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Investor sentiment and the risk–return relation: A two-in-one approach

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Abstract

Traditional finance theory posits a positive risk–return relation, but empirical evidence is inconclusive. Retail investor sentiment has long been viewed as a distorting factor, while more recently institutional investor sentiment is thought to play a role. We examine the separate and joint impacts of retail and institutional investor sentiments on the risk-return relation. We find, at both market and firm levels, the risk-return relation is more likely to be distorted by the two investor-type sentiments jointly, rather than separately. We further find a cross-sectional pattern, with the risk-return relation being more sensitive to investor sentiment for stocks with specific characteristics.

KEYWORDS

beta-return relation, institutional investor sentiment, mean–variance relation, retail investor sentiment, risk-return relation

JEL CLASSIFICATION

G12, G14, G41

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1 | INTRODUCTION

Finance theory posits a positive risk–return relation, but the empirical evidence is not always supportive. Departures from this theorized relation suggest asset mispricing and are indicative of market instability. Investor sentiment has been shown to distort the risk–return relation (Antoniou et al., 2016; Yu & Yuan, 2011) and hence has a potentially destabilizing impact on financial markets, with retail investor sentiment conventionally viewed as the irrational culprit,[1] while institutional investors have been largely viewed as rational, informed traders capable of bringing the markets back into line. Findings in Cohen et al. (2002), for example, support the stabilizing impact of institutional investors driving stock prices toward fundamental values. In contrast, other studies offer evidence of the destabilizing impact of institutional investors due to herding (Cai et al., 2019) and/or positive feedback trading (Nofsinger & Sias, 1999). Bohl et al. (2009) argue that this can only be construed as indirect evidence and so as such does not necessarily imply that institutional investors destabilize stock prices.[2] On the contrary, they suggest that institutional investors may stabilize stock prices, especially if they counter irrational retail investor sentiment. We directly test this proposition by examining not only the separate impacts of institutional and retail investors' sentiments on the risk–return relation, but also their joint impact. In doing so we respond to recent developments in theoretical models (Sheng et al., 2022) and call for greater attention to be given to the interplay between investor types (Spyrou, 2013).

The standard financial framework theorizes a positive risk–return relation, showing that bearing high (low) risk should be compensated by high (low) returns (Merton, 1973, 1980). Empirical findings diverge, however, with evidence of positive, negative, and mixed relations.[3] Behavioural studies highlight the importance of investor sentiment in the determination of asset prices. De Long et al. (1990a), for example, propose a model in which informed investors trade together with noise investors and report that the latter's participation triggers systematic risk, imposing limits on arbitrage and leading to persistent mispricing (see, also, Palomino, 1996; Shefrin & Statman, 1994). The theory is supported by empirical evidence from the US market as well as global markets, revealing a persistent negative impact of investor sentiment on stock market returns (Baker & Wurgler, 2006, 2007; Brown & Cliff, 2004, 2005; Da et al., 2011, 2015; Lemmon & Portniaguina, 2006; Schmeling, 2009; Wang et al., 2021, 2022). The influence of investor sentiment has been linked to the likelihood of stock market crises (Chen et al., 2020; Zouaoui et al., 2011).[4] Yu and Yuan (2011) combine the mean–variance relation and investor sentiment, arguing that first, retail investors are unsophisticated and, hence, likely to misestimate the variance of returns, distorting the positive mean–variance relation as theorized, and second, retail investors are more willing to trade when feeling optimistic than pessimistic due to limits on short selling (Barber & Odean, 2008). Therefore, one can observe

[1]DeVault et al. (2019, p. 985) note that this traditional view has been *explicitly repeated in the nearly 70 years* following the pioneering work of Drew et al. (1950), citing Shleifer and Summers (1990), Lee et al. (1991), Neal and Wheatley (1998), Nagel (2005), Barberis and Xiong (2012), and Da et al. (2015), among others, by way of example.

[2]Using the Polish stock market as the sample, Goodfellow et al. (2009) report that institutional investors do not exhibit herding.

[3]See, Campbell (1987), Baillie and DeGennaro (1990), Baker et al. (2011), Geoffrey Booth et al. (2016), Brandt and Kang (2004), Brandt and Wang (2010), Campbell and Hentschel (1992), Fiore and Saha (2015), French et al. (1987), Glosten et al. (1993), Guo and Whitelaw (2006), Harvey (2001), Ludvigson and Ng (2007), Lundblad (2007), Pástor et al. (2008), Rossi and Timmermann (2015), Scruggs (1998), Turner et al. (1989), Wang et al. (2017), and Whitelaw (1994).

[4]Other studies demonstrate a more specific impact of event-driven sentiment on stock markets, including sunshine (Hirshleifer & Shumway, 2003), aviation disasters (Kaplanski & Levy, 2010), sporting events (Edmans et al., 2007), war (Hudson & Urquhart, 2015), religious events (Gavriilidis et al., 2016), air pollution (Lepori, 2016), and music (Edmans et al., 2021).

that during high-sentiment periods, the positive mean–variance relation would be distorted by the elevated presence of noise traders, while amid low-sentiment periods when noise traders stay in the sidelines, a positive mean–variance relation is present,[5] which is confirmed by their empirical results. Similarly, at the firm level, Antoniou et al. (2016) argue that retail investors trade more over high- than low-sentiment periods. However, their elevated trading concentrates on high-beta stocks (Barber & Odean, 2000, 2001; van Binsbergen et al., 2022), leading high-beta stocks to be overpriced, which is followed by low returns and hence, the collapse of the capital asset pricing model (CAPM) and distortion of the positive beta–return relation. Conversely, the CAPM would be more likely to hold during periods when retail investors feel pessimistic and so trade less, which is supported by their empirical results.

Emerging evidence, however, appears to challenge the conventional wisdom that retail investors are solely to blame for irrational markets while institutional investors are sophisticated and less susceptible to noise and biases in trading. A number of theoretical underpinnings emerge in the literature. First, institutional sentiment trading is partially driven by reputational effects. Institutional investors, like investment managers, tend to follow other managers even when they have opposing fundamental information, such that their performance is close to the average and so they do not stand out from the crowd (Chelley-Steeley et al., 2019). As pointed out in Scharfstein and Stein (1990), if fund managers do not adopt sentiment trading and if their performance is worse than that of other fund managers, they may be classified as underperforming managers even when their performance is at times better, suggesting that institutional investors have a strong motivation to employ sentiment trading and to follow others as they aim to obtain average profits rather than stand out and risk their reputation (Dasgupta et al., 2011; Prendergast & Stole, 1996; Rajan, 2006; Trueman, 1994). Graham (1999), for example, reports that when analysts have high reputation or low ability, or if their private information contradicts strong public information, they tend to herd lest they stand out and perform worse.

Another manifestation of the reputational effects, as posited in Chelley-Steeley et al. (2019), is that institutional investors hope to retain their clients and deter them from moving to rival institutions. If their clients exhibit sentiment while institutional investors do not follow or trade on sentiment, it is conceivable that such clients will close their positions with the managers, who consequently face declining revenues. In an attempt to maintain their clients, therefore, institutional investors may choose to trade on sentiment, albeit originating initially from their clients rather than themselves. More recently, examining three components of institutional

[5]Following the two-agent model in De Long et al. (1990a), Yu and Yuan (2011) provide a theoretical model proposing that the mean–variance relation in stock markets follows:

$$E\left(R_1^{ex}\right) = \sigma^2\left(R_1^{ex}\right) \cdot \frac{\left\{\frac{S_0}{N_1 + N_2 - K}\right\}}{\left[\frac{1}{\alpha} \cdot \frac{N_1}{N_1 + N_2 - K} + \frac{N_2 - K}{N_1 + N_2 - K} \cdot \frac{1}{N_2 - K} \sum_{i=N_1+1}^{N_1+N_2-K} \frac{1}{(1+\varepsilon_i)\alpha}\right]} - \frac{1}{S_0} \frac{\frac{1}{N_2 - K} \sum_{i=N_1+1}^{N-K} \frac{\eta_i}{1+\varepsilon_i}}{\frac{N_1}{N_2 - K} + \frac{1}{N_2 - K} \sum_{i=N_1+1}^{N-K} \frac{1}{1+\varepsilon_i}},$$

where $N = N_1$ (the number of informed traders) + N_2 (the number of sentiment traders); S_0 is the stock price at time 0; K is the number of sentiment traders whose short-sale constraints are binding; ε_i is the noise in investor i's variance estimation; η_i is the noise in investor i's expectation estimation; and α is the CARA risk-aversion coefficient. The mean–variance relation is largely determined by two factors: (i) the average inverse risk-aversion attitude of stock market participants (i.e., $[\cdot]$), and (ii) the average of stock market participants' stock holding (i.e., $\{\cdot\}$). Yu and Yuan (2011) posit that high investor sentiment undermines the positive mean–variance relation by reducing the average stock holdings of market participants (i.e., $\{\cdot\}$) and by increasing the average of the inverse risk-aversion attitudes of stock market participants (i.e., $[\cdot]$). See, the appendix of Yu and Yuan (2011), for detailed derivation and proof.

demand shocks, including trades from investor flows, from managers' decisions, and from reinvested dividends, and computing correlations between changes in sentiment and changes in institutional investors' attraction to risk stocks, DeVault et al. (2019) evidence that managers decisions take up 97% of the time-series correlation, compared with only 2% for investor flows, implying that the underlying investor flows contribute to institutional investor sentiment to a much lesser extent. In addition, due to both reputational effects and risk management constraints, institutional investors are unwilling to deviate from their benchmark (Arnott, 2003; Cao et al., 2017; Maug & Naik, 2011). Risk budgeting and asset allocation rebalancing may lead institutional investors to reduce their stock exposure when sentiment decreases either by shifting from risky to safer stocks, or by shifting away from stocks.

Second, trading on sentiment can be profitable. High (low) sentiment would lead to high (low) short-term returns (Brown & Cliff, 2005), and considering limits to arbitrage (Lewellen, 2011; Ljungqvist & Qian, 2016; Mitchell et al., 2002), it becomes optimal to trade on, rather than arbitrage against, sentiment. This is particularly the case when there are positive-feedback traders in stock markets: In a theoretical model proposed by De Long et al. (1990b), arbitrageurs may contribute to price movements and maximize profits by riding the bubble since positive-feedback traders will purchase stocks at high prices later (Abreu & Brunnermeier, 2002, 2003). Brunnermeier and Nagel (2004), for example, document that hedge funds did not correct stock prices during the technology bubble, but instead, they heavily invested in technology stocks, as they were aware of the upturn and thus rode the bubble. Related, Griffin et al. (2011) confirm a similar role of independent investment advisors and mutual funds in the technology bubble, as they were found to actively invest the most capital in the technology sector during this period.

Along related lines, DeVault et al. (2019) find, contrary to the intuition that institutional investors are immune to sentiment trading, that an increase in investor sentiment, as measured by some common proxies, is associated with an increase in institutional investors' demand for risky stocks, alongside a decrease in retail investors' demand, suggesting that institutional investors are more likely to be noise traders. Elsewhere, institutional investors are seen to succumb to other behavioural biases such as herding (e.g., Choi & Sias, 2009; Holmes et al., 2013; Kremer & Nautz, 2013; Sias, 2004) and this is linked with investor sentiment (Blasco et al., 2012; Cui et al., 2019).[6] Wang (2018) suggests that if institutional investors are noise traders, their elevated trading during bullish periods may also undermine the risk-return tradeoff and provides initial empirical evidence in support in the US stock market, the evidence of which is further confirmed at the firm level (Wang, 2020) and in a global context (Wang & Duxbury, 2021).

This paper combines the above three strands of studies together by examining the impact of both retail and institutional investor sentiment on the risk-return tradeoff. Before proceeding, since we conduct a wide range of empirical tests at various levels (market and firm) in this paper, to avoid confusion and misunderstanding, we clarify the terminology used here. We use *the risk–return relation* as the generic expression, which includes the more specific terms *the mean–variance relation* and *the beta–return relation*. For these more specific terms, the former is used to refer to the market or index level relationship and the latter to refer to firm-level relationship.

[6]Similarly, Antoniou et al. (2013) and Altanlar et al. (2019) argue that information-based traders, not only noise-based traders, may also be influenced by sentiment.

Our paper is motivated by the following reasons. First, as market participants, retail investors and institutional investors both exert impacts on stock markets and therefore, the impact of investor sentiment on the risk-return tradeoff is, in nature, a result of both, rather than one, and thus the inclusion of the two investor types is, therefore, more in line with a real market context.

Second, the inclusion of both retail and institutional investor-type sentiments helps to reveal their separate impact on the risk–return relation. One potential concern for conclusions drawn from the prior studies appears to be that the documented impact of one investor type, retail or institutional, might be due to two investor types, retail and institutional. As shown below in Section 2, with two sentiment measures, we are able to classify our sample into four subsamples: (i) one when both investor types are bearish, (ii) one when only retail investors are bullish, (iii) one when only institutional investors are bullish, and (iv) one when both investor types are bullish, whereby we can investigate the impact of retail (institutional) investor sentiment on the risk-return relation with institutional (retail) investor sentiment being controlled, revealing a clean impact of retail or institutional investor sentiment on the risk-return relation, as well as the joint impact of both.

Third, the extant literature confirms a cross-sectional impact in the sentiment–return relation, reporting that stocks that are hard to value and difficult to arbitrage, such as small stocks, young stocks, and high-volatility stocks, are more likely to be affected by investor sentiment (Baker & Wurgler, 2006, 2007; Bathia & Bredin, 2013; Ding et al., 2018; Schmeling, 2009; Wang et al., 2021), while, to our best knowledge, no evidence is documented for the cross-sectional impact of investor sentiment on the risk-return relation. Equally importantly, two sentiment measures offer us an opportunity to test the difference, if any, in the impact of retail and institutional investor sentiment on the cross-sectional risk–return relation and, where applicable, to explore the main forces across stock characteristics.

We adopt two weekly sentiment proxies, American Association of Individual Investors (AAII) and Investors Intelligence (II), for retail and institutional investor sentiment, respectively. We start from the market level, that is, the mean–variance relation. Conditional volatility is measured by five models including the rolling window (RW), the mixed-data sampling (MIDAS), GARCH, GJR-GARCH, and EGARCH, in that the mean–variance relation can be dependent on volatility models (Ghysels et al., 2005; Harvey, 2001; Turner et al., 1989; Yu & Yuan, 2011). Contrary to the extant literature showing a significant, negative impact of retail and institutional investor sentiment on the mean–variance relation, we find the documented negative impact is more likely to be a collective result of the two investor types: During high-sentiment periods, the joint impact of the two investor types would bring a negative impact on the positive mean–variance relation shown in low-sentiment periods, thereby distorting the positive mean–variance relation. Our findings are robust to a series of alternative specifications including (i) using a composite sentiment proxy, (ii) removing macro and market factors from investor sentiment, (iii) using alternative sample separation criteria, (iv) using alternative sentiment proxies, (v) using an alternative market index, and (vi) controlling for the financial crisis period.

We then move on to the firm level, that is, the beta–return relation. Stock betas are obtained from three asset pricing models including the CAPM (Sharpe, 1964), the three-factor model (Fama & French, 1993), and the four-factor model (Carhart, 1997), and with (i) 5-year (Fama & MacBeth, 1973; Petkova, 2006), (ii) 2- to 5-year (as available, Antoniou et al., 2016; Fama & French, 1992), and (iii) 3-year (Lewellen, 2015) estimation windows. We find, similar to the evidence of the mean–variance relation at the market level, that while retail and institutional investor sentiments have limited individual impacts on the beta–return relation, their joint impact distorts the positive beta–return relation over high-sentiment periods. The implications of this finding are twofold: To begin with, we report new evidence regarding the impact of investor sentiment on the risk–return relation to this literature, and in addition, based on our results, we document the importance of the inclusion of the two investor-type sentiments, thereby offering a new empirical framework to this literature. Overall, both our market- and firm-level tests support the destabilizing impact of sentiment on the risk–return relation, thus failing to support the view in Bohl et al. (2009) that institutional investors might serve to counter retail investor sentiment, while supporting findings in Chelley-Steeley et al. (2019) that institutional investors may trade on retail investor sentiment, and more widely, in Hart and Kreps (1986), Lakonishok et al. (1991), Allen and Gorton (1993), Shleifer and Vishny (1997), Brunnermeier and Nagel (2004), Stein (2009), Hong et al. (2012), Choi et al. (2015), and Cao et al. (2017) that institutional investors may destabilize stock markets. Thus, market inefficiency, as evidenced here by distortion of the risk–return tradeoff, or instability, is more likely to be caused by the two investor types jointly, rather than in isolation. Based on our findings, we would like to call for future studies of investor sentiment to take the two investor types into account jointly in their empirical tests, or at least, to control one sentiment when examining the other. Such a recommendation is not limited in scope to the risk–return relation, but is applicable more generally and in a wider context, such as the impact of investor sentiment on stock market returns, and the spillovers of investor sentiment, and so on. We note it is important, therefore, to consider both investor types when, for instance, designing trading strategies or formulating policies attempting to stabilize stock markets.

Studies of the sentiment–return relation document that hard-to-value and difficult-to-arbitrage stocks, such as small, young, volatile, unprofitable, nonpaying, extreme growth, and/or distress stocks, are more sensitive to investor sentiment (Baker & Wurgler, 2006, 2007), which can be exploited via long-short trading strategies (Ding et al., 2021). We extend the cross-sectional test to the impact of investor sentiment on the mean–variance relation. Separating all stocks into 10 deciles based on 10 characteristics, including market equity, firm age, total risk, return on equity, dividends to equity, property, plant, and equipment over assets, research and development expense over assets, book-to-market equity ratio, external finance, and sales growth, we reveal a cross-sectional impact of retail and institutional investor sentiments on the mean–variance relation. Empirical findings, however, present a feature of duality: First, we, for the first time, confirm the existence of the cross-sectional impact of investor sentiment on the mean–variance relation, adding parallel evidence to the cross-sectional impact of investor sentiment on the stock market returns, documented by Baker and Wurgler (2006) initially, and some other studies such as Schmeling (2009) in a global context and Ding et al. (2021) more recently. Second, however, the theorized sentiment-sensitive/-insensitive classifications in the context of the sentiment–return relation become indeterminant and mixed, that is, we find instances of more (less) mean–variance distortion for sentiment-insensitive (sentiment-sensitive) stocks, in contrast to cross-sectional theorizing concerning the sentiment–return relation, though this may be explained by our different research focus, that is, the mean–variance relation. Therefore, we suggest that future studies referring to the sensitivity of stocks to investor sentiment should not take the documented cross-sectional evidence based on the sentiment–return relation for granted in other research topics.

