiency. These results provide support for both the conventional notion that higher institutional ownership leads to high price efficiency and our hypothesis that this relation weakens for stocks that are more affected by investor sentiment.

To better investigate the impact of sentiment beta, we perform dependent portfolio sorting. The dependent portfolio-sorting procedure allows us to examine the relation between institutional ownership and noise share while controlling for sentiment beta. At the end of each quarter $t-1$, 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 dependent portfolio sorting provides a quantitatively similar result, as reported in Panel B of Table 3. The difference-in-differences is 5.02%, significantly at 1% level, consistent with the independent sorting result.

[Insert Table 3 around here]

4.2 Stock-Level Regression Analysis

4.2.1 Fama-MacBeth Regression

The results from portfolio-sorting analysis can be driven by factors such as liquidity, size, or short interest that have been documented to have impacts on price efficiency. To address this concern, we conduct stock-level regression analysis which controls for lagged noise share and stock characteristics. Specifically, we first sort stocks into 5 groups based on their sentiment beta in each quarter, and within each group we estimate the following equation based on Fama and MacBeth (1973) procedure (henceforth FMB regression), following Boehmer and Kelley (2009) and Cao et al. (2018),

$$NoiseShare_{iq} = \alpha_0 + \beta_1 IO_{i,q-1} + \beta_2 NoiseShare_{i,q-1} + \sum_{k=3}^{6} \beta_k X_{i,q-1} + \beta_7 ln(ILLIQ)_{iq} + \epsilon_{iq} \tag{11}$$

where $NoiseShare_{iq}$ 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 $q-1$. It is included to account for the mean reversion of price efficiency. $X_{i,q-1}$ is a set of stock characteristics variables at the end of quarter $q-1$, including short interest ratio ($ln(SIR)$), closing price ($ln(PRC)$), total assets ($ln(ASSET)$), and book-to-market ratio ($ln(BM)$). The liquidity is contemporaneously associated with price efficiency. Cao et al. (2018) control the contemporaneous liquidity in model specification to examine whether the efficiency improvement is simply attributable to that improved liquidity. We control for contemporaneous illiquidity ($ln(ILLIQ)$)[9]. These variables are transformed into natural logarithm form to address the skewness in their distribution. Inferences are drawn from the time-series of coefficient estimates using the Fama and MacBeth (1973) method, with the standard error in all estimations corrected for autocorrelation using the Newey and West (1987) method.

[9]Note that including lagged illiquidity gives the quantitatively similar result.

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

Table 4 reports the FMB regression results for 5 sentiment beta groups. Column (1) presents the results for the full sample as a benchmark, while Column (2) through (6) shows the regression analysis progressing from the lowest to the highest sentiment beta group. Overall, institutional ownership is significantly negatively associated with noise share, supported by a significantly negative coefficient in Column (1). The finding is consistent with that of Boehmer and Kelley (2009) and Cao et al. (2018).

[Insert Table 4 around here]

From Column (2) to (6), the β_1 coefficients are significant at 1% level and increase nearly monotonically from -6.24 to -2.58. This pattern indicates that the negative relation between institutional ownership and noise share weakens as sentiment beta increases. In terms of economic significance, for the low-sentiment-beta group one standard deviation increase in institutional ownership decreases noise share by 1.76 percentage points, while for the high-sentiment beta group one standard deviation increase in institutional ownership only decreases noise share by 0.76 percentage points. The impact nearly halves, from the low- to the high-sentiment-beta group. Besides, R^2, known as goodness-of-fit, is 10.4% for estimation of low-sentiment-beta group. It declines to 5.7% for the estimation of the high-sentiment-beta-group. The declining R^2 demonstrates the diminishing ability of the institutional ownership in explaining variation in noise share[10].

To statistically test the difference between two β_1 coefficients, we estimate the following FMB regression,

$$\begin{aligned} NoiseShare_{iq} = &\alpha_0 + \beta_1 IO_{i,q-1} + \beta_2 D_1 + \beta_3 D_5 + \beta_4 (D_1 * IO_{i,q-1}) + \beta_5 (D_5 * IO_{i,q-1}) \\ &+ \sum_{k=6}^{9} \beta_k X_{i,q-1} + \beta_{10} ln(ILLIQ)_{iq} + \epsilon_{iq} \end{aligned} \tag{12}$$

[10]One may concern across different groups of stock based on sentiment beta, the predictive power of control variables can affect the R squared. We conduct univariate regression of noise share on institutional ownership, obtaining R squared equal to 7.46% and 3.3% for the low- and high-sentiment-beta groups, respectively. This aligns with our findings.

where D_1 and D_5 are dummy variables for low (high) sentiment beta group, $D_1 * IO_{i,q-1}$ and $D_5 * IO_{i,q-1}$ are interaction terms between institutional ownership and low- and high-sentiment-beta dummy. β_1 measures the average impact of institutional ownership on noise share, while β_4 and β_5 measure the differential impact of institutional ownership on noise share for stocks with low- and high-sentiment-beta, respectively. We should expect β_4 to be significantly negative, and β_5 to be significantly positive, and the difference between β_4 and β_5 to be significantly different from zero. We tabulate the result in Panel B of Table 4.

β_4 is significantly negative as -1.094 and β_5 is significantly positive as 2.624, indicating the impact of institutional ownership on noise share is stronger (weaker) for low- (high-) sentiment-beta stocks. This is consistent with findings from grouped regression. The difference between β_4 and β_5 is 3.718 and its F statistic is 27.06, indicating two beta coefficients are significantly different at 1% level. Our hypothesis 1 is then confirmed, the efficiency-enhancing effects of institutional ownership on stock price should significantly attenuate if the stock price is more sensitive to investor sentiment.

The grouped FMB regression allows us to qualitatively conclude that sentiment beta attenuates the IO-Efficiency relation. To better quantitatively examine 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 regression. Specifically, we estimate the following FMB regression,

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

$|SBeta|_{i,q-1}$ and $IO * |SBeta|$ are two additional variables included in equation. In this regression, β_1 and β_3 are coefficients of interest. β_1 is expected to be negative, while β_3 should be positive and significant to demonstrate an attenuating impact of sentiment beta on the IO-Efficiency relation.

Table 5 reports the regression result. Both β_1 and β_3 have expected sign and significant at 1% level. Again, this corroborates the finding that sentiment beta undermines the IO-Efficiency relation. The impact of institutional ownership is given by $-9.275+1.584*|SBeta|$, as shown in Column (6) in Table 5. For example, as sentiment beta increases from 1.94 (mean of low-sentiment-beta-group) to 3.29 (mean of high-sentiment-beta-group), the impact of institutional ownership on noise share increases from -6.202 to -4.064, marking a 34.5% increase.

[Insert Table 5 around here]

4.2.2 Panel Regression

In the above analysis, we confirm the cross-sectional impact of sentiment beta on the IO-efficiency relation. To further validate this relation, we employ panel regression, which offers three key advantages. First, it captures dynamic effects by accounting for time-varying changes in sentiment beta within firms over a 40-year period. Second, it controls for unobserved heterogeneity through stock and quarter fixed effects, isolating the relation from time-invariant and macroeconomic influences. Third, by clustering standard errors at both stock and quarter levels, panel regression ensures robust statistical inference. These advantages enable a more comprehensive examination of the dynamic and robust effects of sentiment beta on the IO-efficiency relation.

Table 6 presents the results of the panel regression, with standard errors clustered at the stock and quarter levels. Columns (1) to (5) report the baseline regression for each sentiment beta group, while Column (6) includes the interaction term of sentiment beta and institutional ownership. The results remain consistent: the coefficient on institutional ownership decreases monotonically from the low- to high-sentiment-beta groups, and its significance diminishes. For the high-sentiment-beta group, the IO-efficiency relation is not significant, confirming that sentiment beta attenuates this relation. The significant interaction term further supports the robustness of these findings. These results imply that the impact of institutional ownership on efficiency depends dynamically on sentiment beta, both across firms and within firms over time, reinforcing the role of sentiment beta in moderating the IO-efficiency relation.

[Insert Table 6 around here]

4.2.3 Summary

Overall, our findings support the IO-efficiency relation documented by Boehmer and Kelley (2009) and Cao et al. (2018), showing that higher institutional ownership reduces pricing errors and enhances informational efficiency. Extending this, our study focuses on the impact of sentiment beta on the IO-efficiency relation. Both FMB and panel regressions reveal that sentiment beta attenuates this relation, with higher sentiment beta weakening the effect of institutional ownership on price efficiency. These results underscore the dynamic role of sentiment beta in shaping the IO-efficiency relation.

4.3 Robustness Checks

We repeat our analysis in Equation 13 by replacing the $NoiseShare$ with HM price delay and return autocorrelation, which have a correlation of 0.23 and 0.47 to $NoiseShare$ respectively. To be consistent with the notion that sentiment beta attenuates the IO-Efficiency relation, we also expect that sentiment beta attenuates the impact of institutional ownership on reducing price delay and return autocorrelation. That is, the interaction term should be significantly positive for both regressions.

Table 7 reports the result. Columns (1) to (3) present the FMB regression results, while Columns (4) to (6) present the panel regression results. As expected, in FMB regression with price delay (autocorrelation) as the price efficiency measure, the coefficient on the interaction term is 0.026 (0.014), both significant at 1% level. Thus, though different price efficiency measures are estimated using different information sets, and hence capture the different dimensions of price efficiency, the weakening impact of sentiment beta on the IO-Efficiency relation remains significant. The results also hold qualitatively similar in panel regression.

[Insert Table 7 around here]

In Panel B of Table 7, we replace the independent variable with the number of institutions. We find similar results relative to our baseline analysis. For instance, in Column (1), we observe that a larger number of institutions holding a share is associated with a lower noise share (indicating higher price efficiency). This relation is attenuated by sentiment beta, as evidenced by the significant coefficient of 0.246 on the interaction term between sentiment beta and the number of institutions. Similarly, when using alternative price efficiency measures (HM price delay and return autocorrelation) and replacing institutional ownership with the number of institutions, the interaction term between sentiment beta and the number of institutions remains significantly positive across both FMB and panel regressions.

