Institutional Investor Sentiment and the Mean-Variance Relationship: Global Evidence

Abstract

Although a cornerstone of traditional finance theory, empirical evidence in support of a positive mean-variance relation is far from conclusive, with the behavior of retail investors commonly thought to be one of the root causes of departures from this expected relationship. The behavior of institutional investors, conventionally thought to be sophisticated and rational, has recently come under closer scrutiny, including in relation to investor sentiment. Drawing together these two strands of literature, this paper examines the impact of institutional investor sentiment on the mean-variance relation in six regions, including Asia (excl. Japan), Eastern Europe, Eurozone, Japan, Latin America, and the US, and across thirty-eight markets. Empirical evidence supports the differential impact of institutional investor sentiment on the mean-variance relation (i.e., positive or negative), both across regions and across markets. In particular, for markets with cultural proneness to overreaction and a low level of market integrity institutional investor sentiment tends to distort the risk-return tradeoff.

Keywords: Individualism; Institutional investor sentiment; Market integrity; Mean-variance relation; Overreaction; Uncertainty avoidance

JEL classification: G12; G14; G15; G41

1. Introduction

The traditional financial framework theorizes a positive mean-variance relation, i.e., risk-return tradeoff, with high (low) risk compensated by high (low) returns (Merton, 1973 & 1980). Empirical evidence, however, is inconclusive, with extant literature reporting evidence of either a positive, negative, or mixed relationship.[1] If, as postulated, asset prices derive from discounted future cash flows, behavioral factors, such as investor sentiment, should have no persistent impact on markets (e.g., Fama, 1965 & 1970), and nor, therefore, on the mean-variance relationship. Behavioral studies, however, challenge this perspective, especially in relation to the persistent impact of investor sentiment on stock markets. De Long et al. (1990), for example, develop a model where informed and uniformed investors trade together, and reveal that the latter's participation provokes systematic risk derived from stochastic shifts in investor sentiment, imposing limits on arbitrage and leading to persistent mispricing (see, also, Campbell and Kyle, 1993; Shefrin and Statman, 1994; Palomino, 1996). The theory is supported by voluminous empirical research, both on the US and globally, confirming the persistent impact of investor sentiment on stock returns.[2] More specifically, a small number of studies explore the role of investor sentiment in the mean-variance relation. The mechanism for this influence, as argued in Yu and Yuan (2011), builds on two arguments. First, retail investors are noise traders and likely to misestimate the variance of returns, thereby distorting the mean-variance relation. Second, retail investors are more

[1] Examples across the three streams include, in the positive (French et al., 1987; Baillie and DeGennaro, 1990; Campbell and Hentschel, 1992; Scruggs, 1998; Guo and Whitelaw, 2006; Ludvigson and Ng, 2007; Lundblad, 2007; Pástor et al., 2008; Rossi and Timmermann, 2015), negative (Campbell, 1987; Whitelaw, 1994; Brandt and Kang, 2004; Brandt and Wang, 2010; Baker et al., 2011; Fiore and Saha, 2015; Booth et al., 2016), and mixed (Turner et al., 1989; Glosten et al., 1993; Harvey, 2001; Wang et al., 2017) camps.

[2] See, Brown and Cliff (2004 & 2005), Lemmon and Portniaguina (2006), Baker and Wurgler (2006 & 2007), and Da et al., (2011 & 2015), etc. for US evidence, and Schmeling (2009), Bathia and Bredin (2013), and Wang et al. (2021), etc. for global evidence. Where such studies examine the impact of sentiment generally, others demonstrate the more specific impact of event-driven sentiment on stock markets, including sunshine (Hirshleifer and Shumway, 2003), aviation disasters (Kaplanski and Levy, 2010), sporting events (Edmans et al., 2007; Pantzalis and Park, 2014. Sakkas and Urquhart, 2017), war (Hudson and Urquhart, 2015), religious events (Gavriilidis et al., 2016), and air pollution (Lepori, 2016).

willing to trade when feeling optimistic than pessimistic due to limits on short selling (Barber and Odean, 2008). These two arguments combine to suggest the risk-return tradeoff is likely to be distorted by the increased presence of retail investors during high-sentiment periods.[3] Yu and Yuan (2011) confirm this for the US stock market, while similar findings are supported in European stock markets (Wang, 2018a) and at the stock level (i.e., a beta-return tradeoff, Antoniou et al., 2016; Shen et al., 2017).

Conventional wisdom posits that institutional investors are more sophisticated and so less susceptible to behavioral biases than retail investors, thus it is the latter and not the former that are to blame when markets depart from notions of efficiency or presumed theoretical relationships. Such a view of institutional investors has come under close scrutiny, however, with growing evidence that institutional investors too are prone to behaviors such as the disposition effect (e.g., Locke and Mann, 2005; Andreu et al., 2020) and herding (e.g. Sias, 2004; Choi and Sias, 2009; Gavriilidis et al., 2013; Holmes et al., 2013), while they have also been shown to be responsible for calendar anomalies such as the Monday effect (Ülkü and Rogers, 2018). Gilad and Kliger (2008) show experimentally that professionals' decisions are open to priming manipulation, suggesting they may be more intuitive and less analytic, thus further supporting the view that institutional investors are not infallible. Of direct relevance in our context, DeVault et al. (2019) find, contrary to the general intuition that institutional

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

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

where $N = N_1$ (the number of informed traders) + N_2 (the number of sentiment traders); S_0 is the ex-dividend stock price at time 0; K is the number of sentiment traders shows 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., {·}), and (ii) the average of stock market participants' stock holding (i.e., [·]). As per Yu and Yuan (2011), high investor sentiment undermines the risk-return tradeoff by reducing the average stock holdings of market participants (i.e., {·}) and by increasing the average of the inverse risk-aversion attitudes of stock market participants (i.e., [·]). For detailed derivation and proof, see, Appendix of Yu and Yuan (2011).

investors are immune to sentiment trading, that they, rather than retail investors, tend to be noise traders (see, also, Chelley-Steeley et al., 2017).[4] While their sentiment trading can be partly explained by institutional investment styles including risk management, reputational concerns, momentum trading, herding, bubble riding, and underlying investor flows,[5] a '*substantial*' part remains unexplained (DeVault et al., 2019, p. 986). Wang (2018b) suggests that if institutional investors are noise traders, their elevated trading during bullish periods might also undermine the risk-return tradeoff,[6] and provides initial empirical evidence in support using the US-based Investors Intelligence (II) sentiment measure constructed from investment newsletter writers.[7]

This paper extends the scant literature linking institutional investor sentiment and the mean-variance relationship to a global context comprising thirty-eight stock markets, including both developed and emerging. We are motivated by the following reasons. First, extending to an international dataset allows for the examination of new hypotheses. The impact of retail

[4] The finding is consistent with prior literature documenting that institutional investors are not completely free of behavioral biases, and hence their trading may lead to irrational market outcomes (e.g., Malmendier and Tate, 2005; Baker and Wurgler, 2012; Ben-David et al., 2013; Glaser et al., 2013; Holmes et al., 2013; Greenwood and Shleifer, 2014; Gavriilidis et al., 2020).

[5] Of relevance to risk management and reputational concerns, for example, DeVault et al. (2019) document that those institutional investors that avoid holding and trading risky stocks, such as insurance companies, pensions, banks, along with unclassified institutional investors, contribute little to the aggregate sentiment trading, while those that prefer holding and trading risky stocks, and are sensitive to lag performance, such as mutual funds, hedge funds, and independent advisors, contribute much to the aggregate sentiment trading. Similarly, prior literature confirms that hedge funds are more likely to ride bubbles than other types of institutions (Brunnermeier and Nagel, 2004), and indeed they exhibit the greatest propensity for sentiment trading after controlling for institutional size. There are also several other arguments from the rational paradigm explaining institutional investors' irrationality. For instance, Blankespoor et al. (2020) conclude that institutional investors can rationally under-use (i.e., inattention) accounting information disclosures due to the processing costs (Green et al., 2011; McLean and Pontiff, 2016; Bhattacharya et al., 2018; Calluzzo et al., 2019), agency conflicts or lack of incentives to maximize long-term profits (Yan and Zhang, 2007; Edelen et al., 2016). Our approach, however, is a behavioral one, first examining the impact of institutional investor sentiment on the mean-variance relation and second exploring what potentially leads to their noise trading, and so we do not elaborate further with respect to such rational alternatives as inattention.

[6] In theory, unlike retail investors who are reluctant to sell short, institutional investors can trade against overpricing of stocks by short selling due to their expertise and information advantage, so that one of the cornerstones stated in Yu and Yuan (2011) might be untenable. In practice, however, most institutional investors are also unwilling to sell short because of direct short-selling costs and indirect institutional constraints (Nagel, 2005).

[7] Wang (2020) examines the beta-return relationship for US stocks and reports supporting evidence, again based on the II sentiment measure.

investor sentiment is known to be market-specific (Schmeling, 2009; Wang, 2018a; Wang et al., 2021) and the same might be expected to be true of institutional investor sentiment. Using a collection of global markets, we expect to observe a differential impact of institutional investor sentiment on the mean-variance relation across regions, since institutional investors' dispositions and behaviors are naturally distinct due to factors such as cultural dimensions and market integrity (e.g., La Porta et al., 1998; Grinblatt and Keloharju, 2001; Beckmann et al., 2008; Aggarwal and Goodell, 2009; Zingales, 2015). To the extent that regional and market differences are detected, we can examine whether culturally- and institutionally-driven behavioral biases influence the impact of institutional investor sentiment on the mean-variance relation.[8] Second, a global sample incorporating both developed and emerging markets helps to provide additional insights into the role of institutional investor sentiment that are unlikely to be observed if sample markets have similar economic conditions and exclude those at different stages of development (Ferreira et al., 2012). Third, an enlarged global dataset provides out-of-sample evidence in comparison with the US market, which is desirable in surveying market anomalies (Griffin et al., 2003; Ang et al., 2009). Fourth, a panel dataset comprising multiple stock markets can dramatically enhance the power of statistical analyses (Ang and Bekaert, 2007; Schmeling, 2009).[9]

[8] For the important role that culture and market integrity play in finance, see, Grinblatt and Keloharju (2001), Guiso et al. (2008), Beugelsdijk and Frijns (2010), Zouaoui et al. (2011), Aggarwal et al. (2012), Bilinski et al. (2013), Ahern et al. (2015), Eun et al. (2015), Zingales (2015), and Scharfstein (2018).

[9] Our interest in institutional investors is also driven by the worldwide increasing trend of institutional investor equity ownership. In some developed markets, for example, by 2007, institutional ownership has reached at around 35.7% in Finland, 30.9% in France, 33.5% in Ireland, 37.9% in the UK, and 57.8% in the US, and notably, most developed markets consistently demonstrate an upward trend in the institutional ownership (Aggarwal et al., 2011). A similar pattern is also observed in emerging markets: The average institutional ownership over 2004–2016 is, for instance, 17.9% in Brazil, 11.4% in Chile, and 18.7% in Poland, which can be attributed to financial market sophistication, the growing importance of corporate governance, and the advancement of the private pension fund industry (Alvarez et al., 2018).

Sentiment is illusive. A range of retail investor sentiment proxies, constructed by various approaches,[10] are available, while those for institutional counterparts are limited. We adopt the sentix as the proxy for institutional investor sentiment. Constrained by data availability, we incorporate thirty-eight stock markets in six regions: Asia (excl. Japan), Eastern Europe, Eurozone, Japan, Latin America, and the US. Conditional volatility is measured via five models including the rolling window (RW), GARCH, GJR-GARCH, EGARCH, and the mixed-data sampling (MIDAS), to allow for the fact that the mean-variance relation can be dependent on volatility models (Turner et al., 1989; Harvey, 2001; Ghysels et al., 2005; Yu and Yuan, 2011).

We start with analyzing the regional mean-variance relation (i.e., at the panel level). Results from the whole sample, i.e., an unconditional test, exhibit a negative mean-variance relation in all five non-US regions. We then separate the entire sample into bullish and bearish subsamples based on institutional investor sentiment to explore its role in the mean-variance relation, i.e., a conditional test, and find regional differences. In Asia (excl. Japan) and Eastern Europe, there is a positive mean-variance relation amid bearish times, while institutional investors' elevated trading over bullish times distorts the risk-return tradeoff. In the Eurozone, by contrast, there is a negative mean-variance relation over bearish periods, while such distortion becomes less evident when institutional investors become bullish. Latin America and the US markets present similar results to the Eurozone markets, though with limited significance, while for Japan, as well as the whole world, results are sensitive to the choice of volatility model. Overall, results are robust to different specifications controlling for retail investor sentiment and economic conditions, and to the adoption of a shorter but

[10] Prior literature measures retail investor sentiment via four main approaches including direct, indirect, composite, and innovative. See, Baker and Wurgler (2007), Wang et al. (2018a), and Duxbury et al. (2020), for summaries of various proxies adopted in extant literature. See, Lee et al. (1991), Swaminathan (1996), Brown (1999), Fisher and Statman (2000), Antweiler and Frank (2004), Baker and Wurgler (2006), Kumar and Lee (2006), Wang et al. (2006), Qiu and Welch (2006), Tetlock (2007), Frazzini and Lamont (2008), McLean and Zhao (2013), Kim and Kim (2014), Huang et al. (2015), Bathia and Bredin (2018), Bennani (2020), and Wang et al. (2021), for empirical applications.

more balanced dataset. We replicate the tests for individual markets separately, with a higher degree of heterogeneity in the impact of institutional sentiment on the mean-variance relationship.

The differential impact of institutional sentiment on the mean-variance relationship suggests disparate institutional investor behavior across regions—that is, they are sentiment traders in some regions but not in others. To provide insights into the potential determinants of such differences, we explore the influence of two aspects: cultural dimensions and market integrity. Evidence suggests that in markets with collectivistic and uncertainty-avoiding cultures, institutional investors' increased trading tends to undermine the risk-return tradeoff, while in markets with individualistic and uncertainty-accepting cultures, their heightened presence reduces the risk-return tradeoff distortion. Both collectivism and uncertainty avoidance indicate proneness to overreaction, and by constructing a parsimonious overreaction indicator via principal component analysis (PCA), we confirm that institutional investors in markets with cultural inclination to overreaction are more likely to distort the risk-return tradeoff and thus to be sentiment traders. In addition, in markets with high-level integrity, institutional investors' increased participation over bullish periods would make the risk-return tradeoff less distorted.

The paper proceeds as follows. Section 2 develops testable hypotheses. Section 3 presents data on institutional investor sentiment and stock markets. Section 4 details the approaches to measure conditional volatility and to assess the mean-variance relation. Section 5 provides empirical results at both regional and market levels, followed by cross-market investigations into the determinants of differences in the impact of institutional investor sentiment on the mean-variance relation in Section 6. Section 7 concludes.

2. Hypothesis development

In this paper, we firstly investigate the impact of institutional investor sentiment on the mean-variance relation, based on two assumptions. First, institutional investors are unwilling to sell short amid low-sentiment periods because of direct short-selling costs and indirect institutional constraints (Nagel, 2005) and so tend to be more active during high-sentiment periods when they are optimistic about future stock markets. Second, as revealed by Wang (2018b) and DeVault et al. (2019), institutional investors can be noise traders and thus misestimate variance and attenuate the risk-return tradeoff. The two assumptions collectively lead to one implication: The heavy presence of institutional investors over high-sentiment periods would distort the positive mean-variance relation as theorized in standard financial theories (see, Footnote 3).

Note, however, that extant studies confirm the impact of investor sentiment to be market-specific (Schmeling, 2009; Bathia and Bredin, 2013; Wang, 2018a; Wang et al., 2021). Our global study, extending the prior evidence reported by Wang (2018b) on the US market, incorporates thirty-eight international markets, and therefore we expect to reveal different patterns of the impact of institutional investor sentiment on the mean-variance relation. To this end, we test the following alternative hypotheses:

Hypothesis 1a. The heavy presence of institutional investors over high-sentiment periods would distort the mean-variance relation.

Hypothesis 1b. The heavy presence of institutional investors over high-sentiment periods would not distort the mean-variance relation.