The paper proceeds as follows. Section 2 presents data on investor sentiment and the stock market and illustrates the approach for sample classification. Section 3 details models to test the impact of investor sentiment on the risk-return relation at the market level, that is, the mean–variance relation, and provides empirical results, along with a battery of robustness tests. Section 4 tests the impact of investor sentiment on the risk-return relation at the firm level, that is, the beta–return relation, followed by the cross-sectional analyses in Section 5. Section 6 concludes.

2 | DATA

2.1 | Investor sentiment

We source AAII and II from Refinitiv for retail and institutional investor sentiments, respectively, from 1987 to 2018. As survey-based sentiment proxies, AAII and II data are directly compiled from responses of retail and institutional investors, respectively, and thus are clean measures of the target investor types, precluding the possibility that they capture sentiment of the other investor type (DeVault et al., 2019). AAII conducts weekly sentiment surveys among its members, asking respondents where they think the stock market will be in 6 months: up, down, or the same, accordingly classifying them as bullish, bearish, or neutral. Since the AAII survey is targeted toward retail investors, it is primarily a measure of retail investor sentiment (Brown & Cliff, 2004). II compiles weekly sentiment from market newsletters and again, marks them as bullish, bearish, or neutral, based on their expectations of future market movements. The newsletter writers are mainly current or retired market professionals, and therefore II is interpreted as a proxy for institutional sentiment (Wang, 2018).[7]

As a valid and high-quality sentiment proxy for institutional investors, II is widely adopted in the extant literature, especially when the two investor types are examined together (Chau et al., 2016; Verma & Verma, 2008; Wang et al., 2006); however, we would like to highlight two points. First, II measures sentiment at the aggregate level and does not distinguish institutional investor types. Ideally, we would wish to categorize institutional investor types, such as hedge funds, mutual funds, pensions, banks, insurance companies, and independent investment advisors, as sentiments across these groups might differ due to disparate trading strategies and regulatory requirements, potentially leading to differential impacts on the risk–return relation (Asness et al., 2012; Li et al., 2017; Miller et al., 2022; Pan et al., 2018; Wang & Zheng, 2022; Ward et al., 2020). For example, institutions such as banks, insurance companies, and pensions tend to avoid trading risky stocks, signifying that they may contribute less to the aggregate institutional investor sentiment, compared with mutual funds, independent advisors, and hedge funds. DeVault et al. (2019) reveal that the latter account for a disproportionately large share of institutional sentiment trading: They account for 50% of institutional ownership but contribute to 89% of sentiment trading. Due to data limitation, however, we are unable to make such a differentiation in this paper so rely on the aggregate II measure.

[7]For survey-based sentiment proxies, such as AAII and II employed in our paper, there may be a potential gap between how people respond to the survey and how they behave in markets (Baker & Wurgler, 2007). For retail investors, in particular, those responding to the weekly AAII survey may not trade on a weekly basis. Such noisy aspects of the data might bring to mind questions about the link between investor sentiment and risk–return relation we examine here. However, we offer a number of reassurances based on our empirical design. First, we do not use the weekly AAII observations but the annual ones. Therefore, the annual average which synthesizes all sentiment-related information within a given year will likely smooth out any short-term, transient variation over the period. Second, AAII values do not directly enter our regression models but rather are used as a means of sample separation. In this sense, the likelihood of generating an opposite classification (i.e., from bullish to bearish, or otherwise) would be low.

TABLE 1 Summary statistics of annual AAII and II, 1987–2018.

This table reports the summary statistics of annual AAII and II bullish indices, over the period 1987–2018. In particular, we report the mean (σ), the standard deviation (σ), the maximum value (Max.), the minimum value (Min.), and the number of bullish years. The annual AAII and II bullish indices are computed by averaging the within-year weekly AAII and II.

	μ	σ	Max.	Min.	No. of bullish years
AAII	0.383	0.054	0.493	0.272	16
II	0.463	0.055	0.572	0.336	20

Second, institutional investors trade on behalf of retail investors so II may contain retail investor sentiment due to reputational effects. As explained in Section 1, institutional investors will hope to retain their clients and to do so, therefore, trade on sentiment that is initially originated from their clients rather than themselves. Hence, a part of institutional investor sentiment may actually reflect retail investor sentiment. In this paper, we follow the reasoning in Chelley-Steeley et al. (2019) and classify this "intentional" part as institutional investor sentiment. In support of this perspective, we note that DeVault et al. (2019), examining three components of institutional demand shocks (including trades from investor flows, from managers' decisions, and from reinvested dividends) and computing correlations between changes in sentiment and changes in institutional investors' attraction to risk stocks. They find that managers decisions account for 97% of the time-series correlation, compared with only 2% for investor flows, implying that the underlying investor flows contribute to institutional investor sentiment to a much lesser extent. Related, we compute the correlation between AAII and II adopted in our paper, and find it is 0.461 ($p = 0.000$), thus, while the two investor-type sentiments might move together, they are far from perfectly correlated. We conclude, therefore, that the two investor-type sentiments have sufficient unique variation to distinguish their impact on the risk–return relation.

To assess the impact of retail and institutional investor sentiments on the risk–return relation, we separate the full sample into bullish and bearish subsamples, based on the sentiment of the two investor types. When categorizing bullish and bearish subsamples, Yu and Yuan (2011) and Antoniou et al. (2016) adopt the annual sentiment index from Baker and Wurgler (2006), identifying year $(T+1)$ as bullish (bearish) when the BW index in year T is positive (negative). While, by definition, there is only one annual BW index at the end of each year, rather than merely capturing sentiment at that specific (end of year) timepoint, it contains all sentiment information in the given year. We also employ the 1-year window and identify year $(T+1)$ based on the annual AAII and II for year T, $S_{AAII,T}$ and $S_{II,T}$, computed as the average of within-year weekly sentiment observations, containing all sentiment information across year T. For AAII, if $S_{AAII,T}$ is above the all-sample average (0.383 as shown in Table 1 below), year $(T+1)$ is classified as a bullish year for retail investors, while for II, if $S_{II,T}$ is above 0.450, the benchmark of institutional investors' bullishness as originally designed by the survey, year $(T+1)$ is classified as a bullish year for institutional investors.[8] We then use these classifications to generate four subsamples: (i) one when both investor types are bearish, (ii)

[8]As shown in Table 1, the all-sample average for II is 0.463, very close to 0.450.

one when only retail investors are bullish, (iii) one when only institutional investors are bullish, and (iv) one when both investor types are bullish. In doing so, we directly test the proposition put forward by Bohl et al. (2009): If institutional investors stabilize stock prices and counter retail investor sentiment, we should anticipate observing a stabilizing impact of institutional investors on the risk–return relation that is destabilized by retail investors. When both investor types are bullish, the net destabilizing impact on the risk-return relation should, therefore, be weaker than that when only retail investors are bullish due to the stabilizing impact of institutional investors. If we find otherwise, that is, that the destabilizing impact on the risk–return relation is stronger when both investor-types are bullish, we provide direct evidence in support of Chelley-Steeley et al.'s (2019) proposition that institutional investors trade on retail investor sentiment and distort the risk–return relation.

A potential concern related to our sample separation approach is that if bullish and bearish weeks within a year switch too frequently, then the classification as a bullish or bearish year may be less clearcut. To directly address this concern, we conduct three further checks. First, we count the total number of switches for AAII and II over our sample period. A 'switch' is defined as a change from a bullish week to a bearish week, or from a bearish week to a bullish week. For a period of W weeks, by definition, the minimum number of switches is zero, that is, containing only bullish or bearish weeks, while the maximum is $(W-1)$, meaning that bullish weeks and bearish weeks switch every week. In our sample from 1987 to 2018, AAII has 1641 weekly observations and the number of switches is 400, suggesting that on average a switch occurs once every 4.092 weeks (or 12.707 switches in 1 year), and II has 1670 weekly observations and the number of switches is 181, meaning that on average a switch occurs once every 9.176 weeks (or 5.352 switches in 1 year). Therefore, on average the switching between sentiment regimes is not so frequent across the whole sample period.

Second, we count the total number of switches for retail and institutional investor sentiments every year and find the year with the maximum number of switches. We here define a sentiment 'cluster' as continuous weeks without a switch. For example, if we have a bullish (bearish) cluster with W weeks, it means that the continuous W weeks are bullish (bearish) only. Also, the 'cluster length' is defined as the total number of weeks contained by the cluster. For AAII, the maximum number of switches per year is 19 times in 2009, with 24 bullish weeks and 28 bearish weeks forming 9 bullish clusters and 10 bearish clusters, respectively. It means that the average cluster length is 2.667 weeks for bullish clusters and 2.800 weeks for bearish clusters. For II, the maximum number of switches per year is 15 times in 2016, with 30 bullish weeks and 22 bearish weeks, forming 8 bullish clusters and 9 bearish clusters, respectively, signifying that the average cluster length is 3.750 weeks and 2.444 weeks for bullish and bearish clusters, respectively. As a result, in the 2 years with the maximum number of switches in our data, the bullish and bearish subsamples for both AAII and II do not switch frequently and fall well below the theoretical maximum of 51 switches in a given year.

Third, we locate all cases in which bullish and bearish weeks switch every week and find the longest run of weeks where this weekly switching continues, as well as those in which bullish and bearish weeks do not switch and find the longest run of weeks for weekly nonswitching. For AAII, the longest run of weekly switching occurs in 1999 and lasts 7 weeks, with 4 bullish weeks and 3 bearish weeks. Looking closely at the 7 weeks, we notice that the average sentiment for the 3 bearish weeks is 0.373, slightly below the AAII benchmark 0.383, while the average sentiment for the 4 bullish weeks is 0.425, much higher than the benchmark. Hence, while sentiment subsamples switch frequently in this 7-week period, the sentiment per se tends to be generally bullish, in line with the final classification of 1999 identified by our main approach. The longest run of weekly nonswitching lasts 52 weeks across 2015 and 2016, with 46 weeks in 2016, which is much longer than the longest run of weekly switching. For II, the longest run of weekly switching occurs in 2016 and lasts 6 weeks, with 3 bullish and 3 bearish weeks. The average sentiment of the 3 bullish weeks is 0.467, while the average sentiment of the 3 bearish weeks is 0.429, both of which are close to the benchmark 0.450, implying that the institutional investors waver between bullishness and bearish in that period. The longest run of weekly nonswitching lasts 117 weeks across 1993, 1994, and 1995, with 38, 52, and 27 weeks in 1993, 1994, and 1995, respectively, which, again is much longer than the longest run of weekly switching. Given the short weekly switching run lengths (7 and 6 weeks for AAII and II, respectively) and the long weekly nonswitching run lengths (52 and 117 weeks for AAII and II, respectively), we conclude that high-frequency switching between sentiment regimes does not persist in our sample period.

Graphically, we plot weekly AAII and II in Figure 1, showing that while both investor-type sentiments fluctuate around their average values, the extreme change, in terms of magnitude that may cause difficulties and confusion in identifying sentiment subsamples, is rarely seen. Together, the three further checks and graphical depiction in Figure 1 serve to demonstrate that frequent switching between sentiment subsamples does not occur often

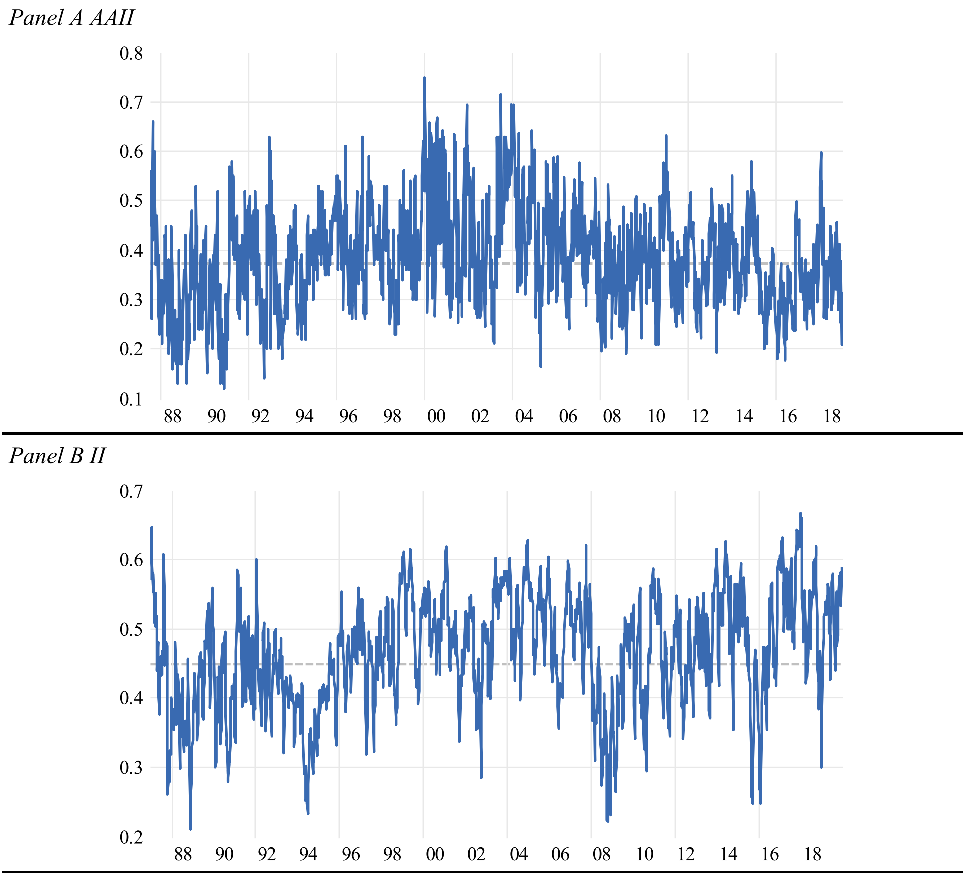

FIGURE 1 Plots of weekly AAII and II. The weekly AAII (Panel A) and II (Panel B) is shown. The *X*-axis denotes the year from 1987 to 2018, and the *Y*-axis is the level of retail and institutional investor sentiments, as reported by AAII and II, respectively. The dashed line in each figure denotes the benchmark for the bullish and bearish sample separation.

TABLE 2 Summary statistics of monthly NYSE/AMEX, 1988–2019.

This table reports the summary statistics of monthly NYSE/AMEX market returns, over the period 1988–2019. In particular, we report the mean (μ), the variance (σ^2), the skewness (Skew.), and the kurtosis (Kurt.) for excess market returns and realized volatility. Realized volatility is computed from within-month daily market returns. The reported mean and the variance for excess market returns are multiplied by 100. The reported mean and the variance for realized volatility are multiplied by 100 and 10,000, respectively. In addition to the whole sample period, we also report the high- and low-sentiment periods for retail (R) and institutional (I) investors, along with their joint (J) high- and low-sentiment periods.

	Excess market returns				Realized volatility			
	μ	σ^2	Skew.	Kurt.	μ	σ^2	Skew.	Kurt.
Whole sample	0.645	0.153	−0.699	2.073	0.223	0.191	7.563	73.768
High sentiment (R)	0.253	0.169	−0.878	2.688	0.287	0.322	6.365	48.192
Low sentiment (R)	1.036	0.135	−0.396	0.824	0.159	0.053	4.711	30.073
High sentiment (I)	0.413	0.133	−0.960	2.788	0.229	0.248	7.700	68.939
Low sentiment (I)	1.031	0.185	−0.511	1.296	0.212	0.098	3.524	15.110
High sentiment (J)	0.120	0.154	−0.915	2.724	0.288	0.366	6.358	45.949
Low sentiment (J)	1.099	0.169	−0.279	0.392	0.189	0.083	3.942	19.542

and is short-lived, giving us confidence in our final sample classification between bullish and bearish periods.

Table 1 presents descriptive statistics of annual AAII and II. Over the sample period, institutional investors tend to be more optimistic than retail investors, as evidenced by mean (0.463 and 0.383, $p = 0.000$), maximum (0.572 and 0.493), and minimum (0.336 and 0.272) sentiment values for the two groups. Variations of retail and institutional investor sentiment, however, are very similar (0.055 and 0.054, $p = 0.946$), indicating that while institutional investors are free of extreme optimism or pessimism (Wang & Duxbury, 2021), retail investors tend to exhibit the same pattern. A total of 16 and 20 years are categorized as bullish years for retail and institutional investors, respectively, of which both investors are bullish for 13 years, retail-only for 3 years, and institutional-only for 7 years.

2.2 | Stock market

We collect NYSE/AMEX market returns from the CRSP compiled by the WRDS, over 1988–2019.[9] Descriptive statistics are present in Table 2. Average monthly returns are higher in bearish than in bullish periods, for retail (*diff.* = 0.783%, $p = 0.050$), institutional (*diff.* = 0.618%, $p = 0.098$), and their joint measure (*diff.* = 0.979%, $p = 0.052$), while the volatility appears not to show significant difference across periods. In addition, the literature well reports that stock returns show negative skewness and, in our sample, the overall skewness of the entire periods (−0.699) is mainly driven by high-sentiment periods (−0.878 vs. −0.396 for retail investor sentiment, −0.960 vs. −0.511 for

[9]AAII and II span from 1987 to 2018 while stock market data span from 1988 to 2019. The 1-year gap is due to the sample classification approach. We do not extend the sample beyond 2019 to avoid the impact of the COVID-19 pandemic.

institutional investor sentiment, and −0.915 vs. −0.279 for the joint sentiment), in line with Yu and Yuan (2011). The above patterns are consistent with the sentiment hypothesis. Scheinkman and Xiong (2003) suggest that sentiment follows a mean-reverting process, so the distribution of sentiment conditional on high-sentiment periods should have a long right tail. Since high sentiment increases contemporaneous prices and decreases expected returns, the return distribution should have a more negative skewness. Also, the mean of realized volatility is close to the variance of market returns, and the difference is due to Jensen's inequality (Ghysels et al., 2005).