Overall, our findings suggest that the impact of sentiment beta on the IO-Efficiency relation is robust to alternative measures of both price efficiency and institutional holdings. These results confirm that sentiment beta consistently moderates the role of institutional investors in enhancing price efficiency across different specifications.

4.4 Additional Subsample Analysis

Given that our sample spans a 40-year period during which institutional ownership has significantly increased, we assess how the findings have evolved over time. From Figure 1, we observe that both institutional ownership and short interest were relatively low and increased at a modest rate before 2000. Since then, both have risen sharply until the global financial crisis. Afterward, institutional ownership resumed its increase at a lower rate, while short interest declined and stabilized at a level of around 4.5%. Thus, we designate 2000Q1 as the cutoff point and divide the full sample into two periods, one spanning from 1980Q2 to 1999Q4, and the other from 2000Q1 to 2022Q2. Each covers an approximate 20-year window, and within each we repeat the analysis conducted in Table 4.

Table 8 reports the regression results for two subsample analyses. First, institutions have overall contributed to price efficiency over the past four decades. For both subsamples and across the five sentiment beta groups, the coefficients of institutional ownership are significantly negative at the 1% level. This indicates that higher institutional ownership leads to a lower noise share. Additionally, the increasing participation of institutional investors over time has also enhanced their positive impacts on price efficiency. Taking the low-sentiment-beta group of stocks as an example, the absolute value of the coefficient increases from 4.33 to 7.91, moving from the first half to the second half of the sample period. This is further confirmed by short interest, which has long served as a proxy for arbitrage trades (Boehmer et al., 2008, 2010; Hanson & Sunderam, 2014). Higher institutional ownership tends to facilitate short-selling activities by ensuring sufficient stock loan supply. The short interest is significantly and negatively associated with noise share (see Panel B of Table 8) across all five sentiment beta groups in the second half of the sample period. Notably, this pattern was not observed during the first half.

[Insert Table 8 around here]

Second, the cross-sectional impact of sentiment beta is more pronounced in the second half of the sample period. In the first half, moving from the low- to high-sentiment-beta groups, the coefficients of institutional ownership do not exhibit an obvious pattern. Though the coefficient for the high-sentiment-beta group is higher than that of the low-sentiment-beta group, the difference is not statistically significant. Panel C of Table 8 reports the results of test on coefficient differences. The difference between the high- and low-sentiment-beta groups is 1.65, but not significant. However, in the second half, the coefficient monotonically increases from -7.91 to -2.46. The difference, equal to 5.54, is statistically significant at 1% level. Thus, this pattern is pronounced mainly in the second half of the sample period.

5 The Arbitrage Asymmetry Feature of Investor Sentiment

Motivated by arbitrage asymmetry proposed by Stambaugh et al. (2012, 2015), we examine the time series impact of investor sentiment in this section. Investor sentiment also manifests its impact on the stock market over time. During optimistic (pessimistic) sentiment periods, overpricing (underpricing) in the stock market is more likely in general, and stocks that are prone to sentiment impacts are expected to be more significantly affected during these periods. Stambaugh et al. (2012) show that sentiment's ability to forecast long-short return spreads primarily stems from its predictability of returns on the short leg. They explain that this effect arises due to arbitrage asymmetry. When sentiment is high, sentiment-driven noise traders exhibit a strong positive demand for many stocks; but when sentiment is low, they lack an equivalent negative demand, often due to constraints or unwillingness to engage in short selling. In a later research on the idiosyncratic volatility (IVOL) puzzle, Stambaugh et al. (2015) find investor sentiment exerts a greater effect on the negative IVOL-return relation among overpriced stocks than on the positive IVOL-return relation among underpriced stocks. Thus, in this section, we examine the implications of arbitrage asymmetry for the impact of sentiment beta on the IO-Efficiency relation (Hypothesis 2).

When applied to our analysis of the impact of sentiment beta on the IO-Efficiency relation, arbitrage asymmetry predicts a more pronounced weakening effect of sentiment beta during pessimistic quarters. Optimistic periods typically feature market-wide overpricing, as reflected in the BW investor sentiment measure, which is constructed from market-wide trading proxy variables capturing prevailing optimism or pessimism. Consequently, we expect a widespread weakening of the IO-Efficiency relation across all five sentiment beta groups during optimistic quarters. In other words, the coefficients on institutional ownership in Equation 11 are expected to be higher (i.e., less negative) across the five sentiment beta groups during optimistic quarters, indicating a weaker impact.

Conversely, during moderate or pessimistic quarters, the direct influence of investor sentiment diminishes, allowing sentiment beta to become more discernible. In these scenarios, stocks with a high sentiment beta are disproportionately affected relative to their low-sentiment-beta counterparts, due to differences in sensitivity to investor sentiment across the cross-section. Accordingly, we expect the coefficients on institutional ownership to be lower (i.e., more negative) across the five sentiment beta groups, with a more pronounced difference between low- and high-sentiment-beta groups during pessimistic quarters.

To explore the investor sentiment implications, we first define the optimistic (pessimistic) sentiment quarters as those where beginning-of-quarter BW investor sentiment is above (below) the median level over the full sample from 1980Q1 to 2022Q2. This binary split is in line with the practices in previous literature, such as Stambaugh et al. (2015), DeVault et al. (2019), and Chen et al. (2021). In each subsample, we repeat the analysis of Equation 11 for five sentiment-beta groups.

Table 9 reports the regression results for both optimistic and pessimistic sentiment quarters. Again, all coefficients of institutional ownership are significantly negative at 1% level, corroborating the finding that institutions overall contribute to the price efficiency. Our primary focus is instead on examining how the coefficients on institutional ownership differ both across sentiment beta groups and between optimistic and pessimistic quarters. First, as expected, institutional ownership has a weaker impact on price efficiency during optimistic quarters. The difference in IO coefficients between optimistic and pessimistic quarters ranges from 2.34 to 3.28 across the lower four sentiment beta groups and is statistically significant. One notable finding is that for the high sentiment beta group, the coefficients on institutional ownership do not show significant variation (i.e., an insignificant difference of -0.25) in either optimistic or pessimistic quarters. This suggests that the cross-sectional weakening effect of sentiment predominantly stems from stocks in high-sentiment-beta groups. These stocks present consistent challenges to institutions in maintaining price efficiency across various time periods.

[Insert Table 9 around here]

Second, and more importantly, the weakening effect of sentiment beta is more pronounced in pessimistic quarters. From low- to high-sentiment-beta groups, the coefficient on IO increases from -7.40 to -2.46, indicating a sharp decline in IO's impact on price efficiency. Figure 4 visualizes the absolute value of coefficients across both sentiment beta groups and between optimistic and pessimistic quarters. Panel C of Table 9 reports the formal test of the coefficient difference. The difference is 5.08, significant at 1% level. We also investigate the impact of extreme investor sentiment on the IO-Efficiency relation and refine our analysis by partitioning quarters into three groups, high-/medium-/low-sentiment quarters (top

25%/middle 50%/bottom 25%). The results, which are qualitatively similar, are presented in the Appendix.

[Insert Figure 4 around here]

Overall, our findings lend support to Stambaugh et al. (2015)'s arbitrage asymmetry framework. Specifically, our analysis shows that the IO-Efficiency relation is weaker across nearly all five sentiment beta groups during optimistic quarters, suggesting that arbitrage risk and difficulty are stronger in these periods. Additionally, our results corroborate our hypothesis that the weakening effect of sentiment beta is more pronounced in pessimistic quarters, where stocks with a high sentiment beta are disproportionately impacted relative to their low-sentiment-beta counterparts.

6 Institutional Investors' Reaction to Sentiment Beta

We then examine the institutions' response to sentiment impact. Prior analysis in Section 4.4 reveals that the weakening effect of sentiment beta is more pronounced in the second half of the sample period, during which institutional investors significantly increased their ownership and dominated the market. This concurrent pattern leads us to investigate how institutional investors, as a group, adjust their allocation strategies in response to sentiment-driven market conditions. Institutions may increase their exposure to high-sentiment-beta stocks in the second half of the period, potentially amplifying sentiment-driven trading patterns and contributing to a significantly weaker IO-Efficiency relation. Thus, in the following analysis, we test Hypothesis 3, which examines the relation between institutional ownership and sentiment beta.

To explore whether institutional investors riding with sentiment, or the presence of limits to arbitrage, deters the arbitrage and leads to a weaker relation between institutional ownership and price efficiency, we consider examining how they respond to sentiment beta. Specifically, we follow Glushkov (2006) and estimate the following FMB regression,

$$IO_{it} = \alpha_0 + \beta_1 |SBeta|_{i,t-1} + \sum_{k=2}^{K} \beta_k X_{ki,t-1} + \epsilon_{it}, \tag{14}$$

If institutional investors exploit the sentiment impacts, β_1 is expected to be positive; whereas if they trade against sentiment beta, β_1 should be significantly negative.

Table 10 reports the regression result. In Column (1), β_1 is -0.022, significant at 1% level, indicating that a 1.35 increase in sentiment beta leads to a 2.97 percentage-point decrease in institutional ownership[11], moving from low- to high-sentiment-beta averages. Column (2) further introduces the control variables that have impacts on institutional ownership. The coefficient on sentiment beta halves, yet remains significant at 1% level. In addition, as expected, institutional investors prefer larger, less risky, and liquid stocks, largely consistent with existing literature (e.g., Boehmer and Kelley, 2009; Nagel, 2005).