Next, to the extent that differences across regions and markets are observed, we explore the potential determinants of the impact of institutional investor sentiment on the mean-variance relation from the perspectives of culture and market integrity. Institutional investors tend to trade when feeling optimistic about future stock markets, with the extent to which they trade positively related to their overconfidence level (e.g., Menkhoff et al., 2006; Puetz and Ruenzi, 2011). A conspicuous indicator of overconfidence is individualism capturing people's propensity to value internal attributes to differentiate themselves from others (Hofstede, 2001). A high degree of individualism relates to high levels of overconfidence, more risk-taking behaviors, and commitment of cognitive biases, especially in the investment context (Chui et al., 2010; Li et al., 2013; Shao et al., 2013; Chen et al., 2015; Kashefi-Pour et al., 2020). Conversely, collectivism reflects the extent to which people behave in groups rather than as individuals (Hofstede, 2001). By implication, correlated trading is expected to be stronger in collectivistic than individualistic markets, resulting in more evident overreaction in collectivistic markets (Markus and Kitayama, 1991; Beckmann et al., 2008).

On the one hand, individualism implies overconfidence that may not be rationalized by reality, while, on the other hand, collectivism entails herd-like behavior, potentially triggering overreaction. Institutional investors' noise trading behaviors might result either from individualism or collectivism. If institutional investors in individualistic cultures succumb to noise to a higher degree than those in collectivistic cultures, we would expect to observe a more distorted incremental change in the risk-return tradeoff during bullish periods in individualistic markets, while the opposite holds otherwise. To this end, we test the following alternative hypotheses:

Hypothesis 2a. The risk-return tradeoff tends to be more distorted in individualistic markets over high-sentiment periods.

Hypothesis 2b. The risk-return tradeoff tends to be more distorted in collectivistic markets over high-sentiment periods.

Uncertainty avoidance reflects the extent to which people oppose or attempt to limit uncertainty or ambiguity. High uncertainty avoidance signifies low risk tolerance and conservative behaviors (Hofstede, 2001). Institutional investors in high uncertainty-avoiding markets, therefore, tend to overreact to market fluctuations, and we can expect institutional investors in high uncertainty-avoiding markets to be more subject to sentiment trading. Thus, we would expect to observe a greater distorting influence on the mean-variance relation. Hence, we test the following alternative hypotheses:

Hypothesis 3a. The risk-return tradeoff tends to be more distorted in markets with high uncertainty avoidance over high-sentiment periods.

Hypothesis 3b. The risk-return tradeoff tends to be less distorted in markets with high uncertainty avoidance over high-sentiment periods.

Finally, a high level of market integrity improves information flow and dissemination, making markets more efficient (La Porta et al., 1998; Zouaoui et al., 2011; Wang et al., 2021), so the mean-variance relation is expected to be less distorted by institutional investor sentiment in markets with high market integrity. Hence, we test the following alternative hypotheses:

Hypothesis 4a. The risk-return tradeoff tends to be more distorted in markets with low market integrity over high-sentiment periods.

Hypothesis 4b. The risk-return tradeoff tends to be less distorted in markets with low market integrity over high-sentiment periods.

3. Data

3.1 Institutional investor sentiment

We source sentix economic sentiment survey data, compiled by the sentix GmbH, from Refinitiv for six major regions including Asia (excl. Japan), Eastern Europe, the Eurozone, Japan, Latin America, and the US, over January 2003 to December 2015.[11] While the sentix survey is open to investors in general, responses from institutional and retail investors are clearly distinguished since the registration of the former, such as fund managers, traders, economists, and analysts, is verified by sentix to ensure data quality.[12] Respondents are asked about their opinions regarding the current and future economic situations, and we use the future expectations in our analysis only. The survey result is computed as a qualitative diffusion indicator, ranging from –100 (strongly deteriorating) to 100 (strongly improving), with zero being the neutral value indicating an unchanged expectation relative to the current situation. While the sentiment data provided by sentix is unquestionably of high quality (see, Footnote 12) and has been adopted in sentiment literature (Schmeling, 2007; Corredor et al., 2013; Schneider, 2014; Debata et al., 2018; Gao et al., 2020),[13] some comments are in order.

Unlike market-level surveys where respondents are asked about expectations concerning local markets, sentix respondents are asked about expectations for major regions across the world. Thus, institutional investor sentiment in a given region is not solely the product of institutional investors in that region, which might initially raise questions concerning the data.

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[11] In addition to the economic sentiment survey used here, sentix also conducts many other surveys, including a weekly sentiment survey related to strategic biases. While potentially of relevance, we do not employ the weekly survey here due to its relatively limited coverage of the markets, including China, Eurozone, Germany, Japan, and the US, which is at odds with our global study.

[12] For more quality control measures, see, https://www.sentix.de/index.php/en/Philosophy/ein-wort-zum-thema-datenqualitaet.html. One potential concern is that the sentix proxy is a reflection of expected economic conditions and thus does not carry irrational component. As we reveal below in one of our robustness tests in Part 5.1.3, our proxy contains noise elements beyond the rational component and the results remain consistent when we take the potential influence of the economic expectations into account.

[13] The sentix online platform has also been used in experimental studies examining institutional investor behavior (e.g., Menkhoff et al., 2013), further substantiating the quality of both the data and the provider.

However, this feature of the data is not a concern here given our focus on institutional investors and empirical design. First, as professionals, institutional investors form future expectations based on a range of objective factors such as political stability, macroeconomic situations, etc., based on data drawn from similar sources. Therefore, while it may not be true of retail investors, it is anticipated that the expectations of institutional investors, irrespective of their location, are likely to be largely consistent concerning a given region's future economy and market performance. Second, as discussed below, rather than employing actual sentix values, we follow Yu and Yuan (2011), among others, to use sentix measures for sample separation purposes based on whether the annual average is above or below the neutral value (zero). This annual average synthesizes all sentix information within one year, thus smoothing out any short-term, transient variation over the period. In this sense, it is unlikely to generate an opposite classification (i.e., from bullish to bearish, or otherwise) when conducting our sub-sample separation. Third, the monthly sentix is compiled from diffusion computation that allocates weights based on the proportion of responses. In rare cases when institutional investors' responses are biased, the impact on the final sentix measure is largely suppressed.

As with other survey-based proxies, such as UBS/Gallup, investor confidence indices, and consumer confidence indices, the sentix, or specifically the responses to the sentix survey questions, could intrinsically succumb to various subjective factors (Baker and Wurgler, 2007). As explained above, this inherent drawback associated with surveys is overcome in our empirical design as the annual average sentix is less noisy, making it infeasible to generate an opposite sample separation result. On the contrary, the survey-based sentix has its own merits. As a group of institutional investors and sentix respondents, mutual fund managers' trading is partly affected by underlying retail investors' purchases and redemptions. For alterative, market-based sentiment proxies, such as institutional investors' trading volume, a high (low) level can mistakenly ascribe high (low) retail investor sentiment to high (low) institutional investor sentiment. This can be problematic as the sentiment of the two parties do not always move together (Shleifer, 2000). Using survey-based proxies, Schmeling (2007) evidences that institutional and retail investor sentiment represents '*smart money*' and '*noise trader risk*', respectively (p. 143), and institutional investors would purposefully trade optimistically (pessimistically) when retail investors are pessimistic (optimistic). In Appendix A, we provide the number of years when sentiment of two parties is in the same direction (bullish or bearish), confirming that institutional and retail investor sentiment do not always move together. This is unproblematic, however, as our sentix proxy allows us to isolate institutional investors' sentiment (willingness to trade).

Table 1 presents descriptive statistics for the sentix measure by region. On average, institutional investors are bullish over 2003–2015 as indicated by the positive mean across all regions. Institutional investors are the most optimistic about the Asia (excl. Japan) region (13.891) and least optimistic about the US region (0.234). While sentix is designed to vary between –100 and 100, the highest and lowest sentix values observed are 52.500 (Asia, excl. Japan) and –47.500 (the Eurozone), respectively, implying that institutional investors are normally free of extreme optimism or pessimism. Table 2 presents pairwise correlations between regions based on the monthly sentix, with an average of correlation of 0.751 suggesting a medium-level synchronous trend across all six regions.

<Table 1 & 2>

3.2 Sample separation

To examine the impact of institutional investor sentiment on the mean-variance relationship, for each region we separate the full sample into bullish/bearish subsamples in the manner of Yu and Yuan (2011) and Antoniou et al. (2016). Both studies adopt the annual sentiment index from Baker and Wurgler (2006, BW index) in their sample separation, categorizing year ($T + 1$) as a bullish (bearish) year when the BW index in year T is positive (negative). While, by definition, this produces one annual BW index at the end of each year, rather than merely capturing sentiment at that specific timepoint, it contains all sentiment information across the given year. Following Yu and Yuan (2011) and Antoniou et al. (2016), we employ the one-year window and for each region I we classify year ($T + 1$) as a bullish (bearish) year if the annual sentix for year T, computed as the average of twelve within-year monthly sentix observations ($sentix_{AVG,I,T}$) and thus containing all sentiment information across year T, is above (below) the neutral value zero (Wang, 2018b). Table 1 provides the number of years classified as bullish and bearish. For all regions, the number of bullish years exceeds the number of bearish years, again suggesting institutional investors are bullish overall.

While our separation of bullish and bearish subsamples is based on institutional investor sentiment, we do not explicitly disentangle the impact of retail investor sentiment. If retail investor sentiment moves together with institutional investor sentiment, our separation would not be exclusively determined by the latter and it would be challenging to identify the impact of institutional investor sentiment on the mean-variance relationship. However, evidence in Shleifer (2000), Schmeling (2007) and Wang (2018b) supports the view that retail investor and institutional investor sentiments do not covary[14]. To further corroborate this view, we compute the correlation between annual regional institutional investor sentiment and annual market retail investor sentiment proxied by the consumer confidence index (CCI).[15] The

[14] For example, Wang (2018b) computes correlations between US institutional investor sentiment proxied by the Investors Intelligence (II) and four retail investor sentiment proxies, with coefficients ranging from –0.122 to 0.332 suggesting a very low level of co-movement.

[15] The CCI is confirmed to be a suitable proxy for retail investor sentiment. Qiu and Welch (2006) argue that if investors are bullish (bearish) about the economy, they are also likely to be bullish (bearish) about stock markets and vice versa. In support of this, they report a strong positive correlation between the CCI and another sentiment proxy, namely the UBS/Gallup Index of Investor Optimism (see, also, Lemmon and Portniaguina, 2006; Derrien and Kecskés, 2009; Greenwood and Shleifer, 2014; Gao and Süss, 2015). CCIs are available in thirty-seven of the thirty-eight markets covered by sentix, excluding Malaysia. In several markets such as

unreported correlations average 0.259 across all markets. Such low correlation supports the view that retail investor and institutional investor sentiments do not covary, thus confirming our subsample separation is mainly determined by institutional investor sentiment.

3.3 Stock market

Daily and monthly stock market data are sourced from the DataStream Total Market Equity Index that reflects the overall performance of a specific stock market, spanning from 2004 to 2016.[16] Constrained by sentix data availability, we include thirty-eight stock markets across the globe. They are from various regions with different economic development conditions (i.e., developed/emerging), making our selection a representative international sample.

<Table 3>

Table 3 displays descriptive statistics of the monthly excess market returns and realized volatility. The majority of markets generate positive monthly returns over the sample periods (exceptions are Cyprus, Greece, Italy, Portugal, Slovenia, and Brazil). Also, returns in most markets are negatively skewed (such as Bulgaria, Cyprus, and Malta) and all are leptokurtic, in line with Lux (1998) and Chen et al. (2001). Variance of market returns (σ^2 in Column (I)) is close to the mean of realized volatility (μ in Column (II)) and the differences between the two lies in Jensen's inequality (Ghysels et al., 2005). Realized volatility is positively skewed and leptokurtic for all markets, across all regions.

Slovenia, South Korea, and Philippines, the starting months of CCIs are later than January 2003. CCIs in four markets, namely Chile, Japan, Philippines, and Russia, are (partially) reported at a quarterly interval, but it does not affect our correlation computation as we use the annual average of CCIs within the given year. Details of sources and data frequency of CCIs for each market are reported in Appendix A.

[16] Sentix data ranges from 2003 to 2015 while stock market data ranges from 2004 to 2016. The one-year timing difference is due to the fact that we use sentix data in year T to determine the institutional investors' optimism or pessimism in year ($T + 1$).

4. Methodology

To reveal the mean-variance relation, we employ five different approaches, including the rolling window model (RW), GARCH, GJR-GARCH, EGARCH, and MIDAS, to measure conditional volatility in that the presented mean-variance relation is subject to the choice of volatility models (Ghysels et al., 2005; Lundblad, 2007; Yu and Yuan, 2011).

4.1 Rolling window model

The RW model measures volatility following,

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

where $Var_t(R_{t+1})$ is the conditional volatility for predicting 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 normally-used number of trading days in one month (Yu and Yuan, 2011; Wang, 2018b).

4.2 GARCH, GJR-GARCH, and EGARCH

For GARCH, GJR-GARCH, and EGARCH, we first estimate the mean equation,

$$r_{t+1} = \mu + \varepsilon_{t+1}, \quad (2)$$

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,

$$\sigma_{t+1}^2 = \omega + \alpha\varepsilon_t^2 + \beta\sigma_t^2, \quad (3)$$

$$\sigma_{t+1}^2 = \omega + \alpha_1\varepsilon_t^2 + \alpha_2 I_t\varepsilon_t^2 + \beta\sigma_t^2, \quad (4)$$

$$\sigma_{t+1}^2 = exp\left\{\omega + \alpha_1[|\varepsilon_t|/\sqrt{\sigma_t^2}] + \alpha_2[\varepsilon_t/\sqrt{\sigma_t^2}] + \beta ln\sigma_t^2\right\}, \quad (5)$$

for GARCH, GJR-GARCH, and EGARCH, respectively. The term I_t in Eq. (4) is the dummy variable for bad news (i.e., $\varepsilon_t^2 < 0$) to account for the leverage effect, i.e., allowing for asymmetry in the response of the conditional volatility to return innovations (Glosten et al., 1993). We store daily conditional volatility series, σ_{t+1}^2, and compute monthly conditional volatility as the linear sum of daily conditional volatility (Engle, 2001; Corsi, 2009),

$$Var_t(R_{t+1}) = E_t(\sum_{d=1}^{N_t} \sigma_{t+d}^2). \quad (6)$$

4.3 MIDAS

MIDAS has a similar structure of RW but differs in horizon, flexibility, and the weighting system, following,

$$Var_t(R_{t+1}) = 22\sum_{d=0}^{252} \omega_d r_{t-d}^2, \quad (7)$$

where r_{t-d} is the demeaned daily return and the subscript (t – d) corresponds to the date t minus d days; ω_d is the weight on r_{t-d}^2, following,

$$\omega_d(\kappa_1, \kappa_2) = \frac{exp\{\kappa_1 d + \kappa_2 d^2\}}{\sum_{d=0}^{252} exp\{\kappa_1 d + \kappa_2 d^2\}}; \quad (8)$$

where κ_1 and κ_2 are the parameters in the weight function. The monthly conditional volatility is hence filtered by the previous 252 trading days (Ghysels et al., 2005).

4.4 The mean-variance relation

An unconditional test for the mean-variance relation is to regress monthly returns (R_{t+1}) on monthly conditional volatility [$Var_t(R_{t+1})$],

$$R_{t+1} = \alpha + \beta Var_t(R_{t+1}) + \xi_{t+1}. \quad (9)$$

where β reflects the mean-variance relation, and prior literature suggests that β could be positive, negative, or close to zero. To examine the impact of institutional investor sentiment on the mean-variance relation, we estimate a conditional regression,

$$R_{t+1} = \alpha_1 + \alpha_2 D_t + \beta_1 Var_t(R_{t+1}) + \beta_2 Var_t(R_{t+1}) D_t + \xi_{t+1}, \quad (10)$$

where D_t is the dummy variable for the bullish subsample, i.e., $D_t = 1$ for the bullish subsample while $D_t = 0$ for the bearish subsample. The mean-variance relations over bearish and bullish periods are reflected by β_1 and ($\beta_1 + \beta_2$), respectively, and therefore, β_2 is the incremental change in the mean-variance relation driven by institutional investors' increased participation over bullish periods and it is the focus of our analysis. If institutional investors are noise traders and tend to misestimate the mean-variance relation, their elevated trading over bullish periods would distort the theoretical risk-return tradeoff, i.e., a negative β_2. On the contrary, we would obtain a positive β_2 if institutional investors are sophisticated traders.[17]

5. Empirical results

This section presents empirical results on the impact of institutional investor sentiment on the mean-variance relation. Subsection 5.1 reports the results at the regional level, followed by the results from individual markets in Subsection 5.2.