3 | RISK–RETURN TRADEOFF AT THE MARKET LEVEL: MEAN–VARIANCE RELATION

In this section, we examine the impact of retail and institutional investor sentiments on the risk-return relation at the market level, that is, the mean–variance relation. We start from explaining the specifications for testing the mean–variance relation and for filtering conditional volatility in Sections 3.1 and 3.2, respectively. Results are provided in Section 3.3, followed by a battery of robustness tests in Section 3.4.

3.1 | Testing the mean–variance relation

An unconditional test for the mean–variance relation is to regress monthly returns (R_{t+1}) on monthly conditional volatility [$Var_t(R_{t+1})$] in a time-series way (Ghysels et al., 2005; Wang, 2018; Yu & Yuan, 2011),

$$R_{t+1} = \alpha + \beta Var_t(R_{t+1}) + \varepsilon_{t+1}. \tag{1}$$

where β reflects the mean–variance relation across the whole sample period unconditional on investor sentiment, and prior literature suggests that β can be positive, negative, or close to zero. To reveal the impact of retail and institutional investor sentiment on the mean-variance relation, we estimate a conditional regression,

$$\begin{aligned} R_{t+1} = {} & \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_t(R_{t+1}) + \beta_2 Var_t(R_{t+1}) D_t^{ret} + \beta_3 Var_t(R_{t+1}) D_t^{ins} \\ & + \varepsilon_{t+1}, \end{aligned} \tag{2}$$

where D_t^{ret} and D_t^{ins} are dummy variables identifying retail and institutional investor sentiments, respectively, and take the value one (zero) when these sentiments are bullish (bearish), respectively;[10] β_1 is the mean-variance relation over tranquil periods when neither retail nor institutional investors are bullish; β_2 (β_3) measures the incremental change in the mean–variance relation due to retail (institutional) investors' being bullish while institutional (retail) investors being bearish; and $(\beta_2 + \beta_3)$ is the incremental change due to both being bullish; $(\beta_1 + \beta_2)$, $(\beta_1 + \beta_3)$, and $(\beta_1 + \beta_2 + \beta_3)$, therefore, denote the mean–variance relations when retail investors, institutional investors, and both investor types are bullish, respectively. If retail investors or institutional

[10] Retail and institutional investor sentiments do not enter Equation (2) directly. We use them to separate the entire sample into four subsamples by adding dummy variables, D_t^{ret} and D_t^{ins}.

investors are noise traders and misestimate the mean–variance relation, their elevated trading over bullish periods would distort the theoretical risk-return tradeoff, that is, a negative β_2 or β_3. Our model follows the prior studies such as Yu and Yuan (2011), Wang (2018), and Wang and Duxbury (2021), and is estimated in a time-series way; however, extended by applying two investor types, thus we can distinguish the impact of retail and institutional investor sentiments.

3.2 | Volatility models

We use five different approaches, including the RW, the mixed-data sampling (MIDAS), GARCH, GJR-GARCH, and EGARCH, to measure conditional volatility since the presented mean–variance relation is subject to the choice of volatility models (Ghysels et al., 2005; Wang & Duxbury, 2021; Yu & Yuan, 2011). While ideally, we hope to reveal consistent results across the five models, it appears to be difficult, if not impossible, to achieve so, especially considering the number of tests we run. In this paper, we define that a significant mean–variance relation, either negative or positive, can be confirmed if (i) three out of the five volatility models generate significant results, and (ii) at least one significant result should come from RW or MIDAS, that is, that a significant relation cannot be confirmed if three significant results are all from the GARCH-type models.

3.2.1 | RW model

The RW model employs the realized volatility of the current month as the conditional volatility (French et al., 1987), following,

$$Var_t(R_{t+1}) = \sigma_t^2 = \frac{22}{N_t}\sum_{d=1}^{N_t} r_{t-d}^2, \tag{3}$$

where $Var_t(R_{t+1})$ is the conditional volatility for forecasting next-month market returns R_{t+1}; σ_t^2 is the realized volatility in month t; r_{t-d} is the demeaned daily market return in month t, computed by subtracting the within-month mean daily return from daily raw returns; N_t is the number of actual trading days in month t; and 22 is the conventionally adopted number of trading days in 1 month (Wang, 2018; Yu & Yuan, 2011), and ensures the conditional volatility to be expressed at the monthly interval. We use the upper-case R for monthly returns, while lower-case r for daily returns, which might be slightly equivocal but avoids being cumbersome.

3.2.2 | Mixed-data sampling model

The MIDAS has a similar estimation structure of RW but differs in horizon, flexibility, and the weighting system (Ghysels et al., 2005), following,

$$Var_t(R_{t+1}) = 22\sum_{d=0}^{252} \omega_d r_{t-d}^2, \tag{4}$$

where r_{t-d} is the demeaned daily return, computed by subtracting the within-month mean daily return from daily raw returns, in line with the RW, and the subscript $(t-d)$ corresponds to the date t minus d days; ω_d is the weight on r_{t-d}^2, following,

$$\omega_d(\kappa_1, \kappa_2) = \frac{\exp\{\kappa_1 d + \kappa_2 d^2\}}{\sum_{d=0}^{252} \exp\{\kappa_1 d + \kappa_2 d^2\}}, \tag{5}$$

where κ_1 and κ_2 are the parameters in the weight function and estimated by maximizing the likelihood function together with Equation (4) and Equations (1) or (2) as explained above. With weights (ω_d) sum up to one, 22 in Equation (4) again ensures the conditional volatility is in monthly units. Different from RW relying on the prior month's returns with equal weights, the monthly conditional volatility filtered by MIDAS relies on the previous 252 trading days with a different weighting system following the exponential form (Ghysels et al., 2005).

3.2.3 | GARCH, GJR-GARCH, and EGARCH

For GARCH, GJR-GARCH, and EGARCH, we first estimate the mean equation at the daily interval, following,

$$r_{t+1} = \mu + \varepsilon_{t+1}, \tag{6}$$

where r_{t+1} is the daily market return at day $(t + 1)$; μ is the conditional mean of the daily market return; and ε_{t+1} is the residual. The daily conditional volatility models are in GARCH (1,1) specification due to its wide applicability (Bollerslev et al., 1992; Hansen & Lunde, 2005), following,

$$\sigma_{t+1}^2 = \omega + \alpha\varepsilon_t^2 + \beta\sigma_t^2, \tag{7}$$

$$\sigma_{t+1}^2 = \omega + \alpha_1\varepsilon_t^2 + \alpha_2 I_t\varepsilon_t^2 + \beta\sigma_t^2, \tag{8}$$

$$\sigma_{t+1}^2 = \exp\left\{\omega + \alpha_1\left[|\varepsilon_t|/\sqrt{\sigma_t^2}\right] + \alpha_2\left[\varepsilon_t/\sqrt{\sigma_t^2}\right] + \beta\ln\sigma_t^2\right\}, \tag{9}$$

for GARCH, GJR-GARCH, and EGARCH, respectively. The term I_t in Equation (8) is the dummy variable for bad news (i.e., $\varepsilon_t^2 < 0$) to account for the leverage effect, that is, allowing for asymmetry in the response of the conditional volatility to return innovations (Glosten et al., 1993). We store daily conditional volatility series obtained from Equations (5), (6), and (7), σ_{t+1}^2, and accumulate monthly conditional volatility, $Var_t(R_{t+1})$, as the linear sum of daily conditional volatility (Corsi, 2009; Engle, 2001),

$$Var_t(R_{t+1}) = E_t\left(\sum_{d=1}^{N_t}\sigma_{t+d}^2\right). \tag{10}$$

3.3 | Mean–variance relation

Results of the market-level mean–variance relation appear in Table 3. We firstly look at the unconditional results that are based on the entire sample period, that is, irrespective of investor sentiment, are suggestive of a negative mean–variance relation for market returns, in line with Campbell (1987), Whitelaw (1994), Ghysels et al. (2005), and Baker et al. (2011). GJR-GARCH,

TABLE 3 Excess market returns against conditional volatility.

This table reports the results of the impact of retail and institutional investor sentiment on the mean–variance relation. Pane (A) presents the results from the entire sample by estimating,

$$R_{t+1} = \alpha + \beta Var_t(R_{t+1}) + \varepsilon_{t+1},$$

where β reflects the mean–variance relation, and prior literature suggests that β can be positive (i.e., the risk-return tradeoff), negative, or close to zero; R_{t+1} is the excess stock returns, and $Var_t(R_{t+1})$ is the conditional volatility computed by five different ways, that is, the RW, three GARCH-family models, including GARCH, GJR-GARCH, and EGARCH, and MIDAS. Pane (B) presents the results conditional on retail and institutional investor sentiment. We follow Yu and Yuan (2011) and Antoniou et al. (2016), among others, employ the 1-year window and identify year $(T+1)$ based on the annual AAII and II for year T, $S_{\text{AAII,T}}$ and $S_{\text{II,T}}$, computed as the average of within-year weekly sentiment observations, containing all sentiment information across year T. For AAII, if $S_{\text{AAII,T}}$ is above the all-sample average, year $(T+1)$ is classified as a bullish year for retail investors (Wang, 2018), while for II, if $S_{\text{II,T}}$ is above 0.450, the benchmark of institutional investors' bullishness as originally designed, year $(T+1)$ is classified as a bullish year for institutional investors. The regression specification follows,

$$R_{t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_t(R_{t+1}) + \beta_2 Var_t(R_{t+1}) D_t^{ret} + \beta_3 Var_t(R_{t+1}) D_t^{ins} + \varepsilon_{t+1},$$

where D_t^{ret} and D_t^{ins} denote bullish periods for retail and institutional investors, respectively; β_1 is the mean–variance relation over tranquil periods when neither is bullish; β_2 (β_3) measures the incremental change in the mean–variance relation due to retail (institutional) investors' being bullish while institutional (retail) investors being bearish; and $(\beta_2 + \beta_3)$ is the incremental change due to both being bullish; $(\beta_1 + \beta_2)$, $(\beta_1 + \beta_3)$, and $(\beta_1 + \beta_2 + \beta_3)$, therefore, denote the mean-variance relations when retail investors, institutional investors, and both investor types are bullish, respectively. [a], [b] and [c] represent statistical significance at the 1%, 5% and 10% level, respectively.

	Entire (A)		Bullish and nonbullish (B)							
Model	β	Adj. R^2	β_1	β_2	$\beta_1+\beta_2$	β_3	$\beta_1+\beta_3$	$\beta_2+\beta_3$	$\beta_1+\beta_2+\beta_3$	Adj. R^2
RW	−0.989[b]	0.010	2.325[c]	−2.733	−0.408	−1.066	1.259	−3.798[a]	−1.473[a]	0.030
MIDAS	−1.024[b]	0.008	2.827[b]	−2.824	0.004	−1.601	1.226	−4.425[a]	−1.597[a]	0.031
GARCH	−0.887	0.004	3.730[b]	−2.676	1.054	−2.666	1.064	−5.342[a]	−1.612[a]	0.034
GJR-GARCH	−1.002[c]	0.006	3.265[b]	−2.717	0.540	−2.114	1.142	−4.830[a]	−1.574[a]	0.029
EGARCH	−1.078	0.003	4.493[b]	−3.170	1.324	−3.403	1.091	−6.572[a]	−2.079[b]	0.031

for example, presents that a 1% upward (downward) revision in conditional volatility would cause a 1.002% decrease (increase) in market returns. The results largely change after taking investor sentiment into account, as suggested by conditional results. Amid bearish periods, a risk-return tradeoff is shown in all five volatility models, consistent with French et al. (1987), Baillie and DeGennaro (1990), Scruggs (1998), Guo and Whitelaw (2006), Pástor et al. (2008), Rossi and Timmermann (2015): GJR-GARCH, this time, shows that a 1% upward (downward) revision in conditional volatility would cause a 3.265% increase (decrease) in market returns. The results line up well with economic intuition concerning reasonable levels of risk-aversion (Ghysels et al., 2005) and match a variety of empirical studies (Hall, 1988, and references therein). While Yu and Yuan (2011) and Wang (2018) find a negative influence of retail and institutional investor sentiment on the mean–variance relation, respectively, we find an insignificant, negative impact, implying that the reported negative impact of retail or institutional investor sentiment on the mean–variance relation in extant studies appears not to universally hold when controlling for institutional or retail investor sentiment. This would seem to give support to Bohl et al.'s (2009) conjecture that institutional investors may act to counter retail investor sentiment. However, the joint impact of retail and institutional investor sentiments, captured by $(\beta_2 + \beta_3)$, is consistently significantly negative, indicating that the distortion of the risk-return tradeoff is not achieved by one group of participants but both groups collectively. The joint impact, ranging from −3.798 (RW) to −6.572 (EGARCH), is fairly strong so that it reverses the originally positive mean–variance relation exhibited amid bearish periods, ranging from −1.473 (RW) to −2.079 (EGARCH): On average, a 1% change in monthly conditional volatility during bullish periods would lead to an around 1.667% change in monthly market returns. Finally, we see from adjusted R^2 that the inclusion of investor sentiment much enhances the explanatory power.[11] Overall, our results confirm a negative impact of investor sentiment on the mean–variance relation, but different from the existing evidence, our conclusion is drawn based on the joint impact of retail and institutional investor sentiment, not the two separately. Contrary to Bohl et al.'s (2009) conjecture, we conclude that institutional investors do not counter retail investor sentiment and indeed contribute jointly to the destabilizing impact of sentiment on the risk-return relation, as argued in Chelley-Steeley et al. (2019). Our findings, from the perspective of the impact of investor sentiment, add further evidence of the destabilizing impact of institutional investors on stock markets (Allen & Gorton, 1993; Brunnermeier & Nagel, 2004; Cao et al., 2017; Choi et al., 2015; Hart & Kreps, 1986; Hong et al., 2012; Lakonishok et al., 1991; Shleifer & Vishny, 1997; Stein, 2009).

3.4 | Robustness checks

In this section, we present a battery of robustness checks, including (i) using a composite sentiment proxy, (ii) removing macro and market factors from investor sentiment, (iii) using alternative sample separation criteria, (iv) using alternative sentiment proxies, (v) using an alternative market index, and (vi) controlling for the financial crisis period. Results consistently confirm the negative joint impact of retail and institutional investor sentiments on the mean–variance relation.

3.4.1 | A composite sentiment proxy

We first consider combining retail and institutional investor sentiments together by constructing a new parsimonious proxy via the principal component analysis (PCA). In our main test, we view retail and institutional investors as two separate groups and look into their individual impacts (i.e., when one group exhibits bullishness while the other exhibits bearishness), and the joint impact (i.e., when both contemporaneously exhibit bullish/bearish sentiments), on the mean–variance relation. In this robustness check, conceptually, we regard the two groups of investors as one, that is, sentiment traders, and thus their bullishness or bearishness is a net reflection of all irrational traders' opinions.

To elucidate, we extract the common information from the weekly AAII and II. The first principal component (PC) explains 79.334% of the total variance and we use it as our new composite sentiment proxy. For each year, we compute the annual sentiment values by averaging the within-year weekly values and compare them with the all-sample average. Same

[11]While the overall adjusted R-squares are low, this is common in explaining market returns (Schmeling, 2009; Wang et al., 2021).

TABLE 4 Robustness test: using a composite sentiment proxy.

This table reports the results of the impact of retail and institutional investor sentiment on the mean-variance relation, following,

$$R_{t+1} = \alpha_1 + \alpha_2 D_t^{PCA} + \beta_1 Var_t(R_{t+1}) + \beta_2 Var_t(R_{t+1}) D_t^{PCA} + \varepsilon_{t+1},$$

where D_t^{PCA} denotes bullish periods for sentiment investors. To obtain the composite proxy, S_{PCA}, we extract the common information from the weekly AAII and II. Panel A presents results from equal-weighted PCA, while Panel B presents results from weighted PCA by assigning 20% to retail investor sentiment, AAII, and 80% to institutional investor sentiment, II. The first PC explains 79.334% of the total variance and we use it as our new sentiment proxy. For each year, we compute the annual sentiment values by averaging the within-year weekly values and compare them with the all-sample average. [a], [b] and [c] represent statistical significance at the 1%, 5% and 10% level, respectively.

Model	β_1	β_2	$\beta_1 + \beta_2$
Panel A: Equal-weighted PCA			
RW	2.060[c]	−3.371[b]	−1.311[a]
MIDAS	2.504[c]	−3.884[a]	−1.380[b]
GARCH	3.393[b]	−4.717[a]	−1.324[b]
GJR-GARCH	2.934[c]	−4.238[b]	−1.304[b]
EGARCH	3.755[b]	−5.328[a]	−1.574[b]
Panel B: Weighted PCA (20% vs. 80%)			
RW	2.199[b]	−2.942[a]	−0.744
MIDAS	2.214[b]	−3.113[a]	−0.899
GARCH	3.134[a]	−4.103[a]	−0.969
GJR-GARCH	2.752[a]	−3.602[a]	−0.851
EGARCH	3.454[a]	−4.760[a]	−1.306

as the process for AAII and II, we classify each year to bullish or bearish based on the median approach. In particular, this new composite sentiment proxy generates 14 bullish years, very similar to the main test (13), with 1 year excluded and 2 other years included. Results in Panel A of Table 4 support our main findings, reporting a positive mean–variance relation, over bearish periods, and a distortion over bullish periods, with the latter potentially driven by heightened sentiment trader participation (Yu & Yuan, 2011).