To better understand the impact of sentiment beta on institutional investors, we also investigate whether the institutions' responses to positive- and negative-sentiment-beta stocks differ. Recall that stocks with positive (negative) sentiment beta primarily have their demand driven by momentum (contrarian) sentimental traders. We first include a dummy variable for stocks with raw sentiment beta, i.e., $I_{SBeta>0} = 1$. Column (3) of Table 10 reports the result. The interaction term of sentiment beta and the dummy of raw sentiment beta has a coefficient of -0.013 and is significant at 1% level, while the coefficient on sentiment beta is an insignificant -0.004. This indicates that institutional investors hold fewer stocks with positive exposure to sentiment changes while remaining relatively insensitive to stocks with negative exposure to sentiment changes.

[Insert Table 10 around here]

We then investigate how institutions' response to sentiment beta evolves with time. Align with practice in section 4, we partition into two subsamples, with one ranging from 1980Q1 to 1999Q4 and the other ranging from 2000Q1 to 2022Q2. We repeat the analysis conducted in Table 10.

Table 11 reports the result for subsample analysis. First, institutional investors traded against sentiment beta over the past four decades. The coefficient for the first-half subsample is -0.02 and is significant at 1% level. Though it increases to -0.004, it remains significantly negative at 5% level. This increase implies that institutional investors are trading less against sentiment, yet their contrarian stance is still evident. This is also supported by the coefficients of the interaction term (See Columns 2 and 6). It slightly increases from -0.017 in the first half to -0.010 in the second half; however, these values are not significantly different from each other. This implies that institutions' attitudes toward stocks with positive sentiment exposure remain relatively consistent across both periods. Second,

[11] The means of sentiment beta in low- and high-group are 1.94 and 3.29. Thus, a 1.35 increase in sentiment beta leads to 2.97% decrease in institutional ownership (1.35*0.022=3.08%).

nevertheless, institutional investors slightly shifted their preferences. There is some evidence that institutional investors shifted their preferences toward riskier stocks. For example, the coefficient of standard deviation changes from significantly negative to positive, though it is not statistically significant. This echoes the findings of Bennett et al. (2003), who document that institutions exhibited a shift of preference to smaller and riskier securities that offer "greener pastures" since 1990s. They also add that this change of aggregate preference arose from each class of institution, rather than changes in the importance of different classes. Moreover, institutions have shown an increased preference for liquid stocks.

[Insert Table 11 around here]

Overall, our findings reveal that although institutional investors slightly shift their preference to riskier stocks from the first half to the second half of the sample and respond less contrarily to sentiment beta, they stay trading against sentiment's impact. We consider two reasons. First, institutions make decisions based more on factors other than sentiment beta. Given the same model setting with the same variables, the goodness-of-fit of the model is higher for regression in the second half, which is around 40% . This implies the explanatory power of our control variables on institutional ownership has improved. Second, as institutional ownership increases, the ownership of individual investors, who are natural candidates for sentimental traders, decline,s and hence the overall sentiment impact has been more moderate. Figure 5 plots the time series of coefficients of sentiment beta ($|SBeta|$) from regression stated in Equation 14 with the BW sentiment index. As observed, the time series of coefficients is negatively correlated with sthe entiment index. Since 2000, the sentiment index has been more moderate, so has the institutions' reaction to sentiment beta.

So far, we find that institutional investors trade against sentiment beta, and slightly shift their preferences and emphasize factors other than sentiment beta in investment decision-making. However, it is unclear how these behaviors link to price efficiency. Bennett et al. (2003) show that all classes of institutions (e.g., mutual fund, hedge fund, bank) have shifted their preference towards riskier stocks, which in general have higher exposure to sentiment, since the 1990s. Within the institution group, different classes can differ from each other. For example, Akbas et al. (2015) show that mutual funds are "dumb money" exacerbating anomalies, whereas hedge funds are "smart money" correcting anomalies. This evidence, along with our findings, suggests that institutional investors across all classes, whether due to universal shifting preferences or heterogeneous preferences among classes, base their investment decisions on a combination of sentiment consideration and other factors, such as liquidity and volatility.

We then follow Nagel (2005) and Boehmer and Kelley (2009), decomposing institutional ownership into components. Nagel (2005) regresses institutional ownership on stock's size to purge size effects and obtain "residual institutional ownership". Boehmer and Kelley (2009), in an attempt to address that the contribution of institutional ownership to price efficiency does not arise from the improvement of liquidity, regress institutional ownership on liquidity to have liquidity-predicted IO and residual IO, and show that residual IO contributes to the price efficiency. In our context, we decompose institutional ownership into two components: sentiment-beta-driven IO and residual IO. Sentiment-beta-driven IO can be regarded as the institutional ownership predicted by stocks' sentiment beta, which accounts for sentimental trading. Thus, the residual IO, subsequently referred to as discretionary IO, reflects the discretion of institutions based on fundamental factors other than sentiment beta. We follow Nagel (2005), first performing the logit transformation for institutional ownership to improve the regression's specification and then estimating the following cross-section regression in each quarter t,

$$\text{logit}\,(IO_{i,t}) = \log\left(\frac{IO_{i,t}}{1-IO_{i,t}}\right) = \alpha + \beta|SBeta|_{i,t-1} + \varepsilon_{i,t}, \tag{15}$$

we obtain sentiment-beta-driven institutional ownership as $Predicted\_IO = \hat{\alpha}+\hat{\beta}|SBeta|_{i,t-1}$, and discretionary institutional ownership, $Residual\_IO$. It is expected that discretionary IO is negatively related to noise share if institutions are sophisticated and incorporate fundamental information into stock prices.

Table 12 reports the result. To make the transformed institutional ownership comparable, we first regress noise share on logit institutional ownership and other control variables. The coefficient, -0.493, therefore serves as a benchmark. As expected, the discretionary institutional ownership negatively predicts the noise share, implying that institutions' discretion based on fundamental information rather than sentiment beta contributes to the informational efficiency of stock prices. Column 2 and 3 includes $Residual\_IO$ and $Predicted\_IO$ as explanatory variable, respectively. Notably, the coefficient for residual IO is significantly negative at -0.566. In contrast, the coefficient for sentiment-beta-driven predicted IO is positive. This suggests that ownership driven by sentiment-beta may impair price efficiency, although this finding is only marginally significant. In Column 4, we include both predicted and residual IO and observe similar results.

[Insert Table 12 around here]

[Insert Figure 5 around here]

Overall, our findings suggest that sentiment-beta-driven institutional ownership does not significantly affect the price efficiency, while the decision based on factors other than sentiment beta, such as fundamental information, significantly contributes to the price efficiency.

7 Conclusion

Higher institutional ownership is associated with higher informational efficiency of stock prices (Boehmer & Kelley, 2009; Cao et al., 2018). This study investigates the impact of investor sentiment on this IO-Efficiency relation. Investor sentiment has long been documented to affect both the stock price efficiency (Baker & Wurgler, 2007; Edmans et al., 2022; Stambaugh et al., 2015, among others), and institutional investors' decision-making (Chen et al., 2021; Gao et al., 2023; Massa & Yadav, 2015, among others). While prior studies have largely focused on the time-series impact of investor sentiment (Gao et al., 2020; Stambaugh et al., 2012, among others), this study shifts the focus to the cross-sectional implication of investor sentiment by examining the impact of sentiment beta on IO-Efficiency in a broad sample of NYSE/AMEX/NASDAQ listed common stock between 1980Q1 and 2022Q2. We find that sentiment beta attenuates the IO-Efficiency relation, where as sentiment beta increases the negative relation between institutional ownership and noise share weakens.

We then examine how the impact of sentiment beta varies across periods of differing investor sentiment. Our results indicate a broad attenuation of the IO-Efficiency relation during optimistic quarters, as institutional ownership's influence on price efficiency weakens across nearly all sentiment beta groups. Furthermore, the impact of sentiment beta on the IO-Efficiency relation appears negligible in optimistic quarters, whereas it remains significant in pessimistic quarters. This asymmetry supports the arbitrage constraints framework proposed by Stambaugh et al. (2015), which suggests that institutional investors face greater challenges in correcting mispricing when sentiment is high, as widespread optimism fuels sustained demand from noise traders. In contrast, during low-sentiment periods, sentiment beta plays a more discernible role in shaping institutional ownership's effectiveness in promoting price efficiency.

We also examine the dynamics of sentiment beta's impact over time. We find that the impact of sentiment beta is more pronounced in the second half of our sample period through 2000Q1 to 2022Q2, during which institutional investors grow to dominate the market. We continue to rule out the possibility that the attenuation impact of sentiment beta is attributable to institutional investors themselves being sentimental traders. First, institutional investors overall trade against sentiment beta. Second, by decomposing institutional ownership into sentiment-driven and discretionary components, we show that discretionary IO can significantly improve the informational efficiency of stock prices, whereas sentiment-driven IO cannot. This suggests that decisions made by institutional investors, based on stock characteristics other than sentiment beta, contribute to price efficiency, reinforcing their role in maintaining it.

Overall, our findings highlight the cross-sectional impact of investor sentiment on both institutional investors and the informational efficiency of stock prices. The conventional studies on investor sentiment assume that sentiment captures individual investors' aggregate sentiment-driven demands. However, DeVault et al. (2019) highlight the relations between investor sentiment, and individual and institutional investors are far more complicated. There is also evidence that institutions either irrationally trade with (e.g., Brunnermeier and Nagel, 2004) or rationally time (e.g., Chen et al., 2021) the investor sentiment, raising questions on the arbitrageur role of institutional investors. This study contributes by providing direct evidence on the interrelation among investor sentiment, institutional investors, and price efficiency.

While our results demonstrate an association, they do not necessarily establish causation. Future research can advance the literature by developing a clear causal framework that links market sentiment to institutions' trading behavior and, subsequently, to price efficiency. However, this remains a challenging endeavor due to the complexities of isolating causal effects in financial markets, particularly given the nuanced relation between institutional investors and investor sentiment. Furthermore, the interplay among these three factors warrants deeper exploration in future studies to shed light on this traditional yet evolving topic.

