The conditional impact of investor sentiment in global stock markets: A two-channel examination

Abstract: While investor sentiment has been shown to have a robust, direct impact on stock returns, we know little about how it impacts returns through an indirect channel from conditional volatility. We conduct a global study of investor sentiment across 40 international stock markets to examine the impact of investor sentiment on stock returns via both direct and indirect channels and how the impact varies across bull and bear market regimes. Using turnover ratio as the sentiment proxy and applying GARCH-type models, we confirm a conditional impact of investor sentiment on stock returns via both channels: In bull regimes, optimistic (pessimistic) shifts in investor sentiment would increase (decrease) stock returns, while in bear regimes, optimistic (pessimistic) shifts would decrease (increase) stock returns.

Keywords: Conditional volatility; investor sentiment; market regime; stock return; turnover ratio

JEL Classification: G12; G15; G41

1. Introduction

Standard financial theories leave little space for investor sentiment as it is regarded to have no persistent impact on markets (Fama, 1965); however, De Long et al. (1990, henceforth DSSW) argue that investor sentiment can affect asset prices, and noise traders are able to make profits and survive the markets over the long term (see, also, Campbell and Kyle, 1993; Shefrin and Statman, 1994; Palomino, 1996; Wang, 2001). In particular, the impact of investor sentiment on stock returns is realized via two main channels: direct and indirect. The direct channel refers to an impact of the direction of shifts in investor sentiment (henceforth SiIS), while the indirect channel refers to an impact of the magnitude of SiIS via conditional volatility. Each channel has two specific effects: the hold-more effect and the price-pressure effect for the direct channel, and the Friedman effect and the create-space effect for the indirect channel. The impact of investor sentiment on stock returns, hence, can be boiled down to a net result of the interaction between the two channels, or four effects (see, Appendix A). While prior literature pays much attention to the direct channel (Baker and Wurgler, 2006; Schmeling, 2009; Wang et al., 2021), Lee et al., (2002, henceforth LJI) examine both channels in the US stock market, reporting that the direction of SiIS positively affects stock returns, and the magnitude of optimistic (pessimistic) SiIS brings about downward (upward) revisions in conditional volatility and then higher (lower) future stock returns.

Elsewhere, other studies confirm that investors exhibit varying behaviors in different market regimes (Gervais and Odean, 2001; Nofsinger, 2005; Li and Luo, 2017), building on which, some studies reveal a conditional impact of investor sentiment. Chung et al. (2012), for example, show that investor sentiment has predictive power only during economic expansions rather than recessions due to the asymmetric sentiment-driven overpricing and underpricing. Similarly, Karlsson et al. (2009), Yu and Yuan (2011), and Antoniou et al. (2016) evidence that sentiment investors trade more aggressively over high-sentiment periods, and hence their high presence and unsophistication of stock trading would distort the risk-return tradeoff at both market and firm levels (see Subsection 2.1 for further discussion).

In this paper we contribute to understanding of how investor sentiment impacts stock returns in two distinct ways, leading to a number of unique findings. First, we extend DSSW and LJI to a wider scope by incorporating a total of 40 leading international stock markets. This enlarged dataset is important due to the significant distinctions across diverse markets, in particular with respect to returns and market efficiency (Bekaert and Harvey, 2002), cultural dimensions (Aggarwal and Goodell, 2009; Beugelsdijk and Frijns, 2010; Aggarwal et al., 2012; Eun et al., 2015), and market integrity (Schmeling, 2009; Wang et al., 2021), all of which . Schmeling (2009), for example, examines the impact of investor sentiment on a total of 18 industrialized stock markets, thereby revealing that the impact of investor sentiment is stronger in markets with cultural tendency to overaction and low-level market integrity. In addition, the importance of other non-US developed markets (such as the UK and Japan) and emerging markets (such as China) in the world's financial markets demands an extension of current evidence to the global level, thus a global examination is needed (Goetzmann et al., 2005; Giannetti and Ongena, 2009; Eun and Lee, 2010; Conover, 2011; Fernandes, 2011; Shek et al., 2018). Further, an enlarged global sample facilitates out-of-US tests for the earlier findings in LJI, which is crucial in exploring the global relevance of market anomalies (Ang et al., 2009) and revealing cross-market similarities and differences. Second, we are the first to examine the two-channel impact of investor sentiment on stock market returns in a conditional framework allowing for varying investor behaviors across different market regimes (specifically, bull and bear conditions). This is important and necessary not only to ensure that intra-market unconditional results are not simply the product of averaging out opposing effects across market conditions, but also to ensure that inter-market differences in unconditional results are not merely capturing variation in prevalence of bull and bear conditions across markets.