In addition, considering that institutional investors play an increasingly important role in stock market trading (Johnson et al., 2010),[12] we assign different weights to retail and institutional investors for the composite index and, with the same eigenvalues obtained as above, we assign 20% to the former while 80% to the latter, making the final composite proxy more driven by institutional investors and less driven by retail investors. Then, we compute the all-sample average and use it as the benchmark to classify bullish and bearish periods. Results presented in Panel B of Table 4 are largely consistent with our main results and the equal-weighted composite proxy results. Results from our main tests and the equal-weighted composite proxy both show that during bullish periods,

[12]See, https://www.nasdaq.com/articles/who-is-trading-on-u.s.-markets-2021-01-28 (accessed on 24/02/2023).

the distortion of the mean-variance relation caused by the joint investor sentiment is strong enough to turn the mean-variance relation negative, statistically significantly so. For the weighted composite proxy results, the mean-variance relation is insignificantly negative, ranging from −0.744 (RW) to −1.306 (EGARCH), suggesting a relatively weaker distortion in the sense that the relation departs from the theorized statistically significant positive relation.[13]

3.4.2 | Removing macro and market factors

Investor sentiment can reflect expectations based on fundamentals as well as irrational beliefs (Derrien & Kecskés, 2009; Han et al., 2022; Lemmon & Portniaguina, 2006; Wang et al., 2021). Taking this into account, following Baker and Wurgler (2006), Antoniou et al. (2013), Kadilli (2015), and Gric et al. (2022), we extract the pure irrational component from investor sentiment that is unrelated to fundamentals by regressing AAII and II on contemporaneous and lagged values of a number of macro and market variables as below,

$$S_{AAII,t} = a + b\Psi_t + \eta_{AAII,t}, \tag{11}$$

$$S_{II,t} = a + b\Psi_t + \eta_{II,t}, \tag{12}$$

where $S_{AAII,t}$ and $S_{II,t}$ is the monthly AAII and II, respectively, computed as the average of the monthly within-week observations; ψ_t is a matrix containing a range of macro and market variables, including unemployment rate, industrial production growth, inflation rate measured from the consumer price index, default spread measured as the difference in yield between Moody's BAA and AAA corporate bonds, term spread measured as the difference yield of 10-year treasury bond and 3-month T-Bill, currency fluctuation measured as monthly change in 26 market US dollar index, detrended short-term interest rate, excess return on market portfolio ($R_m - R_f$), as well as pricing factors including *SMB*, *HML*, *MOM*, *RMW*, and *CMA* (see, Bathia et al., 2016; Lemmon & Portniaguina, 2006; Schmeling, 2009; Wang et al., 2021). The residuals from Equations (14) and (15), $\eta_{AAII,t}$ and $\eta_{II,t}$ represent the irrational component, which is not explained by fundamentals, of retail and institutional investor sentiments, respectively. We use this irrational component as the index for sample separation. Results in Panel A of Table 5 support our argument that the joint impact of retail and institutional investor sentiments distorts the mean–variance relation.[14]

[13]Our results hold in a range of different weighting allocations such as 25% versus 75% and 30% versus 70%, further confirming the robust impact of the joint investor sentiment on the mean-variance relation.

[14]We thank one anonymous referee for the suggestion to check the impact of fundamentals perceived by retail and institutional investors on the mean–variance relation, notwithstanding our evidence of irrational sentiment-based trading. We subtract the residuals (the pure irrational element of investor sentiment, $\eta_{AAII,t}$ and $\eta_{II,t}$) from dependent variable (investor sentiment as measured by AAII and II for retail and institutional investors, respectively, $S_{AAII,t}$ and $S_{II,t}$), and store the difference (the rational element of investor sentiment reflecting fundamentals). We then compute the all-sample average for both investor sentiments and classify our sample into four subsamples. Contrary to our main sample separation based on the two investor sentiments, the new subsample is derived from fundamentals that are perceived by retail and institutional investors. Finally, we run identical empirical tests as for investor sentiment. Untabulated results show that fundamentals and the mean–variance relation tend to be significantly negatively related for institutional investor, while insignificantly positively related for retail investors. Campbell and Cochrane (1999) posit a theoretical model in which the agent's utility depends on the difference between current consumption and the average of past consumption, or habit, presenting that time-varying risk aversion may generate a counter-cyclical risk-return relation (see, also, Yu & Yuan, 2011). Results here suggest that the fundamentals perceived by institutional investors are more in line with the fundamentals per se compared with those perceived by retail investors, indicating that institutional investors are relatively more fundamentals-based than retail investors, though this does not preclude their irrational sentiment-based trading as per our main results.

TABLE 5 More robustness tests.

This table reports the results of the impact of retail and institutional investor sentiment on the mean–variance relation from four robustness tests. Panel A controls for macro and market factors by extracting the pure irrational component from investor sentiment that is unrelated to fundamentals by regressing AAII and II on contemporaneous and lagged values of a number of macro and market variables as below,

$$S_{AAII,t} = a + b\Psi_t + \eta_{AAII,t},$$

$$S_{II,t} = a + b\Psi_t + \eta_{II,t}$$

where $S_{AAII,t}$ and $S_{II,t}$ is the monthly AAII and II, respectively, computed as the average of the monthly within-week observations; ψ_t is a matrix containing a range of macro and market variables, including unemployment rate, industrial production growth, inflation rate measured from the consumer price index, default spread measured as the difference in yield between Moody's BAA and AAA corporate bonds, term spread measured as the difference yield of 10-year treasury bond and 3-month T-Bill, currency fluctuation measured as monthly change in 26 market US dollar index, detrended short-term interest rate, excess return on market portfolio ($R_m - R_f$), as well as pricing factors including *SMB*, *HML*, *MOM*, *RMW*, and *CMA*. The residuals from the two equations, $\eta_{AAII,t}$ and $\eta_{II,t}$ represent the irrational component, which is not explained by fundamentals, of retail and institutional investor sentiment, respectively. We use this irrational component as the index for sample separation. Panel B adopts alternative sample separation based on the number of bullish/bearish weeks (Panel B.1) or months (Panel B.2) within a year. Panel C selects alternative investor sentiment proxies. Panel D employs NASDAQ, as an alternative index to NYSE/AMEX. And Panel E controls for the crisis period following the National Bureau of Economic Research (NBER) business cycle dating. [a], [b], and [c] represent statistical significance at the 1%, 5%, and 10% level, respectively.

Model	β_1	β_2	$\beta_1+\beta_2$	β_3	$\beta_1+\beta_3$	$\beta_2+\beta_3$	$\beta_1+\beta_2+\beta_3$
Panel A: Controlling for macro and market factors							
RW	3.604	−2.696	0.907	−2.572	1.031	−5.268[c]	−1.665[a]
MIDAS	4.032	−2.917	1.115	−2.879	1.152	−5.796[c]	−1.764[a]
GARCH	5.305	−3.406	1.898	−3.560	1.744	−6.966[c]	−1.662[a]
GJR-GARCH	3.767	−2.736	1.031	−2.724	1.043	−5.460	−1.693[a]
EGARCH	4.083	−2.994	1.089	−3.284[c]	0.799	−6.278[c]	−2.195[a]
Panel B.1: Alternative sample separation based on the number of bullish/bearish weeks							
RW	2.255[c]	−2.727	−0.473	−0.968	1.286	−3.696[a]	−1.441[a]
MIDAS	2.738[b]	−2.928	−0.190	−1.361	1.377	−4.290[a]	−1.552[a]
GARCH	3.607[b]	−3.002	0.606	−2.152	1.456	−5.153[a]	−1.546[b]
GJR-GARCH	3.144[b]	−2.874	0.270	−1.789	1.355	−4.663[a]	−1.520[a]
EGARCH	4.342[b]	−3.620	0.723	−2.692	1.650	−6.312[a]	−1.970[b]
Panel B.2: Alternative sample separation based on the number of bullish/bearish months							
RW	2.262[c]	−2.846	−0.585	−0.870	1.392	−3.716[a]	−1.454[a]
MIDAS	2.758[c]	−3.004	−0.246	−1.327	1.431	−4.331[a]	−1.574[a]
GARCH	3.669[b]	−3.027	0.642	−2.226	1.443	−5.253[a]	−1.584[a]
GJR-GARCH	3.168[b]	−2.898	0.270	−1.821	1.347	−4.719[a]	−1.551[a]
EGARCH	4.426[b]	−3.592	0.834	−2.864	1.562	−6.456[a]	−2.030[b]
Panel C.1: Alternative proxies: BW index and II							
RW	0.688	1.437	2.125	−3.415	−2.728	−1.978	−1.290[b]

(Continues)

TABLE 5 (Continued)

Model	β_1	β_2	$\beta_1+\beta_2$	β_3	$\beta_1+\beta_3$	$\beta_2+\beta_3$	$\beta_1+\beta_2+\beta_3$
MIDAS	1.030	1.521	2.551	−3.966	−2.936	−2.445[c]	−1.415[b]
GARCH	1.956	1.899	3.854	−5.330[c]	−3.374	−3.431[b]	−1.475[b]
GJR-GARCH	1.223	1.470	2.693	−4.104	−2.881	−2.633[c]	−1.410[b]
EGARCH	2.440	0.096	2.535	−4.450	−2.011	−4.354[b]	−1.915[b]
Panel C.2: Alternative proxies: BW index and sentix (shortened sample size)							
RW	2.199	−3.036	−0.830	−3.529	−1.390[c]	−6.565[c]	−5.312[b]
MIDAS	2.705	−3.306	−0.600	−4.177	−1.472[b]	−7.482[c]	−5.884[b]
GARCH	3.584[c]	−3.519	0.065	−5.104[b]	−1.520[b]	−8.623[b]	−6.361[b]
GJR-GARCH	3.281	−3.689	−0.408	−4.748[b]	−1.467[b]	−8.437[c]	−6.559[b]
EGARCH	4.656[c]	−3.871	0.785	−6.884[a]	−2.228[b]	−10.755[c]	−7.362[b]
Panel D: NASDAQ market index							
RW	2.705	−1.141	1.564	−3.000	−0.295	−4.142[b]	−1.436[a]
MIDAS	3.203[c]	−1.223	1.981	−3.508	−0.305	−4.731[b]	−1.528[a]
GARCH	4.132[b]	−1.449	2.683	−4.288[b]	−0.156	−5.737[a]	−1.605[a]
GJR-GARCH	3.500[c]	−1.333	2.167	−3.680[c]	−0.181	−5.012[b]	−1.513[b]
EGARCH	4.334[c]	−1.276	3.058	−4.669[b]	−0.335	−5.945[b]	−1.611[b]
Panel E: Controlling for the crisis period							
RW	3.803[a]	−3.066	0.737	−0.461	3.342[c]	−3.527[c]	0.276
MIDAS	4.450[a]	−3.366	1.084	−0.671	3.779[c]	−4.037[c]	0.413
GARCH	5.274[a]	−3.210	2.064	−2.019	3.255	−5.230[b]	0.044
GJR-GARCH	5.276[a]	−4.371	0.905	0.118	5.394[b]	−4.253	1.023
EGARCH	6.125[a]	−3.497	2.628[b]	−1.891	4.234[b]	−5.389[c]	0.737

3.4.3 | Using alternative sample separation criteria

Notwithstanding the checks and graphical analysis reported in above in Section 2.1, here we consider the robustness of our results to our main sample separation criteria. To this end, we apply two alternative sample separation criteria to reidentify the bullish and bearish subsamples, based on the number of bullish and bearish weeks and months within a year.[15] For weeks, if we have more (fewer) bullish weeks than bearish weeks in year T, we classify year $(T+1)$ as bullish (bearish). In one case for the retail investor sentiment, AAII, the number of bullish weeks equals that of bearish weeks (26 weeks for both), so in this instance we follow the main approach as discussed in Section 2.1. For months, if we have more (fewer) bullish months than bearish (months) in year T, we classify year $(T+1)$ as bullish (bearish). In several cases

[15]We thank one anonymous referee for suggesting the two alternative criteria.

where the number of bullish months equals that of bearish months (i.e., 6 months for both), we follow the weekly approach. Overall, the two new approaches generate similar subsamples to our main approach, offering reassurance for the validity of the latter: For example, the average approach and the weekly approach generate exactly the same bullish/bearish separation for retail investors. We rerun our main analyses using the weekly and monthly separations. Results reported in Panel B.1 and B.2 of Table 5 are in line with our main finding based on the average approach.

3.4.4 | Using alternative sentiment proxies

We consider employing alternative sentiment proxies in this robustness test to ensure that our reported impact is due to investor sentiment rather than the selected sentiment proxies (Altanlar et al., 2019; Gao et al., 2021; Karampatsas et al., 2022). Here, we perform two different tests. In the first test, we replace AAII with the BW index as compiled by Baker and Wurgler (2006). Unlike the AAII index directly compiled from investor sentiment surveys, the BW index, as a composite sentiment indicator, extracts sentiment from markets based on five individual sentiment proxies including the closed-end fund discount, the number of IPOs, the average 1st-day returns on IPOs, the equity share in new issues, and the dividend premium. While an indirect sentiment proxy, being based on market-related factors the BW index is proximate to the financial markets (Duxbury et al., 2020), reflecting the impact of sentiment on trading behaviour in financial markets. It is the seminal sentiment proxy of its kind and has been widely used in prior studies of retail investor sentiment such as Derrien and Kecskés (2009), Yu and Yuan (2011), Shefrin (2015), Antoniou et al. (2016), and Dong and Doukas (2020). In the second, we replace AAII and II with the BW index and sentix, respectively. Unlike the II survey where market newsletters are mainly from the US market, sentix respondents are worldwide institutional investors, thus reflecting the global appeal of the US market and capturing a broader perspective of institutional investor sentiment. The sentix has also been used in studies of institutional investor sentiment such as Schmeling (2007), Naifar (2016), Gao et al. (2021), and Wang and Duxbury (2021). As sentix data are available from 2003, the second test is based on a reduced sample period over 2004–2019. Results reported in Panels C.1 and C.2 of Table 5 are broadly in line with our main finding that the impact of investor sentiment on the mean-variance relation is more likely to be a joint outcome of both retail and institutional investors. Hence, our results are robust to the choice of sentiment proxy.

3.4.5 | Other robustness checks

We employ another market index, NASDAQ, as an alternative to NYSE/AMEX, and control for the crisis period following the National Bureau of Economic Research (NBER) business cycle dating.[16] Results in Panels D and E of Table 5 largely support our main findings that the joint impact of retail and institutional investor sentiments brings a robust, negative impact on the mean-variance relation.

[16]Kadilli (2015), and Wang et al. (2022), for example, reveal that the impact of investor sentiment varies across market regimes and so we control for crisis times so as to ensure the robustness of our results.

4 | RISK–RETURN TRADEOFF AT THE FIRM LEVEL: BETA–RETURN RELATION

The risk–return relation is also embodied at the firm level, that is, a beta–return relation. We extend our analysis, therefore, to check if the observed market-level impact of investor sentiment holds at the firm level as well.

The CAPM posits a positive linear beta-return relation, that is, that bearing high-beta stocks should be rewarded by high returns while bearing low-beta stocks can only expect low returns (Sharpe, 1964). Fama and French (1992), however, reveal a flat relation between betas and returns, reasons of which are explored from various perspectives such as market frictions, misspecification of systematic risk, and inefficiency of market proxies (Brennan et al., 2012; Frazzini & Pedersen, 2014; Jagannathan & Wang, 1996; Roll & Ross, 1994). Antoniou et al. (2016) suggest that as unsophisticated traders, retail investors trade more over high-sentiment periods while less over low-sentiment periods (Grinblatt & Keloharju, 2009; Lamont & Thaler, 2003). Their elevated trading does not influence stocks equally but concentrates on high-beta stocks (Barber & Odean, 2000, 2001; Hong & Sraer, 2016; van Binsbergen et al., 2022), leading high-beta stocks to be overpriced, which is followed by low returns and hence, the collapse of the CAPM, or the positive security market line (SML). By contrast, the CAPM would hold over gloomy periods when retail investors feel pessimistic, which is supported by their empirical results showing a positive beta-return relation over pessimistic periods while a negative relation over optimistic periods. Wang (2020) subsequently confirms the same pattern for institutional investors. Here, we extend such considerations by taking both retail and institutional investor sentiment into account. Stock betas are collected from the WRDS Beta Suite. We choose (i) 5-year (Fama & MacBeth, 1973; Petkova, 2006), (ii) 2- to 5-year (as available, Antoniou et al., 2016; Fama & French, 1992), and (iii) 3-year (Lewellen, 2015) estimation windows for monthly betas. Since at the market level, the mean–variance relation is subject to volatility models as explained in Section 3, stock betas applied for the beta–return relation are estimated from three asset pricing models including the CAPM (Sharpe, 1964), the three-factor model (Fama & French, 1993), and the four-factor model (Carhart, 1997).[17]

4.1 | Portfolio analyses

We assign stock betas into ten deciles (from $d1$ to $d10$), lowest betas in $d1$ and highest betas in $d10$, and compute the average monthly returns for each beta portfolio.[18] Results appear in Table 6. Over the entire sample period, a U-shaped pattern is observed, with the lowest-beta and the highest-beta stocks having higher returns and those in the middle having lower returns. Despite this, the average return of the highest-beta stocks (1.944%) is slightly higher than that of the lowest-beta stocks (1.321%). In low-sentiment periods when retail and/or institutional investor are bearish, average returns of the highest-beta stocks are 2.926%, 3.012%, and 3.418% during periods when retail, institutional, and both investor types are bearish,

[17]While an alternative to the RW approach would be to calculate annual betas from weekly returns, due to persistence in betas in the former approach, for reasons of comparability and considering the sample size we follow prior studies (as cited in the text) and use monthly betas for estimations.

[18]Betas employed in the portfolio analyses are from the CAPM model applying the 5-year estimation window. Using betas from the three- and the four-factor models or applying the 3- and 2- to 5-year estimation windows, do not affect our findings.

TABLE 6 Average returns of beta-sorted portfolios.

This table reports average returns of beta-sorted portfolios over the entire sample, as well as the high- and low-sentiment periods for retail (R) and institutional (I) investors, along with their joint (J) high- and low-sentiment periods. Returns (in %) are computed as the average monthly returns of each beta portfolio. Lowest-beta stocks are grouped into the lowest-numbered decile (i.e., d1) while highest-beta stocks are grouped into the highest-numbered decile (i.e., d1). The last column (d10 – d1) computes return differences between the highest-beta and lowest-beta portfolios. [a], [b] and [c] represent statistical significance at the 1%, 5% and 10% level, respectively.