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Tables

Table 1: Descriptive Statistics

This table reports descriptive statistics for the sample variables, all of which are constructed at quarterly level, covering the period from 1980Q1 to 2022Q2. It reports the time-series means of cross-section mean, median, standard deviation for all variables, except for investor sentiment index ($SENT$) whose statistics are directly calculated based on the time series data. The table also reports means and standard deviations of variables for High (Low) sentiment periods, defined as quarters with sentiment level falls within the top (Bottom) 25%. Panel A reports the price efficiency measures. $Noise$ is the variance contribution of pricing error in stock return, and $NoiseShare$ is share of variance attributable to $Noise$, following Brogaard et al. (2022b). HM is the delay of stock price responses to market-wide information, following Hou and Moskowitz (2005). $AutoCorr$ is the absolute value of first-order autocorrelation of daily stock return, following Chordia et al. (2005). Panel B reports the institutional ownership. IO is the ratio of aggregate common shares held by 13F institutional investors to total quarter-end shares outstanding, and No.of IO indicates the number of institutional investors. Panel C reports the sentiment measures. $SENT$ is the quarterly-average of the monthly BW sentiment index Baker and Wurgler (2006). $Sbeta$ is original sentiment beta, which is the loading on change of sentiment index estimated under Fama-French 3-factor model using a 36-month window, while $|SBeta|$ refers to Bayesian-Stein shrunk sentiment beta, the weighted average of sentiment beta and shrinkage target derived from prior information, following Glushkov (2006). 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. SD is the quarterly standard deviation of daily stock return. PRC is the quarter-end adjusted closing price, and $ASSET$ is the quarter-end book value of assets. BM is the book-value of equity to market value of equity. All continuous variables are winsorized at 1% and 99% within each quarter.

						High		Low	
	Mean	Median	Std	Min	Max	Mean	Std	Mean	Std
Panel A: Price Informational Efficiency									
$Noise$(%)	1.96	1.71	1.07	0.55	5.82	1.97	1.09	1.82	1.03
$NoiseShare$(%)	34.71	30.61	16.49	10.87	84.92	35.14	16.84	33.37	15.83
HM	0.47	0.43	0.28	0.04	0.99	0.54	0.29	0.40	0.28
$AutoCorr$	0.15	0.12	0.12	0.01	0.50	0.15	0.12	0.14	0.11
Panel B: Institutional Ownership									
IO	0.49	0.51	0.24	0.02	0.91	0.41	0.22	0.56	0.25
No. of IO	128	78	155	6	897	95	125	157	180
Panel C: Sentiment Measures									
$SENT$	0.23	-0.02	0.05	-0.89	2.64	1.11	0.65	-0.40	0.22
$SBeta$	0.06	0.04	2.73	-7.77	8.43	0.04	1.94	0.07	3.15
$\|SBeta\|$	2.41	2.21	0.70	1.68	5.30	1.75	0.52	2.81	0.80
Panel D: Stock Characteristics									
$ILLIQ$	0.17	0.03	0.45	0.00	2.92	0.17	0.37	0.17	0.48
SIR	0.03	0.02	0.03	0.00	0.18	0.02	0.02	0.04	0.04
SD(%)	2.68	2.41	1.26	0.72	7.26	2.63	1.27	2.50	1.17
PRC($)	24.50	17.65	21.59	5.17	126.48	22.15	20.13	25.76	22.06
$ASSET$($m)	4,942	704	15,073	17	113,167	3,650	10,912	6,096	18,584
BM	0.66	0.58	0.42	0.06	2.18	0.67	0.41	0.70	0.45

Table 2: Stock Characteristics and Sentiment Beta: Sorted on Sentiment Beta

This table reports the average price efficiencies, institutional ownership, and stock characteristics within each of 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 2022Q2. Sentiment beta portfolios are constructed by sorting stocks on lagged Bayesian-Stein shrunk sentiment beta, 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.

	$\|SBeta\|$	$Noise$	$NoiseShare$	HM	$AutoCorr$	IO
Low	1.94	1.63	35.04	0.44	0.15	0.51
2	2.03	1.66	34.97	0.44	0.15	0.52
2	2.20	1.73	34.84	0.44	0.15	0.52
4	2.47	1.86	34.30	0.45	0.15	0.52
High	3.29	2.23	33.46	0.47	0.14	0.50
High-Low Mean	1.35***	0.60***	-1.58***	0.04***	-0.01***	-0.02**
High-Low T-value	(14.04)	(15.34)	(-6.02)	(4.95)	(-6.31)	(-2.20)
	SIR	$ILLIQ$	SD	$ln(PRC)$	$ln(ASSET)$	$ln(BM)$
Low	0.02	0.15	2.23	3.02	7.05	-0.60
2	0.02	0.15	2.27	3.01	6.99	-0.60
3	0.03	0.16	2.37	2.98	6.87	-0.61
4	0.03	0.16	2.56	2.91	6.58	-0.63
High	0.04	0.16	3.12	2.72	5.92	-0.75
High-Low Mean	0.01***	0.01	0.90***	-0.30***	-1.14***	-0.15***
High-Low T-value	(8.39)	(0.63)	(14.27)	(-10.65)	(-17.03)	(-8.42)

Table 3: Noise Share Sorted by Sentiment Beta and Institutional Ownership

This table reports the average noise share for 25 portfolios constructed by sorting on institutional ownership (IO) and sentiment beta ($|SBeta|$), covering the sample period from 1980Q2 to 2022Q2. Panel A reports for independent sorts, first sorting stocks on beginning-of-quarter sentiment beta to 5 quintile groups and then independently sorting stocks on beginning-of-quarter institutional ownership to 5 quintile groups, in each quarter. Panel B reports for dependent sorts, first sorting stocks on beginning-of-quarter sentiment beta to 5 quintile groups, within which sorting on beginning-of-quarter institutional ownership into 5 groups, in each quarter. 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.

Panel A: Independent Sorting

	Low IO	2	3	4	High IO	HML	All Stocks
Low $\|SBeta\|$	43.37	36.46	33.68	32.06	30.97	-12.40***	35.31
						(-13.75)	
2	42.98	36.48	33.96	32.14	30.90	-12.08***	35.29
						(-13.88)	
3	42.62	36.67	33.68	32.08	30.79	-11.83***	35.17
						(-12.36)	
4	40.69	35.92	33.33	32.10	30.77	-9.92***	34.56
						(-12.60)	
High $\|SBeta\|$	37.71	34.28	32.80	31.52	30.62	-7.09***	33.39
						(-11.48)	
HML	-5.67***	-2.18***	-0.88***	-0.54***	-0.35	**5.32*** **	-1.92***
	(-10.56)	(-6.29)	(-3.38)	(-2.67)	(-1.62)	**(11.17)**	(-8.30)
All Stocks	41.473	35.963	33.489	31.979	30.81	-10.66***	34.74
						(-13.35)	

Panel B: Dependent Sorting

	Low IO	2	3	4	High IO	HML
Low $\|SBeta\|$	42.99	36.03	33.27	31.97	30.90	-12.09***
						(-13.89)
2	42.60	35.94	33.51	31.92	30.85	-11.75***
						(-13.49)
3	42.25	35.94	33.34	31.85	30.79	-11.46***
						(-12.02)
4	40.36	35.42	33.09	31.93	30.70	-9.63***
						(-12.31)
High $\|SBeta\|$	37.75	34.30	32.97	31.59	30.69	-7.07***
						(-11.49)
HML						**5.02*** **
						(10.21)

Table 4: FMB Regression of Noise Share on Institutional Ownership Conditional on Sentiment Beta

This table reports estimates from the Fama-Macbeth Regression procedure, where the estimates are time-series means of coefficients from cross-sectional regressions of noise share ($NoiseShare_{i,q}$) on lagged institutional ownership ($IO_{i,q-1}$) and other control variables based on sentiment beta groups, covering sample period from 1980Q2 to 2022Q2. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Panel A reports estimates for 5 sentiment beta subsamples, where Column 1 reports estimated coefficients from subsample of stocks with sentiment beta being the lowest 20%, while Column 5 reports for subsample of stocks with highest 20% in sentiment beta. Panel B reports the test for the coefficient difference. D_1 and D_5 are dummy variables for stocks with lowest 20% and highest 20% in sentiment beta, $D_1 * IO$ and $D_5 * IO$ are the interaction of dummy terms and institutional ownership, whose difference is the test of interest.

Panel A: FMB Regression of Noise Share on IO for 5 Sentiment Beta Groups

	(1) Full Sample	(2) $Low\|SBeta\|$	(3) 2	(4) 3	(5) 4	(6) $High\|SBeta\|$
$IO_{i,q-1}$	**-4.159*** **	**-6.236*** **	**-5.354*** **	**-5.676*** **	**-3.905*** **	**-2.580*** **
	(-8.10)	**(-8.66)**	**(-7.73)**	**(-10.75)**	**(-8.59)**	**(-5.65)**
$NoiseShare_{i,q-1}$	0.091***	0.079***	0.086***	0.078***	0.073***	0.053***
	(9.45)	(8.17)	(7.60)	(7.39)	(6.15)	(6.83)
$ln(ILLIQ)_{i,q}$	15.900***	15.921***	16.085***	16.708***	15.611***	15.515***
	(7.28)	(7.28)	(8.02)	(8.43)	(7.81)	(9.08)
$ln(SIR)_{i,q-1}$	-14.590***	5.213	-8.921	-32.304**	-20.854**	-18.273**
	(-5.44)	(0.37)	(-0.88)	(-2.15)	(-2.03)	(-2.35)
$ln(PRC)_{i,q-1}$	0.160	0.373***	0.469***	0.298*	-0.058	-0.132
	(2.66)	(2.66)	(3.44)	(1.69)	(-0.34)	(-0.77)
$ln(ASSET)_{i,q-1}$	0.038	0.062	-0.094	0.024	0.065	0.067
	(0.66)	(0.66)	(-1.21)	(0.30)	(1.04)	(0.96)
$ln(BM)_{i,q-1}$	0.429***	0.265	0.614***	0.216	-0.014	0.249
	(1.48)	(1.48)	(3.89)	(1.20)	(-0.09)	(1.54)
N	270,132	50,506	50,164	49,357	47,835	44,399
adj. R^2	8.7%	10.4%	10.0%	9.4%	7.8%	5.7%
No. of Groups	169	169	169	169	169	169

Panel B: Test the Difference of Coefficient on IO

IO	D_1	D_5	$D_1 * IO$	$D_5 * IO$	$D_5 * IO - D_1 * IO$
-4.403***	0.964***	-2.215***	**-1.094** **	**2.624*** **	**3.718*** **
(-12.35)	(3.22)	(-6.19)	**(-2.21)**	**(5.10)**	**(27.06)**

Table 5: FMB Regression of Noise Share on Institutional Ownership and Sentiment Beta

This table reports estimates from the Fama-Macbeth Regression procedure, where the estimates are time-series means of coefficients from cross-sectional regressions of noise share on lagged institutional ownership and sentiment beta, and other control variables, covering sample period from 1980Q2 to 2022Q2. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. $IO * |SBeta|$ is the interaction term of institutional ownership and sentiment beta.