5.1 Regional results

We start with the regional analysis and present the results in Table 4. Note that, we treat Japan and the US stock markets as two regions in order to be consistent with sentix data

[17] Note that Eq. (9) and (10) are for estimating individual markets since we do not specify any scripts for cross sections. Regarding models at the global and regional levels, we estimate these two regressions using the panel fixed-effect approach, which allows each individual market to have different constants when all markets enter the regressions jointly. For exact specifications, see, Table 4.

compilation. We first present results from an unconditional test (i.e., based on the entire sample), followed by discussions on a conditional test (i.e., bullish/bearish separation). Three robustness tests are provided as well.

5.1.1 An unconditional test

Three regions including Asia (excl. Japan), Eastern Europe, and Eurozone exhibit a significantly negative mean-variance relation consistently across all five volatility models, supporting one stream of extant evidence on the negative mean-variance relation. For example, the mean-variance relation varies from –2.360 (EGACH) to –1.903 (GJR-GARCH) for the Eurozone, and from –1.170 (EGARCH) to –0.916 (GARCH) for Eastern Europe, signifying that a 1% upward (downward) revision in conditional volatility would be associated with an around 2.063% and 0.996% decrease (increase) in Eurozone and Eastern Europe market returns on average, respectively. While the negative mean-variance relation is insignificant for Japan and Latin America, the consistent results across all five volatility models at least indicate some thoughts counter to the risk-return tradeoff as theorized in the traditional financial framework.

<Table 4>

Differently, the US stock market presents a weakly positive mean-variance relation varying from 0.021 (RW) to 0.200 (GARCH) i.e., risk-return tradeoff, consistent with the traditional financial theory despite being insignificant, partially in line with French et al. (1987), Campbell and Hentschel (1992), Guo and Whitelaw (2006), and Rossi and Timmermann (2015), among others. The reported negative mean-variance relation at the global level appears to be a net outcome of all six regions.

5.1.2 A conditional test: the role of institutional investor sentiment

We then assess the role of institutional investor sentiment in the determination of the mean-variance relation and results evidently confirm its important implication. When institutional investors are pessimistic, conditional volatility tends to be positively related to market returns in Asia (excl. Japan), Eastern Europe, and the US i.e., risk-return tradeoff, but negatively related to market returns in the Eurozone, Japan, and Latin America, along with the whole world. As per the RW, a 1% upward (downward) revision in conditional volatility would cause a 3.926% increase (decrease) in Asia (excl. Japan) market returns but a 1.173% decrease (increase) in Latin America market returns. Compared with unconditional findings that the US is the only market exhibiting a positive mean-variance relation, conditional results over bearish periods reveal three regions exhibiting the risk-return tradeoff, with Asia (excl. Japan) and Eastern Europe showing a significant and robust result across five volatility models.

The elevated presence and trading of institutional investors driven by optimism significantly distorts the presented risk-return tradeoff in Asia (excl. Japan) and Eastern Europe. As per EGARCH, a 1% upward (downward) revision in conditional volatility would cause a 1.297% decrease (increase) in Asia (excl. Japan) market returns, significantly different from the relation in bearish periods. The results confirm the latest emerging evidence that institutional investors' trading can be noisy (Chelley-Steeley et al., 2017; DeVault et al., 2019) and their higher participation would distort the risk-return tradeoff. By contrast, institutional investors' increased trading would help to ease the distortion of risk-return tradeoff in the Eurozone. Although the mean-variance relation remains negative (e.g., –1.410 suggested by MIDAS), it is significantly less negative than that in bearish periods, i.e., a significant incremental change (0.962), indicating a positive influence of institutional investor sentiment on restoring the risk-return tradeoff. The similar result is also found in Latin America, with limited significance though.

The insignificant results for the US market over bullish periods are inconsistent with Wang (2018b) documenting a significant distortion of the risk-return tradeoff, possibly arising from differences in the sample selection and separation. In Wang (2018b), the sample period is from 1971 to 2016 which is much longer than ours, and institutional investor sentiment proxied by II is characterized by a three-regime separation defining not only bullish and bearish periods, but also neutral periods when institutional investors feel neither optimistic nor pessimistic. To mitigate the potential influence of differences above, we apply the II separation to our sample period over 2004–2016 and adjust the II to bullish and non-bullish (including bearish and neutral) periods. Unreported results reveal an insignificant impact of institutional investor sentiment on the mean-variance relation as well, consistent with our presented findings.

While results from Japan and the whole world present heterogeneity across different volatility models, the divergences in the impact of institutional investor sentiment in different regions are clearly provided. Meanwhile, it is reassuring that inconsistent results obtained by different volatility models are rather limited and in fact this inconsistency further validates our adoption of multiple volatility models and results from one single volatility model might be misleading, as endorsed in Ghysels et al. (2005) and Yu and Yuan (2011), among others.

Overall, we document that the impact of institutional investor sentiment on the mean-variance relation varies across different regions, supporting both Hypothesis 1a and 1b depending on region. Asia (excl. Japan) and Eastern Europe stock markets exhibit a similar pattern to that observed in the US, whereby institutional investors' increased trading brings a negative impact to the mean-variance relation, while Eurozone and Latin America stock markets present otherwise. Note that disparate findings across regions do not raise concerns over our results. Rather, different patterns of the mean-variance relation globally are to be expected and represent an opportunity to examine impact of a range of factors such as cultural dimensions and market integrity on the influence of institutional sentiment on the mean-variance relation.[18] Indeed, we interpret the mixed results as strong support for our premise that a global examination of the impact of institutional investor sentiment is warranted and results from the US do not hold globally.

5.1.3 Robustness tests

Although institutional and retail investor sentiment are only weakly correlated as discussed in Subsection 3.1, it is still possible that retail investor sentiment plays a role in the impact of institutional investor sentiment on the mean-variance relation. While we observe an upward trend of institutional investor ownership across the world (see, Footnote 9), retail investors still prevail in some markets. The average institutional ownership over 2004–2016 in China, Greece, and Indonesia, for example, was around 6.0%, 5.9%, and 3.4%, respectively (Alvarez et al., 2018),[19] implying a potentially strong impact on the risk-return tradeoff from the retail investors' side. In order to isolate the impact of institutional investor sentiment, we account for retail investor sentiment, in the following,

$$R_{i,t+1} = \alpha_{1,i} + \alpha_{2,i} D_{i,t}^{ins} + \alpha_{3,i} D_{i,t}^{ind} + \beta_1 Var_{i,t}(R_{i,t+1}) + \beta_2 Var_{i,t}(R_{i,t+1}) D_{i,t}^{ins} + \beta_3 Var_{i,t}(R_{i,t+1}) D_{i,t}^{ind} + \xi_{i,t+1}, \quad (11)$$

where D_t^{ins} and D_t^{ind} denote bullish periods for institutional and retail investors, respectively. Here, β_2 reflects the influence of institutional investor sentiment on the mean-variance relation when the impact of retail investor sentiment is controlled. Table 5 reports qualitatively consistent results with Table 4. Over tranquil periods when neither party is bullish, a positive mean-variance relation is observed in Asia (excl. Japan), Eastern Europe,

[18] We provide insights into the influence of cultural dimensions and market integrity in Section 6.

[19] See, also, Barber et al. (2007 & 2009) and Kuo et al. (2015).

and the US, while a negative relation is found in the Eurozone, and Latin America. Over bullish periods, the higher presence of institutional investors in Asia, Eastern Europe, and the US tend to distort the risk-return tradeoff, while, on the contrary, in the Eurozone and Latin America institutional investors help to restore the theorized positive risk-return tradeoff, confirming that controlling for retail investor sentiment does not undermine our presented results.[20, 21] This robustness test further suggests that the impact of institutional investor sentiment is distinct from that of retail investor sentiment and as a result should not be ignored in this sentiment literature.

<Table 5>

It is also interesting to consider the impact of retail investor sentiment on the risk-return tradeoff while accounting for the role of institutional investors (β_3 in Eq. 11. above). A higher presence of retail investors brings about a negative impact on the risk-return tradeoff in Asia (excl. Japan), Latin America, and particularly the US, where a significantly negative impact is supported in all five volatility models, in line with Yu and Yuan (2011). An insignificant, but positive impact of retail investor sentiment is observed in European markets, including Eastern Europe and Eurozone, contrary to Wang (2018a) who reports a significantly negative impact in fourteen European markets. Such disparate results might be attributed to differences in sample markets and the separation approach across the two studies. A pool of

[20] Note that Japanese retail investors are bearish over our sample period 2004–2016, and therefore results are identical to those in Table 4. This also indicates that individual and institutional investor sentiment do not always move together, and our previous separation is mainly determined by institutional investor sentiment.

[21] Prior evidence (Sentana and Wadhwani, 1992; Koutmos, 1997) indicates that investors' positive feedback trading is stronger amid down conditions (see, Koutmos, 2014, for a review of related literature), and it is, therefore, possible that our results of the negative incremental impact on the mean-variance relation ($\beta_{2,i}$) in Asia (excl. Japan) and Eastern Europe may be due to the higher level of portfolio insurance strategies and the extensive execution of stop-loss orders from retail investors. Such an impact is expected to be trivial, however, since, i) compared with bullish periods, retail investors are less willing to trade over bearish periods due to the short-sale constraints (Yu and Yuan, 2011), and ii) down conditions (i.e., economic downturns) do not necessarily indicate bearish periods (in the sentiment sense): Chung et al. (2012), for instance, show that sentiment can be higher over recessions while lower over expansions. Comparing the incremental changes reported in Table 4 and 5, we find that they are very close to each other, suggesting the impact of retail investors' positive feedback trading plays a negligible role in our results.

twenty-five markets (six from Eastern Europe and nineteen from Eurozone) in our sample provides greater variation across both economic conditions (developed/emerging) and geographic locations, both of which are important to explain investors' trading behaviors (e.g., Bekaert and Harvey, 2002; Kwok and Tadesse, 2006; Grinblatt et al., 2011 & 2012; Cole et al., 2014), than achieved in the fourteen developed European markets examined in of Wang (2018a). By splitting the entire sample into four subsamples based on both institutional/retail investors and bullish/bearish sentiment, we are able to isolate the impact of institutional and retail investor sentiments on the mean-variance relation, while Wang (2018a) considers retail investor sentiment only, without controlling for institutional investor sentiment.[22]

Next, we account for economic conditions that might be expected to influence the impact of investor sentiment (Chung et al., 2012). The National Bureau of Economic Research (NBER) regards real GDP as the most accurate indicator measuring economic activities because an expansion or a recession has a wide-ranging impact on the economy as a whole, not just on a specific sector. Therefore, we use real GDP as the sample separation criterion for each market.[23] Following Yu and Yuan (2011), we adopt a median-split approach. In particular, we first compute the year-on-year real GDP growth and find its median. As the median is sensitive to the sample period, we compute it based on all historical values. We then identify the high (low) regime if the real GDP growth is above (below) the median, and the regression is,

[22] A small difference in sample period across the two studies is not expected to contribute to the disparate findings.

[23] See, https://www.nber.org/cycles/jan08bcdc_memo.html, for details. While the NBER also considers several other indicators to determine the economic cycle, real GDP is '*the single best measure of aggregate economic activity*'. Unlike the CCI which reflects ex-ante household (or retail investors in our context) expectations, the GDP is an ex-post measurement of the aggregate economy, thus the separations obtained from the two indicators are unique. We checked the correlation between annual CCI and annual GDP in all markets, finding a medium-level average correlation of 0.678.

$$R_{i,t+1} = \alpha_{1,i} + \alpha_{2,i} D_{i,t}^{ins} + \alpha_{3,i} D_{i,t}^{ec} + \beta_1 Var_{i,t}(R_{i,t+1}) + \beta_2 Var_{i,t}(R_{i,t+1}) D_{i,t}^{ins} + \beta_3 Var_{i,t}(R_{i,t+1}) D_{i,t}^{ec} + \xi_{i,t+1}, \quad (12)$$

where D_t^{ec} denotes high regimes, and β_2 reflects the impact of institutional investor sentiment on the mean-variance relation when the economic condition is controlled. Table 6 presents results consistent with the main analysis.

<Table 6>

It is possible that our sentix proxy does not capture irrational sentiment, but rather is a reflection of macro information about time-varying risk premia (i.e., expectations of future economic conditions).[24] While sentix measures have been widely employed as a valid sentiment proxy capturing noise in stock markets (see, e.g., Schmeling, 2007; Corredor et al., 2013; Schneider, 2014; Debata et al., 2018; Gao et al., 2020), to rule out the influence on our results of expectations of future economic conditions, following Schmeling (2009) and Wang et al. (2021), we take account of expected economic conditions (EEC). More specifically, we employ the most common indicator for the EEC in each market, such as the purchasing management index (PMI) reported by Institute for Supply Management (ISM) for the US, TANKAN business conditions reported by Bank of Japan for Japan, and the economic sentiment indicator (ESI) reported by Directorate-General for Economic and Financial Affairs (DG ECFIN) for most European markets (for details, see, Appendix B). We have EEC data for thirty sample markets in five regions except for Latin America, but we believe that it is still a well-diversified global sample. Similar to Baker and Wurgler (2006), Sibley et al. (2016), Zheng et al. (2018), we regress our regional sentix proxy on market EEC to capture the residual series, thus excluding economic expectations and hence reflecting pure irrational sentiment. Then we use this new series as the benchmark of sample separation and replicate our main regressions above. Table 6 shows that the impact of institutional investor

[24] We thank an anonymous reviewer for pointing out this possibility.

sentiment in bullish periods across different regions is consistent with the main results reported in Table 4, thus ensuring our findings are driven by irrational sentiment and not by expectations of future economic conditions, thus supporting our behavioral story over an alternative rational explanation. In this regard, our findings complement those of Henglebrock et al. (2013), who use German and US data to examine market reaction to the publication of survey-based investor sentiment indicators (specifically, sentix in the case of Germany). Their findings are consistent with the view that investor sentiment is related to mispricing (i.e., irrational) and inconsistent with a rational story whereby sentiment indicators provide information about future expected returns (i.e., future economic conditions).[25] To further ensure the robustness of our results we conduct two further tests to address unbalanced subsamples and to allow for the influence of global institutional investor sentiment across regions. As can be seen in Table 1, all regions have more bullish than bearish periods, leading to unbalanced subsamples and so to reduce the imbalance, we remove the first two years (2004 and 2005) as these are bullish for all regions. We run identical regressions as in the main analysis and unreported results remain qualitatively unchanged. Finally, we control for the influence of institutional investor sentiment in other regions on the mean-variance relation.[26] In particular, we follow Baker et al. (2012) in applying principal component analysis (PCA) to extract a global institutional investor sentiment measure from institutional investor sentiment across all regions. Then, for each region, we apply PCA again to extract the common information from regional as well as global institutional investor sentiment, and therefore, this new sentiment consists of both regional and global components, thus capturing additional information beyond regional

[25] If the predictive ability of sentiment-return relation is due to expectations of future economic returns, Henglebrock et al. (2013, p.902) argue that "in a rational setting the publication of sentiment measures can have a) an immediate price effect but no long-term effect … , or b) a long-term effect and an immediate price reaction in the opposite direction … ." Inconsistent with a rational explanation based on expected future returns or economic conditions, they find that the immediate market response is in the same, not the opposite, direction.