As implied in DSSW, the indirect channel requires the volatility estimation since the magnitude of SiIS forms conditional volatility in the first step, explicitly stressing the application of volatility models. We employ sentiment-augmented multivariate GARCH-family models given their flexibility in modifications compared with others such as the rolling window model and the mixed data sampling approach (MIDAS). For consistency purposes, we adopt three GARCH-family models, GARCH-M, GJR-GARCH-M, and EGARCH-M, as different volatility models may present inconsistent mean-variance relation results (Ghysels et al., 2005; Yu and Yuan, 2011).

We adopt turnover ratio as our primary sentiment proxy following Baker et al. (2012). Baker and Stein (2004) argue that short-sale constraints drive noise traders to trade when they feel optimistic rather than pessimistic, meaning that irrational investors' optimism (pessimism) is reflected by ascending (descending) turnover ratio (see, also, Boubaker et al., 2019). In addition, given its daily availability, turnover ratio is suitable for capturing volatility and presenting the mean-variance relation. Also, this widely accessible indicator is computed directly from stock markets and hence explicitly captures investor sentiment in stock rather than other financial markets.

We start with evaluating the relation between investor sentiment and stock returns based on full samples for each market, i.e., an unconditional test. The three GARCH-family models provide broadly consistent results, with the EGARCH-M model providing the best suitability. While there is some heterogeneity in results, investor sentiment is a critical factor in predicting stock returns for most markets. For the direct channel, optimistic (pessimistic) SiIS lead to higher (lower) stock returns, and for the indirect channel, optimistic (pessimistic) SiIS cause upward (downward) revisions in conditional volatility and then higher (lower) stock returns due to the presented risk-return tradeoff. The direct channel appears to be stronger than the indirect one due to its wider impact, but in several markets we find that the indirect channel is the only route via which investor sentiment can affect stock returns, lending credence to our distinguishing between the direct and the indirect channels, and suggesting that only examining the direct channel is potentially misleading because the impact of investor sentiment via the indirect channel is missed.

To reveal the conditional impact of investor sentiment, we distinguish bull and bear regimes following Pagan and Sossounov (2003) and replicate our empirical approaches for bull and bear subsamples jointly, i.e., a conditional test. Results support the conditional impact of investor sentiment on stock returns. For the direct channel, SiIS and stock returns are positively related in bull regimes but negatively related in bear regimes. In particular, optimistic (pessimistic) SiIS result in higher (lower) stock returns in bull regimes, but lower (higher) stock returns in bear regimes. For the indirect channel, however, investor sentiment demonstrates both conditional and unconditional impacts. Optimistic (pessimistic) SiIS cause upward (downward) revisions in conditional volatility in both regimes; nonetheless, higher (lower) conditional volatility yields higher (lower) stock returns in bull regimes but lower (higher) stock returns in bear regimes. The two channels conceptually provide a consistent finding: Optimistic (pessimistic) SiIS lead to higher (lower) stock returns in bull regimes but lower (higher) stock returns in bear regimes. It would be extraordinary to obtain perfectly consistent results in a global sample of 40 stock markets like ours, so the high level of consistency in our results is quite remarkable, with only one market exhibiting significantly opposite pattern for direct (China) and indirect (India) channel. While culture and market integrity have been shown to influence the impact of investor sentiment on stock market returns (Schmeling, 2009), our finding shows that with a clearly defined market condition and specifications, the impact can be largely consistent. Prior studies of the sentiment-return relation are built upon (i) the theoretical underpinning of a positive contemporaneous sentiment-return relation and thus a negative intertemporal sentiment-return relation (Brown and Cliff, 2005), and (ii) a constant sentiment-return relation over the sample period. Our conditional findings, however, appear to place both under closer scrutiny, indicating the importance of distinguishing the sentiment impact across market conditions.

The twin-concepts of bull and bear regimes from Pagan and Sossounov (2003) describe the *index movement trends*, i.e., growth/decline. In a supplementary conditional test, we re-distinguish up and down states based on Cooper et al. (2004), which, unlike bull and bear regimes, depicts the *relative index level*, i.e., high/low. As might be expected, findings differ from those based on the bull/bear test; however, we find that sentiment investors tend to exert wider significant influences over up than down markets, revealing another form of the conditional impact of investor sentiment on stock returns and further supporting the necessity of adopting conditional tests.