	(1)	(2)	(3)	(4)	(5)	(6)
$IO_{i,q-1}$	-11.565***		-12.735***	-19.819***	-11.973***	-9.275***
	(-16.21)		(-16.83)	(-16.81)	(-13.66)	(-8.37)
$\|SBeta\|_{i,q-1}$		-0.550***	-0.901***	-2.306***	-2.193***	-1.511***
		(-4.42)	(-8.02)	(-11.04)	(-11.07)	(-6.05)
$IO \times \|SBeta\|_{i,q-1}$				**3.058*****	**2.694*****	**1.584*****
				(10.33)	**(8.70)**	**(3.31)**
$NoiseShare_{i,q-1}$	0.204***	0.224***	0.180***	0.178***	0.119***	0.079***
	(9.91)	(9.87)	(8.61)	(8.51)	(8.19)	(8.86)
$ln(ILLIQ)_{i,q}$					19.052***	15.650***
					(15.86)	(8.68)
$ln(SIR)_{i,q-1}$						-11.295**
						(-2.28)
$ln(PRC)_{i,q-1}$						0.188*
						(1.87)
$ln(ASSET)_{i,q-1}$						0.005
						(0.08)
$ln(BM)_{i,q-1}$						0.262**
						(2.19)
N	395,633	336,635	336,635	336,635	335,648	242,261
adj. R^2	10.2%	6.7%	10.0%	10.2%	14.6%	8.7%
No. of Groups	169	169	169	169	169	169

Table 6: Robustness Check by Estimating Panel Regression

This table reports estimates from panel regression of noise share on lagged institutional ownership, and/or sentiment beta, and other control variables, with stock fixed effects and quarter fixed effects. The first 5 Columns repeat the analysis in Table 4, while Column 6 repeats the analysis in Table 5. T-statistics, computed based on robust standard errors clustered at both stock and quarter levels, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Sentiment Beta Group					
	Low $\lvert SBeta\rvert$	2	3	4	High $\lvert SBeta\rvert$	
$IO_{i,q-1}$	-5.613***	-4.562***	-3.530***	-2.817***	-1.008	-4.451***
	(-4.89)	(-4.25)	(-3.69)	(-2.96)	(-1.05)	(-5.67)
$NoiseShare_{i,q-1}$	0.003	0.024***	0.014**	0.002	-0.046***	0.024***
	(0.40)	(3.82)	(2.07)	(0.34)	(-7.49)	(6.09)
$ln(ILLIQ)_{i,q}$	13.724***	13.682***	16.515***	17.859***	15.327***	14.845***
	(8.23)	(9.05)	(10.43)	(12.16)	(11.20)	(12.64)
$ln(SIR)_{i,q-1}$	3.503	-1.074	-2.158	-4.188	-1.727	-1.741
	(1.07)	(-0.30)	(-0.70)	(-1.57)	(-0.71)	(-0.91)
$ln(PRC)_{i,q-1}$	1.748***	1.485***	1.013***	0.865***	0.640**	1.075***
	(5.07)	(4.27)	(3.75)	(3.35)	(2.42)	(5.87)
$ln(ASSET)_{i,q-1}$	-1.026***	-0.652**	-0.668***	-0.472*	-0.337	-0.556***
	(-3.73)	(-2.14)	(-2.71)	(-1.83)	(-1.55)	(-4.21)
$ln(BM)_{i,q-1}$	0.906***	0.866***	0.317	0.467*	0.534**	0.554***
	(3.03)	(3.24)	(1.24)	(1.80)	(2.34)	(4.04)
$\lvert SBeta\rvert_{i,q-1}$						-0.234
						(-1.56)
$IO \times \lvert SBeta\rvert_{i,q-1}$						**0.383***
						(1.66)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	49,467	49,155	48,271	46,869	43,567	241,888
adj. R^2	19.0%	17.5%	16.8%	14.4%	12.2%	15.6%

Table 7: Robustness Check using the Alternative Measures of Dependent and Independent Variable

This table reports the estimates of robustness checks using alternative measures of price (in)efficiency and/or institutional holdings. Columns 1 to 3 (Column 4 to 6) present the Fama-MacBeth Regression (panel regression) estimates with the dependent variable being NoiseShare, HM price delay, and Autocorrelation respectively. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags (robust standard errors clustered at both stock and quarter levels) for Fama-MacBeth (panel) regression, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. For brevity, we only tabulate the coefficients on key explanatory variables. Panel A uses institutional ownership as the independent variable, while Panel B replaces it with the number of institutions.

	FMB Regression			Panel Regression		
	$NoiseShare_{iq}$	HM_{iq}	$AutoCorr_{iq}$	$NoiseShare_{iq}$	HM_{iq}	$AutoCorr_{iq}$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Independent Variable is Institutional Ownership						
$IO_{i,q-1}$	**-9.275*****	**-0.180*****	**-0.059*****	**-4.451*****	**-0.181*****	**-0.024*****
	(-8.37)	(-8.80)	(-7.36)	(-5.67)	(-11.81)	(-4.39)
$\|SBeta\|_{i,q-1}$	-1.511***	-0.013***	-0.012***	-0.234	-0.010***	-0.002**
	(-6.05)	(-3.51)	(-6.57)	(-1.56)	(-3.75)	(-2.02)
$IO \times \|SBeta\|_{i,q-1}$	**1.584*****	**0.026*****	**0.014*****	**0.383***	**0.010*****	**0.003****
	(3.31)	(3.74)	(4.46)	(1.66)	(3.01)	(2.00)
lagged DV	0.079***	0.267***	0.089***	0.024***	0.159***	0.029***
	(8.86)	(18.31)	(8.82)	(6.09)	(24.42)	(5.52)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock, Quarter FE	/	/	/	Yes	Yes	Yes
N	242,261	242,261	242,261	241,888	241,888	241,888
Adj. R^2	8.7%	34.2%	9.2%	15.6%	49.2%	15.6%
Panel B: Independent Variable is Number of Institutions						
$INST_{i,q-1}$	**-2.366*****	**-0.077*****	**-0.022*****	**-1.181*****	**-0.104*****	**-0.014*****
	(-5.69)	(-8.71)	(-7.92)	(-3.87)	(-15.54)	(-7.07)
$\|SBeta\|_{i,q-1}$	-1.663***	-0.023**	-0.016***	-0.421	-0.020***	-0.003*
	(-3.69)	(-2.52)	(-4.00)	(-1.12)	(-3.17)	(-1.94)
$INST \times \|SBeta\|_{i,q-1}$	**0.246****	**0.005****	**0.002****	**0.098**	**0.004*****	**0.001****
	(2.34)	(2.54)	(2.46)	(1.20)	(2.92)	(1.98)
lagged DV	0.078***	0.249***	0.084***	0.025***	0.151***	0.028***
	(8.77)	(15.99)	(8.54)	(6.13)	(23.91)	(5.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock, Quarter FE	/	/	/	Yes	Yes	Yes
N	242,261	242,261	242,261	241,888	241,888	241,888
Adj. R^2	8.7%	35.2%	9.5%	15.5%	49.6%	15.7%

Table 8: FMB Regression Subsample Analysis: 19980Q2 to 1999Q4 and 2000Q1 to 2022Q2

This table reports estimates from the Fama-Macbeth Regression procedure, where the estimates are time-series means of coefficients from cross-sectional regressions of noise share on lagged institutional ownership and other control variables based on sentiment beta groups. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Panel A reports the estimates from analysis on subperiod from 19980Q2 to 1999Q4, while Panel B reports for subperiod from 2000Q1 to 2022Q2. Panel C reports the test result of coefficient on IO between low- and high-sentiment-beta groups.

