Investor Sentiment, Institutional Ownership, and Informational Price Efficiency

Xiaoqi Yu*

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Abstract

Investor sentiment affects both the institution's decision and stock market efficiency, raising questions about its impact on the well-documented positive relationship 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. This effect is more pronounced in the latter half of the sample period (1980Q1–2022Q2), and in quarters following low levels of sentiment. We further show that institutions trade against sentiment-driven mispricing, with strategies grounded in fundamentals significantly contributing to price efficiency. We contribute by providing direct evidence linking sentiment beta, institutional ownership, and stock price efficiency, highlighting how sentiment moderates the IO-Efficiency relationship

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*Xiaoqi Yu is a PhD student at the University of Glasgow. Email: xiaoqi.yu@glasgow.ac.uk

1 Introduction

Institutional investors, due to their informational advantage and expertise, have long been documented to trade against investor sentiment and improve the informational efficiency of stock prices (Boehmer & Kelley, 2009; Cao et al., 2018). However, a recent study by DeVAULT et al. (2019) argues that investor sentiment actually captures the aggregate demand shock from institutional investors. As such, the trading by institutions may not help improve the price efficiency. While previous literature extensively focuses on the time-series impacts of investor sentiment on institutional investors (e.g., Chen et al., 2021; Massa and Yadav, 2015) and financial market anomalies (e.g., Stambaugh et al., 2012, 2015), there is limited understanding of its cross-sectional impacts on the relation between institutional investors and stock price efficiency.

This study uses sentiment beta to explore how investor sentiment moderates the efficiency-enhancing role of institutional ownership. By examining this interaction, the paper provides critical insights into the limitations and conditional nature of institutional influence, offering valuable implications for both market participants and policymakers in sentiment-driven markets.

We begin by defining our key variables that measure price efficiency and the cross-sectional impact of investor sentiment. First, we employ noise share ($NoiseShare$) as the primary price (in)efficiency measure. According to the Efficient Market Hypothesis (Fama, 1970), the efficient stock price should reflect all available information and adjust quickly to new information and hence it follows a random walk process. Following Brogaard et al. (2022b) and Hasbrouck (1993), we decompose stock return into an efficient random-walk term that captures market-wide, and firm-specific private and public information, and an noise term. The parameters are estimated in the Vector Autoregression (VAR) system. The noise term hence captures the pricing error, the deviation of the stock price from the informationally efficient price. Normalizing the variance of noise by total return variance yields noise share, gauging the relative contribution of noise to the variation in stock price. A higher noise share indicates lower price efficiency.

Second, we employ sentiment beta to capture the cross-sectional impact of investor sentiment. Following Baker and Wurgler (2007), Glushkov (2006), and Chen et al. (2021), we estimate individual stock's sentiment beta as the coefficient in the time series regression of stock excess return on change in Baker and Wurgler (2006, 2007) investor sentiment after controlling for Fama and French (1993) 3 risk factors and Pástor and Stambaugh (2003) liquidity factor, using a 3-year window of monthly data. Sentiment beta measures the sensitivity of stock return to the change of BW investor sentiment, and higher sentiment beta indicates the stock is more affected by investor sentiment in the cross-section.

We then explore the impact of investor sentiment on the IO-Efficiency relation by empirically testing how sentiment beta affects the relation between 13F institutional ownership and noise share, using a broad cross-section of NYSE/AMEX/NASDAQ-listed common stocks between 1980Q1 and 2022Q2. We start with portfolio sorting analysis. Stocks are sorted into 25 (5×5) portfolios based on sentiment beta ($SBeta$) and institutional ownership (IO) independently at quarter $t-1$, and for each portfolio we report the average noise share at quarter t. 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 noise share between low- and high-IO portfolios significantly attenuates when sentiment beta increases. We also conduct the dependent sort 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 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-sentiment-beta group 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. In addition, our results preserve in robustness analyses by estimating in panel regression setting and using alternative price efficiency measures.

Our sample period spans a 40-year window from 1980 to 2022, during which market conditions have evolved significantly. Institutional investors have grown to dominate the market (See Figure 1), at meantime investor sentiment has become more moderate (See Figure 2). We hence continue to examine how our main finding evolves over time. We consider two subsample analyses. First, we designate 2000Q1 as the cutoff point and divide the full sample into two, with each covering an appropriate 20-year window. We show that IO-Efficiency relation is stronger in the second half in general. However, as we move from the low- to high-sentiment-beta stock group, the difference in coefficients between the first-half and the second-half narrows. For the high-sentiment-beta group, the coefficients of the two subsample regressions are similar. This suggests that, first, the growing presence of institutions improves the price efficiency overall, and second, the impact of sentiment beta on IO-Efficiency relation remains robust over time.

Second, we divide the full sample into two based on the time series of investor sentiment. Specifically, high (low) sentiment quarters are defined as quarters with investor sentiment level higher (lower) than the full-sample median. We find that the IO-Efficiency relation is significantly weaker following high-sentiment quarters, consistent with the arbitrage asymmetry argument proposed by Stambaugh et al. (2015). When sentiment is high, noise traders exhibit strongly positive demand, but they do not show a correspondingly strong negative demand when sentiment is low. This asymmetry results in widespread overpricing and heightened limits to arbitrage during high-sentiment periods, thereby weakening the IO-Efficiency relationship as expected. Conversely, following low-sentiment quarters, the impact of sentiment beta becomes more pronounced, as stocks are disproportionately influenced by sentiment during these periods. Last, again, for the high-sentiment-beta group, the IO-Efficiency remains equivalently low, regardless of whether it follows quarters of high or low sentiment.