[26] We thank a second anonymous reviewer for suggesting this line of enquiry.

institutional sentiment. Market samples are then separated into bullish and bearish subperiods based on this new sentiment measure. The resulting in the designation between high-/low-sentiment is identical to our original approach and thus regression results are also identical to those reported in Table 4.[27]

5.2 Individual market results

Given the divergent evidence presented in the regional analysis, we expect to find heightened differential results based on market-level tests, which we will exploit in Section 6 when examining cultural dimensions and market integrity as determinants of cross-market differences. In line with expectations, Table 7 reveals more pronounced heterogeneity across markets. For the unconditional test, with the exception of Malaysia and Colombia, all markets show a negative mean-variance relation. For the conditional test, stock markets in Asia (excl. Japan) and Eastern Europe tend to show a positive mean-variance relation, while those in Eurozone and Latin America exhibit a negative relation during bearish periods. Both these findings are consonant with the regional evidence. Over bullish periods, institutional investors tend to distort the risk-return tradeoff for stock markets in Asia (excl. Japan) and Eastern Europe, but this is not so for stock markets in Eurozone and Latin America . In addition to the differing direction of influence, magnitude also varies a lot across markets. For example, the average impact of institutional investors' elevated trading on the mean-variance relation is as great as around –30.684% in Malaysia and –16.583% in Taiwan, which is much stronger than observed in other markets.

<Table 7>

Around half of the markets in the sample show a significant mean-variance relation over the entire sample or during bearish periods, which is surprising given our relatively short

[27] Despite employing a large number of robustness tests to rule out alternative explanations for our findings, other possible explanations may exist (e.g., long-term fall of real interest rates). We leave such possibilities to future research.

thirteen-year samples from 2004 to 2016 for each market. Pástor et al. (2008) stress the importance of sample length in examining the mean-variance relation, arguing that it is '*noteworthy*' (p. 2863) and '*striking*' (p. 2880) to find statistically significant mean-variance relations from short-period samples. Similarly, Lundblad (2007) asserts short sample periods are the main challenge in estimating the mean-variance relation, suggesting a significant relation can be discovered only when the predictability of the conditional volatility to returns is '*more pronounced*' (p. 124).

The number of markets with a significant mean-variance relation during bullish periods reduces to a large extent. In EGARCH results, for instance, only seven out of thirty-six markets (about one fifth) support a significant mean-variance relation, and this has two types: (i) the positive relation over bearish periods is reversed to become negative (e.g., Russia and Taiwan, from 14.773 to –4.195); and (ii) the negative relation over bearish periods is intensified (e.g., Bulgaria, from –2.166 to –3.071, and Cyprus, from –2.073 to –3.772). The remaining twenty-nine stock markets do not demonstrate significant relationships and this has three main types: (i) the risk-return tradeoff over bearish periods fades (e.g., Malaysia, from 34.733 to 1.159); (ii) the negative relation over bearish periods becomes less undermined (e.g., Belgium, from –2.772 to –1.386, and France, from –2.153 to –0.282); and (iii) the insignificant relation over bearish periods remains insignificant (e.g., Malta, from –5.569 to –2.279, and Portugal, from –0.800 to –2.964).[28] We explore these differential results further in the following Section 6.

[28] Our findings have implications for investors, who might adopt institutional investor sentiment as an indicator for their investment. Investors in the Taiwan stock market, for example, can increase their risk exposure amid low-sentiment periods when there is positive mean-variance relation, while reduce their risk exposure over high-sentiment periods when there is a negative mean-variance relation. The profitability of trading strategies is not the focus of our research and so we do not elaborate further here.

6. Cross-market investigations

Given the cross-market differences in the impact of institutional investor sentiment on the mean-variance relation we observe, we explore possible determinants and explanations from the perspective of cultural dimensions and market integrity.[29] Recall that sentix respondents are asked about expectations of major regions across the world, thus institutional investor sentiment in a given region is not solely the product of institutional investors in that region. This does not preclude our examination of the influence of cultural dimensions on the impact of institutional investor sentiment on the mean-variance relation, however, because this will be driven by those investors trading in a given stock market, more so than by sentiment survey respondents. As discussed earlier, in Section 3, the sentix survey represents a good measure of institutional investor sentiment in a specific region, for three reasons, including consistency of professionals' expectation for a given region, the application of the one-year window for sample separation, and the adoption of the qualitative diffusion method. Note also that the sentix measure has been used by Schmeling (2007) to examine the impact of one cultural dimension, individualism, on retail investor sentiment. We extend this approach in two ways. First, we consider an additional cultural dimension, uncertainty avoidance, and second, we apply it in the context of institutional investor sentiment.

6.1 Cultural dimensions

The national cultural framework has been widely applied in prior studies of finance professionals and managers. Beckmann et al. (2008) examine the influence of national culture on asset managers' views and behaviors. Relying on four of the cultural dimensions, they find that cultural divergences are '*most helpful*' (p. 641) in understanding differences in asset managers' views and behaviors across countries. Shao et al. (2013) explore the relation between individualism and horizons and types of corporate investment, documenting that

[29] Testable hypotheses are provided in Section 2.

firms in individualistic markets tend to invest more in long- than short-term assets, and invest more in R&D projects, but not in physical assets. More recently, Kashefi-Pour et al. (2020) investigate national cultural effects, including individualism, uncertainty avoidance, power distance, and masculinity, on corporate investment-cash flow sensitivity (ICFS), reporting a stronger cash flow-investment relation in countries with a higher level of individualism, uncertainty avoidance, power distance, and masculinity (see, also, Li et al., 2013; Chen et al., 2015; Griffin et al., 2017). In recognition of its influence on financial decision making generally, we examine whether national culture (specifically the two most relevant cultural dimensions—individualism and uncertainty avoidance) helps characterize the differential impact of institutional investor sentiment on the mean-variance relation across regions.

<Table 8>

We collect data on individualism (IDV) and uncertainty avoidance index (UAI) from Hofstede's website.[30] Scores, ranging from 0 to 100, are assigned to thirty-seven sample markets (Cyprus is the exception, see, Table 8). High (low) IDV means high individualism (collectivism) levels, and high (low) UAI denotes high (low) uncertainty avoidance levels. We rank the thirty-seven markets based on each of the two scores in a descending order and separate them into upper (above-median) and lower (below-median) groups, giving us eighteen stock markets for each group with the median one being excluded. We then run the following,

$$R_{i,t+1} = \alpha_{1,i} + \alpha_{2,i}D_{i,t} + \beta_{1,u,i}Var_{i,t}(R_{i,t+1}) + \beta_{2,u,i}Var_{i,t}(R_{i,t+1})D_{i,t} + \beta_{1,l,i}Var_{i,t}(R_{i,t+1}) + \beta_{2,l,i}Var_{i,t}(R_{i,t+1})D_{i,t} + \xi_{i,t+1}, \quad (13)$$

where the impact of institutional investor sentiment in the upper-layer (lower-layer) markets is reflected by $\beta_{2,u,i}$ ($\beta_{2,l,i}$). Results are reported in Table 9.

<Table 9>

[30] We are grateful to Prof. Geert Hofstede for making the data available at https://www.hofstede-insights.com.

For both individualism (Panel A) and uncertainty avoidance (Panel B), a negative mean-variance relation is observed amid bearish periods for upper and lower layers. Over bullish periods, however, institutional investors' elevated trading in individualistic markets contributes to a weakening of the negative mean-variance relation, while exacerbating the distortion in collectivistic markets. These findings support the view that institutional investors in collectivistic cultures tend to be sentiment traders because of their herding-led overreaction, while those in individualistic cultures overall are less likely to be sentiment traders, echoing Hypothesis 2a.[31] For high uncertainty-avoiding markets, the negative mean-variance relation over bearish periods tends to be further enhanced over bullish periods, while for low uncertainty-avoiding markets, the strong negative mean-variance relation over bearish periods is weakened by institutional investors' increased participation over bullish periods, supporting Hypothesis 3a. The two cultural dimensions proffer the same implication, with institutional investors in either collectivistic or high uncertainty-avoidance markets tending to overreact. Our empirical evidence, hence, reveals that institutional investors in markets with a cultural tendency to overreaction are more likely to succumb to sentiment trading. To confirm this, we construct a new culture-related overreaction index (OVR) by extracting the common information from IDV and UAI via principal component analysis (PCA). The two PCs can explain all of the total variance by definition and OVR values are provided in Table 8. Panel C of Table 9 supports our argument that institutional investors' high presence in bullish periods tends to distort the risk-return tradeoff in markets that are culturally susceptible to overreaction.[32]

[31] Three GARCH-family models seem to show a more negative mean-variance relation over bullish periods for individualistic than collectivistic markets, but this is beyond the discussion of this paper as our focus is on the incremental impact of institutional investors' higher presence, i.e., the change in the mean-variance relation from bearish to bullish periods, and whether cultural dimensions impact this change.

[32] While the first PC does not have a very high degree of expressiveness (around 54.11%), grouping results and estimation results remain consistent if the OVR is constructed based on the first PC.

6.2 Market integrity

We consider seven market integrity variables, including anti-director rights (ADR), government corruption (GVC), accounting standards (ACS), efficiency of judicial systems (EJS), the rule of law (ROL), risk of expropriation (ROE), and risk of contract repudiation (RCR), all sourced from La Porta et al. (1998).[33] Scores are assigned to each factor with high scores indicating high-level market integrity. As the seven variables capture different aspects of market integrity, instead of examining them individually, we use PCA to form a composite indicator of overall market integrity capturing common information across the variables. We employ the first two PCs (explaining about 80.73% of the total variance) and construct the market integrity indicator (MKI) for each market based on available data (see, Table 8).

While the sample is reduced to twenty-one markets due to data limitations, it remains a representative global sample since it covers five main regions and includes both developed and emerging markets. Again, we rank the twenty-one markets based on the MKI scores in a descending order and split them into upper (above-median) and lower (below-median) groups. Each group incorporates ten individual markets (with the mid-point market excluded) and results are presented in Panel D of Table 9. In upper layer comprising high integrity markets, institutional investors' increased participation during bullish periods promotes a risk-return tradeoff that is less undermined, while the impact is insignificant and mixed for lower layer markets. In the presence of more advanced market institutions, with associated high levels of market efficiency, institutional investors' trading is less likely to distort the risk-return tradeoff, supporting Hypothesis 4a.

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[33] One potential concern relating to the application of data in La Porta et al. (1998) is that market institutions in some markets, especially emerging markets, may have developed rapidly in recent years and as such data from pre-1998 may be inappropriate to represent the current situation. However, we employ the market institution data as a grouping criterion only rather, than including it as a variable directly entering the regression models, and arguably, markets with relatively weaker market institutions before 1998 would be expected to remain relatively weaker compared with those with more advanced market institutions, i.e., the rank among markets is not expected to change dramatically. Note also, the La Porta et al. (1998) data continue to be used in recent studies (see, Bilinski et al., 2013; Ahern et al., 2015; Scharfstein, 2018), justifying our adoption.

<Table 10>

As a robustness check, we control for retail investor sentiment because their trading is influenced by cultural dimensions and market integrity as well (Schmeling, 2009). Results in Table 10 are largely consistent with those in Table 9, confirming that both cultural dimensions and market integrity can affect the influence of institutional investor sentiment on the mean-variance relation. In particular, institutional investors in low IDV, high UAI, high OVR, and low MKI markets are prone to be sentiment traders and their increased trading during bullish times undermines the risk-return tradeoff. As the national culture in a given market is resistant or slow to change, we propose by way of a policy suggestion that a more complete system of market integrity is more likely to help ease the irrational impact of institutional investor sentiment, thereby improving market efficiency.

7. Conclusions

Traditional financial theory posits a positive mean-variance relation—that is, high (low) risk generates high (low) returns. Conventional wisdom views institutional investors are more sophisticated and so less susceptible to behavioral biases and sentiment than retail investors, thus it is the latter and not the former that are to blame when markets depart from notions of efficiency or presumed theoretical relationships. Following growing evidence that institutional investors too are prone to behavioral bias and are also sentiment traders (Chelley-Steeley et al., 2017; Wang, 2018b; DeVault et al., 2019), we explore the impact of institutional investor sentiment on the mean-variance relation in thirty-eight international stock markets, across six regions. In unconditional tests we find a negative mean-variance relation in all five non-US regions; only the US exhibits a positive relationship. In conditional tests based on bull and bear subsample splits, we examine institutional investor sentiment and explore its role in the mean-variance relation. We find differential results across both regions and markets. At the region level, we find evidence that institutional investors' elevated trading distorts the mean-variance relation in Asia (excl. Japan) and Eastern Europe, while in the Eurozone, institutional investors' increased participation tends to support a positive mean-variance relation. Our results are robust to different specifications controlling for retail investor sentiment, economic conditions, and economic expectations, and to dataset adjustment. Disparate results at the individual market level allow us to explore potential determinants of the differential influence of institutional investor sentiment on the mean-variance relation by exploiting differences with respect to cultural dimensions and market integrity. We find in markets with collectivistic and uncertainty-avoiding cultures, and in those with lower levels of market integrity, that institutional investors sentiment is more to distort the mean-variance relation. We conclude, therefore, that previous evidence obtained from the US market (Wang, 2018b; DeVault et al., 2019) cannot be applied unreservedly to other markets, without first considering differences in cultural dimensions and market institutions.

Appendix A. Consumer confidence index

Markets	Sources	Frequency	No. of years congruent
Asia (excl. Japan)			
China	National Bureau of Statistics of China	Monthly	11
Indonesia	Bank Indonesia	Monthly	5
Malaysia	–	–	
Philippines	Bangko Sentral ng Pilipinas	Quarterly	5
South Korea	The Bank of Korea	Monthly	7
Taiwan	The Research Center for Taiwan Economic Development	Monthly	5
Thailand	University of the Thai Chamber of Commerce	Monthly	3
Eastern Europe			
Bulgaria	Directorate-General for Economic and Financial Affairs[1]	Monthly	4
Czech Republic	Czech Statistical Office	Monthly	6
Hungary	GKI Economic Research Co.	Monthly	4
Poland	DG ECFIN	Monthly	4
Romania	DG ECFIN	Monthly	4
Russia	Federal State Statistics Service	Quarterly	4
Eurozone			
Austria	Oesterreichische Nationalbank	Monthly	5
Belgium	National Bank of Belgium	Monthly	5
Cyprus	DG ECFIN	Monthly	5
Estonia	Estonian Institute of Economic Research	Monthly	5
Finland	Statistics Finland	Monthly	8
France	National Institute for Statistics and Economic Studies	Monthly	4
Germany	DG ECFIN	Monthly	4
Greece	DG ECFIN	Monthly	5
Ireland	DG ECFIN	Monthly	7
Italy	National Institute of Statistics	Monthly	6
Latvia	DG ECFIN	Monthly	5
Lithuania	Statistics Lithuania	Monthly	5
Luxembourg	DG ECFIN	Monthly	6
Malta	DG ECFIN	Monthly	5
Netherlands	Statistics Netherlands	Monthly	7
Portugal	National Institute of Statistics	Monthly	5
Slovakia	Statistical Office of the Slovak Republic	Monthly	5
Slovenia	Statistical Office of the Republic of Slovenia	Monthly	5
Spain	Ministry of the Economy and Finance	Monthly	6
Japan	Cabinet Office	Quarterly/Monthly	8
Latin America			
Brazil	Fundacao Getulio Vargas	Monthly	5
Chile	Central Bank of Chile	Quarterly	11
Colombia	Foundation for Higher Education and Development	Monthly	10
Mexico	Instituto Nacional de Estadistica, Geografia e Informatica	Monthly	4
US	The Conference Board	Monthly	2

This table presents sources and data frequency of consumer confidence index used for each market, along with the number of years when individual and institutional investor sentiment is in the same direction (No. of years congruent).

[1] DG ECFIN and henceforth.