Panel A: Sub-period 1980Q2-1999Q4					
	(1)	(2)	(3)	(4)	(5)
	$Low\|SBeta\|$	2	3	4	$High\|SBeta\|$
IO	**-4.332*** **	**-3.394*** **	**-4.791*** **	**-3.070*** **	**-2.715*** **
	(-4.125)	**(-2.875)**	**(-5.266)**	**(-3.674)**	**(-3.059)**
$NoiseShare$	0.077***	0.091***	0.087***	0.074***	0.046***
	(4.610)	(4.108)	(4.250)	(3.289)	(3.473)
$ln(ILLIQ)$	8.937***	9.631***	10.131***	8.381***	9.939***
	(3.365)	(4.878)	(5.040)	(3.977)	(4.622)
$ln(SIR)$	17.706	-8.357	-60.294*	-34.000	-31.458*
	(0.599)	(-0.391)	(-1.985)	(-1.587)	(-1.974)
$ln(PRC)$	0.080	0.226	0.096	-0.535**	-0.581**
	(0.386)	(1.090)	(0.306)	(-2.117)	(-2.057)
$ln(ASSET)$	0.133	-0.070	0.003	0.051	0.177
	(0.779)	(-0.597)	(0.020)	(0.524)	(1.428)
$ln(BM)$	-0.088	0.549*	-0.053	-0.449**	0.135
	(-0.320)	(1.829)	(-0.175)	(-2.314)	(0.444)
N	13,210	13,036	12,606	11,552	9,532
adj. R^2	4.9%	5.3%	5.7%	4.5%	2.3%
No. of Groups	79	79	79	79	79

Panel B: Sub-period 2000Q1-2022Q2					
	(1)	(2)	(3)	(4)	(5)
	$Low\|SBeta\|$	2	3	4	$High\|SBeta\|$
IO	**-7.906*** **	**-7.075*** **	**-6.453*** **	**-4.638*** **	**-2.462*** **
	(-10.143)	**(-14.702)**	**(-12.668)**	**(-13.613)**	**(-6.869)**
$NoiseShare$	0.082***	0.083***	0.070***	0.072***	0.058***
	(7.749)	(9.232)	(8.869)	(7.116)	(6.987)
$ln(ILLIQ)$	22.052***	21.751***	22.481***	21.957***	20.409***
	(8.796)	(8.408)	(9.285)	(9.655)	(11.202)
$ln(SIR)$	-5.754*	-9.416**	-7.734**	-9.313***	-6.700***
	(-1.740)	(-2.595)	(-2.276)	(-4.289)	(-3.201)
$ln(PRC)$	0.631***	0.683***	0.476***	0.361**	0.261*
	(3.877)	(4.281)	(2.702)	(2.117)	(1.850)
$ln(ASSET)$	-0.001	-0.116	0.043	0.077	-0.030
	(-0.012)	(-1.110)	(0.428)	(0.959)	(-0.467)
$ln(BM)$	0.576***	0.671***	0.453**	0.369**	0.349**
	(2.885)	(4.912)	(2.481)	(2.015)	(2.421)
N	37,296	37,128	36,751	36,283	34,867
adj. R^2	15.2%	14.1%	12.6%	10.7%	8.3%
No. of Groups	90	90	90	90	90

Panel C: Test the Difference of Coefficient on IO between High- and Low-SBeta Groups						
	IO	D_1	D_5	$D_1 * IO$	$D_5 * IO$	$D_5 * IO - D_1 * IO$
1980Q2-199Q4	-3.587***	0.208	-1.057**	-0.000	1.645*	1.645
	(-6.07)	(0.59)	(-2.52)	(-0.01)	(1.87)	(1.96)
2000Q1-2022Q2	-5.119***	1.628***	-3.231***	-2.053***	3.484***	5.537***
	(-15.45)	(4.26)	(-8.01)	(-4.17)	(7.36)	(65.76)

Table 9: FMB Regression Subsample Analysis: High and Low Sentiment Quarters

This table reports estimates from the Fama-Macbeth Regression procedure, where the estimates are time-series means of coefficients from cross-sectional regressions of noise share on lagged institutional ownership and other control variables based on sentiment beta subsamples. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Panel A reports the estimates from analysis following high sentiment quarters, while Panel B reports for low sentiment quarters. Panel C reports the test result of coefficient on IO between low- and high-sentiment-beta groups.

Panel A: High Sentiment Quarters

	(1) $Low\|SBeta\|$	(2) 2	(3) 3	(4) 4	(5) $High\|SBeta\|$
IO	**-5.061*** **	**-3.706*** **	**-4.313*** **	**-2.658*** **	**-2.706*** **
	(-5.230)	**(-3.256)**	**(-6.069)**	**(-3.980)**	**(-3.434)**
$NoiseShare$	0.087***	0.092***	0.085***	0.084***	0.050***
	(5.932)	(4.843)	(4.316)	(4.304)	(4.139)
$ln(ILLIQ)$	13.245***	14.921***	14.101***	12.985***	13.430***
	(5.326)	(6.527)	(5.834)	(5.607)	(5.844)
$ln(SIR)$	3.241	-6.614	-39.675*	-24.875	-28.133*
	(0.193)	(-0.405)	(-1.709)	(-1.309)	(-1.960)
$ln(PRC)$	0.174	0.128	0.188	-0.471*	-0.345
	(0.714)	(0.634)	(0.643)	(-1.940)	(-1.358)
$ln(ASSET)$	0.179	-0.037	0.082	0.099	0.160*
	(1.144)	(-0.305)	(0.668)	(1.298)	(1.689)
$ln(BM)$	-0.017	0.450*	0.122	-0.302	0.403
	(-0.065)	(1.724)	(0.443)	(-1.471)	(1.600)
N	20,842	20,726	20,208	19,165	16,998
adj. R^2	7.1%	8.0%	7.3%	5.5%	4.4%
No. of Groups	84	84	84	84	84

Panel B: Low Sentiment Quarters

	(1) $Low\|SBeta\|$	(2) 2	(3) 3	(4) 4	(5) $High\|SBeta\|$
IO	**-7.396*** **	**-6.983*** **	**-7.023*** **	**-5.137*** **	**-2.456*** **
	(-7.869)	**(-11.978)**	**(-10.289)**	**(-9.675)**	**(-4.487)**
$NoiseShare$	0.072***	0.080***	0.071***	0.062***	0.055***
	(5.401)	(7.883)	(8.490)	(5.826)	(6.853)
$ln(ILLIQ)$	18.566***	17.235***	19.283***	18.205***	17.575***
	(5.960)	(5.399)	(6.836)	(6.170)	(8.290)
$ln(SIR)$	7.161	-11.201	-25.019*	-16.879**	-8.530
	(0.371)	(-1.422)	(-1.792)	(-2.102)	(-1.122)
$ln(PRC)$	0.571***	0.807***	0.408**	0.351*	0.078
	(4.129)	(4.947)	(2.465)	(1.889)	(0.280)
$ln(ASSET)$	-0.055	-0.151	-0.034	0.032	-0.026
	(-0.505)	(-1.566)	(-0.324)	(0.339)	(-0.296)
$ln(BM)$	0.544**	0.776***	0.310	0.271	0.097
	(2.204)	(4.403)	(1.410)	(1.366)	(0.513)
N	29,664	29,438	29,149	28,670	27,401
adj. R^2	13.6%	11.9%	11.5%	10.1%	7.1%
No. of Groups	85	85	85	85	85

Panel C: Test the Difference of Coefficient on IO between High- and Low-SBeta Groups

	IO	D_1	D_5	$D_1 * IO$	$D_5 * IO$	$D_5 * IO - D_1 * IO$
High Sentiment	-3.276***	0.558	-1.319**	-0.703	1.633**	2.336**
	(-5.482)	(1.431)	(-3.455)	(-1.062)	(2.207)	(5.54)
Low Sentiment	-5.517***	1.366***	-3.100***	-1.479*	3.604***	5.083***
	(-16.174)	(2.954)	(-6.156)	(-1.856)	(6.183)	(26.50)

Table 10: The Reaction of Institutional Ownership to Sentiment Beta

This table reports estimates from the Fama-Macbeth Regression procedure, where the estimates are time-series means of coefficients from cross-sectional regressions of institutional ownership on sentiment beta, and other control variables, covering sample period from 1980Q1 to 2022Q2. T-statistics, computed based on Newey-West standard errors Newey and West (1987) with 5 lags, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Column 4 and 5 display the estimates for subsample of stocks with negative and positive raw sentiment beta ($SBeta$), respectively.

	(1)	(2)	(3)	(4)	(5)
				$Sbeta < 0$	$Sbeta > 0$
$\|SBeta\|$	-0.022***	-0.011***	-0.004	-0.005	-0.016***
	(-3.91)	(-3.49)	(-1.40)	(-1.56)	(-3.60)
$I_{SBeta>0} * \|SBeta\|$			-0.013***		
			(-3.23)		
$ln(SD)$		-0.507	-0.502	-0.343	-0.627*
		(-1.53)	(-1.55)	(-1.02)	(-1.82)
$ln(ILLIQ)$		-0.444***	-0.443***	-0.468***	-0.433***
		(-13.82)	(-13.74)	(-12.47)	(-14.66)
$ln(SIR)$		1.202***	1.199***	1.354***	1.046***
		(7.60)	(7.67)	(7.37)	(4.71)
$ln(PRC)$		0.037***	0.037***	0.038***	0.036***
		(14.16)	(14.43)	(12.84)	(12.51)
$ln(ASSET)$		0.020***	0.020***	0.020***	0.020***
		(19.02)	(18.82)	(15.73)	(16.27)
$ln(BM)$		-0.017***	-0.017***	-0.020***	-0.014***
		(-9.78)	(-9.55)	(-8.05)	(-4.97)
$I_{SBeta>0}$			0.027***		
			(3.57)		
N	336,635	242,274	242,274	120,307	121,967
adj. R^2	0.7%	32.6%	32.8%	31.7%	33.7%
Number of groups	169	169	169	169	169

Table 11: The Reaction of Institutional Ownership to Sentiment Beta: Subsample Analysis

This table reports estimates from the Fama-Macbeth Regression procedure, where the estimates are time-series means of coefficients from cross-sectional regressions of institutional ownership on sentiment beta, and other control variables, covering sample period from 1980Q1 to 2022Q2. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Panel A reports the estimates from analysis on subperiod from 19980Q2 to 1999Q4, while Panel B reports for subperiod from 2000Q1 to 2022Q2.