One observation from the first subsample analysis is the concurrent existence of the dominating presence of institutions and the stronger cross-sectional impact of sentiment in the second-half of the sample (2000Q1 to 2022Q2). One may concern that institutional investors can be sentimental traders and contaminate the IO-Efficiency relation. Though most previous studies characterize institutional investors as those who bet against sentiment (Barber & Odean, 2008; Kumar & Lee, 2006, among others), some suggest that institutions can trade with sentiment. Brunnermeier and Nagel (2004) and Chen et al. (2021) show that hedge funds knowingly time and ride the sentiment, while DeVAULT et al. (2019) show that institutions can be sentimental traders themselves. Thus, following the previous analysis, we further explore how institutional investors in our sample react to the sentiment beta and the impact of their reactions on informational efficiency. We first show that institutions overall trade against sentiment beta. Then, We decompose the institutional ownership into sentiment-driven and residual components. We find sentiment-driven institutional ownership is not significantly associated with informational efficiency, while residual institutional ownership is significantly and negatively related to price efficiency. This suggests that institutions' decision based on other stock characteristics, such as riskiness and size, contributes to price efficiency. This reinforces institutions' role as arbitrageurs who detect mispricing based on stock characteristics and trade to reduce it.

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 fund 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 relationship 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.

[Insert Figure 1 around here]

[Insert Figure 2 around here]

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 itself difficult to arbitrage, introducing noise trader risk for sophisticated arbitrageurs (Baker & Wurgler, 2006, 2007; Glushkov, 2006). 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 also manifests its impact on the stock market over time. First, investor sentiment can concurrently affect numerous stocks in the same direction (Baker & Wurgler, 2006; Stambaugh et al., 2012). During periods of high sentiment, sentimental traders tend to be overly optimistic, trading more aggressively and driving up demand. This behavior pushes stock prices above their efficient levels, resulting in reduced price efficiency. Conversely, in periods of low sentiment, these traders exhibit negative demand, pulling prices down and similarly leading to lower price efficiency. Second, overpricing would be more prevalent than underpricing due to the short-sale impediment (Miller, 1977; Stambaugh et al., 2015; Yu & Yuan, 2011). From the institutional investor side, many of them are prohibited from taking short positions. Even those who are able to short can be reluctant to take short positions when stocks are overpriced. This is because, even if they are correct about the efficient price level, they face the risk that stock prices continue to climb for an unbearable horizon before they eventually reverse. This risk leads to additional capital invested, or even liquidation at a loss. However, the similar risk is not an equivalent concern for long positions, which are generally without leverage, on underpriced stocks. From the individual investor side, Barber and Odean (2008) document that only 0.29% of individual investors' positions are short positions, emphasizing their reluctance to take short positions due to limited knowledge or behavioral biases.

These short-sale impediments lead to arbitrage asymmetry that it is more difficult to arbitrage against sentiment traders in high sentiment periods. Combining these two arguments leads to that investor sentiment will exert stronger impacts on the relation between institutional ownership and price efficiency in high sentiment periods.

Hypothesis 2: *The weakening effect of sentiment on the relation between institutional ownership and price efficiency should be more pronounced in high sentiment periods.*

The evolving dynamics between institutional ownership and stock price efficiency can be traced back to how institutional investors respond to market sentiment. Massa and Yadav (2015) show mutual fund trade against sentiment and lend support to DeLong et al. (1990) argument that noise trader risk limits the arbitrage. Institutional investors can also participate in sentiment-driven trading. Brunnermeier and Nagel (2004) show that hedge funds rode with the bubble and are net buyers of technology stocks. In each instance, the extent of their ownership becomes less effective in explaining the price efficiency. The weakening effect of sentiment can thus be explained either by the arbitrage risk deterring the trade-against-sentiment position of institutional investors or by the fact that institutional investors net ride with sentiment.

Hypothesis 3a: *Institutional investors trade against sentiment that they decrease their position as sentiment beta increases.*

Hypothesis 3b: *Institutional investors ride with sentiment that they increase their position as sentiment beta increases.*

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.*

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. We collect daily data on stock returns, trading volumes, and prices from Center for Research in Security Prices (CRSP), accounting information from Compustat, institutional holding from Refinitiv 13F filings database. We collect investor sentiment index from Prof. Jeffrey Wurgler's website[1]. The short interest data is primarily collected from Compustat, and partially obtained from Bloomberg[2].

The following selection criteria are employed: 1) the duplicated stock-day observations and observations with missing values of price, return or volume are removed; 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; 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,

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

[2] The primary source of short interest is Compustat, which archives short interest for NYSE and AMEX stocks since January 1973 and NASDAQ stocks since July 2003. The data for NASDAQ stocks before July 2003 is collected from Bloomberg database.

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 $t = 15$. 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)[3].

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

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 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.

[3]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).

[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 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. In each quarter, we estimate the following time series regression of daily stock return on CRSP value-weighted market return,

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

where r_t is the daily stock return, $r_{m,t}$ is the market return on day t. 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 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 measures the extent to which return variation is explained by lagged market return, and hence 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). We compute the absolute value of first-order autocorrelation of daily return,

$$AutoCorr = |\rho_{r_t, r_{t-1}}|, \tag{6}$$

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 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[4]. 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[5]. 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})[6]. 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

[4]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.

[5]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).

[6]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.

To measure the stock-level sentiment exposure, this study employs sentiment beta. 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 t, 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 $|SBeta|$.

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

where,

$$\beta^{\text{prior}}_{t-1} = \frac{1}{N_{t-1}} \sum_{i=1}^{N} |\beta_{i,t-1}|, \sigma^2_{\text{prior},t-1} = \frac{1}{N_{t-1}} \sum_{i=1}^{N} \left(|\beta_{i,t-1}| - \beta^{\text{prior}}_{t-1}\right)^2 \quad (9)$$

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 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 be small and have higher risk. 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 (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,

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

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 $t-1$, 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 t 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-differences is 5.02, significantly at 1% level, consistent with independent sorting result.

[Insert Table 3 around here]

4.2 Stock-Level Regression Analysis

The results from portfolio-sorting analysis can possibly 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 sentiment beta, and within each group we estimate the following equation based on Fama and MacBeth (1973) procedure,

$$NoiseShare_{it} = \alpha_0 + \beta_1 IO_{i,t-1} + \beta_2 NoiseShare_{i,t-1} + \sum_{k=3}^{K} \beta_k X_{i,t-1} + \epsilon_{it} \tag{11}$$

where $NoiseShare_{it}$ is the noise share of stock i at the end of quarter t. $IO_{i,t-1}$ is the institutional ownership at the end of quarter $t-1$. $NoiseShare_{i,t-1}$ is the noise share at the end of quarter $t-1$. It is included to account for the mean reversion of price efficiency. $X_{i,t-1}$ is a set of stock characteristics variables at the end of quarter $t-1$, 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 ($ln(ILLIQ)$)[7]. 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.