Appendix B. Expected economic condition

Markets	Sources	Starting from	No. of years congruent
Asia (excl. Japan)			
China	MNI China Business Sentiment Indicator	March, 2007	8
Indonesia	–	–	–
Malaysia	–	–	–
Philippines	–	–	–
South Korea	Korean Economic Research Institute, Business Survey Index	February, 2003	10
Taiwan	–	–	–
Thailand	Bank of Thailand, Business Sentiment Index	January, 2003	10
Eastern Europe			
Bulgaria	DG ECFIN	January, 2003	10
Czech Republic	DG ECFIN	January, 2003	10
Hungary	DG ECFIN	January, 2003	9
Poland	DG ECFIN	January, 2003	10
Romania	DG ECFIN	January, 2003	10
Russia	MNI Russia Business Sentiment Indicator	March, 2013	2
Eurozone			
Austria	DG ECFIN	January, 2003	10
Belgium	DG ECFIN	January, 2003	10
Cyprus	DG ECFIN	January, 2003	12
Estonia	DG ECFIN	January, 2003	9
Finland	DG ECFIN	January, 2003	12
France	DG ECFIN	January, 2003	12
Germany	DG ECFIN	January, 2003	11
Greece	DG ECFIN	January, 2003	12
Ireland	DG ECFIN	January, 2003	11
Italy	DG ECFIN	January, 2003	10
Latvia	DG ECFIN	January, 2003	11
Lithuania	DG ECFIN	January, 2003	12
Luxembourg	DG ECFIN	January, 2003	12
Malta	DG ECFIN	January, 2003	12
Netherlands	DG ECFIN	January, 2003	12
Portugal	DG ECFIN	January, 2003	12
Slovakia	DG ECFIN	January, 2003	12
Slovenia	DG ECFIN	January, 2003	11
Spain	DG ECFIN	January, 2003	10
Japan	Bank of Japan, TANKAN Business Conditions	January, 2003	9
Latin America			
Brazil	–	–	–
Chile	–	–	–
Colombia	–	–	–
Mexico	–	–	–
US	Institute for Supply Management, Purchasing Manager Index	January, 2003	11

This table presents sources and starting months of expected economic conditions used for each market, along with the number of years when the raw institutional investor sentiment and the new orthogonalized sentiment is in the same direction (No. of years congruent).

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Table 1. Summary statistics of institutional investor sentiment, 2003–2015.

	μ	σ	*Max.*	*Min.*	Bullish	Bearish
Asia (excl. Japan)	13.891	17.000	52.500	–40.000	11	2
Eastern Europe	8.346	17.611	46.000	–44.500	9	4
Eurozone	5.019	20.008	41.500	–47.500	8	5
Japan	6.221	16.170	41.500	–42.500	8	5
Latin America	5.066	12.457	30.000	–42.000	10	3
US	0.234	17.609	28.500	–43.500	8	5

This table shows summary statistics of the monthly sentix across six regions from 2003 to 2015, including the mean (μ), the standard deviation (σ), the maximum value (*Max*.), the minimum value (*Min.*), and the number of bullish and bearish years.

Table 2. Spearman correlation.

	Asia (excl. Japan)	Eastern Europe	Eurozone	Japan	Latin America
Asia (excl. Japan)					
Eastern Europe	0.914				
Eurozone	0.739	0.699			
Japan	0.781	0.761	0.835		
Latin America	0.870	0.808	0.748	0.759	
US	0.730	0.605	0.705	0.587	0.731

This table reports the pairwise Spearman correlations between the monthly sentix across all regions. All correlation coefficients are statistically significant at the 1% level.

Table 3. Summary statistics of monthly excess returns and realized volatility, 2004–2016.

Market	Excess stock returns (I)				Realized volatility (II)			
	μ (×10²)	σ^2 (×10²)	*Skew.*	*Kurt.*	μ (×10²)	σ^2 (×10⁴)	*Skew.*	*Kurt.*
Asia (excl. Japan)								
China	0.374	0.719	–0.123	1.087	0.647	0.364	1.969	3.603
Indonesia	0.802	0.369	–1.154	5.984	0.455	0.429	5.760	46.811
Malaysia	0.293	0.120	–0.369	2.683	0.105	0.024	5.194	36.331
Philippines	0.772	0.233	–0.563	2.829	0.273	0.117	4.710	29.343
South Korea	0.429	0.271	–0.457	2.059	0.379	0.356	6.094	49.872
Taiwan	0.252	0.251	–0.372	0.962	0.326	0.111	2.384	6.077
Thailand	0.450	0.351	–1.069	4.228	0.426	0.420	5.810	41.357
Eastern Europe								
Bulgaria	0.316	0.732	0.361	3.227	0.400	0.280	3.039	11.729
Czech Republic	0.433	0.285	–0.321	1.514	0.385	0.995	9.952	111.109
Hungary	0.223	0.422	–0.621	2.551	0.488	0.652	7.645	73.986
Poland	0.117	0.319	–0.376	1.651	0.337	0.132	3.375	16.467
Romania	0.460	0.811	–0.623	3.918	0.563	0.924	5.872	46.409
Russia	0.486	0.517	–0.658	2.294	0.754	2.710	6.455	47.751
Eurozone								
Austria	0.331	0.340	–1.244	4.593	0.357	0.326	5.743	43.558
Belgium	0.518	0.233	–1.573	6.445	0.287	0.158	4.568	28.075
Cyprus	–0.945	0.879	0.137	1.382	0.660	0.720	4.742	35.447
Estonia	0.633	0.746	0.602	7.074	0.344	0.203	2.739	9.265
Finland	0.261	0.328	–0.285	1.619	0.439	0.244	2.848	10.869
France	0.305	0.202	–0.536	0.805	0.328	0.221	5.343	40.003
Germany	0.430	0.217	–0.652	1.343	0.305	0.323	8.458	88.015
Greece	–0.010	0.854	–0.492	0.432	0.926	1.550	3.698	17.164
Ireland	0.276	0.338	–0.759	2.158	0.419	0.421	4.437	24.744
Italy	–0.034	0.289	–0.260	0.552	0.415	0.300	4.290	26.682
Latvia	0.566	0.390	0.164	4.908	0.329	0.232	4.224	23.309
Lithuania	0.256	0.426	0.470	8.080	0.199	0.162	6.585	55.137
Luxembourg	0.443	0.153	–0.387	1.843	0.204	0.038	3.890	26.136
Malta	0.449	0.191	0.532	0.904	0.118	0.027	4.828	32.036
Netherlands	0.301	0.260	–1.381	4.814	0.317	0.263	5.714	43.770
Portugal	–0.133	0.271	–0.647	1.500	0.300	0.167	5.308	40.654
Slovakia	0.364	0.295	1.374	9.338	0.358	0.264	5.289	36.377
Slovenia	–0.135	0.263	–0.343	1.482	0.192	0.127	7.148	65.048
Spain	0.223	0.288	–0.191	0.558	0.389	0.237	4.360	26.450
Japan	0.361	0.265	–0.452	1.034	0.412	0.452	7.333	69.593
Latin America								
Brazil	–0.157	0.329	–0.415	1.480	0.454	0.408	6.377	51.266
Chile	0.224	0.133	0.292	0.199	0.136	0.050	6.615	56.818
Colombia	0.768	0.324	–0.071	0.886	0.258	0.227	6.661	52.577
Mexico	0.735	0.175	–0.625	1.774	0.224	0.109	5.411	40.874
US	0.596	0.170	–0.834	3.033	0.310	0.411	5.494	35.615

This table presents summary statistics of monthly excess market returns (Column I) and realized volatility (Column II) of all our sample markets. In particular, we report the mean (μ), the variance (σ^2), the skewness (*Skew*.), and the excess kurtosis (*Kurt*.). Realized volatility is computed from the within-month daily market returns.

Table 4. Regional results.

	Entire (I)		Bullish and bearish (II)					
Market	β_i	*prob.*	$\beta_{1,i}$	*prob.*	$\beta_{2,i}$	*prob.*	$\beta_{1,i} + \beta_{2,i}$	*prob.*
Panel A: Rolling window								
Asia (excl. Japan)	–0.993***	(0.004)	3.926***	(0.005)	–5.122***	(0.000)	–1.196***	(0.001)
Eastern Europe	–0.949***	(0.000)	1.617**	(0.030)	–2.841***	(0.000)	–1.224***	(0.000)
Eurozone	–1.960***	(0.000)	–2.379***	(0.000)	1.106***	(0.004)	–1.273***	(0.000)
Japan	–0.571	(0.356)	–0.368	(0.846)	–0.182	(0.928)	–0.551	(0.403)
Latin America	–0.625	(0.156)	–1.173**	(0.030)	1.702*	(0.068)	0.528	(0.496)
US	0.021	(0.967)	0.293	(0.590)	–2.640	(0.115)	–2.234	(0.135)
World	–1.323***	(0.000)	–1.636***	(0.000)	0.445*	(0.084)	–1.191***	(0.000)
Panel B: GARCH								
Asia (excl. Japan)	–0.709*	(0.089)	4.480***	(0.004)	–5.468***	(0.001)	–0.988**	(0.027)
Eastern Europe	–0.916***	(0.002)	2.540***	(0.002)	–3.880***	(0.000)	–1.340***	(0.000)
Eurozone	–1.942***	(0.000)	–2.313***	(0.000)	0.962**	(0.024)	–1.351***	(0.000)
Japan	–0.513	(0.523)	–0.209	(0.936)	–0.274	(0.920)	–0.483	(0.569)
Latin America	–0.222	(0.685)	–0.718	(0.276)	1.758	(0.130)	1.040	(0.295)
US	0.200	(0.766)	0.497	(0.493)	–2.876	(0.198)	–2.379	(0.258)
World	–1.303***	(0.000)	–1.429***	(0.000)	0.159	(0.594)	–1.270***	(0.000)
Panel C: GJR-GARCH								
Asia (excl. Japan)	–0.764*	(0.061)	4.912***	(0.003)	–5.850***	(0.000)	–0.938**	(0.022)
Eastern Europe	–0.923***	(0.001)	2.498***	(0.003)	–3.806***	(0.000)	–1.309***	(0.000)
Eurozone	–1.903***	(0.000)	–2.306***	(0.000)	1.010**	(0.015)	–1.296***	(0.000)
Japan	–0.692	(0.391)	–0.916	(0.696)	0.322	(0.897)	–0.594	(0.492)
Latin America	–0.430	(0.446)	–0.906	(0.185)	1.560	(0.182)	0.654	(0.508)
US	0.114	(0.870)	0.485	(0.515)	–3.524	(0.121)	–3.039	(0.154)
World	–1.308***	(0.000)	–1.491***	(0.000)	0.248	(0.399)	–1.244***	(0.000)
Panel D: EGARCH								
Asia (excl. Japan)	–1.044**	(0.025)[b]	4.958***	(0.003)	–6.255***	(0.000)	–1.297***	(0.006)
Eastern Europe	–1.170***	(0.002)[a]	3.336***	(0.001)	–5.174***	(0.000)	–1.840***	(0.000)
Eurozone	–2.360***	(0.000)[a]	–2.698***	(0.000)	0.861*	(0.091)	–1.838***	(0.000)
Japan	–1.078	(0.330)	–0.693	(0.825)	–0.370	(0.912)	–1.063	(0.371)
Latin America	–0.833	(0.248)	–1.304	(0.119)	1.831	(0.226)	0.527	(0.695)
US	0.136	(0.880)	0.689	(0.489)	–3.611	(0.152)	–2.922	(0.204)
World	–1.707***	(0.000)[a]	–1.641***	(0.000)	–0.148	(0.682)	–1.789***	(0.000)
Panel E: MIDAS								
Asia (excl. Japan)	–0.983**	(0.015)	4.737***	(0.003)	–5.946***	(0.000)	–1.210***	(0.003)
Eastern Europe	–1.022***	(0.000)	2.316***	(0.006)	–3.726***	(0.000)	–1.410***	(0.000)
Eurozone	–2.149***	(0.000)	–2.565***	(0.000)	1.121**	(0.011)	–1.445***	(0.000)
Japan	–0.678	(0.379)	–0.514	(0.826)	–0.126	(0.959)	–0.640	(0.436)
Latin America	–0.574	(0.281)	–1.117*	(0.083)	1.793*	(0.096)	0.677	(0.477)
US	0.080	(0.899)	0.412	(0.543)	–3.134	(0.127)	–2.722	(0.160)
World	–1.452***	(0.000)	–1.677***	(0.000)	0.306	(0.301)	–1.371***	(0.000)

(*continued*)

Table 4. (*continued*)

This table reports regional results of the impact of institutional investor sentiment on the mean-variance relation. Column (I) presents the results from the entire sample and Column (II) presents the results conditional on institutional investors' optimism and pessimism.

***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5. Robustness tests: The influence of retail investor sentiment.

Market	$\beta_{1,i}$	*prob.*	$\beta_{2,i}$	*prob.*	$\beta_{3,i}$	*prob.*	$\beta_{1,i} + \beta_{2,i}$	*prob.*	$\beta_{1,i} + \beta_{3,i}$	*prob.*	$\beta_{1,i} + \beta_{2,i} + \beta_{3,i}$	*prob.*
Panel A: Rolling window												
Asia (excl. Japan)	3.873**	(0.016)	–4.959***	(0.002)	–0.591	(0.474)	–1.087**	(0.012)	3.282**	(0.050)	–1.677**	(0.019)
Eastern Europe	1.617**	(0.030)	–2.843***	(0.000)	3.687	(0.681)	–1.227***	(0.000)	5.304	(0.556)	2.461	(0.784)
Eurozone	–2.327***	(0.000)	1.202***	(0.003)	0.325	(0.478)	–1.125***	(0.000)	–2.002***	(0.000)	–0.800	(0.117)
Japan	–0.368	(0.846)	–0.182	(0.928)	–	–	–0.551	(0.403)	–	–	–	–
Latin America	–1.002	(0.107)	2.147*	(0.053)	–0.442	(0.676)	1.145	(0.345)	–1.444	(0.112)	0.703	(0.368)
US	2.021	(0.229)	–3.652	(0.119)	–3.482*	(0.051)	–1.631	(0.313)	–1.461**	(0.010)	–5.113**	(0.033)
World	–1.479***	(0.000)	0.319	(0.238)	–0.243	(0.473)	–1.160***	(0.000)	–1.722***	(0.000)	–1.402***	(0.000)
Panel B: GARCH												
Asia (excl. Japan)	4.455**	(0.015)	–5.469***	(0.003)	–0.083	(0.932)	–1.101*	(0.092)	4.372**	(0.019)	–1.097	(0.163)
Eastern Europe	2.540***	(0.002)	–3.891***	(0.000)	15.640	(0.229)	–1.349***	(0.000)	18.181	(0.163)	14.290	(0.271)
Eurozone	–2.199***	(0.000)	1.012**	(0.026)	0.247	(0.637)	–1.187***	(0.001)	–1.952***	(0.000)	–0.940	(0.104)
Japan	–0.209	(0.936)	–0.274	(0.920)	–	–	–0.483	(0.569)	–	–	–	–
Latin America	–0.492	(0.517)	2.313*	(0.075)	–0.528	(0.687)	1.821	(0.231)	–1.020	(0.364)	1.293	(0.195)
US	3.086	(0.134)	–3.176	(0.285)	–4.656**	(0.033)	–0.090	(0.966)	–1.570**	(0.026)	–4.746	(0.119)
World	–1.220***	(0.000)	0.004	(0.990)	–0.308	(0.431)	–1.216***	(0.000)	–1.528***	(0.000)	–1.524***	(0.000)
Panel C: GJR-GARCH												
Asia (excl. Japan)	4.968***	(0.010)	–5.923***	(0.002)	–0.115	(0.900)	–0.955*	(0.077)	4.852**	(0.012)	–1.070	(0.153)
Eastern Europe	2.498***	(0.003)	–3.816***	(0.000)	15.797	(0.196)	–1.319***	(0.000)	18.295	(0.135)	14.478	(0.236)
Eurozone	–2.166***	(0.000)	1.036**	(0.019)	1.036**	(0.019)	–1.130***	(0.001)	–1.982***	(0.000)	–0.947*	(0.094)[c]
Japan	–0.916	(0.696)	0.322	(0.897)	–	–	–0.594	(0.492)	–	–	–	–
Latin America	–0.761	(0.335)	1.877*	(0.081)	–0.220	(0.870)	1.116	(0.471)	–0.981	(0.394)	0.896	(0.369)
US	2.760	(0.205)	–3.300	(0.264)	–4.372*	(0.056)	–0.540	(0.787)	–1.612**	(0.020)	–4.912	(0.104)
World	–1.295***	(0.000)	0.100	(0.745)	–0.277	(0.470)	–1.194***	(0.000)	–1.571***	(0.000)	–1.471***	(0.000)

(*continued*)

Table 5. (*continued*)