	Panel A: Subperiod 1980:Q1 – 1999:Q4				***Panel B: Subperiod 2000:Q1 – 2022:Q2***			
			$SBeta < 0$	$SBeta > 0$			$SBeta < 0$	$SBeta > 0$
$\lvert SBeta \rvert$	-0.020***	-0.011**	-0.012**	-0.027***	-0.004**	0.002	0.001	-0.007***
	(-3.59)	(-2.03)	(-2.01)	(-3.36)	(-2.25)	(0.94)	(0.23)	(-3.17)
$I_{SBeta>0} * \lvert SBeta \rvert$		-0.017**				-0.010***		
		(-2.11)				(-4.40)		
$ln(SD)$	-1.275**	-1.257**	-0.954*	-1.499***	0.168	0.161	0.193	0.139
	(-2.55)	(-2.56)	(-1.90)	(-2.90)	(0.56)	(0.55)	(0.55)	(0.46)
$ln(ILLIQ)$	-0.301***	-0.299***	-0.312***	-0.301***	-0.570***	-0.569***	-0.605***	-0.549***
	(-13.29)	(-13.19)	(-10.04)	(-14.08)	(-19.43)	(-19.46)	(-16.82)	(-20.53)
$ln(SIR)$	0.568***	0.573***	0.932***	0.221	1.759***	1.748***	1.723***	1.771***
	(2.80)	(2.87)	(2.77)	(0.65)	(20.93)	(20.68)	(20.94)	(19.06)
$ln(PRC)$	0.027***	0.027***	0.029***	0.026***	0.045***	0.045***	0.045***	0.045***
	(11.13)	(11.73)	(7.70)	(7.73)	(15.90)	(16.02)	(14.44)	(16.05)
$ln(ASSET)$	0.023***	0.023***	0.025***	0.021***	0.018***	0.018***	0.017***	0.019***
	(16.41)	(16.44)	(15.53)	(11.90)	(15.88)	(15.49)	(13.31)	(12.90)
$ln(BM)$	-0.019***	-0.019***	-0.025***	-0.013***	-0.015***	-0.015***	-0.015***	-0.015***
	(-8.33)	(-8.22)	(-6.40)	(-3.24)	(-6.83)	(-6.71)	(-7.30)	(-4.38)
$I_{SBeta>0}$		0.031**				0.024***		
		(2.13)				(5.29)		
N	59,945	59,945	29,769	30,176	182,329	182,329	90,538	91,791
adj. R^2	24.2%	24.4%	23.0%	26.1%	39.9%	40.1%	39.3%	40.3%
Number of groups	79	79	79	79	90	90	90	90

Table 12: The Impact of Discretionary IO and Sentiment-Beta-Driven IO on Noise Share

This table reports estimates from the Fama-Macbeth Regression procedure, where the estimates are time-series means of coefficients from cross-sectional regressions of noise share on institutional ownership (logit IO, discretionary IO, and/or sentiment-beta-driven IO), and other control variables, covering sample period from 1980Q1 to 2022Q2. T-statistics, computed based on Newey and West (1987) standard errors with 5 lags, are presented in parentheses. The superscripts *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$logitIO$	-0.493***			
	(-7.784)			
$Residual\_IO$		-0.566***		-0.563***
		(-7.63)		(-7.70)
$Predicted\_IO$			2.438	2.348
			(1.11)	(1.04)
$NoiseShare$	0.093***	0.083***	0.085***	0.083***
	(9.61)	(9.28)	(9.37)	(9.26)
$ln(ILLIQ)$	16.610***	16.810***	17.829***	16.717***
	(8.85)	(8.47)	(9.11)	(8.45)
$ln(SIR)$	-15.207***	-13.992***	-18.808***	-12.297**
	(-3.42)	(-2.93)	(-3.90)	(-2.58)
$ln(PRC)$	0.115	0.211**	0.002	0.154
	(1.14)	(2.08)	(0.02)	(1.57)
$ln(ASSET)$	-0.011	-0.005	-0.090	-0.044
	(-0.19)	(-0.09)	(-1.60)	(-0.77)
$ln(BM)$	0.474***	0.349***	0.353***	0.336***
	(3.97)	(2.80)	(2.93)	(2.73)
N	270,132	241,995	241,995	241,995
adj. R^2	8.6%	8.4%	8.2%	8.5%
Number of groups	169	169	169	169

Figures

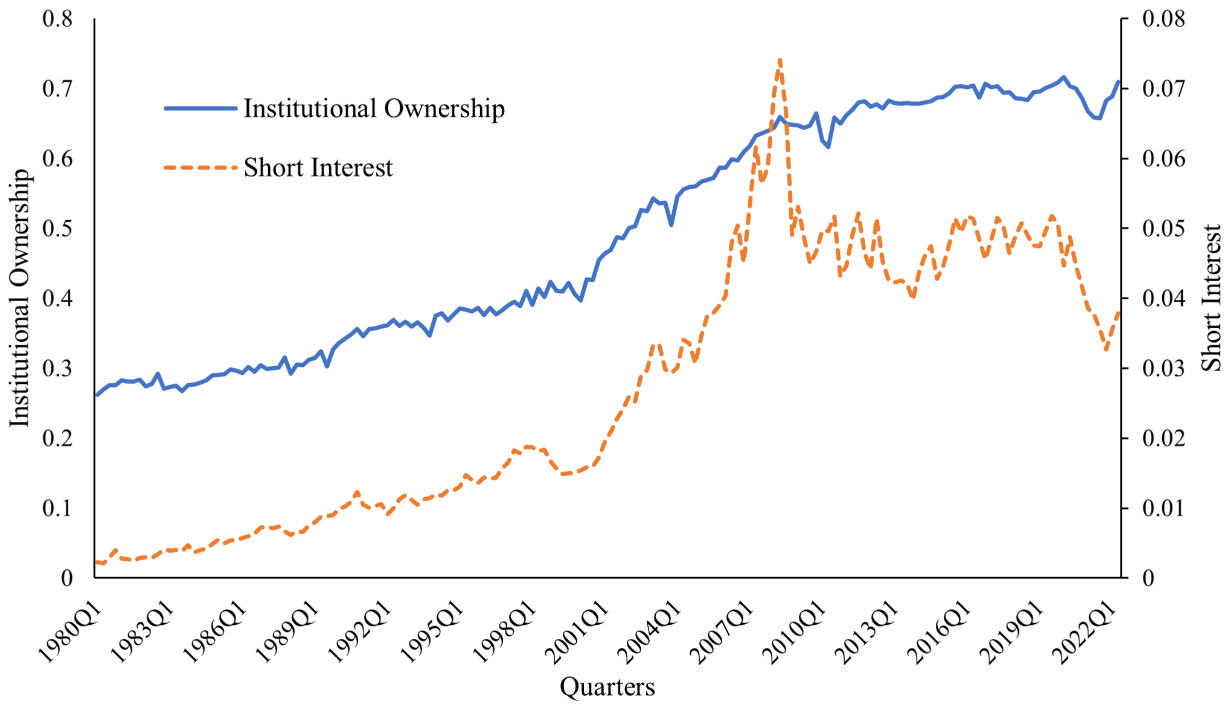

Figure 1: The Time Series of Institutional Ownership and Short Interest

This graph plots the time-series trend in equal-weighted average levels of institutional ownership, and short interest for sample stocks, covering the period from 1980Q1 to 2022Q2. Institutional ownership is the fraction of shares held by 13F institutional investors to total shares outstanding, and short interest is the fraction of aggregate shares held short to total shares outstanding.

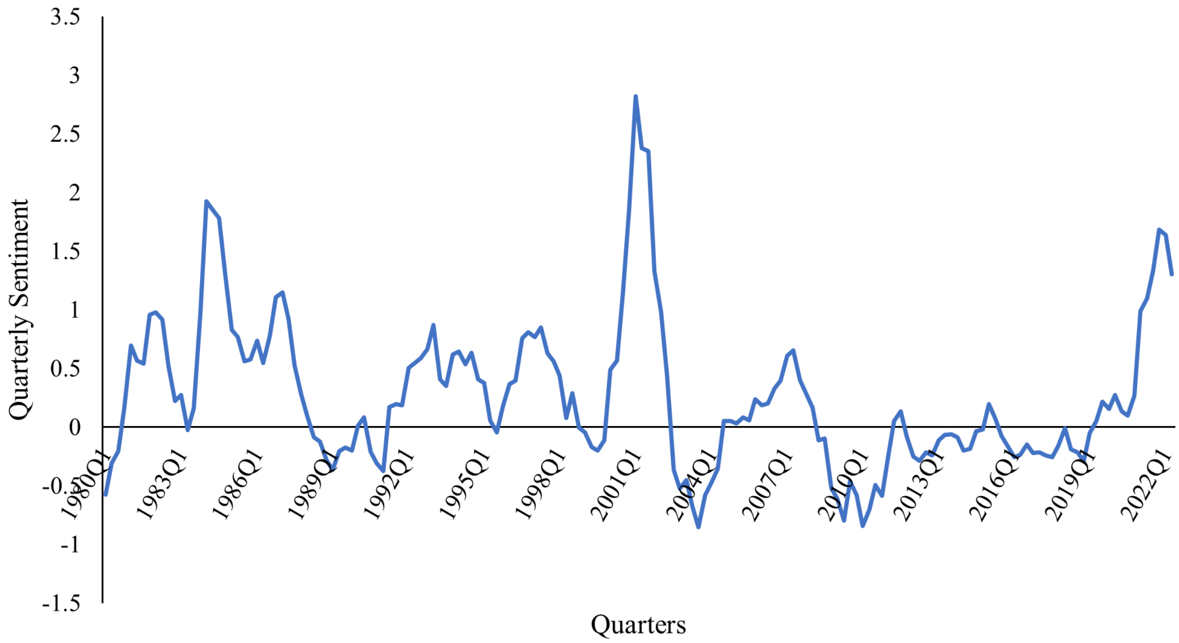

Figure 2: The Quarterly Investor Sentiment Index

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.