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 regression results for 5 sentiment beta groups. From Column (1) to Column (5), the regression analysis progresses from the lowest to the highest sentiment beta group. 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 owner-

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

ship 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-sentiment-beta group 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[8].

To statistically test the difference between two β_1 coefficients, we estimate the following equation based on Fama and MacBeth (1973) procedure,

$$\begin{aligned} NoiseShare_{it} =& \alpha_0 + \beta_1 IO_{i,t-1} + \beta_2 D_1 + \beta_3 D_5 + \beta_4 (D_1 * IO_{i,t-1}) + \beta_5 (D_5 * IO_{i,t-1}) \\ &+ \beta_6 NoiseShare_{i,t-1} + \sum_{k=7}^{K} \beta_k X_{i,t-1} + \epsilon_{it} \end{aligned} \tag{12}$$

where D_1 and D_5 are dummy variables for low (high) sentiment beta group, $D_1 * IO_{i,t-1}$ and $D_5 * IO_{i,t-1}$ 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 weaken if the stock price is more sensitive to investor sentiment.

[Insert Table 4 around here]

[8]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.

Overall, our findings support the IO-Efficiency relation documented by Boehmer and Kelley (2009) and Cao et al. (2018) that higher institutional ownership leads to a lower pricing error and hence higher informational efficiency. Beyond this, our focus is the impact of sentiment beta on the IO-Efficiency relation. Our findings suggest that, although institutions overall contribute to price efficiency, the strength of their impact is contingent on sentiment beta. For stocks with higher sentiment beta, the IO-Efficiency relation is attenuated.

4.3 Robustness Checks

4.3.1 The Incremental Impact of Sentiment Beta

First, as a robustness check, we include the interaction term of sentiment beta and institutional ownership in regression to better quantitatively examine the incremental effect of sentiment on the IO-Efficiency relation revealed in the above analysis. Specifically, we estimate the following equation on the full sample based on Fama and MacBeth (1973) procedure,

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

$|SBeta|_{i,t-1}$ 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]

4.3.2 Panel Regression

Second, we estimate our baseline equation in the panel regression setting by controlling for stock fixed effect and quarter fixed effect. We confirm the cross-section impact of sentiment beta on the IO-Efficiency relation in the above analysis. Given that our sample spans a large number of stocks and a long time period of 40 years, panel regression allows us to examine the dynamic impact of sentiment beta that varies both across stock and within stock over time while controlling for unobserved heterogeneity.

Table 6 reports the result of panel regression, with standard error clustered at the stock level. Column 1 to 5 presents the baseline regression for each sentiment beta group, while Column 6 presents the regression including the interaction term of sentiment beta and institutional ownership. The results remain qualitatively similar. The coefficient on institutional ownership decreases monotonically from the low- to high-sentiment-beta groups, as does the significance level of the coefficients. For the high-sentiment-beta group, the relation between institutional ownership and noise share is not significant, corroborating our finding that sentiment beta attenuates the IO-Efficiency relation. The coefficient on the interaction term of sentiment beta and institutional ownership is significant, further strengthening the robustness of our result.

[Insert Table 6 around here]

4.3.3 Using Alternative Price Efficiency Measure

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. As expected, in 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.

[Insert Table 7 around here]

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.

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.

[Insert Table 8 around here]

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 high (low) 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 risk 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.

When applied to our analysis on the impact of sentiment beta on the IO-Efficiency relation, the arbitrage asymmetry predicts a more pronounced weakening effect of sentiment beta following periods of low investor sentiment. High sentiment periods typically feature overpricing in the stock market, reflecting a market-wide phenomenon. In addition, by construction, the BW investor sentiment captures the prevailing market optimism or pessimism as it is based on market-wide trading proxy variables. Thus, we expect a universal attenuation of the IO-Efficiency relation across all five sentiment beta groups following periods of high sentiment. This is because the pervasive optimistic mood homogenizes the impact across stocks, diminishing the variation in IO-Efficiency relations. On the contrary, during periods of moderate or negative sentiment, the influence of sentiment beta becomes more discernible. In these scenarios, stocks with a high sentiment beta are disproportionately influenced compared to their low-sentiment-beta counterparts, due to the varied sensitivities to investor sentiment in the cross-section. That is, we expect that the coefficients on IO across

5 sentiment beta groups will be higher (because they are negative) following high sentiment periods, however, the difference of coefficients between low- and high-sentiment-beta groups will be more significant following low sentiment periods.

To explore the investor sentiment implications, we first define the high- and low-sentiment quarters. High (Low) sentiment quarters are those with beginning-of-quarter BW investor sentiment levels higher (lower) than the median sentiment 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 high- and low-sentiment-quarter subsamples. First, again, all coefficients of institutional ownership are significantly negative at 1% level, corroborating the finding that institutions overall contribute to the price efficiency. Second, as expected, the coefficients on IO are larger following the high sentiment period for four sentiment beta groups, spanning from the lowest quintile to the 4th quintile. The high-minus-low difference in coefficients ranges from 2.34 to 3.28. This trend, however, does not extend to the high sentiment beta group. The high-minus-low difference is -0.25, which is close to zero, implying no significant difference. Third, the variation of coefficients across sentiment beta groups is more pronounced following low sentiment quarters. The coefficients exhibit an almost monotonic increase from -7.40 to -2.46 following quarters of low sentiment, resulting in a cross-group difference of 4.94. In contrast, following quarters of high sentiment, they increase more modestly by 2.36, from -5.06 to -2.71.