Market	$\beta_{1,i}$	*prob.*	$\beta_{2,i}$	*prob.*	$\beta_{3,i}$	*prob.*	$\beta_{1,i} + \beta_{2,i}$	*prob.*	$\beta_{1,i} + \beta_{3,i}$	*prob.*	$\beta_{1,i} + \beta_{2,I} + \beta_{3,i}$	*prob.*
Panel D: EGARCH												
Asia (excl. Japan)	4.842**	(0.015)	–6.361***	(0.001)	0.375	(0.707)	–1.518**	(0.022)	5.217***	(0.008)	–1.144	(0.134)
Eastern Europe	3.336***	(0.001)	–5.191***	(0.000)	15.490	(0.234)	–1.856***	(0.000)	18.826	(0.148)	13.634	(0.294)
Eurozone	–2.529***	(0.000)	0.834*	(0.098)	0.035	(0.956)	–1.695***	(0.000)	–2.494***	(0.000)	–1.661**	(0.016)
Japan	–0.693	(0.825)	–0.370	(0.912)	–	–	–1.063	(0.371)	–	–	–	–
Latin America	–1.083	(0.251)	2.434*	(0.079)	–0.325	(0.842)	1.351	(0.468)	–1.407	(0.327)	1.026	(0.466)
US	4.355	(0.124)	–3.961	(0.293)	–6.623**	(0.028)	0.393	(0.874)	–2.268**	(0.021)	–6.229	(0.109)
World	–1.416***	(0.000)	–0.286	(0.443)	–0.353	(0.444)	–1.702***	(0.000)	–1.769***	(0.000)	–2.055	(0.000)
Panel E: MIDAS												
Asia (excl. Japan)	4.761***	(0.010)	–5.953***	(0.001)	–0.243	(0.793)	–1.192**	(0.024)	4.518**	(0.017)	–1.435*	(0.063)
Eastern Europe	2.317***	(0.006)	–3.734***	(0.000)	9.902	(0.388)	–1.417***	(0.000)	12.219	(0.288)	8.485	(0.459)
Eurozone	–2.483***	(0.000)	1.181***	(0.010)	0.305	(0.561)	–1.302***	(0.000)	–2.177***	(0.000)	–0.997*	(0.085)
Japan	–0.514	(0.826)	–0.126	(0.959)	–	–	–0.640	(0.436)	–	–	–	–
Latin America	–0.923	(0.213)	2.281*	(0.087)	–0.437	(0.730)	1.358	(0.353)	–1.360	(0.212)	0.921	(0.337)
US	2.705	(0.183)	–3.711	(0.187)	–4.376**	(0.042)	–1.007	(0.605)	–1.671**	(0.016)	–5.383*	(0.064)
World	–1.481***	(0.000)	0.158	(0.610)	–0.294	(0.448)	–1.323***	(0.000)	–1.775***	(0.000)	–1.617***	(0.000)

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

***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6. Robustness tests: Controlling for economic conditions and expected economic condition

	Controlling for economic conditions (I)						Controlling for expected economic condition (II)					
Market	$\beta_{1,i}$	*prob.*	$\beta_{2,i}$	*prob.*	$\beta_{1,i} + \beta_{2,i}$	*prob.*	$\beta_{1,i}$	*prob.*	$\beta_{2,i}$	*prob.*	$\beta_{1,i} + \beta_{2,i}$	*prob.*
Panel A: Rolling window												
Asia (excl. Japan)	3.846**	(0.013)	–5.182***	(0.001)	–1.336***	(0.009)	2.540	(0.210)	–4.199**	(0.044)	–1.199	(0.564)
Eastern Europe	1.653**	(0.026)	–2.904***	(0.003)	–1.251**	(0.066)	–0.156	(0.649)	–1.491***	(0.002)	–1.646***	(0.000)
Eurozone	–2.360***	(0.000)	1.190***	(0.003)	–1.170***	(0.000)	–2.194***	(0.000)	1.081***	(0.006)	–1.113***	(0.000)
Japan	–0.101	(0.960)	–0.206	(0.922)	–0.307	(0.642)	–0.523	(0.421)	0.226	(0.945)	–0.297	(0.927)
Latin America	–0.310	(0.707)	2.051**	(0.025)	1.741	(0.112)	–	–	–	–	–	–
US	–1.222**	(0.030)	–0.710	(0.696)	–1.933	(0.263)	–2.822	(0.588)	–2.822*	(0.097)	–2.531	(0.116)
World	–1.633***	(0.000)	0.510*	(0.073)	–1.122***	(0.000)	–1.281***	(0.000)	–0.176	(0.508)	–1.411***	(0.000)
Panel B: GARCH												
Asia (excl. Japan)	4.925***	(0.004)	–5.451***	(0.003)	–0.526	(0.418)	4.677**	(0.040)	–6.167***	(0.009)	–3.167	(0.178)
Eastern Europe	2.567***	(0.002)	–4.251***	(0.000)	–1.684**	(0.027)	–0.120	(0.772)	–1.481***	(0.010)	–1.601***	(0.000)
Eurozone	–2.294***	(0.000)	1.019**	(0.020)	–1.276***	(0.000)	–2.108***	(0.000)	0.943**	(0.029)	–1.166***	(0.001)
Japan	0.263	(0.925)	–0.384	(0.895)	–0.121	(0.887)	–0.405	(0.630	–0.456	(0.896)	–0.860	(0.804)
Latin America	0.008	(0.994)	2.103*	(0.066)	2.110	(0.117)	–	–	–	–	–	–
US	–1.182*	(0.092)	–0.867	(0.665)	–2.049	(0.254)	0.476	(0.507)	–2.941	(0.195)	–2.465	(0.252)
World	–1.405***	(0.000)	0.249	(0.449)	–1.156***	(0.000)	–1.263***	(0.000)	–0.147	(0.631)	–1.725***	(0.000)
Panel C: GJR-GARCH												
Asia (excl. Japan)	5.110***	(0.004)	–5.666***	(0.002)	–0.555	(0.348)	4.621**	(0.043)	–5.981**	(0.011)	–2.981	(0.205)
Eastern Europe	2.523***	(0.003)	–4.145***	(0.000)	–1.623**	(0.030)	–0.158	(0.696)	–1.444**	(0.010)	–1.602***	(0.000)
Eurozone	–2.288***	(0.000)	1.060**	(0.013)	–1.228***	(0.001)	–2.126***	(0.000)	1.039**	(0.014)	–1.087***	(0.001)
Japan	–0.404	(0.874)	0.177	(0.947)	–0.227	(0.765)	–0.592	(0.484)	–0.441	(0.892)	–1.033	(0.748)
Latin America	–0.273	(0.791)	1.926*	(0.075)	1.653	(0.231)	–	–	–	–	–	–
US	–1.353**	(0.049)	–0.565	(0.802)	–1.919	(0.317)	0.474	(0.519)	–3.713	(0.108)	–3.239	(0.138)
World	–1.470***	(0.000)	0.335	(0.298)	–1.135***	(0.000)	–1.298***	(0.000)	–0.064	(0.831)	–1.362***	(0.000)

(*continued*)

Table 6. (*continued*)

	Controlling for economic conditions (I)						**Controlling for expected economic condition (II)**					
Market	$\beta_{1,i}$	*prob.*	$\beta_{2,i}$	*prob.*	$\beta_{1,i} + \beta_{2,i}$	*prob.*	$\beta_{1,i}$	*prob.*	$\beta_{2,i}$	*prob.*	$\beta_{1,i} + \beta_{2,i}$	*prob.*
Panel D: EGARCH												
Asia (excl. Japan)	5.052***	(0.005)	–5.979***	(0.001)	–0.927	(0.188)	4.794**	(0.036)	–6.491***	(0.006)	–3.491	(0.141)
Eastern Europe	3.348***	(0.001)	–5.504***	(0.000)	–2.156**	(0.022)	–0.178	(0.731)	–1.966***	(0.008)	–2.144***	(0.000)
Eurozone	–2.737***	(0.000)	0.876*	(0.073)	–1.861***	(0.000)	–2.472***	(0.000)	0.899*	(0.081)	–1.572***	(0.000)
Japan	0.264	(0.940)	–0.714	(0.844)	–0.450	(0.710)	–0.923	(0.433)	–0.685	(0.844)	–1.608	(0.640)
Latin America	–0.537	(0.669)	2.042*	(0.087)	1.505	(0.358)	–	–	–	–	–	–
US	–1.722*	(0.076)	–1.822	(0.421)	–3.544	(0.172)	0.680	(0.487)	–3.840	(0.132)	–3.160	(0.179)
World	–1.622***	(0.000)	–0.033	(0.933)	–1.656***	(0.000)	–1.539***	(0.000)	–0.274	(0.462)	–1.813***	(0.000)
Panel E: MIDAS												
Asia (excl. Japan)	4.976***	(0.004)	–6.172***	(0.001)	–1.195**	(0.045)	4.102*	(0.072)	–5.806**	(0.014)	–2.806	(0.232)
Eastern Europe	2.342***	(0.005)	–3.702***	(0.001)	–1.360*	(0.097)	–0.162	(0.688)	–1.619***	(0.004)	–1.781***	(0.000)
Eurozone	–2.582***	(0.000)	1.118**	(0.010)	–1.465***	(0.000)	–2.349***	(0.000)	1.105**	(0.013)	–1.243***	(0.000)
Japan	–0.300	(0.906)	–0.066	(0.980)	–0.366	(0.661)	–0.591	(0.464)	–0.253	(0.939)	–0.844	(0.795)
Latin America	–0.243	(0.808)	2.134*	(0.052)	1.891	(0.150)	–	–	–	–	–	–
US	–1.357**	(0.046)	–0.139	(0.950)	–1.496	(0.362)	0.404	(0.545)	–3.318	(0.112)	–2.914	(0.140)
World	–1.684***	(0.000)	0.388	(0.237)	–1.296***	(0.000)	–1.400***	(0.000)	–0.160	(0.599)	–1.560***	(0.000)

This table reports results from two robustness tests: controlling economic conditions in Column (I) and controlling for the expected economic conditions (EEC) in Column (II).

***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7. Individual market results.

	Entire (I)		Bullish and bearish (II)					
Market	β	*prob.*	β_1	*prob.*	β_2	*prob.*	$\beta_1 + \beta_2$	*prob.*
Panel A: Rolling window								
Asia (excl. Japan)								
China	–2.223**	(0.050)	4.858	(0.259)	–7.529*	(0.092)	–2.671**	(0.021)
Indonesia	–0.292	(0.696)	8.274*	(0.058)	–8.731**	(0.048)	–0.457	(0.540)
Malaysia	2.115	(0.239)	28.332***	(0.006)	–26.746**	(0.011)	1.586	(0.371)
Philippines	–1.648	(0.148)	6.954	(0.317)	–8.627	(0.221)	–1.673	(0.146)
South Korea	–0.679	(0.335)	1.324	(0.678)	–2.110	(0.519)	–0.786	(0.276)
Taiwan	–1.730	(0.153)	8.131*	(0.016)	–11.373***	(0.002)	–3.242***	(0.008)
Thailand	–0.715	(0.328)	0.796	(0.819)	–1.549	(0.663)	–0.753	(0.306)
Eastern Europe								
Bulgaria	–2.214*	(0.089)	–2.416	(0.332)	0.278	(0.924)	–2.138	(0.163)
Czech Republic	–0.192	(0.658)	6.112*	(0.089)	–6.422*	(0.076)	–0.310	(0.475)
Hungary	–1.125*	(0.083)	1.789	(0.331)	–3.338*	(0.090)	–1.549**	(0.024)
Poland	–1.461	(0.244)	2.745	(0.316)	–5.275*	(0.087)	–2.530*	(0.069)
Romania	–0.473	(0.532)	1.142	(0.467)	–2.133	(0.235)	–0.991	(0.250)
Russia	–1.191***	(0.001)	3.378**	(0.016)	–4.817***	(0.001)	–1.440***	(0.000)
Eurozone								
Austria	–2.392***	(0.003)	–2.409***	(0.007)	–0.690	(0.789)	–3.098	(0.201)
Belgium	–3.802***	(0.000)	–4.438***	(0.000)	2.576	(0.340)	–1.862	(0.451)
Cyprus	–2.767***	(0.002)	–2.024*	(0.057)	–2.209	(0.292)	–4.233**	(0.019)
Estonia	–3.382**	(0.028)	–5.500***	(0.004)	6.505*	(0.061)	1.005	(0.729)
Finland	–2.072**	(0.025)	–2.326**	(0.045)	0.771	(0.708)	–1.555	(0.361)
France	–1.409*	(0.068)	–1.842**	(0.039)	1.863	(0.346)	0.021	(0.990)
Germany	–1.259*	(0.056)	–1.614**	(0.025)	2.466	(0.202)	0.852	(0.634)
Greece	–0.736	(0.232)	–2.270	(0.181)	1.769	(0.331)	–0.500	(0.449)
Ireland	–3.118***	(0.000)	–3.658***	(0.000)	3.168	(0.117)	–0.491	(0.792)
Italy	–0.450	(0.571)	–0.576	(0.561)	0.447	(0.800)	–0.129	(0.930)
Latvia	–2.574**	(0.013)	–3.897***	(0.002)	5.064**	(0.033)	1.167	(0.560)
Lithuania	–3.419***	(0.008)	–3.190**	(0.021)	–4.442	(0.287)	–7.632*	(0.052)
Luxembourg	–2.258	(0.162)	–2.458	(0.215)	0.253	(0.945)	–2.204	(0.473)
Malta	–4.070*	(0.054)	–5.605**	(0.037)	4.782	(0.275)	–0.824	(0.811)
Netherlands	–1.740**	(0.029)	–2.254**	(0.011)	3.941	(0.122)	1.687	(0.479)
Portugal	–1.408	(0.170)	–1.301	(0.274)	–0.784	(0.762)	–2.085	(0.365)
Slovakia	–1.262	(0.136)	–0.917	(0.307)	1.020	(0.702)	0.103	(0.967)
Slovenia	–4.738***	(0.000)	–4.569***	(0.000)	5.936	(0.247)	1.367	(0.783)
Spain	–0.326	(0.715)	–0.529	(0.626)	1.012	(0.643)	0.483	(0.801)
Latin America								
Brazil	–1.115	(0.124)	–1.254	(0.124)	1.623	(0.489)	0.369	(0.867)
Chile	–2.473*	(0.059)	–2.417	(0.118)	–0.988	(0.747)	–3.405	(0.197)
Colombia	0.388	(0.684)	–0.764	(0.700)	1.480	(0.514)	0.716	(0.514)
Mexico	–0.046	(0.964)	–0.288	(0.813)	1.894	(0.469)	1.606	(0.487)

(*continued*)

Table 7. (*continued*)