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d10 – d1
Entire sample	1.321	1.035	1.036	1.041	1.041	1.065	1.178	1.157	1.274	1.944	0.623[b]
High sentiment (R)	1.492	1.184	1.155	1.144	0.957	0.939	0.871	0.865	0.576	0.470	−1.022[a]
Low sentiment (R)	1.156	0.892	0.952	1.146	1.063	1.256	1.252	1.432	1.729	2.926	1.770[a]
High sentiment (I)	1.246	1.138	1.182	1.219	1.087	1.097	1.109	1.123	0.930	1.193	−0.053
Low sentiment (I)	1.384	0.837	0.806	0.907	0.956	1.094	1.187	1.269	1.651	3.012	1.644[a]
High sentiment (J)	1.526	1.243	1.320	1.254	1.071	0.970	0.877	0.879	0.526	0.250	−1.276[a]
Low sentiment (J)	1.396	0.859	0.858	1.036	0.940	1.280	1.203	1.371	1.832	3.418	2.023[a]

respectively, more than double the average returns of the lowest-beta stocks that are 1.156%, 1.384%, and 1.396%, with consistently significant differences ($d10-d1$). In contrast, during high-sentiment periods, the lowest-beta stocks yield higher returns than the highest-beta stocks, instead. During the periods when both retail and institutional investors are bullish, for example, the average return of the lowest-beta stocks (1.526%) is more than five times of that of the highest-beta stocks (0.250%), suggesting the collapse of the CAPM positing a positive beta–return relation.

4.2 | Regression analyses

Similar to the market-level tests, we firstly estimate an unconditional equation, following:

$$R_{i,t} = \alpha + \beta Beta_{i,t} + \gamma \Psi_t + \varepsilon_{i,t}, \tag{13}$$

where $R_{i,t}$ is the return of stock i in month t and $Beta_{i,t}$ is the beta of stock i in month t, obtained from three asset pricing models including the CAPM (Sharpe, 1964), the three-factor model (Fama & French, 1993), and the four-factor model (Carhart, 1997), and for 5-year (Fama & MacBeth, 1973; Petkova, 2006; Shen et al., 2017), 2- to 5-year (as available, Antoniou et al., 2016; Fama & French, 1992), and 3-year (Lewellen, 2015) estimation windows. Moreover, we control for $R_m - R_f$, SMB, HML, MOM, RMW, and CMA as in Carhart (1997) and Fama and French (2015, 2018) in matrix Ψ_t.[19] Models here are estimated as the fixed-effect panel regression with robust and clustered standard errors. To examine the impact of retail and

[19]In particular, $R_m - R_f$ is the market portfolio return minus the risk-free rate; *SMB*, *HML*, *MOM*, *RMW*, and *CMA* represent differences between the returns on diversified portfolios of small and big stocks, high and low B/M stocks, stocks with robust and weak profitability, and stocks of conservative and aggressive firms, respectively.

institutional investor sentiment on the beta–return relation, we apply a conditional equation, following:

$$R_{i,t} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Beta_{i,t} + \beta_2 Beta_{i,t} D_t^{ret} + \beta_3 Beta_{i,t} D_t^{ins} + \gamma_1 \Psi_t + \gamma_2 \Psi_t D_t^{ret} + \gamma_3 \Psi_t D_t^{ins} + \varepsilon_{i,t}. \quad (14)$$

where again, D_t^{ret} and D_t^{ins} denote bullish periods for retail and institutional investors, respectively, taking the value one, and zero otherwise. Results in Table 7 largely reflect our portfolio analyses above and are broadly consistent across the three pricing models and the three beta estimation windows.[20] Using the 5-year estimation window as an example, while the unconditional results from the entire sample report positive estimates, ranging from 0.109 (four-factor model) to 0.191 (CAPM), they are overall of rather limited statistical and economic significance, implying a flat beta-return relation as documented in Fama and French (1992). For conditional results, we find a positive beta–return relation amid bearish periods (β_1) across all three beta models, which, however, is significantly undermined by the joint impact of retail and institutional investor sentiments ($\beta_2 + \beta_3$), but not by either individually. Therefore, our results confirm the CAPM to normally hold over low-sentiment periods, that is, an upward-sloping SML, but to fail over high-sentiment periods.

Like our results of the mean–variance relation at the market level, the results of the beta–return relation at the firm level confirm the negative impact of investor sentiment on the risk-return relation, with the sentiment-led distortion to the risk-return relation more likely to be a joint impact of two investor types, rather than either group in isolation. Our results, to some extent, find support in the recent study by Doukas and Han (2021) based on an augmented sentiment index (AS) constructed by extracting the common information from three most-widely adopted sentiment indicators, including the BW index, the University of Michigan Consumer Sentiment Index (MCSI), and Conference Board Consumer Confidence Index (CBCCI), as their findings reveal an upward-sloping SML in bad states (low-sentiment periods) while a downward-sloping SML in good states (high-sentiment periods). The three indicators—BW, MCSI, and CBCCI—cover a large share of market participants, so the combined AS measure in Doukas and Han (2021) is conceptually similar to our two-in-one approach to examining retail and institutional investor sentiments jointly.

5 | THE CROSS-SECTIONAL IMPACT

Literature widely documents a cross-sectional impact of retail investor sentiment on stock returns, evidencing that hard-to-value and difficult-to-arbitrage stocks, such as small stocks, young stocks, and unprofitable stocks, are more affected (Baker & Wurgler, 2006; Ding et al., 2018; Schmeling, 2009; Wang et al., 2021). In this section, we survey the cross-sectional impact of retail and institutional investor sentiments on the mean–variance relation.[21]

[20]Results remain consistent when we remove control variables and adopt the Fama and MacBeth (1973) approach.

[21]In particular, as described below, empirical analyses are based on indices, so we use 'the mean–variance relation' terminology here.

TABLE 7 Excess stock returns against betas.

This table reports the results of the impact of retail and institutional investor sentiment on the beta–return relation. Pane (A) presents the results from the entire sample, while Pane (B) presents the results conditional on retail and institutional investor sentiment. Stock betas are from the WRDS Beta Suite. We choose 5-year (Fama & MacBeth, 1973; Petkova, 2006), 2- to 5-year (as available, Antoniou et al., 2016; Fama & French, 1992), and 3-year (Lewellen, 2015) estimation windows for monthly betas. Stock betas are estimated from three asset pricing models including the CAPM (Sharpe, 1964), the three-factor model (Fama & French, 1993), and the four-factor model (Carhart, 1997). We also control for pricing factors including $R_m - R_f$, SMB, HML, MOM, RMW, and CMA following Wang (2020). Unreported p values are based on robust and clustered standard errors. [a], [b], and [c] represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Entire (A)		Bullish and nonbullish (B)							
Model	β	**Adj. R^2**	β_1	β_2	$\beta_1+\beta_2$	β_3	$\beta_1+\beta_3$	$\beta_2+\beta_3$	$\beta_1+\beta_2+\beta_3$	**Adj. R^2**
Panel A: The main test using a rolling 5-year estimation window for monthly betas										
CAPM	0.191	0.086	1.228[b]	−0.903	0.326	−0.819	0.409	−1.721[a]	−0.493	0.096
Three-factor	0.177	0.093	0.801[c]	−0.579	0.228	−0.684	0.117	−1.263[c]	−0.462	0.102
Four-factor	0.109	0.099	0.729	−0.694	0.036	−0.565	0.164	−1.258[c]	−0.529[c]	0.109
Panel B: Robustness test using a rolling 2- to 5-year estimation window (as available) for monthly betas										
CAPM	0.356	0.095	1.678[a]	−1.138	0.539	−1.134	0.443	−2.272[a]	−0.593[b]	0.105
Three-factor	0.346	0.105	1.175[b]	−0.806	0.369	−0.917	0.258	−1.723[b]	−0.548[b]	0.113
Four-factor	0.279	0.111	1.144[b]	−0.878	0.266	−0.853	0.290	−1.732[a]	−0.588[b]	0.118
Panel C: Robustness test using a rolling 3-year estimation window for monthly betas										
CAPM	0.253	0.090	1.404[a]	−0.926	0.479	−0.915	0.490	−1.841[a]	−0.437	0.100
Three-factor	0.238	0.097	0.909[c]	−0.693	0.215	−0.798	0.110	−1.491[b]	−0.583[b]	0.110
Four-factor	0.157	0.104	0.885[c]	−0.769	0.115	−0.740	0.144	−1.510[b]	−0.625[b]	0.114

5.1 | Portfolio construction

Following Baker and Wurgler (2006) and Ding et al. (2018, 2021), we select a total of 10 stock characteristics and group them into four classifications, including (i) size, age, and risk, (ii) profitability and dividend policy, (iii) asset tangibility, and (iv) growth opportunities and/or distress.

Size, age, and risk characteristics include market equity, firm age, and total risk. Market equity, *ME*, is the price times shares outstanding from CRSP in the June before year *T*. Firm age, *Age*, is the number of years between the firm's first appearance on CRSP and year *T*. Total risk, *Sigma*, is the annual standard deviation of monthly returns for twelve months ending in the June before year *T*. Profitability and dividend policy characteristics include return on equity, *E/BE* and dividends to equity, *D/BE*. The former is measured as earnings (*E*), income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19), divided by book equity (*BE*), shareholders equity (Item 60) plus balance sheet deferred taxes (Item 35), which is positive for profitable firms but zero for unprofitable firms. The latter is measured as dividends per share (*D*) at the ex-date (Item 26) times shares outstanding (Item 25) from Compustat divided by *BE*. Asset tangibility characteristics include property, plant, and equipment (Item 7) over assets, *PPE/A*, and research and development expense (Item 46) over assets, *RD/A*. Growth opportunities and/or distress characteristics include book-to-market equity ratio, external finance, and sales growth. Book-to-market equity ratio, *BE/ME*, is as defined above. External finance, *EF/A*, is the change in assets (Item 6) minus the change in retained earnings (Item 36) divided by assets. Sales growth, *GS*, is the change in net sales (Item 12) divided by prior-year net sales. Data are winsorized each year at 0.5 and 99.5 percentiles.

We construct 10 decile portfolios for each characteristic, from *d*1 to *d*10, and based on their sensitivity to investor sentiment, we identify sentiment-sensitive and sentiment-insensitive portfolios.[22] Baker and Wurgler (2006) and Ding et al. (2018, 2021) argue that small, young, volatile, unprofitable, nonpaying, extreme growth, and/or distress stocks tend to be more sensitive to investor sentiment, and therefore we regard the bottom (top) deciles of *ME*, *Age*, *E/BE*, *D/BE*, and *PPE/A* as the most sentiment-sensitive (sentiment-insensitive) and the top (bottom) deciles of *Sigma* and *RD/A* as the most sentiment-sensitive (sentiment-insensitive). Unlike the seven characteristics above, *BE/ME*, *EF/A*, and *GS* exhibit a multidimensional nature, and in particular, high (low) *BE/ME* (*EF/A* and *GS*) implies distress while low (high) *BE/ME* (*EF/A* and *GS*) implies high growth opportunities, and hence the two ends of the three characteristics tend to be more sensitive to investor sentiment, while the middle deciles tend to be insensitive.

5.2 | Results

For each characteristic, we run a 10-equation system of regressions, following:

$$\begin{aligned} R_{d1,t+1} = {} & \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d1,t}(R_{d1,t+1}) + \beta_2 Var_{d1,t}(R_{d1,t+1}) D_t^{ret} \\ & + \beta_3 Var_{d1,t}(R_{d1,t+1}) D_t^{ins} + \varepsilon_{d1,t+1}, \end{aligned}$$

[22]While our empirical results below reveal a few contradictory findings to the theories and existing evidence regarding which stocks are more prone to sentiment, we keep the classification of sentiment-sensitive and sentiment-insensitive in this way to make the discussion easy to follow.

$$R_{d2,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d2,t}(R_{d2,t+1}) + \beta_2 Var_{d2,t}(R_{d2,t+1}) D_t^{ret} + \beta_3 Var_{d2,t}(R_{d2,t+1}) D_t^{ins} + \varepsilon_{d2,t+1},$$

$$R_{d3,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d3,t}(R_{d3,t+1}) + \beta_2 Var_{d3,t}(R_{d3,t+1}) D_t^{ret} + \beta_3 Var_{d3,t}(R_{d3,t+1}) D_t^{ins} + \varepsilon_{d3,t+1},$$

$$\vdots R_{d9,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d9,t}(R_{d9,t+1}) + \beta_2 Var_{d3,t}(R_{d9,t+1}) D_t^{ret} + \beta_3 Var_{d9,t}(R_{d9,t+1}) D_t^{ins} + \varepsilon_{d9,t+1},$$

$$R_{d10,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d10,t}(R_{d10,t+1}) + \beta_2 Var_{d10,t}(R_{d10,t+1}) D_t^{ret} + \beta_3 Var_{d10,t}(R_{d10,t+1}) D_t^{ins} + \varepsilon_{d10,t+1}. \tag{15}$$

Table 8 presents the results, and Figure 2 plots the average estimates across all five volatility models for 10 deciles for all 10 stock characteristics. Overall, we notice that the impact of retail investor sentiment tends to be more prevalent than that of institutional investor sentiment. For *Age*, *Sigma*, *RD/A*, *BE/ME*, *EF/A*, and *GS*, the impact of institutional investor sentiment on the mean–variance relation is rather limited while that of retail investor sentiment is comparatively wide. Retail investor sentiment could distort the mean-variance relation of bottom deciles of *RD/A* (*d*1–*d*3), bottom and mid deciles of *Sigma* (*d*1 and d3–*d*7), *E/BE* (*d*3–*d*5), *EF/A* (*d*2 and *d*5–*d*6), and *GS* (*d*3–*d*7), and top and mid deciles of *Age* (*d*4–*d*9), *D/BE* (*d*4–*d*7 and *d*10), *PPE/A* (*d*5–*d*10), and *BE/ME* (*d*5–*d*6 and *d*8–*d*9). Recall that in theory, top deciles of *Sigma* and *RD/A* and bottom deciles of *Age*, *D/BE*, and *PPE/A* are regarded as sentiment-sensitive, since firms with higher risk, higher research and development expense, a shorter history, lower dividends, and less property, plant, and equipment are more likely to be salient to noise traders due to the subjectivity of valuations. However, our results suggest otherwise in the context of the mean–variance relation: Retail investors' bullishness, associated with elevated participation (Yu & Yuan, 2011), does not seem to distort the mean–variance relation of the sentiment-sensitive stocks, rather the opposite seems to hold, that is, bottom deciles of *Sigma* and *RD/A* and top deciles of *Age*, referring to firms with lower risk, lower research and development expense, a longer history, higher dividends, and more property, plant, and equipment. Findings from growth opportunities and distress are consistent with the view that retail investor sentiment brings a negative impact on distress firms, represented by top deciles of *BE/ME* and bottom deciles of *EF/A* and *GS*.

The mean–variance relation of characteristics of *ME*, *E/BE*, *D/BE*, *PPE/A*, *RD/A*, *EF/A*, and *GS* is negatively affected by institutional investor sentiment, which, in particular, undermines the mean-variance relation of bottom deciles of *E/BE* (*d*2) and *PPE/A* (*d*1), mid and top deciles of *D/BE* (*d*4, *d*6–*d*8), and top deciles of *ME* (*d*9–*d*10), *RD/A* (*d*9–*d*10), *EF/A* (*d*8), and *GS* (*d*8). The bottom deciles of *ME* and *D/BE* are expected to be more affected by investor sentiment, but our results support the opposite conclusion. While 6 out of the 10 characteristics are affected by both investor sentiment, the impact appears to be on different deciles: For instance, retail investor sentiment, as explained above, would bring a negative impact on the mean-variance relation of the distress firms, as implied by *BE/ME*, *EF/A*, and *GS*, while institutional investor sentiment would distort the mean-variance relation of the growth firms, as suggested by *EF/A* and *GS*.

TABLE 8 Excess market returns against conditional volatility: a cross-sectional test.

This table reports the results of the cross-sectional impact of retail and institutional investor sentiment on the mean–variance relation. We group 10 characteristics as per (i) size, age, and risk (Panel A), (ii) profitability and dividend policy (Panel B), (iii) asset tangibility (Panel C), and (iv) growth opportunities and/or distress (Panel D). Size, age, and risk characteristics include market equity, firm age, and total risk. Market equity, *ME*, is price times shares outstanding from CRSP in the June before year *T*. Firm age, *Age*, is the number of years between the firm's first appearance on CRSP and year *T*. Total risk, *Sigma*, is the annual standard deviation of monthly returns for 12 months ending in the June before year *T*. Profitability and dividend policy characteristics include return on equity, *E/BE* and dividends to equity, *D/BE*. The former is measured as earnings (*E*), income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19), divided by book equity (*BE*), shareholders equity (Item 60) plus balance sheet deferred taxes (Item 35), which is positive for profitable firms but zero for unprofitable firms. The latter is measured as dividends per share (*D*) at the ex-date (Item 26) times shares outstanding (Item 25) from Compustat divided by *BE*. Asset tangibility characteristics include property, plant, and equipment (Item 7) over assets, *PPE/A*, and research and development expense (Item 46) over assets, *RD/A*. Growth opportunities and/or distress characteristics include book-to-market equity ratio, external finance, and sales growth. Book-to-market equity ratio, *BE/ME*, is as defined above. External finance, *EF/A*, is the change in assets (Item 6) minus the change in retained earnings (Item 36) divided by assets. Sales growth, *GS*, is the change in net sales (Item 12) divided by prior-year net sales. We construct 10 decile portfolios for each characteristic, from *d*1 to *d*10, and for each characteristic, we run a 10-equation system of regressions, following,

$$R_{d1,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d1,t}(R_{d1,t+1}) + \beta_2 Var_{d1,t}(R_{d1,t+1}) D_t^{ret} + \beta_3 Var_{d1,t}(R_{d1,t+1}) D_t^{ins} + \varepsilon_{d1,t+1}$$

$$R_{d2,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d2,t}(R_{d2,t+1}) + \beta_2 Var_{d2,t}(R_{d2,t+1}) D_t^{ret} + \beta_3 Var_{d2,t}(R_{d2,t+1}) D_t^{ins} + \varepsilon_{d2,t+1}$$

$$R_{d3,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d3,t}(R_{d3,t+1}) + \beta_2 Var_{d3,t}(R_{d3,t+1}) D_t^{ret} + \beta_3 Var_{d3,t}(R_{d3,t+1}) D_t^{ins} + \varepsilon_{d3,t+1}$$

$$\vdots$$

$$R_{d9,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d9,t}(R_{d9,t+1}) + \beta_2 Var_{d3,t}(R_{d9,t+1}) D_t^{ret} + \beta_3 Var_{d9,t}(R_{d9,t+1}) D_t^{ins} + \varepsilon_{d9,t+1}$$

$$R_{d10,t+1} = \alpha_1 + \alpha_2 D_t^{ret} + \alpha_3 D_t^{ins} + \beta_1 Var_{d10,t}(R_{d10,t+1}) + \beta_2 Var_{d10,t}(R_{d10,t+1}) D_t^{ret} + \beta_3 Var_{d10,t}(R_{d10,t+1}) D_t^{ins} + \varepsilon_{d10,t+1}.$$

[a], [b] and [c] represent statistical significance at the 1%, 5% and 10% level, respectively.