One interesting finding is that, for the high sentiment beta group, the coefficients on institutional ownership do not show significant variation following either high or low sentiment 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. Recall that in Panel B of Table 4 we present the test on the difference in coefficients on institutional ownership between high- and low-sentiment-beta groups. The coefficient of the interaction term of institutional ownership and the dummy of low-sentiment-beta stocks ($D_1 * IO$) is -1.09, significant at 5% level. Considering the average impact, given by the coefficient on IO, is -4.40, this indicates a strengthening impact of institutions on low-sentiment-beta stocks. The coefficient on the interactions between IO and the high-sentiment-beta group ($D_5 * IO$) is 2.62 and is significant at 1% level, demonstrating a stronger impact relative to the low-sentiment-beta group in terms of both magnitude and statistical significance. That is, the IO-relation is significantly attenuated in the high-sentiment-beta group. This pattern becomes more pronounced in the subsample analysis of the time series impact of investor sentiment, presented in Table 9. In terms of both magnitude and statistical significance, the weakening impact of high-sentiment-beta stocks is more pronounced. For example, the coefficients on $D_5 * IO$ ($D_1 * IO$) are 1.633** (-0.703) following high sentiment quarters and 3.604*** (-1.479*) following low sentiment quarters[9].

To refine the analysis on the time series impact of investor sentiment, we shift our focus to the examination of the extremes. Specifically, we partition the quarters into three groups. High (Low) sentiment quarters are defined as quarters where the beginning-of-quarter sentiment level falls within the top (bottom) 25% of all over the full sample, with the middle 50% defined as Medium sentiment quarters. Table 10 reports the regression results. The main focus is coefficients on institutional ownership and the differences between coefficients, so we only tabulate IO's coefficients in Panel A for brevity, together with the test of coefficient difference in Panel B. The universal attenuation of the IO-Efficiency relation across all five sentiment beta groups following periods of high sentiment is more evident when we focus on the top 25% extreme high-sentiment quarters. Both high- and low-sentiment-beta groups do not significantly differentiate themselves from the average stocks following high-sentiment quarters, as evidenced by the non-significance of the two interaction terms and their difference.

Figure 4 graphs the absolute value of coefficients from regressions of 5 sentiment-beta groups for subsamples of high- and low-sentiment quarters, analysis conducted in Table 9. Figure 5 graphs the absolute value of coefficients on IO in Table 10. The lower value indicates a weaker effect of institutional ownership on price efficiency. First, values are lower following high-sentiment quarters, indicating the arbitrage asymmetry where institutions find it harder to arbitrage in high sentiment periods. Second, following high sentiment periods, the impact of sentiment is more universal. Both findings are more pronounced when focusing on extremes of investor sentiment.

Overall, our findings support our hypothesis that the weakening effect of investor sentiment on the IO-Efficiency relation is more pronounced following high sentiment quarters. The IO-Efficiency relation is weaker across almost all 5 sentiment beta groups, suggesting that overall arbitrage risk and difficulty are stronger in high sentiment periods.

[9] The superscripts *, **, and *** here indicate statistical significance at 10%, 5% and 1% level respectively. Including them here is to demonstrate the weakening effect of sentiment beta on IO-Efficiency is predominant in the high-sentiment-beta group.

[Insert Table 9 around here]

[Insert Table 10 around here]

[Insert Figure 4 around here]

[Insert Figure 5 around here]

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 attenuating 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 existence leads us to investigate the role of institutional investors, especially how they as a group alter their strategy in response to the impact of investor sentiment. It is possible that institutions ride with the sentiment in our second half period, leading to a significantly weaker IO-Efficiency relation.

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 estimate the following equation,

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

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

Table 11 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[10], 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).

[10]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%).

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 11 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.

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 11.

Table 12 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, 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.

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 6 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,

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

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 13 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.

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.

[Insert Table 11 around here]

[Insert Table 12 around here]

[Insert Table 13 around here]

[Insert Figure 6 around here]

7 Conclusion

Higher Institutional ownership is associated with higher informational efficiency of stock prices (Boehmer & Kelley, 2009; Cao et al., 2018). This study instead 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 diminishes.

We then investigate how the impact of sentiment beta differs across quarters with varying levels of sentiment. We find a universal attenuation of the IO-Efficiency relation following high sentiment quarters, in that the IO-Efficiency relationships are weaker across all five stock groups categorized by sentiment beta. In addition, the impact of sentiment beta on the IO-Efficiency relation becomes insignificant following high sentiment periods. In contrast, the effect of sentiment beta remains strong following low-sentiment quarters. This finding aligns with the arbitrage asymmetry argument proposed by Stambaugh et al. (2015), which suggests that even sophisticated institutional investors struggle to correct mispricing during high-sentiment periods when noise traders exhibit strongly positive demand for many stocks simultaneously.