	Entire (I)		Bullish and bearish (II)					
Market	β	*prob.*	β_1	*prob.*	β_2	*prob.*	$\beta_1 + \beta_2$	*prob.*
Panel B: GARCH								
Asia (excl. Japan)								
China	–1.186	(0.322)	6.783	(0.125)	–8.526*	(0.064)	–1.742	(0.157)
Indonesia	–0.297	(0.756)	5.400	(0.239)	–5.842	(0.213)	–0.443	(0.647)
Malaysia	1.987	(0.388)	26.337**	(0.022)	–25.033**	(0.033)	1.304	(0.571)
Philippines	–2.695*	(0.086)	12.963	(0.190)	–15.740	(0.117)	–2.777*	(0.077)
South Korea	0.175	(0.855)	5.058	(0.176)	–5.272	(0.173)	–0.214	(0.828)
Taiwan	–2.693*	(0.098)	9.586**	(0.040)	–14.306***	(0.004)	–4.720***	(0.004)
Thailand	–0.234	(0.839)	0.850	(0.867)	–1.091	(0.834)	–0.241	(0.836)
Eastern Europe								
Bulgaria	–2.936**	(0.035)	–2.310	(0.362)	–0.896	(0.767)	–3.206*	(0.053)
Czech Republic	–0.278	(0.679)	8.957*	(0.069)	–9.456*	(0.058)	–0.499	(0.461)
Hungary	–1.250	(0.122)	3.451	(0.126)	–5.405**	(0.026)	–1.954**	(0.022)
Poland	–0.752	(0.629)	4.180	(0.206)	–6.357	(0.206)	–2.177	(0.211)
Romania	–0.343	(0.662)	2.339	(0.184)	–3.361	(0.088)	–1.022	(0.238)
Russia	–0.989**	(0.018)	4.838***	(0.003)	–6.169***	(0.000)	–1.331***	(0.001)
Eurozone								
Austria	–2.041**	(0.023)	–1.998**	(0.044)	–1.125	(0.708)	–3.123	(0.272)
Belgium	–3.013***	(0.005)	–3.490***	(0.004)	2.516	(0.458)	–0.973	(0.758)
Cyprus	–2.737***	(0.004)	–2.066*	(0.082)	–1.724	(0.452)	–3.790*	(0.053)
Estonia	–3.479**	(0.012)	–4.877***	(0.003)	4.858*	(0.085)	–0.019	(0.995)
Finland	–2.133**	(0.038)	–2.603**	(0.042)	1.559	(0.518)	–1.044	(0.609)
France	–1.711*	(0.077)	–2.227**	(0.048)	2.175	(0.390)	–0.053	(0.981)
Germany	–1.014	(0.257)	–1.445	(0.147)	2.650	(0.289)	1.204	(0.598)
Greece	–0.634	(0.319)	–0.766	(0.666)	0.153	(0.936)	–0.614	(0.371)
Ireland	–3.622***	(0.000)	–4.106***	(0.000)	3.374	(0.229)	–0.732	(0.781)
Italy	–0.241	(0.789)	–0.323	(0.777)	0.370	(0.855)	0.046	(0.978)
Latvia	–4.021***	(0.004)	–5.519***	(0.001)	6.471*	(0.054)	0.952	(0.743)
Lithuania	–3.439***	(0.004)	–3.363***	(0.008)	–3.544	(0.374)	–6.907*	(0.067)
Luxembourg	–2.743	(0.223)	–2.248	(0.409)	–2.623	(0.621)	–4.871	(0.284)
Malta	–5.686*	(0.058)	–6.459*	(0.087)	3.087	(0.622)	–3.372	(0.500)
Netherlands	–1.250	(0.147)	–1.613**	(0.088)	3.632	(0.231)	2.019	(0.482)
Portugal	–1.189	(0.271)	–0.822	(0.512)	–2.032	(0.460)	–2.854	(0.242)
Slovakia	–3.462	(0.215)	–1.018	(0.762)	–3.249	(0.585)	–4.267	(0.383)
Slovenia	–5.885***	(0.000)	–5.676***	(0.000)	7.243	(0.253)	1.567	(0.799)
Spain	0.180	(0.867)	0.317	(0.809)	–0.004	(0.999)	0.313	(0.896)
Latin America								
Brazil	–0.819	(0.363)	–0.760	(0.454)	0.686	(0.826)	–0.074	(0.980)
Chile	–2.556	(0.150)	–2.263	(0.217)	–0.936	(0.805)	–3.199	(0.335)
Colombia	0.863	(0.485)	–0.896	(0.731)	2.246	(0.449)	1.350	(0.339)
Mexico	0.864	(0.476)	0.790	(0.585)	2.204	(0.500)	2.994	(0.305)

(*continued*)

Table 7. (*continued*)

	Entire (I)		Bullish and bearish (II)					
Market	β	*prob.*	β_1	*prob.*	β_2	*prob.*	$\beta_1 + \beta_2$	*prob.*
Panel C: GJR-GARCH								
Asia (excl. Japan)								
China	–1.120	(0.327)	6.238	(0.139)	–7.855*	(0.073)	–1.617	(0.167)
Indonesia	–0.518	(0.561)	8.555	(0.163)	–9.133	(0.141)	–0.578	(0.516)
Malaysia	1.560	(0.444)	34.733**	(0.011)	–33.574**	(0.015)	1.159	(0.565)
Philippines	–2.422*	(0.087)	13.443	(0.202)	–15.851	(0.136)	–2.407*	(0.089)
South Korea	–0.017	(0.985)	5.945	(0.168)	–6.244	(0.157)	–0.299	(0.745)
Taiwan	–2.589*	(0.091)	14.773***	(0.006)	–18.968***	(0.001)	–4.195***	(0.005)
Thailand	–0.335	(0.732)	0.716	(0.893)	–1.000	(0.853)	–0.283	(0.773)
Eastern Europe								
Bulgaria	–2.808**	(0.037)	–2.166	(0.385)	–0.907	(0.759)	–3.071*	(0.053)
Czech Republic	–0.298	(0.665)	–9.858*	(0.071)	–10.366*	(0.060)	–0.508	(0.462)
Hungary	–1.194	(0.128)	3.847	(0.109)	–5.644**	(0.027)	–1.796**	(0.027)
Poland	–0.595	(0.686)	5.103	(0.138)	–6.910*	(0.070)	–1.807	(0.260)
Romania	–0.369	(0.626)	2.235	(0.202)	–3.216*	(0.098)	–0.981	(0.237)
Russia	–1.013**	(0.014)	4.843***	(0.005)	–6.159***	(0.001)	–1.316***	(0.001)
Eurozone								
Austria	–2.079**	(0.017)	–1.993**	(0.038)	–1.245	(0.657)	–3.238	(0.218)
Belgium	–2.545***	(0.007)	–2.772***	(0.008)	1.386	(0.651)	–1.386	(0.630)
Cyprus	–2.738***	(0.004)	–2.073*	(0.081)	–1.700	(0.457)	–3.772*	(0.053)
Estonia	–3.481**	(0.012)	–4.888***	(0.003)	4.888**	(0.043)	0.000	(0.999)
Finland	–2.170**	(0.028)	–2.609**	(0.035)	1.378	(0.538)	–1.231	(0.509)
France	–1.662*	(0.094)	–2.153*	(0.065)	1.871	(0.441)	–0.282	(0.895)
Germany	–1.330	(0.213)	–2.094	(0.102)	2.697	(0.266)	0.604	(0.769)
Greece	–0.544	(0.370)	–0.503	(0.762)	–0.047	(0.979)	–0.550	(0.401)
Ireland	–3.442***	(0.000)	–3.891***	(0.000)	3.155	(0.213)	–0.736	(0.756)
Italy	–0.347	(0.704)	–0.421	(0.714)	0.321	(0.874)	–0.100	(0.952)
Latvia	–4.525***	(0.002)	–5.752***	(0.001)	6.339*	(0.088)	0.587	(0.859)
Lithuania	–3.451***	(0.003)	–3.376***	(0.008)	–3.517	(0.377)	–6.893*	(0.067)
Luxembourg	–2.533	(0.241)	–2.146	(0.408)	–2.118	(0.678)	–4.264	(0.331)
Malta	–4.753*	(0.098)	–5.569	(0.192)	3.291	(0.587)	–2.279	(0.641)
Netherlands	–1.170	(0.142)	–1.462*	(0.092)	3.067	(0.275)	1.604	(0.547)
Portugal	–1.265	(0.251)	–0.800	(0.538)	–2.165	(0.416)	–2.964	(0.201)
Slovakia	–3.455	(0.214)	–0.972	(0.771)	–3.389	(0.569)	–4.362	(0.374)
Slovenia	–5.850***	(0.000)	–5.580***	(0.000)	5.779	(0.357)	0.199	(0.974)
Spain	0.270	(0.807)	0.417	(0.764)	–0.030	(0.991)	0.386	(0.862)
Latin America								
Brazil	–1.024	(0.273)	–0.936	(0.374)	0.229	(0.941)	–0.707	(0.806)
Chile	–2.538	(0.128)	–2.579	(0.200)	–0.652	(0.863)	–3.231	(0.313)
Colombia	0.695	(0.570)	–0.747	(0.763)	1.882	(0.510)	1.135	(0.423)
Mexico	0.374	(0.768)	0.353	(0.817)	1.387	(0.673)	1.740	(0.549)

(*continued*)

Table 7. (*continued*)

	Entire (I)		Bullish and bearish (II)					
Market	β	*prob.*	β_1	*prob.*	β_2	*prob.*	$\beta_1 + \beta_2$	*prob.*
Panel D: EGARCH								
Asia (excl. Japan)								
China	–1.061	(0.357)	6.203	(0.137)	–7.793*	(0.073)	–1.590	(0.177)
Indonesia	–0.799	(0.493)	11.093*	(0.086)	–12.128*	(0.065)	–1.035	(0.374)
Malaysia	1.281	(0.637)	38.847***	(0.009)	–38.359**	(0.011)	0.488	(0.856)
Philippines	–3.172*	(0.087)	14.082	(0.175)	–17.412*	(0.100)	–3.329*	(0.073)
South Korea	–0.051	(0.963)	8.700*	(0.065)	–9.276	(0.056)	–0.576	(0.606)
Taiwan	–3.205**	(0.042)	17.565***	(0.006)	–22.101***	(0.001)	–4.536***	(0.003)
Thailand	–0.899	(0.424)	–0.147	(0.979)	–0.677	(0.906)	–0.824	(0.466)
Eastern Europe								
Bulgaria	–3.423**	(0.032)	–2.778	(0.420)	–0.825	(0.832)	–3.602**	(0.046)
Czech Republic	–0.436	(0.680)	8.912	(0.107)	–9.767*	(0.083)	–0.856	(0.425)
Hungary	–1.370	(0.169)	5.142**	(0.050)	–7.619***	(0.008)	–2.476**	(0.019)
Poland	–1.119	(0.507)	3.949	(0.271)	–6.476	(0.111)	–2.527	(0.180)
Romania	–0.548	(0.567)	3.250	(0.128)	–4.774**	(0.046)	–1.525	(0.149)
Russia	–1.184**	(0.035)	5.168***	(0.006)	–6.907***	(0.000)	–1.739***	(0.002)
Eurozone								
Austria	–2.734**	(0.013)	–2.601**	(0.035)	–1.730	(0.598)	–4.331	(0.154)
Belgium	–3.501***	(0.004)	–3.888***	(0.005)	1.573	(0.655)	–2.315	(0.473)
Cyprus	–3.439***	(0.002)	–2.736*	(0.057)	–1.665*	(0.057)	–4.400**	(0.046)
Estonia	–3.877**	(0.016)	–5.541***	(0.004)	5.216	(0.161)	–0.324	(0.919)
Finland	–2.048**	(0.041)	–2.336*	(0.065)	0.868	(0.707)	–1.468	(0.447)
France	–2.091*	(0.099)	–2.747*	(0.080)	1.889	(0.511)	–0.858	(0.722)
Germany	–1.670	(0.239)	–2.842	(0.106)	3.607	(0.246)	0.765	(0.765)
Greece	–0.925	(0.232)	–0.879	(0.644)	–0.060	(0.977)	–0.939	(0.272)
Ireland	–4.548***	(0.000)	–5.190***	(0.000)	3.211	(0.300)	–1.978	(0.488)
Italy	–0.484	(0.674)	–0.318	(0.835)	–0.352	(0.887)	–0.670	(0.731)
Latvia	–4.948***	(0.004)	–5.975***	(0.004)	5.290	(0.248)	–0.685	(0.867)
Lithuania	–3.595**	(0.020)	–3.334**	(0.045)	–5.522	(0.277)	–8.863*	(0.064)
Luxembourg	–3.413	(0.177)	–2.906	(0.359)	–2.353	(0.677)	–5.259	(0.260)
Malta	–3.538	(0.402)	–4.360	(0.431)	3.360	(0.698)	–1.000	(0.880)
Netherlands	–1.550	(0.132)	–2.013*	(0.080)	3.330	(0.285)	1.317	(0.648)
Portugal	–2.021	(0.175)	–1.296	(0.487)	–2.594	(0.432)	–3.890	(0.152)
Slovakia	–2.406	(0.518)	–0.672	(0.889)	–0.873	(0.906)	–1.545	(0.785)
Slovenia	–8.728***	(0.000)	–8.818***	(0.000)	10.039	(0.152)	1.221	(0.855)
Spain	0.219	(0.875)	0.642	(0.730)	–0.694	(0.827)	–0.051	(0.984)
Latin America								
Brazil	–1.442	(0.195)	–1.449	(0.260)	0.740	(0.816)	–0.709	(0.808)
Chile	–3.287	(0.152)	–3.463	(0.224)	–0.410	(0.935)	–3.873	(0.349)
Colombia	0.637	(0.748)	–1.368	(0.707)	2.796	(0.522)	1.428	(0.550)
Mexico	0.416	(0.772)	0.274	(0.875)	1.872	(0.600)	2.146	(0.489)

(*continued*)

Table 7. (*continued*)

Market	Entire (I)		Bullish and bearish (II)					
	β	*prob.*	β_1	*prob.*	β_2	*prob.*	$\beta_1 + \beta_2$	*prob.*
Panel E: MIDAS								
Asia (excl. Japan)								
China	–1.694	(0.155)	6.601	(0.148)	–8.821*	(0.063)	–2.220*	(0.071)
Indonesia	–0.459	(0.606)	8.377**	(0.100)	–9.000*	(0.082)	–0.623	(0.485)
Malaysia	2.148	(0.305)	31.291***	(0.009)	–29.708**	(0.014)	1.583	(0.447)
Philippines	–2.321*	(0.097)	10.296	(0.238)	–12.671	(0.152)	–2.375*	(0.092)
South Korea	–0.415	(0.634)	3.904	(0.308)	–4.571	(0.246)	–0.667	(0.457)
Taiwan	–2.531*	(0.080)	11.168***	(0.009)	–16.168***	(0.001)	–4.202***	(0.004)
Thailand	–0.583	(0.531)	0.731	(0.870)	–1.318	(0.773)	–0.587	(0.532)
Eastern Europe								
Bulgaria	–2.810**	(0.047)	–2.714	(0.332)	–0.130	(0.968)	–2.844*	(0.085)
Czech Republic	–0.274	(0.646)	7.909*	(0.079)	–8.367*	(0.066)	–0.458	(0.445)
Hungary	–1.275	(0.096)	2.963	(0.171)	–4.855**	(0.036)	–1.892**	(0.020)
Poland	–1.251	(0.507)	3.776	(0.236)	–6.312*	(0.078)	–2.536	(0.117)
Romania	–0.460	(0.566)	1.949	(0.269)	–3.063*	(0.098)	–1.114	(0.215)
Russia	–1.197***	(0.003)	4.318***	(0.007)	–5.845***	(0.000)	–1.527***	(0.000)
Eurozone								
Austria	–2.409*	(0.007)	–2.327**	(0.019)	–1.301	(0.652)	–3.929	(0.182)
Belgium	–3.534***	(0.001)	–3.976***	(0.001)	1.966	(0.526)	–2.009	(0.485)
Cyprus	–3.043***	(0.002)	–2.277*	(0.058)	–2.124	(0.359)	–4.401**	(0.027)
Estonia	–3.590**	(0.017)	–5.318***	(0.003)	5.814*	(0.098)	0.496	(0.869)
Finland	–2.304**	(0.021)	–2.537**	(0.043)	0.770	(0.736)	–1.767	(0.357)
France	–1.681*	(0.070)	–2.167**	(0.047)	1.936	(0.407)	–0.231	(0.911)
Germany	–1.468***	(0.100)	–2.029**	(0.045)	2.846	(0.218)	0.817	(0.694)
Greece	–1.243*	(0.056)	–1.495	(0.422)	0.284	(0.886)	–1.211*	(0.083)
Ireland	–3.663***	(0.000)	–4.213***	(0.000)	3.521	(0.164)	–0.692	(0.769)
Italy	–0.439	(0.629)	–0.496	(0.665)	0.272	(0.893)	–0.224	(0.893)
Latvia	–3.675***	(0.005)	–5.012***	(0.001)	5.816*	(0.062)	0.804	(0.767)
Lithuania	–3.577**	(0.006)	–3.358**	(0.016)	–4.559	(0.290)	–7.917*	(0.053)
Luxembourg	–2.623	(0.198)	–2.629	(0.289)	–0.409	(0.931)	–3.038	(0.452)
Malta	–4.966*	(0.067)	–6.095	(0.077)	4.031	(0.476)	–2.064	(0.646)
Netherlands	–1.541*	(0.071)	–1.966**	(0.037)	3.694	(0.194)	1.728	(0.519)
Portugal	–1.494	(0.188)	–1.146	(0.390)	–1.778	(0.524)	–2.924	(0.234)
Slovakia	–2.377	(0.160)	–1.706	(0.362)	1.678	(0.707)	–0.028	(0.994)
Slovenia	–5.671***	(0.000)	–5.551***	(0.000)	8.489	(0.146)	2.938	(0.604)
Spain	–0.105	(0.921)	–0.108	(0.934)	0.423	(0.871)	0.315	(0.889)
Latin America								
Brazil	–1.137	(0.189)	–1.204	(0.220)	1.241	(0.874)	0.037	(0.989)
Chile	–2.864*	(0.066)	–2.635	(0.159)	–1.680	(0.635)	–4.315	(0.153)
Colombia	0.487	(0.685)	–0.872	(0.721)	1.772	(0.529)	0.900	(0.518)
Mexico	0.204	(0.864)	0.093	(0.948)	1.777	(0.566)	1.870	(0.496)

(*continued*)

Table 7. (*continued*)

This table reports individual market results of the impact of institutional investor sentiment on the mean-variance relation. Column (I) presents the results from the entire sample and Column (II) presents the results conditional on institutional investors' optimism and pessimism. We do not report the results for Japan and the US as they are presented in Table 4.