The remainder of this paper proceeds as follows. Section 2 reviews prior literature and develops two testable hypotheses. Section 3 and 4 present data and empirical models, respectively. Section 5 reports results from the entire sample, bull/bear subsamples, along with up/down subsamples in Section 6. Section 7 concludes.

2. Related literature and hypotheses development

2.1 Related literature

2.1.1 The impact of investor sentiment

In standard financial theories, stock prices are computed as the discounted future cash flows, and the impact of investor sentiment is eliminated by arbitrage (Fama, 1965). DSSW develop a framework where sophisticated and uninformed agents trade together, revealing that uninformed investors trading in concert bring systematic risk into stock markets. The risk derived from the stochastic SiIS imposes limits on arbitrage and as a consequence, mispricing caused by investor sentiment is effectively persistent (theoretical discussions, see, also, Campbell and Kyle, 1993; Shefrin and Statman, 1994; Palomino, 1996; Wang, 2001). DSSW boil down the influence mechanism to two channels: direct and indirect. First, the direction of SiIS *directly* affects stock returns, and second, the magnitude of SiIS (i.e., the degree of misperceptions) *indirectly* affects stock returns by shaping conditional volatility. Each channel has two specific effects: the hold-more effect and the price-pressure effect for the direct channel, and the Friedman effect and the create-space effect for the indirect channel. The impact of investor sentiment on stock returns is a net result of the interaction between the two channels, or four effects.

Baker and Wurgler (2006) further ascribe the mispricing to the persistent impact of investor sentiment that is driven by (i) uninformed demand shocks and (ii) limits on arbitrage. First, uninformed demand shocks persist naturally because irrational investors' misbeliefs can be further strengthened by others '*joining on the bandwagon*' (Brown and Cliff, 2005, p. 407). Second, limits on arbitrage impede rational investors from easing the impact of investor sentiment from the market since they are often subject to relatively restricted investment horizons and can hardly accurately forecast how long these irrational effects can persist (Shleifer and Vishny, 1997; Arnold, 2009). Therefore, one can observe that high levels of optimism (pessimism) result in high (low) contemporaneous returns and the mean-reverting property would finally correct overpricing (underpricing) with low (high) subsequent returns.

Extant empirical studies largely support the theoretical analyses. Fisher and Statman (2000) confirm small investor sentiment as '*a reliable contrary indicator of future S&P 500 returns*' (p. 17). Brown and Cliff (2005) find a negative relation between investor sentiment and DJIA returns over the next one to three years. Baker and Wurgler (2006) reveal a cross-sectional impact of investor sentiment, with hard-to-value and difficult-to-arbitrage stocks, such as small, young, and distressed, more affected (see, also, Kumar and Lee, 2006; Lemmon and Portniaguina, 2006; Qiu and Welch, 2006; Joseph et al., 2011; Ding et al., 2018). Schmeling (2009), Bathia and Bredin (2013), and Wang et al. (2021) extend the US evidence to a wider scope by examining 18 developed, Group of Seven, and 50 global markets, respectively, with all reporting a negative sentiment-return relation from the all-country joint dataset examinations, despite the market-specific heterogeneity. Research on the second return moment is also prevalent in the literature. Brown (1999) reports that abnormal levels of investor sentiment heighten the volatility in closed-end fund returns. Wang et al. (2006) find that investor sentiment has the ability to predict future realized volatility, with limited forecasting power, though.[1]

However, prior studies do not explicitly address the two-channel mechanism as specified in DSSW, except for LJI that assesses the impact of investor sentiment, proxied by Investor Intelligence, on three US market indices (i.e., DJIA, S&P500, and NASDAQ) from 5 January 1973 to 6 October 1995. LJI confirms the predictability of investor sentiment to stock returns via both channels: The direction of SiIS positively affects current US stock returns, and the magnitude of optimistic (pessimistic) SiIS brings about downward (upward) revisions in conditional volatility and therefore higher (lower) future stock returns given the estimated negative mean-variance relation.