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 improvethe 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 times (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 on lagged institutional ownership 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)	(2)	(3)	(4)	(5)
	$Low\lvert SBeta\rvert$	2	3	4	$High\lvert SBeta\rvert$
IO	**-6.236*** **	**-5.354*** **	**-5.676*** **	**-3.905*** **	**-2.580*** **
	(-8.66)	**(-7.73)**	**(-10.75)**	**(-8.59)**	**(-5.65)**
$NoiseShare$	0.079***	0.086***	0.078***	0.073***	0.053***
	(8.17)	(7.60)	(7.39)	(6.15)	(6.83)
$ln(ILLIQ)$	15.921***	16.085***	16.708***	15.611***	15.515***
	(7.28)	(8.02)	(8.43)	(7.81)	(9.08)
$ln(SIR)$	5.213	-8.921	-32.304**	-20.854**	-18.273**
	(0.37)	(-0.88)	(-2.15)	(-2.03)	(-2.35)
$ln(PRC)$	0.373***	0.469***	0.298*	-0.058	-0.132
	(2.66)	(3.44)	(1.69)	(-0.34)	(-0.77)
$ln(ASSET)$	0.062	-0.094	0.024	0.065	0.067
	(0.66)	(-1.21)	(0.30)	(1.04)	(0.96)
$ln(BM)$	0.265	0.614***	0.216	-0.014	0.249
	(1.48)	(3.89)	(1.20)	(-0.09)	(1.54)
N	50,506	50,164	49,357	47,835	44,399
adj. R^2	10.4%	10.0%	9.4%	7.8%	5.7%
No. of Groups	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	-11.565***		-12.735***	-19.819***	-11.973***	-9.275***
	(-16.21)		(-16.83)	(-16.81)	(-13.66)	(-8.37)
$\|SBeta\|$		-0.550***	-0.901***	-2.306***	-2.193***	-1.511***
		(-4.42)	(-8.02)	(-11.04)	(-11.07)	(-6.05)
$IO * \|SBeta\|$				**3.058*** **	**2.694*** **	**1.584*** **
				(10.33)	**(8.70)**	**(3.31)**
$NoiseShare$	0.204***	0.224***	0.180***	0.178***	0.119***	0.079***
	(9.91)	(9.87)	(8.61)	(8.51)	(8.19)	(8.86)
$ln(ILLIQ)$					19.052***	15.650***
					(15.86)	(8.68)
$ln(SIR)$						-11.295**
						(-2.28)
$ln(PRC)$						0.188*
						(1.87)
$ln(ASSET)$						0.005
						(0.08)
$ln(BM)$						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 repeat the analysis in Table 5. T-statistics, computed based on robust standard errors clustered at stock level, 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	-5.613***	-4.562***	-3.530***	-2.817**	-1.008	-4.451***
	(-5.94)	(-5.20)	(-3.84)	(-3.23)	(-1.18)	(-7.86)
$NoiseShare$	0.003	0.024***	0.014*	0.002	-0.046***	0.024***
	(0.46)	(4.13)	(2.41)	(0.37)	(-8.05)	(8.35)
$ln(ILLIQ)$	13.724***	13.682***	16.515***	17.859***	15.327***	14.845***
	(12.02)	(12.36)	(14.61)	(15.62)	(13.13)	(23.81)
$ln(SIR)$	3.503	-1.074	-2.158	-4.188	-1.727	-1.741
	(1.14)	(-0.37)	(-0.78)	(-1.65)	(-0.74)	(-1.45)
$ln(PRC)$	1.748***	1.485***	1.013***	0.865***	0.640**	1.075***
	(6.57)	(5.58)	(4.01)	(3.49)	(2.84)	(9.27)
$ln(ASSET)$	-1.026***	-0.652*	-0.668*	-0.472	-0.337	-0.556***
	(-3.83)	(-2.39)	(-2.57)	(-1.84)	(-1.57)	(-4.77)
$ln(BM)$	0.906***	0.866***	0.317	0.467*	0.534**	0.554***
	(3.67)	(3.46)	(1.29)	(1.99)	(2.58)	(5.30)
$\lvert SBeta \rvert$						-0.234*
						(-2.23)
$IO \times \lvert SBeta \rvert$						**0.383****
						(2.80)
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 Alternative Price Efficiency Measures

This table reports estimates from the Fama-Macbeth Regression procedure, where the estimates are time-series means of coefficients from cross-sectional regressions of HM Price Delay / Return Autocorrelation 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)
	DepVar: HM Price Delay		DepVar: Auto-Correlation	
IO	-0.365***	-0.180***	-0.140***	-0.059***
	(-13.00)	(-8.80)	(-15.42)	(-7.36)
$\|SBeta\|$	-0.012***	-0.013***	-0.018***	-0.012***
	(-2.94)	(-3.51)	(-11.97)	(-6.57)
$IO * \|SBeta\|$	**0.053*** **	**0.026*** **	**0.027*** **	**0.014*** **
	(4.94)	**(3.74)**	**(8.37)**	**(4.46)**
HM	0.381***	0.267***		
	(23.15)	(18.31)		
$AutoCorr$			0.202***	0.089***
			(8.89)	(8.82)
$ln(ILLIQ)$		0.219***		0.097***
		(9.42)		(7.26)
$ln(SIR)$		-0.555		-0.070*
		(-1.97)		(-2.08)
$ln(PRC)$		0.003		0.002**
		(1.03)		(3.26)
$ln(ASSET)$		-0.033***		-0.002***
		(-12.70)		(-8.42)
$ln(BM)$		0.039***		0.005***
		(8.29)		(7.00)
N	336,635	242,261	336,635	242,261
adj. R^2	27.3%	34.2%	11.7%	9.2%
No. of Groups	169	169	169	169

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)	(2)	(3)	(4)	(5)
	$Low\|SBeta\|$	2	3	4	$High\|SBeta\|$
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)	(2)	(3)	(4)	(5)
	$Low\|SBeta\|$	2	3	4	$High\|SBeta\|$
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: FMB Regression Subsample Analysis: High, Medium 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 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 key estimates from analysis on high, medium, and low sentiment quarters, while Panel B reports for the test of difference.

Panel A: Coefficients on IO following High, Medium, and Low Sentiment Quarters

	(1)	(2)	(3)	(4)	(5)
	$Low\|SBeta\|$	2	3	4	$High\|SBeta\|$
$High$	-3.683***	-3.612***	-3.425***	-2.558***	-3.074***
	(-3.288)	(-2.913)	(-3.017)	(-4.949)	(-3.492)
$Medium$	-7.592***	-5.861***	-6.428***	-4.022***	-2.514***
	(-9.794)	(-6.777)	(-13.148)	(-5.802)	(-3.502)
Low	-6.079***	-6.066***	-6.407***	-4.991***	-2.227***
	(-3.437)	(-7.085)	(-5.571)	(-7.854)	(-4.360)

Panel B: Test the High-minus-Low Difference

	IO	D_1	D_5	$D_1 * IO$	$D_5 * IO$	$D_5 * IO - D_1 * IO$
High	-2.604***	0.488	-0.705	-0.342	0.593	0.935
	(-4.278)	(1.068)	(-1.279)	(-0.421)	(0.653)	(0.59)
Medium	-4.899***	1.384***	-2.413***	-2.011***	2.985***	4.996***
	(-12.071)	(3.518)	(-4.698)	(-3.727)	(4.342)	(32.68)
Low	-5.192***	0.609	-3.302***	-0.036	3.904***	3.940**
	(-11.412)	(0.831)	(-8.781)	(-0.023)	(10.014)	(5.90)