Model	β_2	β_3	$\beta_2+\beta_3$	β_2	β_3	$\beta_2+\beta_3$	β_2	β_3	$\beta_2+\beta_3$	β_2	β_3	$\beta_2+\beta_3$	β_2	β_3	$\beta_2+\beta_3$
Panel A: Size, age, and risk															
Panel A.1: ME															
	d1			**d2**			**d3**			**d4**			**d5**		
RW	−4.098	−3.155	−7.253[b]	−2.198	−1.434	−3.632[a]	−2.437	−1.149	−3.586[a]	−2.277	−1.131	−3.408[a]	−2.653[c]	−1.225	−3.877[a]

TABLE 8 (Continued)

Model	β_2	β_3	$\beta_2+\beta_3$	β_2	β_3	$\beta_2+\beta_3$	β_2	β_3	$\beta_2+\beta_3$	β_2	β_3	$\beta_2+\beta_3$	β_2	β_3	$\beta_2+\beta_3$
MIDAS	−4.370	−4.030	−8.400[b]	−2.085	−1.866	−3.951[a]	−2.335	−1.619	−3.953[a]	−2.234	−1.614	−3.848[a]	−2.590	−1.792	−4.382[a]
GARCH	−5.081	−4.691	−9.772[a]	−1.529	−2.474[c]	−4.003[a]	−1.713	−2.406[c]	−4.118[a]	−1.767	−2.415[c]	−4.182[a]	−1.911	−2.755[c]	−4.666[a]
GJR-GARCH	−4.839	−4.625	−9.464[b]	−1.757	−2.325	−4.083[a]	−1.976	−2.167	−4.144[a]	−2.056	−2.174	−4.230[a]	−2.305	−2.494	−4.800[a]
EGARCH	−3.876	−8.321	−12.197[b]	−1.839	−3.415[c]	−5.254[a]	−2.191	−3.041[c]	−5.232[a]	−2.170	−3.090[c]	−5.261[a]	−2.668	−3.389[c]	−6.057[a]
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−2.837[c]	−1.126	−3.963[a]	−2.724	−0.607	−3.331[a]	−2.573	−1.157	−3.730[a]	−2.422	−1.418	−3.841[a]	−0.223	−2.682[c]	−2.905[b]
MIDAS	−2.886	−1.653	−4.539[a]	−2.685	−1.172	−3.857[a]	−2.564	−1.687	−4.251[a]	−2.199	−2.204	−4.403[a]	−0.127	−3.306[c]	−3.433[b]
GARCH	−2.506	−2.637[c]	−5.144[a]	−2.171	−2.233	−4.404[a]	−2.206	−2.694	−4.900[a]	−1.370	−3.654[c]	−5.024[a]	0.296	−4.465[b]	−4.169[a]
GJR-GARCH	−2.895	−2.213	−5.108[a]	−2.535	−1.899	−4.434[a]	−2.527	−2.200	−4.728[a]	−1.696	−3.162[c]	−4.857[a]	−0.232	−3.635[b]	−3.867[b]
EGARCH	−2.857	−3.373[c]	−6.230[a]	−2.546	−3.123[c]	−5.669[a]	−2.371	−3.428[c]	−5.799[a]	−1.536	−4.698[b]	−6.234[a]	−0.038	−5.170[b]	−5.208[a]
Panel A.2: Age															
	d1			**d2**			**d3**			**d4**			**d5**		
RW	−1.900	−1.975	−3.874[c]	−2.631	−1.411	−4.043[b]	−3.594	−2.303	−5.897[a]	−4.098[c]	−1.863	−5.961[a]	−4.015[b]	−1.193	−5.208[a]
MIDAS	−1.846	−2.699	−4.545[b]	−2.496	−2.089	−4.585[b]	−3.568	−2.965	−6.533[a]	−4.143[c]	−2.551	−6.695[a]	−4.014[c]	−1.846	−5.860[a]
GARCH	−1.941	−3.688	−5.629[b]	−2.254	−2.959	−5.213[a]	−3.110	−3.851	−6.961[a]	−3.810	−3.572	−7.381[a]	−3.541	−2.941	−6.456[a]
GJR-GARCH	−2.066	−3.399	−5.465[b]	−2.432	−2.754	−5.186[b]	−3.669	−3.479	−7.148[a]	−4.152	−3.212	−7.364[a]	−3.811	−2.641	−6.421[a]
EGARCH	−0.713	−5.130[c]	−5.844[c]	−1.436	−4.504	−5.940[b]	−2.892	−5.323[c]	−8.215[a]	−3.846	−4.894[c]	−8.741[a]	−3.574	−4.299	−7.873[a]
	d6			**d7**			**d8**			**d9**				**d10**	
RW	−4.290[b]	−1.404	−5.695[a]	−4.272[b]	−1.166	−5.438[a]	−3.890[b]	−0.940	−4.831[a]	−4.695[a]	−0.212	−4.908[a]	−4.060[c]	−0.116	−4.176[a]
MIDAS	−4.329[b]	−2.130	−6.459[a]	−4.288[b]	−1.822	−6.110[a]	−3.800[b]	−1.644	−5.444[a]	−4.831[b]	−0.726	−5.567[a]	−4.159[c]	−0.592	−4.751[a]
GARCH	−3.662	−3.346	−7.008[a]	−3.543[c]	−2.979	−6.521[a]	−2.908	−2.814	−5.722[a]	−4.114[c]	−1.786	−5.901[a]	−3.900	−1.438	−5.338[a]
GJR-GARCH	−4.293[c]	−3.021	−7.313[a]	−4.068[c]	−2.590	−6.658[a]	−3.350[c]	−2.588	−5.938[a]	−4.589[b]	−1.588	−6.177[a]	−3.826	−1.381	−5.206[a]
EGARCH	−4.285	−4.625[c]	−8.910[a]	−4.268	−4.202[c]	−8.470[a]	−3.671	−3.759[c]	−7.430[a]	−4.969[c]	−2.682	−7.651[a]	−3.967	−2.732	−6.699[a]

(Continues)

Panel A.3: Sigma

	d1			d2			d3			d4			d5		
RW	−8.278[b]	−3.037	−11.315[a]	−4.241[c]	−2.198	−6.439[a]	−5.311[a]	−1.428	−6.740[a]	−4.443[b]	−1.710	−6.153[a]	−4.001[b]	−1.610	−5.611[a]
MIDAS	−8.256[b]	−3.929	−12.185[a]	−4.304[c]	−2.846	−7.151[a]	−5.555[a]	−1.975	−7.530[a]	−4.351[b]	−2.931	−6.742[a]	−4.022[b]	−2.167	−6.189[a]
GARCH	−7.344[c]	−4.937	−12.281[a]	−3.704	−3.947[c]	−7.651[a]	−4.901[b]	−2.915	−7.816[a]	−3.383	−3.497[c]	−6.880[a]	−3.491[c]	−3.105[c]	−6.596[a]
GJR-GARCH	−6.812[c]	−5.139	−11.951[a]	−3.918	−3.261	−7.179[a]	−5.709[b]	−2.565	−8.275[a]	−3.908[c]	−3.119	−7.027[a]	−3.891[c]	−2.664	−6.555[a]
EGARCH	−7.673	−7.622[c]	−15.295[a]	−4.599	−5.378[c]	−9.977[a]	−6.463[b]	−4.042	−10.505[a]	−4.307	−4.566[b]	−8.873[a]	−3.904	−4.145[c]	−8.049[a]
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−4.148[b]	−0.686	−4.835[a]	−4.751[b]	−1.052	−5.803[a]	−3.678[b]	−0.914	−4.592[a]	−2.927	−1.727	−4.654[a]	−0.761	−1.646	−2.407
MIDAS	−4.171[b]	−1.221	−5.391[a]	−4.847[b]	−1.533	−6.379[a]	−3.687[c]	−1.521	−5.208[a]	−2.861	−2.390	−5.251[a]	−0.610	−2.280	−2.889
GARCH	−3.610[c]	−2.083	−5.693[a]	−4.320[b]	−2.254	−6.574[a]	−3.199	−2.524	−5.723[a]	−2.558	−3.272	−5.830[a]	−0.882	−3.003	−3.885[c]
GJR-GARCH	−4.043[b]	−1.902	−5.945[a]	−4.707[b]	−2.022	−6.729[a]	−3.564	−2.301	−5.865[a]	−2.875	−3.015	−5.890[a]	−0.789	−2.769	−3.558
EGARCH	−4.045[c]	−3.150	−7.195[a]	−5.048[c]	−3.396	−8.444[a]	−3.372	−3.729	−7.101[a]	−2.234	−4.704[c]	−6.938[a]	0.938	−4.337	−3.399

Panel B: Profitability and dividend policy

Panel B.1: E/BE

	d1			d2			d3			d4			d5		
RW	−3.858	−0.852	−4.710[b]	−3.564[c]	−2.877	−6.441[a]	−4.392[b]	−1.606	−6.000[a]	−4.092[b]	−1.573	−5.665[a]	−3.819[b]	−1.255	−5.074[a]
MIDAS	−3.890	−1.410	−5.300[b]	−3.660	−3.559[c]	−7.218[a]	−4.597[b]	−2.227	−6.824[a]	−4.255[b]	−2.169	−6.424[a]	−3.852[c]	−1.907	−5.758[a]
GARCH	−3.784	−2.151	−5.935[b]	−3.242	−4.576[b]	−7.818[a]	−4.124[c]	−3.360[c]	−7.484[a]	−3.934[c]	−3.112	−7.045[a]	−3.353	−2.951	−6.304[a]
GJR-GARCH	−3.999	−2.001	−6.000[b]	−3.714	−4.144[c]	−7.858[a]	−4.768[c]	−2.878	−7.646[a]	−4.281[c]	−2.877	−7.159[a]	−3.709[c]	−2.687	−6.394[a]
EGARCH	−3.216	−3.311	−6.527[b]	−3.613	−6.240[b]	−9.853[a]	−4.969[c]	−4.809[c]	−9.778[a]	−4.459	−4.635[c]	−9.094[a]	−3.652	−4.336[c]	−7.987[a]
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−2.732	−1.557	−4.290[a]	−3.261[c]	−0.973	−4.234[a]	−3.007[c]	−0.996	−4.003[a]	−2.502	−1.342	−3.844[a]	−3.610[c]	−0.978	−4.588[a]
MIDAS	−2.643	−2.231	−4.874[a]	−3.158	−1.659	−4.817[a]	−2.915	−1.629	−4.544[a]	−2.351	−2.089	−4.440[a]	−3.606	−1.569	−5.175[a]
GARCH	−2.155	−3.365[c]	−5.521[a]	−2.526	−2.866	−5.392[a]	−2.386	−2.694	−5.080[a]	−1.779	−3.518[c]	−5.297[a]	−3.312	−2.718	−6.030[a]
GJR-GARCH	−2.325	−3.013	−5.338[a]	−2.799	−2.526	−5.325[a]	−2.581	−2.379	−4.960[a]	−2.102	−2.929	−5.031[a]	−3.339	−2.119	−5.457[a]
EGARCH	−2.268	−4.653[b]	−6.922[a]	−2.901	−3.935[c]	−6.836[a]	−2.522	−4.015[c]	−6.537[a]	−1.522	−4.639[c]	−6.161[a]	−2.825	−3.756	−6.581[a]

Panel B.2: D/BE															
	d1			**d2**			**d3**			**d4**			**d5**		
RW	−3.560	−1.110	−4.670^{b}	−3.630^{c}	−1.332	−4.961^{a}	−4.098^{b}	−0.892	−4.991^{a}	−4.146^{b}	−1.783	−5.929^{a}	−4.315^{a}	−1.473	−5.788^{a}
MIDAS	−3.550	−1.693	−5.242^{b}	−3.619^{c}	−1.897	−5.517^{a}	−3.864^{b}	−1.646	−5.511^{a}	−4.135^{b}	−2.450	−6.585^{a}	−4.524^{b}	−1.988	−6.512^{a}
GARCH	−3.406	−2.472	−5.878^{a}	−3.249	−2.832	−6.080^{a}	−2.761	−3.019	−5.780^{a}	−3.297^{c}	−3.552^{c}	−6.848^{a}	−4.218^{b}	−2.823	−7.040^{a}
GJR-GARCH	−3.538	−2.309	−5.847^{b}	−3.335	−2.504	−5.839^{a}	−3.166	−2.697	−5.863^{a}	−3.776^{c}	−3.382^{c}	−7.158^{a}	−4.727^{b}	−2.536	−7.263^{a}
EGARCH	−2.749	−3.833	−6.582^{b}	−3.485	−3.893^{c}	−7.377^{a}	−3.230	−4.121^{c}	−7.352^{a}	−3.946	−4.830^{b}	−8.776^{a}	−4.955^{b}	−3.974^{c}	−8.929^{a}
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−4.052^{b}	−1.976	−6.028^{a}	−4.083^{b}	−2.006	−6.088^{a}	−2.584	−2.186	−4.770^{a}	−2.801	−1.521	−4.323^{a}	−5.154^{a}	−0.600	−5.754^{a}
MIDAS	−4.167^{b}	−2.687	−6.854^{a}	−4.228^{b}	−2.806	−7.034^{a}	−2.420	−2.976	−5.395^{a}	−2.812	−2.141	−4.953^{a}	−5.266^{b}	−1.364	−6.630^{a}
GARCH	−3.650^{c}	−3.744^{c}	−7.393^{a}	−3.497	−4.268^{c}	−7.766^{a}	−1.665	−4.212^{b}	−5.877^{a}	−2.242	−3.159	−5.401^{a}	−4.697^{b}	−2.758	−7.456^{a}
GJR-GARCH	−4.236^{c}	−3.508^{c}	−7.744^{a}	−4.013^{c}	−3.923^{c}	−7.936^{a}	−1.964	−3.948^{c}	−5.912^{a}	−2.680	−2.802	−5.482^{a}	−5.074^{b}	−2.576	−7.650^{a}
EGARCH	−4.454^{c}	−5.250^{b}	−9.704^{a}	−4.436	−5.593^{b}	−10.029^{a}	−1.663	−5.653^{b}	−7.316^{a}	−3.136	−4.122^{c}	−7.259^{a}	−5.230^{c}	−4.244^{c}	−9.474^{a}
Panel C: Tangibility															
Panel C.1: PPE/A															
	d1			**d2**			**d3**			**d4**			**d5**		
RW	−1.132	−4.365^{c}	−5.497^{a}	−1.447	−2.256	−3.703	−2.692	−1.506	−4.198^{b}	−3.510	−1.834	−5.344^{a}	−5.142^{b}	−0.007	−5.149^{a}
MIDAS	−0.993	−5.242^{b}	−6.235^{a}	−1.312	−2.665	−3.977	−2.535	−2.212	−4.747^{b}	−3.527	−2.393	−5.920^{a}	−5.268^{b}	−0.527	−5.795^{a}
GARCH	−0.768	−6.153^{b}	−6.922^{a}	−1.028	−4.108	−5.136^{c}	−2.042	−3.339	−5.380^{b}	−3.188	−3.276	−6.464^{a}	−4.888^{c}	−1.478	−6.366^{a}
GJR-GARCH	−1.062	−5.886^{b}	−6.948^{a}	−1.178	−3.522	−4.700^{c}	−2.296	−3.080	−5.376^{b}	−3.437	−2.983	−6.420^{a}	−5.356^{b}	−1.267	−6.623^{a}
EGARCH	−0.335	−8.047^{a}	−8.383^{a}	−0.161	−5.088	−5.249	−1.487	−4.378	−5.865^{c}	−3.030	−4.425	−7.455^{a}	−4.793	−2.743	−7.537^{a}
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−5.618^{a}	−0.381	−5.999^{a}	−5.378^{b}	−0.635	−6.013^{a}	−4.809^{a}	−0.494	−5.303^{a}	−5.076^{a}	0.367	−4.709^{a}	−3.941^{b}	−0.087	−4.029^{a}
MIDAS	−5.683^{b}	−1.121	−6.804^{a}	−5.611^{b}	−1.160	−6.770^{a}	−4.950^{b}	−1.105	−6.055^{a}	−4.902^{b}	−0.198	−5.100^{a}	−4.018^{c}	−0.665	−4.683^{a}
GARCH	−4.885^{b}	−2.424	−7.309^{a}	−5.212^{b}	−2.107	−7.319^{a}	−4.583^{b}	−2.078	−6.661^{a}	−3.999^{c}	−1.139	−5.138^{a}	−3.920^{c}	−1.312	−5.232^{a}
GJR-GARCH	−5.710^{b}	−2.151	−7.861^{a}	−5.847^{b}	−1.771	−7.618^{a}	−4.993^{b}	−1.997	−6.990^{a}	−4.106^{c}	−1.114	−5.221^{a}	−3.859^{c}	−1.472	−5.331^{a}
EGARCH	−5.194^{c}	−3.906	−9.100^{a}	−5.811^{c}	−3.264	−9.074^{a}	−4.789^{c}	−3.557	−8.347^{a}	−4.094	−2.390	−6.484^{a}	−3.647	−2.891	−6.537^{a}