***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8. Cultural dimensions and market integrity.

Markets	IDV	UAI	OVR	MKI	Markets	IDV	UAI	OVR	MKI
Asia (excl. Japan)									
China	20	30	20.05	–	South Korea	18	85	59.06	28.65
Indonesia	14	48	33.13	–	Taiwan	17	69	47.80	31.92
Malaysia	26	36	23.95	34.62	Thailand	20	64	44.09	28.11
Philippines	32	44	29.25	25.53	Average	21	54	36.76	29.77
Eastern Europe									
Bulgaria	30	85	58.36	–	Romania	30	90	61.90	–
Czech Republic	58	74	48.95	–	Russia	39	95	64.91	–
Hungary	80	82	53.33	–					
Poland	60	93	62.27	–	Average	50	86	58.29	–
Eurozone									
Austria	55	70	46.30	31.00	Latvia	70	63	40.48	–
Belgium	75	94	62.11	32.72	Lithuania	60	65	42.47	–
Cyprus	–	–	–	–	Luxembourg	60	70	46.01	–
Estonia	60	60	38.93	–	Malta	59	96	64.45	–
Finland	63	59	38.06	38.01	Netherlands	80	53	32.83	34.50
France	71	86	56.68	34.42	Portugal	27	99	68.43	23.18
Germany	67	65	42.07	32.93	Slovakia	52	51	33.04	–
Greece	35	100	68.67	26.86	Slovenia	27	88	60.66	–
Ireland	70	35	20.68	–	Spain	51	86	57.85	31.18
Italy	76	75	48.62	30.41	Average	59	73	48.24	31.52
Japan	46	92	62.38	34.08					
Latin America									
Brazil	38	76	51.53	26.23	Mexico	30	82	56.24	26.68
Chile	23	86	59.47	26.15					
Colombia	13	80	55.81	23.44	Average	26	81	55.76	25.63
US	91	46	27.24	36.33					

This table reports scores of IDV, UAI, OVR, and MKI for each individual markets. In addition to data on individual markets, we also compute and report the arithmetic average IDV, UAI, OVR, and MKI for each region.

Table 9. Cross-sectional results of the impact of institutional investor sentiment on the mean-variance relation.

	Upper group (I)						Lower group (II)					
Model	$\beta_{1,u,i}$	*prob.*	$\beta_{2,u,i}$	*prob.*	$\beta_{1,u,i} + \beta_{2,u,i}$	*prob.*	$\beta_{1,l,i}$	*prob.*	$\beta_{2,l,i}$	*prob.*	$\beta_{1,l,i} + \beta_{2,l,i}$	*prob.*
Panel A Individualism (IDV)												
RW	–2.220***	(0.000)	1.351***	(0.001)	–0.869***	(0.005)	–0.731**	(0.022)	–0.470	(0.176)	–1.201***	(0.000)
GARCH	–2.171***	(0.000)	0.859*	(0.078)	–1.311***	(0.001)	–0.112	(0.762)	–1.026***	(0.009)	–1.138***	(0.000)
GJR-GARCH	–2.221***	(0.000)	0.907*	(0.058)	–1.314***	(0.001)	–0.176	(0.637)	–0.938**	(0.017)	–1.114***	(0.000)
EGARCH	–2.468***	(0.000)	0.405	(0.490)	–2.063***	(0.000)	–0.081	(0.854)	–1.482***	(0.001)	–1.564***	(0.000)
MIDAS	–2.352***	(0.000)	1.109**	(0.019)	–1.244***	(0.001)	–0.490	(0.186)	–0.799**	(0.043)	–1.288***	(0.000)
Panel B Uncertainty avoidance index (UAI)												
RW	–0.990***	(0.001)	–0.178	(0.587)	–1.168***	(0.000)	–2.264***	(0.000)	1.204***	(0.003)	–1.060***	(0.000)
GARCH	–0.404	(0.238)	–0.720*	(0.054)	–1.124***	(0.000)	–2.248***	(0.000)	0.808*	(0.087)	–1.440***	(0.000)
GJR-GARCH	–0.443	(0.196)	–0.650*	(0.081)	–1.093***	(0.000)	–2.330***	(0.000)	0.912**	(0.047)	–1.418***	(0.000)
EGARCH	–0.450	(0.272)	–1.103**	(0.013)	–1.553***	(0.000)	–2.485***	(0.000)	0.434	(0.425)	–2.051***	(0.000)
MIDAS	–0.782**	(0.022)	–0.678**	(0.060)	–1.460***	(0.000)	–2.426***	(0.000)	1.012**	(0.027)	–1.414***	(0.000)
Panel C Overreaction (OVR)												
RW	–0.921***	(0.002)	–0.317	(0.344)	–1.239***	(0.000)	–2.156***	(0.000)	1.043**	(0.018)	–1.113***	(0.002)
GARCH	–0.304	(0.390)	–0.869**	(0.022)	–1.173***	(0.000)	–2.130***	(0.000)	0.665	(0.210)	–1.465***	(0.002)
GJR-GARCH	–0.354	(0.313)	–0.787**	(0.037)	–1.142***	(0.000)	–2.216***	(0.000)	0.765*	(0.065)	–1.421***	(0.001)
EGARCH	–0.319	(0.442)	–1.257***	(0.005)	–1.577***	(0.000)	–2.466***	(0.000)	0.493	(0.242)	–1.973***	(0.000)
MIDAS	–0.778	(0.160)	–0.815*	(0.092)	–1.562***	(0.000)	–2.009***	(0.000)	0.815**	(0.049)	–1.195***	(0.001)
Panel D Market integration (MKI)												
RW	–1.693***	(0.000)	0.940**	(0.046)	–0.753*	(0.095)	–1.254***	(0.001)	0.367	(0.379)	–0.887***	(0.000)
GARCH	–1.512***	(0.000)	0.895*	(0.073)	–0.616	(0.148)	–0.754*	(0.063)	–0.017	(0.971)	–0.771***	(0.009)
GJR-GARCH	–1.562***	(0.000)	0.856*	(0.074)	–0.706	(0.136)	–0.769*	(0.060)	0.019	(0.968)	–0.751***	(0.008)
EGARCH	–1.732***	(0.000)	0.822*	(0.089)	–0.911**	(0.039)	–1.083**	(0.027)	–0.189	(0.727)	–1.272***	(0.000)
MIDAS	–1.803***	(0.000)	0.943**	(0.044)	–0.859*	(0.051)	–1.328***	(0.001)	0.342	(0.443)	–0.986***	(0.001)

(*continued*)

Table 9. (*continued*)

This table presents cross-sectional results. Upper (Column I) and lower (Column II) groups are identified by IDV, UAI, OVR, and MKI in Panel A, B, C, and D, respectively. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 10. Cross-sectional results of the impact of institutional investor sentiment on the mean-variance relation, control for retail investor sentiment

	Upper group (I)												Lower group (II)											
Model	$\beta_{1,u,i}$	*prob.*	$\beta_{2,u,i}$	*prob.*	$\beta_{3,u,i}$	*prob.*	$\beta_{1,u,i}+\beta_{2,u,i}$	*prob.*	$\beta_{1,u,i}+\beta_{3,u,i}$	*prob.*	$\beta_{1,u,i}+\beta_{2,u,i}+\beta_{3,u,i}$	*prob.*	$\beta_{1,l,i}$	*prob.*	$\beta_{2,l,i}$	*prob.*	$\beta_{3,l,i}$	*prob.*	$\beta_{1,l,i}+\beta_{2,l,i}$	*prob.*	$\beta_{1,l,i}+\beta_{3,l,i}$	*prob.*	$\beta_{1,l,i}+\beta_{2,l,i}+\beta_{3,l,i}$	*prob.*
Panel A Individualism (IDV)																								
RW	–2.391***	(0.000)	1.237***	(0.003)	0.690	(0.117)	–1.154***	(0.003)	–1.701***	(0.000)	–0.464	(0.215)	–0.600*	(0.073)	–0.355	(0.320)	–0.449	(0.147)	–0.954***	(0.000)	–1.048***	(0.008)	–1.403***	(0.000)
GARCH	–2.292***	(0.000)	0.828*	(0.093)	0.641	(0.247)	–1.463***	(0.002)	–1.651***	(0.002)	–0.822	(0.113)	–0.004	(0.992)	–0.878**	(0.033)	–0.421	(0.247)	–0.882**	(0.011)	–0.425	(0.365)	–1.303***	(0.000)
GJR-GARCH	–2.315***	(0.000)	0.862*	(0.083)	0.613	(0.274)	–1.452***	(0.002)	–1.702***	(0.002)	–0.840	(0.106)	–0.062	(0.873)	–0.819**	(0.045)	–0.400	(0.262)	–0.880***	(0.001)	–0.457	(0.325)	–1.276***	(0.000)
EGARCH	–2.535***	(0.000)	0.436	(0.470)	0.535	(0.441)	–2.099***	(0.000)	–2.000***	(0.003)	–1.564**	(0.021)	–0.022	(0.962)	–1.363**	(0.047)	–0.269	(0.545)	–1.385***	(0.000)	–0.291	(0.608)	–1.654***	(0.000)
MIDAS	–2.482***	(0.000)	1.050**	(0.023)	0.649	(0.223)	–1.432***	(0.002)	–1.833***	(0.000)	–0.783	(0.103)	–0.373	(0.331)	–0.656*	(0.080)	–0.447	(0.212)	–1.031***	(0.000)	–0.821*	(0.077)	–1.479***	(0.000)
Panel B Uncertainty avoidance index (UAI)																								
RW	–0.901***	(0.003)	–0.071	(0.836)	–0.320	(0.310)	–0.972***	(0.000)	–1.222***	(0.001)	–1.292***	(0.000)	–2.365***	(0.000)	1.112***	(0.007)	0.452	(0.291)	–1.253***	(0.001)	–1.912***	(0.000)	–0.801**	(0.021)
GARCH	–0.311	(0.381)	–0.586	(0.136)	–0.355	(0.337)	–0.897***	(0.001)	–0.666	(0.143)	–1.252***	(0.000)	–2.350***	(0.000)	0.707*	(0.093)	0.530	(0.323)	–1.643***	(0.000)	–1.819***	(0.001)	–1.112**	(0.015)
GJR-GARCH	–0.354	(0.318)	–0.531	(0.173)	–0.329	(0.363)	–0.885***	(0.001)	–0.683	(0.130)	–1.215***	(0.000)	–2.395***	(0.000)	0.814**	(0.082)	0.457	(0.387)	–1.581***	(0.000)	–1.938***	(0.000)	–1.124**	(0.012)
EGARCH	–0.366	(0.388)	–0.980**	(0.036)	–0.312	(0.498)	–1.346***	(0.000)	–0.682	(0.226)	–1.661***	(0.000)	–2.599***	(0.000)	0.323	(0.569)	0.633	(0.313)	–2.276***	(0.000)	–1.966***	(0.002)	–1.642***	(0.002)
MIDAS	–0.665	(0.233)	–0.589	(0.357)	–0.481	(0.423)	–1.253***	(0.004)	–1.145	(0.114)	–1.734***	(0.000)	–2.387***	(0.000)	0.993**	(0.022)	0.406	(0.402)	–1.394***	(0.000)	–1.981***	(0.000)	–0.988**	(0.020)
Panel C Overreaction (OVR)																								
RW	–0.825*	(0.099)	–0.200	(0.564)	–0.359	(0.250)	–1.024***	(0.000)	–1.184***	(0.002)	–1.384***	(0.000)	–2.130***	(0.000)	1.019**	(0.024)	0.055	(0.918)	–1.111***	(0.003)	–2.075***	(0.000)	–1.056*	(0.062)
GARCH	–0.222	(0.546)	–0.739*	(0.064)	–0.325	(0.372)	–0.960***	(0.000)	–0.547	(0.229)	–1.289***	(0.000)	–2.057***	(0.000)	0.649	(0.228)	–0.161	(0.801)	–1.409***	(0.004)	–2.218***	(0.000)	–1.569**	(0.025)
GJR-GARCH	–0.277	(0.447)	–0.671*	(0.088)	–0.303	(0.396)	–0.948***	(0.000)	–0.580	(0.199)	–1.251***	(0.000)	–2.134***	(0.000)	0.776*	(0.089)	–0.209	(0.744)	–1.359***	(0.004)	–2.344***	(0.000)	–1.568**	(0.022)
EGARCH	–0.259	(0.549)	–1.147**	(0.014)	–0.234	(0.602)	–1.407***	(0.000)	–0.494	(0.369)	–1.641***	(0.000)	–2.363***	(0.000)	0.278	(0.645)	–0.269	(0.723)	–2.085***	(0.000)	–2.631***	(0.000)	–2.353***	(0.003)
MIDAS	–0.684	(0.227)	–0.615	(0.340)	–0.465	(0.439)	–1.299***	(0.003)	–1.148	(0.117)	–1.763***	(0.000)	–1.895***	(0.000)	0.933*	(0.054)	0.010	(0.906)	–0.962***	(0.007)	–1.885***	(0.000)	–0.952*	(0.097)
Panel D Market integration (MKI)																								
RW	–1.500***	(0.013)	0.895*	(0.075)	–0.300	(0.637)	–0.606	(0.236)	–1.801***	(0.000)	–0.906	(0.265)	–1.530***	(0.000)	0.575	(0.157)	1.357	(0.169)	–0.955***	(0.000)	–0.173	(0.860)	0.401	(0.687)
GARCH	–1.330**	(0.030)	0.837*	(0.082)	–0.779	(0.302)	–0.494	(0.428)	–2.109***	(0.000)	–1.272	(0.252)	–1.027***	(0.008)	0.172	(0.702)	1.226	(0.298)	–0.855***	(0.005)	0.096	(0.928)	0.268	(0.807)
GJR-GARCH	–1.387***	(0.000)	0.808*	(0.096)	–0.881	(0.249)	–0.579	(0.298)	–2.268***	(0.000)	–1.460	(0.221)	–1.053***	(0.006)	0.219	(0.622)	1.111	(0.306)	–0.835***	(0.003)	0.057	(0.957)	0.276	(0.802)
EGARCH	–1.691***	(0.000)	0.671	(0.203)	–0.964	(0.730)	–1.020	(0.177)	–2.654***	(0.000)	–1.984	(0.127)	–1.394**	(0.026)	0.271	(0.730)	–0.964	(0.284)	–1.405***	(0.000)	0.253	(0.850)	0.243	(0.858)
MIDAS	–1.394***	(0.000)	0.817*	(0.089)	–0.671	(0.364)	–0.576	(0.302)	–2.106***	(0.000)	–1.289	(0.244)	–1.394***	(0.000)	0.363	(0.420)	1.340	(0.220)	–1.031***	(0.000)	–0.054	(0.960)	0.309	(0.781)

(*continued*)

Table 10. (*continued*)

This table presents cross-sectional results, controlling for the retail investor sentiment. Upper (Column I) and lower (Column II) groups are identified by IDV, UAI, OVR, and MKI in Panel A, B, C, and D, respectively.

***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.