Table 11: 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 12: 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***			
			$SBeta < 0$	$SBeta > 0$			$SBeta < 0$	$SBeta > 0$
$\|SBeta\|$	-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)
$I_{SBeta>0} * \|SBeta\|$		-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 13: 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

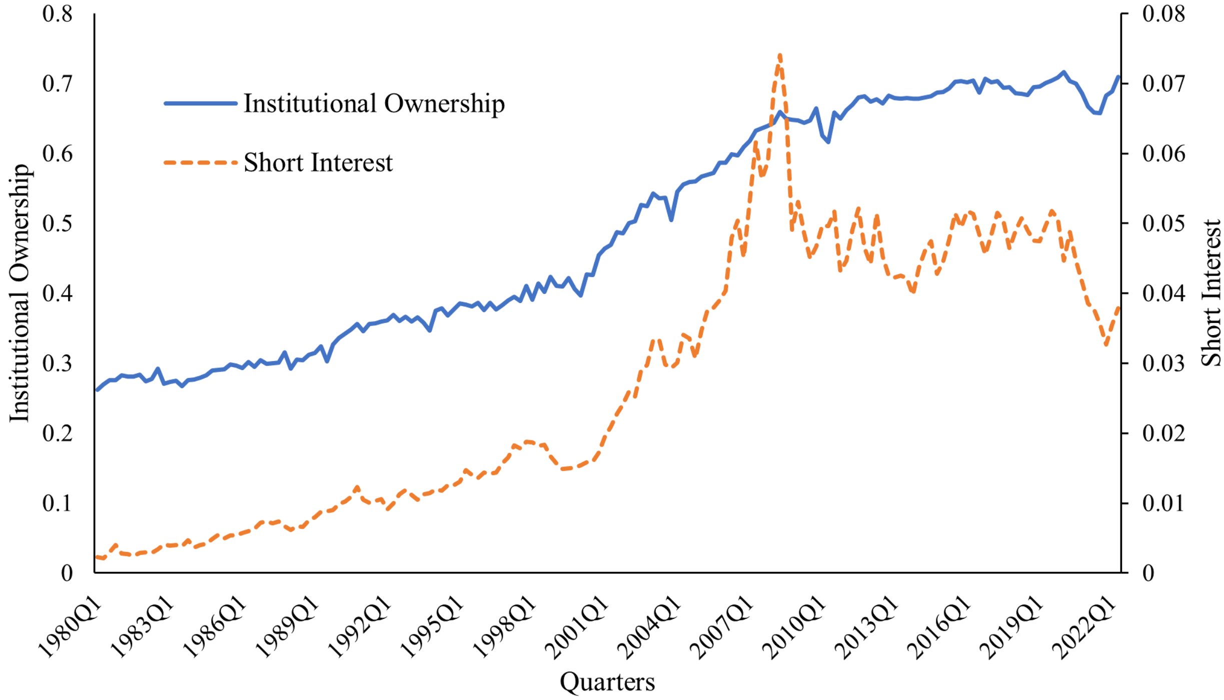

Figure 1: The Time Series of Institutional Ownership and Short Interest

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.

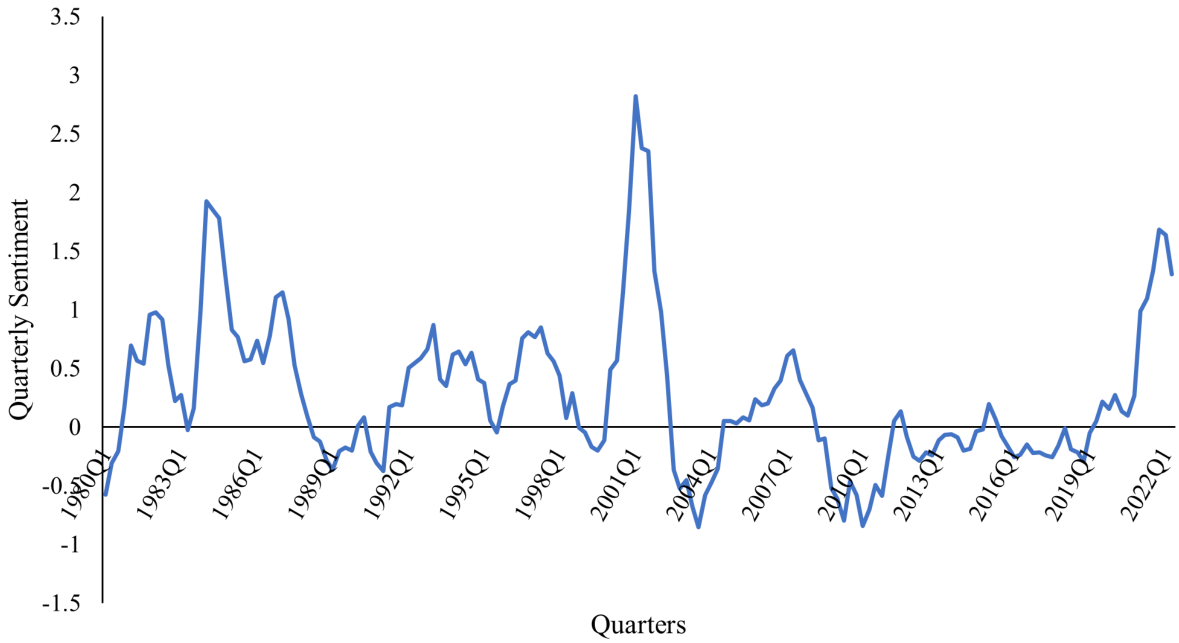

Figure 2: The Quarterly Investor Sentiment Index

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.