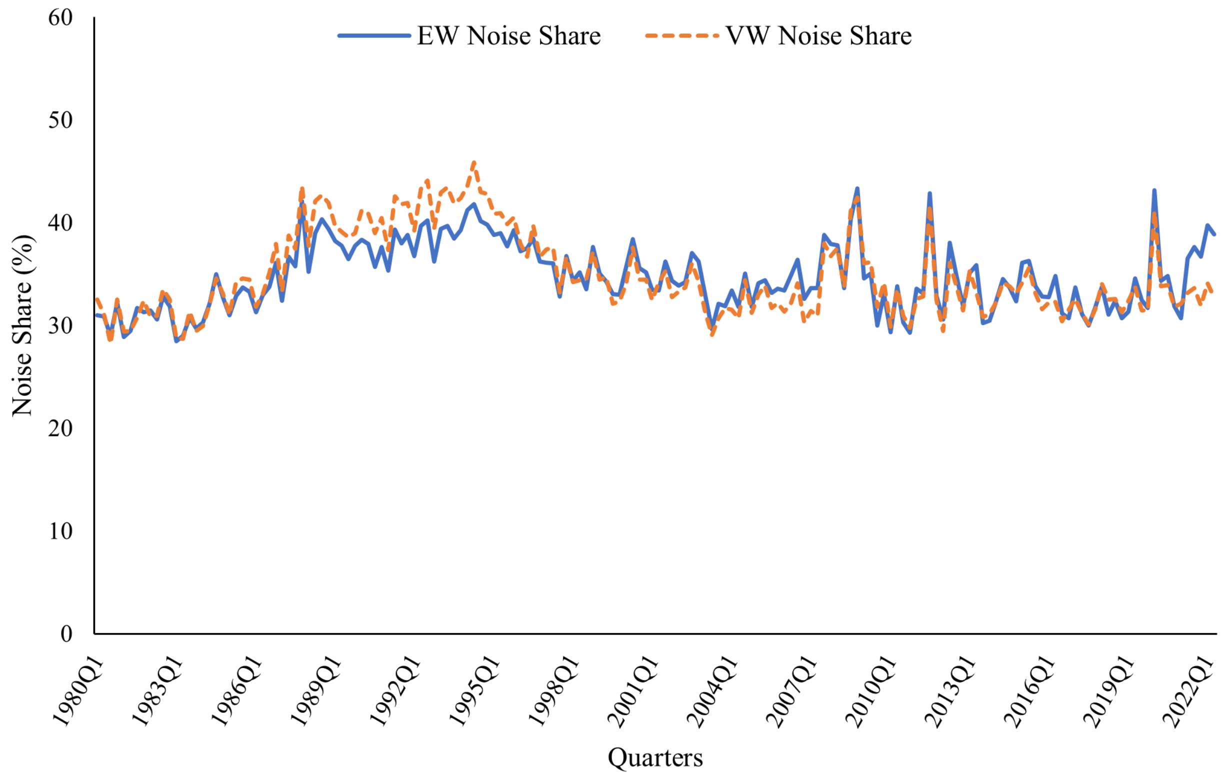

Figure 3: The Time Series Means of Cross-Sectional Average Noise Share

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

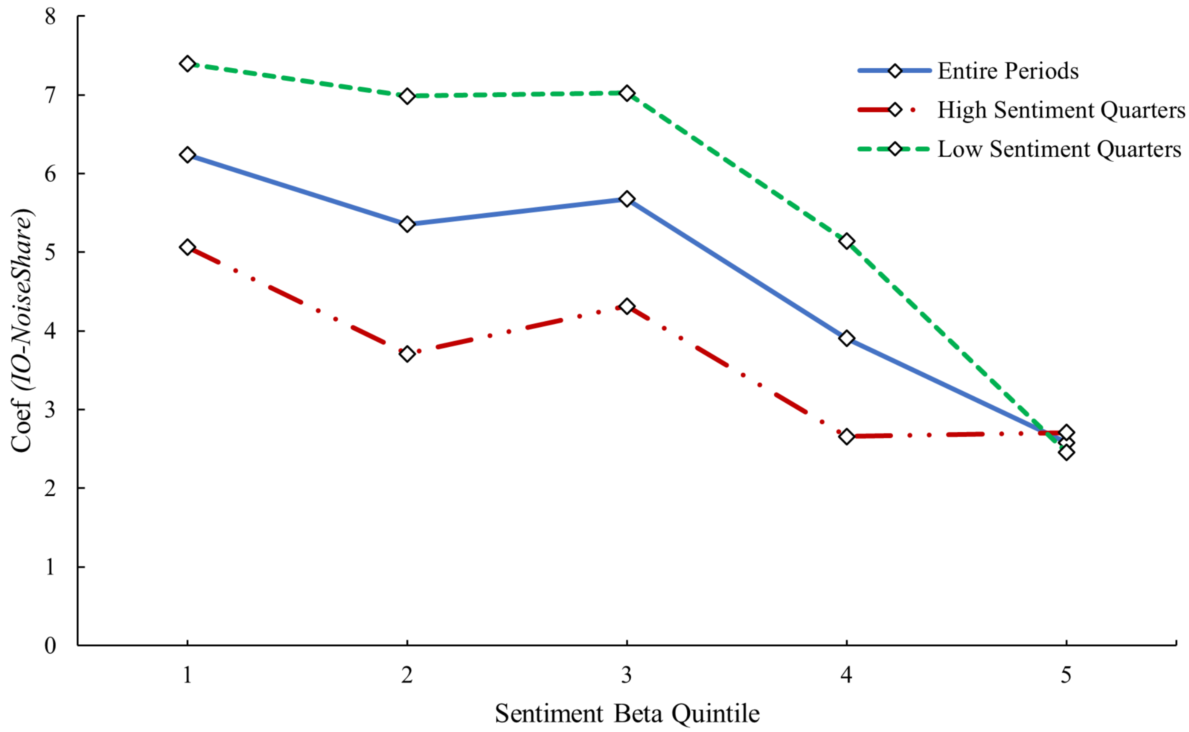

Figure 4: Coefficients of IO for 5 Sentiment-Beta Group: High-, Low-Sentiment Quarters and Entire Period

This graph plots the absolute value of coefficient on IO estimated from Equation 11 for 5 sentiment beta groups following high-, and low-sentiment quarters, as well as across the entire sample period. A higher value indicates stronger IO-Efficiency relation. The full sample is divided into two sub-samples based on the quarterly sentiment level. High (low) sentiment quarters are quarters with beginning-of-quarter BW investor sentiment level higher (lower) than the median sentiment over the full sample. Then the stocks are further sorted into 5 groups based on sentiment beta within each quarter. We then estimate the Equation 11 for these groups, and graph the absolute values of the coefficient on IO.

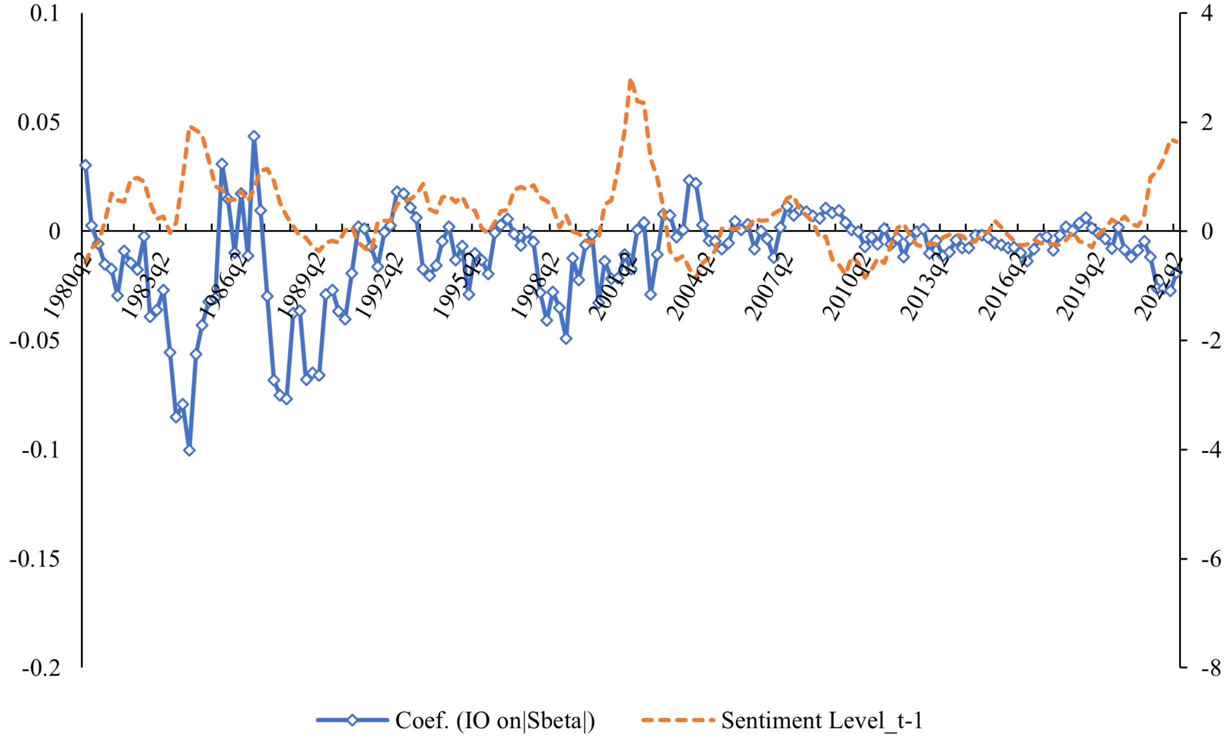

Figure 5: Investor Sentiment and IO's Reaction to Sentiment Beta

This graph plots the coefficients estimated in Equation 14, together with the quarter investor sentiment. With Fama and MacBeth (1973) procedure, we estimate the cross-section regression of institutional ownership on sentiment beta in each quarter, obtaining and graphing time series of coefficients.