Panel C.2: RD/A															
	d1			**d2**			**d3**			**d4**			**d5**		
RW	−3.904[c]	−1.556	−5.460[a]	−4.977[b]	−0.639	−5.616[a]	−5.123[a]	−0.046	−5.169[a]	−5.092[b]	−0.352	−5.443[a]	−5.090[b]	−0.968	−6.058[a]
MIDAS	−3.987[c]	−2.155	−6.142[a]	−4.970[b]	−1.358	−6.328[a]	−5.225[a]	−0.523	−5.748[a]	−4.865[b]	−1.336	−6.200[a]	−4.763[c]	−1.884	−6.647[a]
GARCH	−3.693[c]	−2.942	−6.635[a]	−3.948	−2.747	−6.695[a]	−4.935[b]	−1.402	−6.338[a]	−3.111	−2.851	−5.962[a]	−3.333	−3.757	−7.091[a]
GJR-GARCH	−4.130[c]	−2.664	−6.795[a]	−4.676[c]	−2.502	−7.178[a]	−5.054[b]	−1.311	−6.364[a]	−3.619	−3.120	−6.740[a]	−3.801	−3.285	−7.086[a]
EGARCH	−3.886	−4.597[c]	−8.483[a]	−4.566	−4.017	−8.584[a]	−4.856[c]	−2.435	−7.292[a]	−3.807	−4.103[c]	−7.909[a]	−2.627	−5.171[c]	−7.798[a]
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−2.859	−0.887	−3.746[b]	−4.798[b]	−0.482	−5.280[a]	−2.413	−1.125	−3.538[c]	−0.076	−2.773	−2.848	1.470	−3.630	−2.160
MIDAS	−2.873	−1.447	−4.320[b]	−4.587[c]	−1.258	−5.844[a]	−2.216	−1.796	−4.011[c]	0.288	−3.771	−3.483	1.638	−4.332	−2.694
GARCH	−2.205	−2.729	−4.934[a]	−3.509	−2.681	−6.190[a]	−1.742	−3.094	−4.835[c]	0.603	−5.415[c]	−4.812[c]	1.057	−5.160[c]	−4.103
GJR-GARCH	−2.866	−2.108	−4.974[b]	−3.934	−2.535	−6.469[a]	−1.846	−2.834	−4.679[c]	0.780	−4.997[c]	−4.217	1.569	−4.742[c]	−3.173
EGARCH	−2.768	−3.275	−6.043[b]	−3.104	−4.077	−7.181[a]	−0.643	−3.989	−4.632	1.520	−6.353[b]	−4.833	2.438	−5.986[c]	−3.548
Panel D: Growth opportunities and distress															
Panel D.1: BE/ME															
	d1			**d2**			**d3**			**d4**			**d5**		
RW	−1.991	−1.860	−3.851[b]	−2.135	−1.404	−3.538[b]	−2.766	−0.928	−3.694[b]	−3.304[c]	−0.933	−4.237[a]	−3.565[c]	−0.545	−4.111[a]
MIDAS	−1.806	−2.427	−4.233[b]	−1.990	−2.132	−4.122[b]	−2.696	−1.510	−4.206[b]	−3.375	−1.512	−4.886[a]	−3.690[c]	−1.094	−4.784[a]
GARCH	−1.418	−3.167	−4.585[b]	−1.626	−3.365	−4.991[b]	−2.251	−2.551	−4.802[b]	−2.998	−2.657	−5.655[a]	−3.512	−2.018	−5.530[a]
GJR-GARCH	−1.702	−2.856	−4.558[b]	−1.870	−3.004	−4.874[b]	−2.571	−2.208	−4.779[b]	−3.461	−2.124	−5.585[a]	−3.756[c]	−1.891	−5.637[a]
EGARCH	−0.937	−4.107[c]	−5.043[b]	−1.101	−4.440[c]	−5.540[b]	−2.047	−3.524	−5.572[b]	−3.094	−3.673	−6.768[a]	−3.735	−3.067	−6.803[a]
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−4.029[b]	−1.893	−5.923[a]	−3.283[c]	−1.453	−4.736[a]	−5.004[b]	−2.096	−7.100[a]	−5.262[b]	−3.227	−8.490[a]	−4.210	−3.170	−7.379[a]
MIDAS	−4.140[b]	−2.381	−6.521[a]	−3.370[c]	−1.952	−5.322[a]	−5.316[b]	−2.780	−8.097[a]	−5.436[c]	−4.031	−9.466[a]	−4.324	−4.083	−8.406[a]
GARCH	−3.804[c]	−3.062	−6.866[a]	−3.354	−2.622	−5.976[a]	−5.076[b]	−3.772[c]	−8.847[a]	−5.360[c]	−4.933[c]	−10.293[a]	−4.574	−4.600	−9.174[a]
GJR-GARCH	−4.195[b]	−2.827	−7.022[a]	−3.340	−2.462	−5.802[a]	−5.629[b]	−3.517	−9.146[a]	−5.643[c]	−4.655	−10.299[a]	−4.870	−4.669	−9.539[a]
EGARCH	−4.134	−4.328[c]	−8.462[a]	−3.040	−4.091[c]	−7.131[a]	−6.183[b]	−5.363[b]	−11.546[a]	−4.952	−7.150[b]	−12.102[a]	−3.815	−8.137	−11.952[a]

Panel D.2: EF/A															
	d1			**d2**			**d3**			**d4**			**d5**		
RW	−4.230[c]	−1.849	−6.078[a]	−4.250[c]	−1.988	−6.238[a]	−4.462[c]	−1.820	−6.283[a]	−4.235[c]	−1.721	−5.957[a]	−4.521[b]	−1.631	−6.153[a]
MIDAS	−4.115	−2.464	−6.579[a]	−4.467[c]	−2.530	−6.997[a]	−4.519[c]	−2.543	−7.062[a]	−4.119	−2.514	−6.633[a]	−4.605[c]	−2.336	−6.941[a]
GARCH	−3.652	−3.065	−6.717[a]	−4.315	−3.253	−7.567[a]	−4.080	−3.633	−7.713[a]	−3.450	−3.796	−7.246[a]	−3.935	−3.537	−7.472[a]
GJR-GARCH	−3.862	−2.868	−6.730[a]	−4.839[c]	−2.955	−7.794[a]	−4.459	−3.407	−7.866[a]	−3.616	−3.493	−7.109[a]	−4.644[c]	−3.155	−7.799[a]
EGARCH	−3.336	−4.898	−8.234[a]	−4.590	−4.594	−9.184[a]	−4.114	−5.185[c]	−9.299[a]	−3.291	−5.202[c]	−8.493[a]	−4.289	−5.017[c]	−9.306[a]
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−4.332[b]	−1.572	−5.905[a]	−3.375	−1.888	−5.263[a]	−3.105	−1.702	−4.807[a]	−3.539[c]	−1.322	−4.861[a]	−2.069	−1.078	−3.146[c]
MIDAS	−4.530[b]	−2.158	−6.689[a]	−3.396	−2.600	−5.997[a]	−3.145	−2.439	−5.584[a]	−3.550	−1.966	−5.515[a]	−2.024	−1.694	−3.718[c]
GARCH	−4.362[c]	−3.090	−7.453[a]	−3.107	−3.775	−6.881[a]	−2.987	−3.684[c]	−6.671[a]	−3.170	−3.085	−6.255[a]	−1.970	−2.645	−4.615[b]
GJR-GARCH	−4.804[b]	−2.780	−7.584[a]	−3.393	−3.432	−6.825[a]	−3.117	−3.397[c]	−6.514[a]	−3.498	−2.724	−6.222[a]	−2.214	−2.357	−4.571[b]
EGARCH	−4.725	−4.596[c]	−9.321[a]	−2.873	−5.190[c]	−8.063[a]	−2.539	−5.220[b]	−7.760[a]	−3.125	−4.265	−7.390[a]	−1.238	−3.709	−4.947[c]
Panel D.3: GS															
	d1			**d2**			**d3**			**d4**			**d5**		
RW	−3.895	−1.832	−5.727[b]	−4.071	−1.355	−5.426[a]	−5.152[b]	−0.790	−5.942[a]	−5.293[b]	−1.311	−6.604[a]	−4.982[b]	−1.615	−6.597[a]
MIDAS	−3.997	−2.303	−6.300[a]	−4.214	−1.942	−6.156[a]	−5.286[b]	−1.486	−6.772[a]	−5.411[b]	−1.940	−7.352[a]	−5.309[b]	−2.237	−7.546[a]
GARCH	−4.048	−2.724	−6.771[a]	−4.022	−2.790	−6.812[a]	−4.774[c]	−2.536	−7.311[a]	−4.751[c]	−3.048	−7.799[a]	−4.894[b]	−3.321	−8.215[a]
GJR-GARCH	−4.183	−2.578	−6.761[a]	−4.600	−2.512	−7.112[a]	−5.344[b]	−2.361	−7.705[a]	−5.347[b]	−2.646	−7.992[a]	−5.770[b]	−2.942	−8.712[a]
EGARCH	−3.323	−4.149	−7.473[b]	−4.077	−4.112	−8.189[a]	−5.518[c]	−4.161	−9.678[a]	−5.369[c]	−4.221	−9.590[a]	−6.058[c]	−4.701[c]	−10.758[a]
	d6			**d7**			**d8**			**d9**			**d10**		
RW	−3.639[c]	−1.024	−4.663[a]	−4.106[b]	−1.692	−5.798[a]	−3.582[c]	−1.911	−5.493[a]	−2.728	−1.378	−4.106[a]	−1.359	−1.725	−3.084[c]
MIDAS	−3.777[c]	−1.541	−5.318[a]	−4.267[c]	−2.323	−6.590[a]	−3.571	−2.607	−6.178[a]	−2.654	−1.950	−4.604[a]	−1.150	−2.444	−3.594[c]
GARCH	−3.604	−2.371	−5.975[a]	−4.153[c]	−3.369	−7.522[a]	−3.134	−3.754[c]	−6.888[a]	−2.469	−2.778	−5.247[a]	−0.876	−3.572	−4.448[b]
GJR-GARCH	−3.874[c]	−2.226	−6.100[a]	−4.307[c]	−3.034	−7.341[a]	−3.366	−3.400[c]	−6.766[a]	−2.373	−2.601	−4.974[b]	−1.135	−3.173	−4.307[c]
EGARCH	−3.815	−3.662	−7.477[a]	−4.103	−4.859[c]	−8.962[a]	−2.989	−5.099[b]	−8.088[a]	−1.785	−4.011[c]	−5.796[b]	0.038	−4.585[c]	−4.547[c]

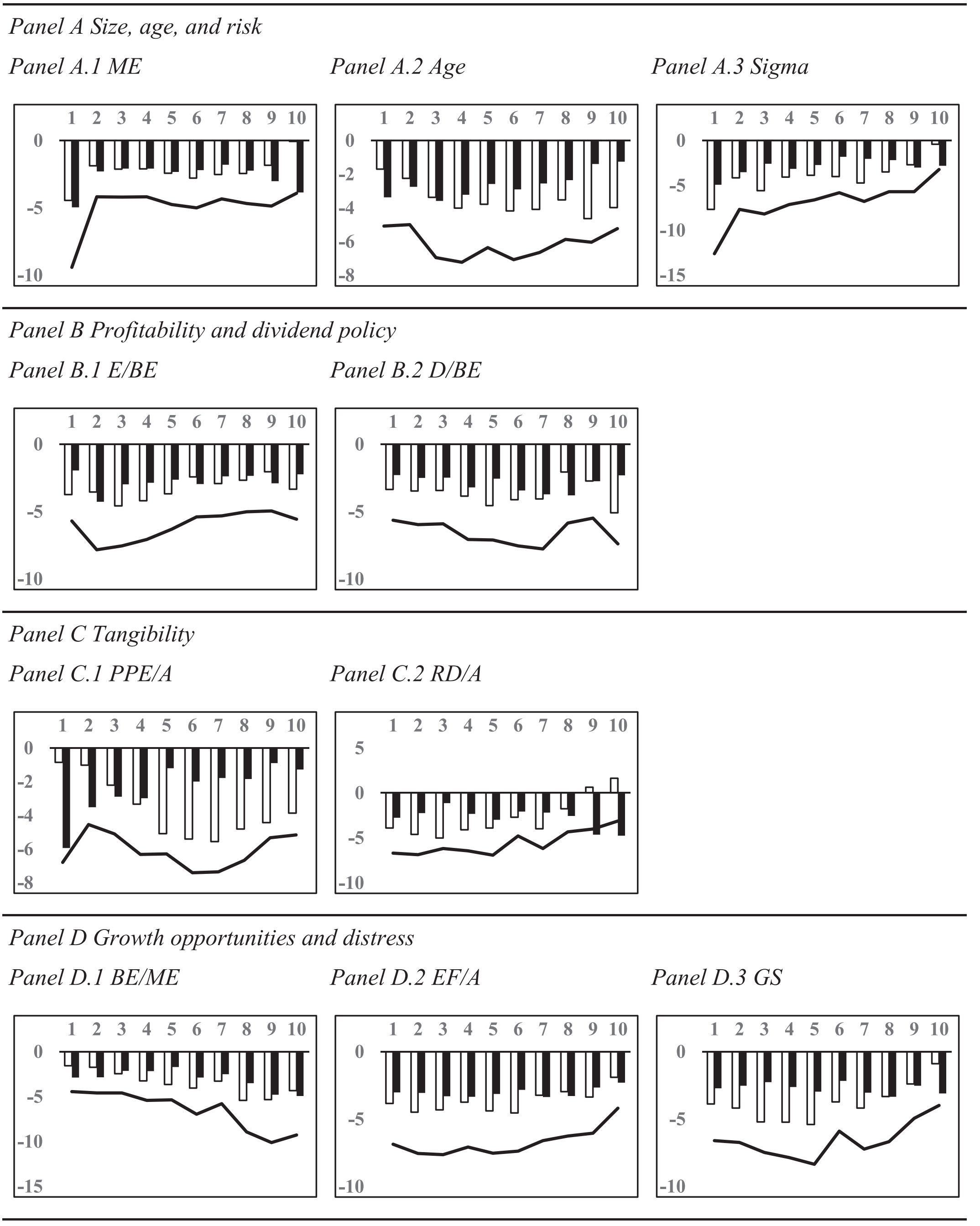

FIGURE 2 Plots of the cross-sectional test results. The cross-sectional test results from the 10-equation system are shown. Each value is computed as the average across all five volatility values. The solid bar is the impact of retail investor sentiment on the mean-variance relation. The clear bar is the impact of institutional investor sentiment on the mean-variance relation. The solid line is the joint impact of retail and institutional sentiment on the mean–variance relation.

Table 8 also reports the joint impact of the two investor types. While the mean-variance relation of $d1$ of the *ME* characteristic are not significantly affected by retail or institutional investor sentiment, the joint impact is of both statistical and economic significance, ranging from −7.253 (RW) to −12.197 (EGARCH), meaning that a 1% increase (decrease) in conditional volatility would cause, on average, a 9.357% decrease (increase) in returns, which is clearly stronger than all other deciles of stocks, especially $d10$: Institutional investor sentiment would significantly distort the mean–variance relation of the $d10$ of the *ME* characteristics, but the joint impact seems to be relatively limited, ranging from −2.905 (RW) to −5.208 (EGARCH). For *D/BE* and *PPE/A* characteristics, the mean-variance relation of some particular deciles of stocks is undermined by retail and institutional investor sentiment, but the joint impact appears not to be much different across deciles. For example, retail and institutional investor sentiment distorts the mean–variance relation of mid and top deciles of *D/BE*, respectively, but the joint impact appears to be flat across deciles, that is, that no distinct spike is found for mid or top deciles. For the remaining characteristics, the joint impact appears to be driven by the individual impact. For instance, retail investor sentiment distorts the mean-variance relation of bottom and mid deciles of *Sigma*, which contributes much to the case for the joint impact. The key implications of testing the joint impact, therefore, are twofold. First, while the joint impact is a result of the interaction between retail and institutional investors, it can reflect patterns that are completely different from the two components, like *ME* and *D/BE*, and therefore testing the retail or institutional investors' impact in isolation and without joint consideration may be misleading. Second, having given due consideration to the joint impact, looking into the two investor types separately makes it possible to reveal the potential main drivers of the presented joint impact, like *Sigma*.

We also find three surprisingly consistent patterns from our results. First, regardless of significance, the impact of retail and institutional investors on the mean–variance relation is mostly negative and no significantly positive case is ever detected, suggesting that the retail and institutional investors' elevated participation during high-sentiment periods is likely to bring a distortion to the theorized positive mean–variance relation and the impact appears to be fairly prevalent across stock characteristics and their associated deciles. Second, no single investor-type sentiment has a significant broad impact on the mean–variance across all deciles of the 10 characteristics. Third, the joint impact of the two investor-type sentiments is significantly negative in most cases with few exceptions, which, (i) confirms our main finding in Section 4 that the joint impact is strong and robust, and (ii) necessitates the inclusion of both groups of investors in any consideration of the impact of noise traders in the market (i.e., consideration of one or other of the investor types in isolation may not provide a complete picture).

Overall, as in the sentiment–return relation, we also evidence a cross-sectional pattern in the impact of sentiment on the mean–variance relation. The difference, however, is evident, with the mean–variance relation of the sentiment-sensitive portfolios not always most affected by retail or institutional investor sentiments. On the contrary, in many scenarios, the mean-variance relation of sentiment-insensitive portfolios is more likely to be distorted.