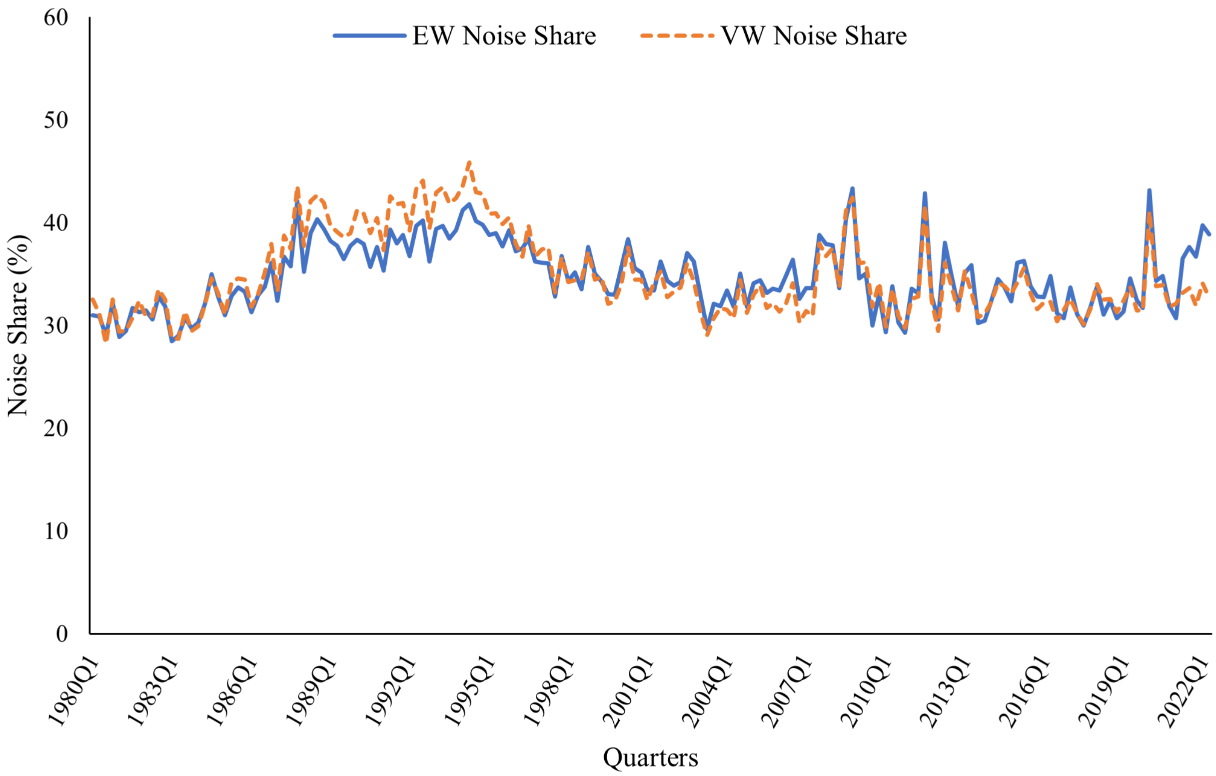

Figure 3: The Time Series Means of Cross-Sectional Average Noise Share

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

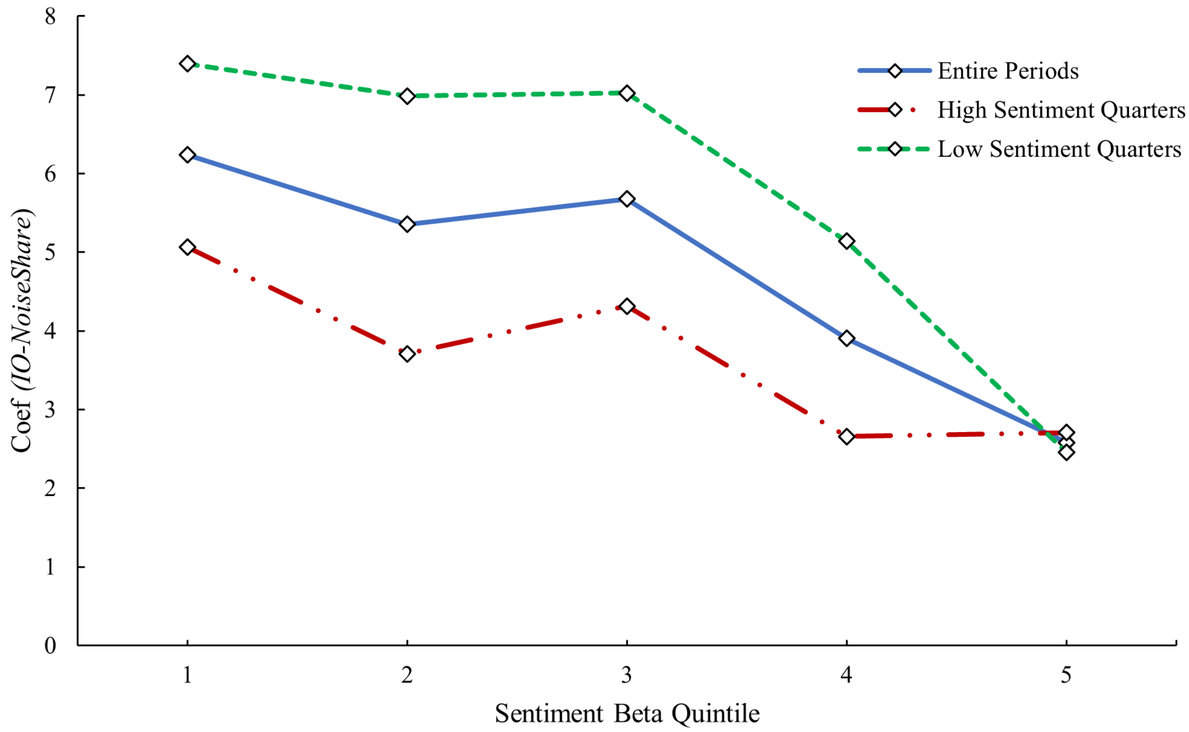

Figure 4: Coefficients of IO for 5 Sentiment-Beta Group: High-, Low-Sentiment Quarters and Entire Period

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.

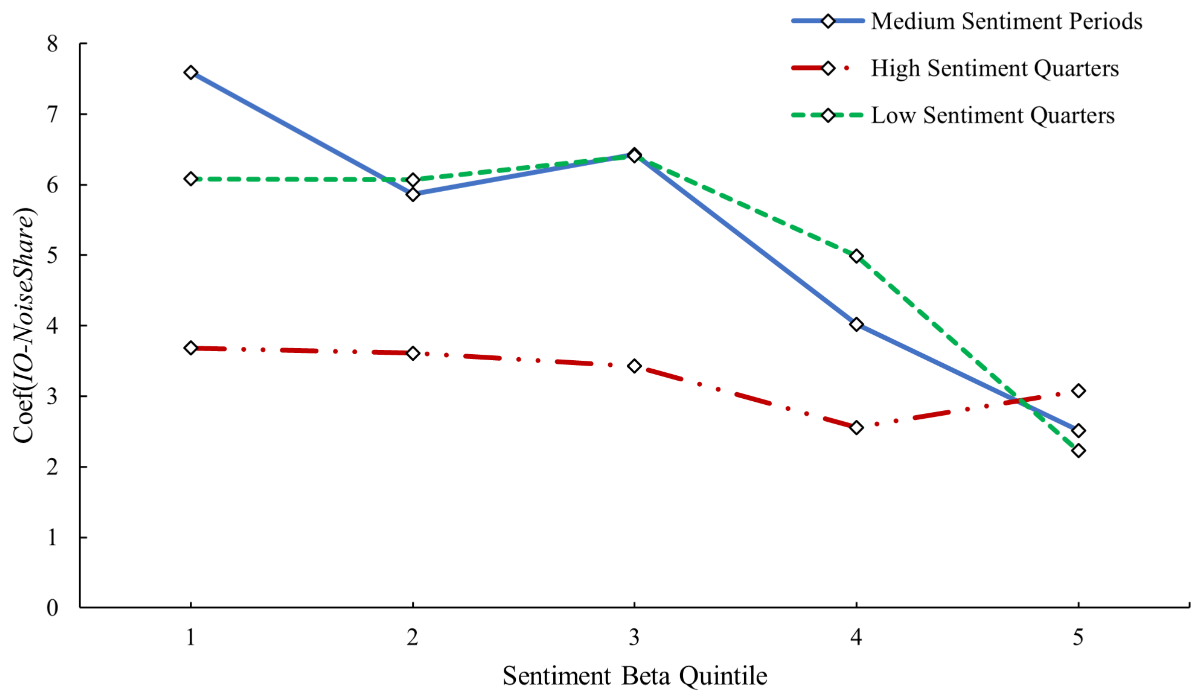

Figure 5: Coefficients of IO for 5 Sentiment-Beta Group: High, Medium, and Low Sentiment Periods

This graph plots the absolute value of coefficient on IO estimated from Equation 11 for 5 sentiment beta groups following high-, medium-, and low-sentiment quarters. A higher value indicates stronger IO-Efficiency relation. The full sample is divided into two subsamples 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.

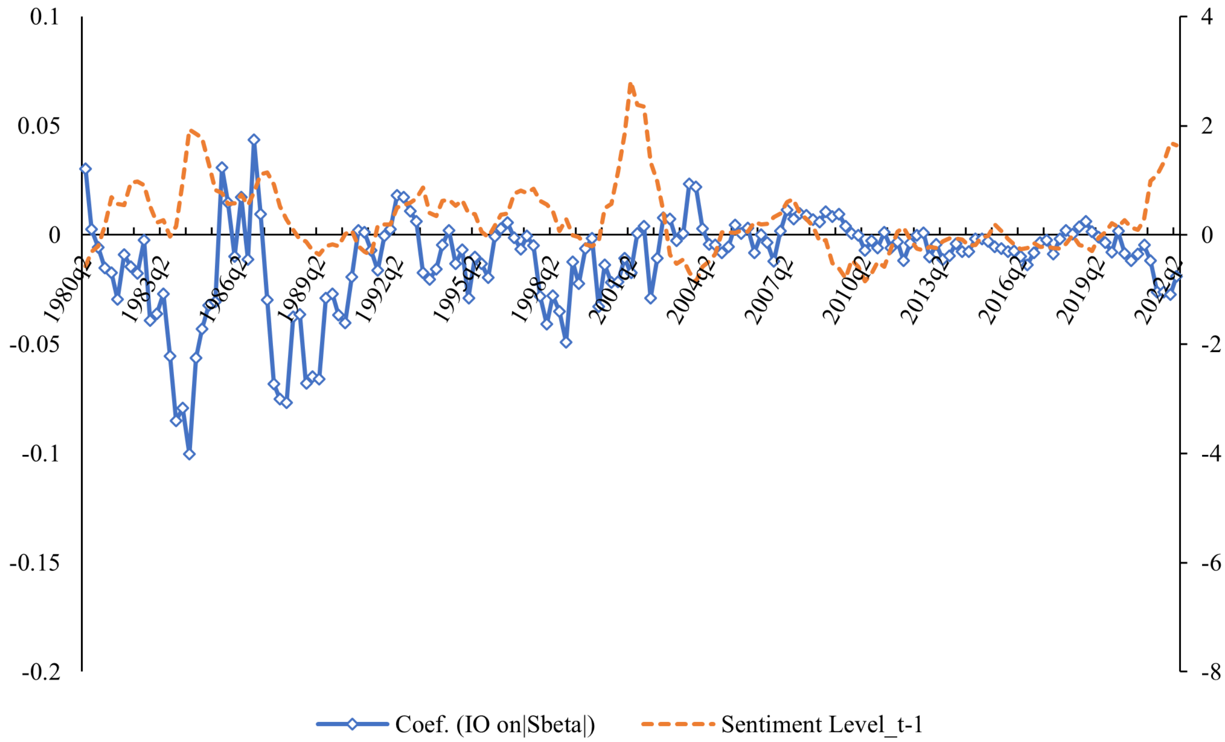

Figure 6: Investor Sentiment and IO's Reaction to Sentiment Beta

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.