Finally, within the system Equation (16), we directly test the differences in estimates of sentiment-sensitive and sentiment-insensitive deciles, using two different groupings. In the first grouping, we only select $d1$, $d10$, and $d5$–$d6$. For *ME*, *Age*, *E/BE*, *D/BE*, and *PPE/A*, $d1$ ($d10$) refers to sentiment-sensitive (sentiment-insensitive) stocks, while for *Sigma* and *RD/A*, $d10$ ($d1$)

refers to sentiment-sensitive (sentiment-insensitive) stocks. Due to the multidimensional nature, we firstly regard $d10$ ($d1$) of *BE/ME* and $d1$ ($d10$) of *EF/A* and *GS* as sensitive (insensitive) stocks to check whether distress or growth opportunities are more prone to investor sentiment, and second, regard $d1$ ($d5$–$d6$) of *BE/ME* and $d10$ (($d5$–$d6$)) of *EF/A* and *GS* as sensitive (insensitive) stocks, $d10$ ($d5$–$d6$) of *BE/ME* and $d1$ (($d5$–$d6$)) of *EF/A* and *GS* as sensitive (insensitive) stocks to separately check growth opportunities and distress. The second grouping extends the first, with $d1$, $d10$, and $d5$–$d6$ replaced as $d1$–$d3$, $d8$–$d10$, and $d4$–$d7$, respectively.[23]

Results in Tables 9 and 10 largely confirm our discussion above, showing a fairly mixed view of whether the impact of investor sentiments on the mean–variance relation is more concentrated on sentiment-sensitive or sentiment-insensitive stocks. For example, the joint impact of retail and institutional investor sentiments distorts the mean-variance relation of small stocks more than large stocks, meaning that sentiment-sensitive stocks are more prone to investor sentiment as documented in the literature, while the opposite applies for low-volatility stocks, commonly viewed as sentiment-insensitive, where the mean–variance relation is more distorted by the joint impact of retail and institutional investor sentiments than is the case for high-volatility stocks.

Overall, the cross-sectional impact of institutional investor sentiment on the mean-variance relation is rather limited and only observed in one characteristic, *PPE/A*, while that of retail investor sentiment is relatively prevalent but is restricted to tangibility (*PPE/A* and *RD/A*) and growth opportunities and distress (*BE/ME*, *EF/A*, and *GS*). While cross-sectional patterns in the sentiment-return relation are widely reported and clear differences exist across sentiment-sensitive and sentiment-insensitive stocks, not only in the US but worldwide (Baker & Wurgler, 2006; Ding et al., 2018; Wang et al., 2021), our findings in the context of the mean–variance relation suggest that the impact of investor sentiment, stemming from retail and/or institutional investors, on stock markets may be more complicated than currently theorized. Our findings complement the evidence of the cross-sectional impact of investor sentiment on stock market returns as in Baker and Wurgler (2006), providing parallel evidence in the context of the mean–variance relation. Notably, we report that hard to value and difficult to arbitrage stocks (i.e., those previously deemed to be sentiment prone in the literature) can be sentiment insensitive, thus it seems necessary for future studies to define sentiment sensitivity subject to the context (i.e., sentiment-return or mean-variance) as opposed to unconditionally.

6 | CONCLUSION

Traditional financial framework theorizes a positive risk-return relation, which is challenged by more recent empirical findings in the area of investor sentiment. Building upon evidence that retail and institutional investors can both be irrational traders, we examine the impact of retail and institutional investor sentiment on the risk–return relation. At the market level, we document a negative impact of investor sentiment on the mean–variance relation, but notably, this impact is driven by the two investor types jointly, rather than individually. This market-level effect is broadly supported by a battery of robustness tests. A further test at the firm level

[23]We do not follow the more common long-short portfolio approach as in Baker and Wurgler (2006), Schmeling (2009), and Wang et al. (2021), in that we need to filter conditional volatility as the second moment of returns, which cannot simply be added or subtracted.

TABLE 9 Results of differences in estimates.

This table reports the results of differences in estimates of sentiment-sensitive (S) and sentiment-insensitive (I) deciles, following two grouping approaches. In the first grouping approach, we select d1, d10, and d5–d6. For ME, Age, E/BE, D/BE, and PPE/A, d1 (d10) refers to sentiment-sensitive (sentiment-insensitive) stocks, while for Sigma and RD/A, d10 (d1) refers to sentiment-sensitive (sentiment-insensitive) stocks. Due to the multidimensional nature, we, following Ding et al. (2021) first regard d10 (d1) of BE/ME and d1 (d10) of EF/A and GS as sensitive (insensitive) stocks to check whether growth opportunities or distress are more prone to investor sentiment, and secondly regard d10 (d5–d6) of BE/ME and d1 ((d5–d6)) of EF/A and GS as sensitive (insensitive) stocks, d1 (d5–d6) of BE/ME and d10 ((d5–d6)) of EF/A and GS as sensitive (insensitive) stocks to separately check growth opportunities and distress. The second grouping approach is expanded based on the first, with d1, d10, and d5–d6 replaced as d1–d3, d8–d10, and d4–d7, respectively. [a], [b], and [c] represent statistical significance at the 1%, 5%, and 10% level, respectively.

	S – I (first approach)			S – I (second approach)		
Model	**Retail**	**Institutional**	**Joint**	**Retail**	**Institutional**	**Joint**
Panel A: Size, age, and risk						
Panel A.1: ME						
RW	−3.875	−0.473	−4.347[c]	−1.171	−0.160	−1.331
MIDAS	−4.243	−0.725	−4.968[c]	−1.300	−0.106	−1.406
GARCH	−5.377	−0.226	−5.603[b]	−1.681	0.414	−1.267
GJR-GARCH	−4.607	−0.991	−5.597[c]	−1.372	−0.040	−1.413
EGARCH	−3.839	−3.151	−6.989[c]	−1.321	−0.494	−1.814
Panel A.2 Age						
RW	2.161	−1.859	0.301	1.507	−1.474	0.034
MIDAS	2.313	−2.107	0.206	1.627	−1.597	0.029
GARCH	1.959	−2.250	−0.291	1.206	−1.487	−0.281
GJR-GARCH	1.760	−2.018	−0.259	1.199	−1.359	−0.159
EGARCH	3.254	−2.399	0.855	2.522	−1.928	0.594
Panel A.3: Sigma						
RW	7.516[b]	1.391	8.907[a]	3.487[b]	0.792	4.280[a]
MIDAS	7.646[c]	1.649	9.296[a]	3.652[b]	0.853	4.506[a]
GARCH	6.462[c]	1.934	8.396[a]	3.103[c]	1.000	4.103[a]
GJR-GARCH	6.023	2.371	8.394[a]	3.070[c]	0.960	4.030[a]
EGARCH	8.611[c]	3.285	11.896[a]	4.689[b]	1.424	6.113[a]
Panel B: Profitability and dividend policy						
Panel B.1: E/BE						
RW	−0.248	0.127	−0.121	−0.898	−0.673	−1.571[c]
MIDAS	−0.284	0.159	−0.125	−1.091	−0.636	−1.728[c]
GARCH	−0.471	0.566	0.095	−1.224	−0.386	−1.610

(Continues)

TABLE 9 (Continued)

Model	S − I (first approach) Retail	Institutional	Joint	S − I (second approach) Retail	Institutional	Joint
GJR-GARCH	−0.660	0.117	−0.543	−1.486	−0.532	−2.019[c]
EGARCH	−0.391	0.445	0.054	−1.643	−0.650	−2.293
Panel B.2: D/BE						
RW	1.594	−0.510	1.084	−0.249	0.325	0.075
MIDAS	1.717	−0.329	1.388	−0.178	0.415	0.236
GARCH	1.291	0.286	1.577	−0.271	0.602	0.332
GJR-GARCH	1.536	0.268	1.803	−0.107	0.605	0.499
EGARCH	2.481	0.411	2.893	0.188	0.724	0.913
Panel C: Tangibility						
Panel C.1: PPE/A						
RW	2.809	−4.277[b]	−1.468	2.852[b]	−2.637[b]	0.214
MIDAS	3.024	−4.576[b]	−1.552	3.027[b]	−2.816[b]	0.211
GARCH	3.152	−4.841[b]	−1.690	2.888[c]	−3.024[b]	−0.136
GJR-GARCH	2.797	−4.414[c]	−1.617	2.807	−2.635[b]	0.173
EGARCH	3.311	−5.157[c]	−1.846	3.516	−2.892[c]	0.624
Panel C.2: RD/A						
RW	5.374[c]	−2.074	3.300	4.328[a]	−1.762	2.566[b]
MIDAS	5.625[c]	−2.177	3.448	4.631[a]	−1.954	2.677[c]
GARCH	4.749	−2.217	2.532	4.165[b]	−2.192	1.972
GJR-GARCH	5.699[c]	−2.077	3.622	4.788[a]	−2.032	2.756[a]
EGARCH	6.324	−1.389	4.935	5.541[a]	−1.759	3.782[b]
Panel D: Growth opportunities and distress						
Panel D.1: BE/ME						
RW	−2.219	−1.310	−3.529[c]	−2.528[c]	−1.434	−3.962[a]
MIDAS	−2.518[c]	−1.656	−4.173[c]	−2.861[c]	−1.608	−4.469[a]
GARCH	−3.156[b]	−1.432	−4.589[b]	−3.238[c]	−1.407	−4.646[a]
GJR-GARCH	−3.167[b]	−1.813	−4.980[b]	−3.333[c]	−1.591	−4.924[a]
EGARCH	−2.878[b]	−4.031	−6.909[a]	−3.622[b]	−2.860	−6.482[a]
Panel D.2: EF/A						
RW	−2.161[b]	−0.771	−2.932[a]	−1.410	−0.518	−1.929[c]
MIDAS	−2.091[b]	−0.770	−2.861[a]	−1.461	−0.479	−1.940[c]
GARCH	−1.683[c]	−0.420	−2.102[b]	−1.307	−0.179	−1.485
GJR-GARCH	−1.648	−0.510	−2.158[b]	−1.444	−0.250	−1.694

TABLE 9 (Continued)

Model	S − I (first approach)			S − I (second approach)		
	Retail	Institutional	Joint	Retail	Institutional	Joint
EGARCH	−2.098[b]	−1.189	−3.287[a]	−1.713	−0.494	−2.207
Panel D.3: GS						
RW	−2.536	−0.108	−2.644	−1.816	0.346	−1.471
MIDAS	−2.847[c]	0.141	−2.706	−2.041	0.424	−1.617
GARCH	−3.171[b]	0.848	−2.323	−2.122	0.685	−1.437
GJR-GARCH	−3.048[c]	0.595	−2.454	−2.418	0.574	−1.844
EGARCH	−3.361[b]	0.435	−2.926	−2.727	0.424	−2.303
Panel E: Growth opportunities						
Panel E.1: BE/ME						
RW	1.807	−0.641	1.166	1.249	−0.191	1.057
MIDAS	2.109	−0.689	1.420	1.480	−0.288	1.191
GARCH	2.240	−0.628	1.613	1.652	−0.438	1.214
GJR-GARCH	2.268	−0.497	1.771	1.638	−0.364	1.274
EGARCH	2.998	−0.409	2.589	2.139	−0.234	1.906
Panel E.2: EF/A						
RW	2.358	0.524	2.882[c]	1.212	0.336	1.548
MIDAS	2.544	0.553	3.096[c]	1.256	0.369	1.625
GARCH	2.179	0.669	2.848	1.005	0.411	1.416
GJR-GARCH	2.510	0.610	3.120	1.171	0.389	1.560
EGARCH	3.269	1.097	4.367[c]	1.494	0.603	2.097
Panel E.3: GS						
RW	2.951	−0.405	2.546	1.948	−0.261	1.688[c]
MIDAS	3.393	−0.555	2.838	2.232[c]	−0.324	1.909[b]
GARCH	3.373	−0.726	2.647	2.191	−0.841	1.850[c]
GJR-GARCH	3.687	−0.589	3.099	2.533[c]	−0.346	2.187[b]
EGARCH	4.974[c]	−0.403	4.571[c]	3.257[b]	−0.204	3.053[b]
Panel F: Distress						
Panel F.1: BE/ME						
RW	−0.412	−1.950	−2.363	−1.280	−1.625	−2.905[a]
MIDAS	−0.409	−2.345	−2.754[c]	−1.382	−1.896	−3.278[a]
GARCH	−0.916	−2.060	−2.976[c]	−1.586	−1.845	−3.431[a]
GJR-GARCH	−0.899	−2.310	−3.210[c]	−1.695	−1.955	−3.650[a]
EGARCH	0.120	−4.440	−4.320[c]	−1.482	−3.094	−4.576[a]

(Continues)

TABLE 9 (Continued)

Model	S – I (first approach)			S – I (second approach)		
	Retail	Institutional	Joint	Retail	Institutional	Joint
Panel F.2: EF/A						
RW	0.197	−0.247	−0.050	−0.198	−0.183	−0.381
MIDAS	0.452	−0.217	0.235	−0.205	−0.110	−0.315
GARCH	0.497	0.249	0.746	−0.302	0.233	−0.069
GJR-GARCH	0.862	0.100	0.962	−0.273	0.139	−0.134
EGARCH	1.171	−0.091	1.080	−0.219	0.109	−0.110
Panel F.3: GS						
RW	0.416	−0.513	−0.097	0.132	0.085	0.217
MIDAS	0.546	−0.414	0.132	0.192	0.100	0.292
GARCH	0.201	0.122	0.324	0.069	0.344	0.413
GJR-GARCH	0.639	0.006	0.645	0.115	0.228	0.343
EGARCH	1.613	0.032	1.645	0.530	0.220	0.750

confirms the joint negative impact of the two investor types on the beta-return relation. Our empirical evidence shows the market inefficiency and hence instability, as embodied by the distortion of the positive risk-return tradeoff in our paper, is more likely to be a result of the two noise trader types, and hence it is necessary to consider both when planning investment strategies or enacting policies attempting to stabilize markets or to improve market efficiency. The implications of this finding are twofold: To begin with, we report new evidence regarding the impact of investor sentiment on the risk–return relation to this literature, and in addition, based on our results, we document the importance of the inclusion of the two investor-type sentiments, thereby offering a new empirical framework to this literature.

We also conduct a cross-sectional analysis by looking into 10 different stock characteristics, documenting a cross-sectional impact of retail and institutional investor sentiment on the mean-variance relation. Empirical findings present a feature of duality: We confirm a cross-sectional impact of retail, institutional, and their collective investor sentiment on the mean-variance relation, supporting the extant evidence, but notably, the theorized sentiment-sensitive and sentiment-insensitive classifications in the context of the sentiment-return relation become indefinite or even opposite, that is, that the mean–variance relation of the theorized sentiment-insensitive (sentiment-sensitive) stocks are more (less) sensitive to investor sentiment, presenting somewhat contradictory evidence to the extant debate.

Bohl et al. (2009) suggest that institutional investors may stabilize stock prices, especially if they counter irrational retail investor sentiment. We directly test this proposition by examining not only the separate impacts of institutional and retail investors' sentiments on the risk–return relation, but also their joint impact. Our finding that institutional investor sentiment plays a substantive joint role in the distortion of the risk-return relation is at odds with Bohl et al. (2009) and contributes to a growing body of evidence documenting the role of institutional investors in the destabilization of financial markets that institutional investors may destabilize stock markets (Brunnermeier & Nagel, 2004; Cao et al., 2017; Choi et al., 2015; Hong et al.,

TABLE 10 Cross-sectional result summary.

This table reports summary results for the cross-sectional tests. 'Yes/S' ('Yes/I') means that there is a cross-sectional difference in the impact of investor sentiment on the mean-variance relation and sentiment-sensitive (-insensitive) stocks are more affected. 'No' means that there is no cross-sectional difference.

Characteristics	Retail	Institutional	Joint	Implications
Panel A: Size, age, and risk				
ME	No	No	Yes/S	Sentiment-sensitive stocks are more affected by the joint impact.
Age	No	No	No	No cross-sectional difference.
Sigma	Yes/I	No	Yes/I	Sentiment-insensitive stocks are more affected by retail investor sentiment and the joint impact.
Panel B: Profitability and dividend policy				
E/BE	No	No	Yes/S	Sentiment-sensitive stocks are more affected by the joint impact.
D/BE	No	No	No	No cross-sectional difference.
Panel C: Tangibility				
PPE/A	Yes/I	Yes/S	No	Sentiment-insensitive stocks are more affected by retail investor sentiment.
				Sentiment-sensitive stocks are more affected by institutional investor sentiment.
RD/A	Yes/I	No	Yes/I	Sentiment-insensitive stocks are more affected by retail investor sentiment and the joint impact.
Panel D: Growth opportunities and distress				
BE/ME	Yes/S	No	Yes/S	Sentiment-sensitive stocks are more affected by retail investor sentiment and the joint impact.
EF/A	Yes/S	No	Yes/S	Sentiment-sensitive stocks are more affected by retail investor sentiment and the joint impact.
GS	Yes/S	No	No	Sentiment-sensitive stocks are more affected by retail investor sentiment.
Panel E: Growth opportunities				
BE/ME	No	No	No	No cross-sectional difference.
EF/A	No	No	Yes/I	Sentiment-insensitive stocks are more affected by the joint impact.
GS	No	No	Yes/I	Sentiment-insensitive stocks are more affected by the joint impact.
Panel F: Distress				
BE/ME	No	No	Yes/S	Sentiment-sensitive stocks are more affected by the joint impact.
EF/A	No	No	No	No cross-sectional difference.
GS	No	No	No	No cross-sectional difference.

2012; Stein, 2009). Of direct relevance, Chelley-Steeley et al. (2019), for example, posit that institutional investors may trade on, rather than against, retail investor sentiment. Likewise, Li et al. (2018) show that institutional investors trade on false news, which has a persistent impact on stock prices potentially decoupling the risk–return relation. Elsewhere, in the herding literature, in which investor sentiment is shown to be a cause of market herding (Blasco et al., 2012), institutional investors have been identified as a destabilizing impact on bond markets (Cai et al., 2019). In addition to new insights in the context of investor sentiment and the risk–return relation, our contribution is to highlight the importance of the interplay between, and hence joint impact of, both retail and institutional investors. In doing so we respond to recent developments in theoretical models (Sheng et al., 2022) and calls for greater attention to be given to the interplay between investor types (Spyrou, 2013).

Our findings imply potentially actionable and reliable trading strategies based on the two investor-type sentiments. For example, amid bearish periods when both investor-types are pessimistic, investors can increase risk exposure by holding high-beta stocks given the positive beta–return relation, whereas over bullish periods when the two investor-types are optimistic, investors can consider reducing risk exposure and incorporate low-beta stocks into their portfolios. An examination of such trading strategies is out of the scope of our paper, and so we leave it to future research to consider.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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