2.1.2 The role of market regimes

Literature suggests that investors' behaviors vary with market regimes (Gervais and Odean, 2001; Nofsinger, 2005; Li and Luo, 2017). Since the impact of investor sentiment is transmitted by investors' trading behaviors, a small stream of research, accordingly, probes the conditional impact of investor sentiment.

One aspect explores the asymmetric impact of investor sentiment across economic expansions and recessions. Daniel et al. (1998) point out that overpricing is present in expansions due to good economic news, while underpricing is present in recessions due to bad economic news. In theory, overpricing and underpricing can be corrected by arbitrage, but it is asymmetric in practice across market conditions. In recessions, arbitrageurs purchase underpriced stocks and drive stock prices back to intrinsic values, while in expansions, short-sale constraints impede negative information from entering the market, leading to substantial overpricing (Ofek et al., 2004). Further, the positive feedback loop encourages uninformed investors to become more optimistic in overpriced

[1] For more empirical studies, see, e.g., Fisher and Statman (2003), Antweiler and Frank (2004), Lemmon and Portniaguina (2006), Baker and Wurgler (2007), Tetlock (2007), Bergman and Roychowdhury (2009), Da et al. (2011 & 2015), etc.

market conditions and therefore to continue purchasing, and the social contagion effect encourages additional uninformed investors to enter the market (neighbors of existing uninformed investors having made profits, Shiller, 2015). As a result, the impact of investor sentiment is stronger in expansions than recessions, which is empirically confirmed in Chung et al. (2012) showing that investor sentiment only exhibit predictive power during expansions.

Another aspect of literature examines high- and low-sentiment periods. Karlsson et al. (2009) and Yuan (2015) state that irrational investors trade aggressively in high- rather than low-sentiment periods, and Yu and Yuan (2011) further argue that since noise traders are likely to misestimate the variance of returns due to their unsophistication, their participation would distort the mean-variance relation. This argument is supported by empirical results from the US as well as European stock markets (Yu and Yuan, 2011; Wang, 2018a). Extending this to the stock level, Antoniou et al. (2016) report an upward sloping security market line (SML) in low-sentiment periods, in line with the classic capital asset pricing model (CAPM) of the standard financial framework, but a downward sloping SML in high-sentiment periods, counter to the CAPM.

2.2 Hypotheses development

As per the DSSW model, the impact of investor sentiment on stock returns is the net outcome of the interaction between two channels, direct and indirect, or four effects including the hold-more effect, the price-pressure effect, the Friedman effect, and the create-space effect.

The hold-more effect leads noise investors to hold more (fewer) risky stocks when they feel optimistic (pessimistic). In other words, the incentive for noise investors to trade increases (decreases) with their optimism (pessimism). Both DSSW and LJI state that the hold-more effect increases noise investors' returns since they bear a larger proportion of risk. This is valid in the long run or trendless periods but does not hold unconditionally in varying market cycles. At the firm level, individual stock returns are proportional to market returns and that proportion is the stock beta. Over bull regimes when market returns increase, higher-beta stocks yield higher returns while the opposite applies in bear regimes. For example, Levy (1974) finds a positive beta-return relation over bull markets but a negative one over bear markets, which remains true in a dual-beta context as high-beta stocks still have higher betas than low-beta stocks in bear regimes (Bhardwaj and Brooks, 1993). We, thus, argue in favor of a conditional pattern of the hold-more effect: Being optimistic (i.e., holding more risky stocks) makes investors better off over bull regimes but worse off over bear regimes, while the opposite holds otherwise (i.e., holding less risky stocks). The price-pressure effect states that the optimism (pessimism) of noise investors exerts pressure on stock prices and therefore reduces risk-bearing returns. The price-pressure effect would negatively affect investors' wealth regardless of market regimes. As a result, the direct channel, i.e., the interaction between the hold-more effect and the price-pressure effect, should vary with market regimes (see, Panel A of Appendix A).

The Friedman effect, also denoted as the 'buy high, sell low' effect, shows that noise investors' misperceptions are stochastic, and they follow others, trading at the worst time and suffering losses. The damage to investors' wealth due to the poor timing ability is, hence, positively related to the variability of their beliefs, or the magnitude of their misperceptions. The create-space effect, on the other hand, argues that the accumulation in the variability of noise traders' misbeliefs increases the price risk, hampering the risk-averse arbitrageurs from taking advantage of noise traders' misperceptions and betting against them. By crowding out arbitrageurs, noise traders create their own space and make profits. Note that investors tend to be overconfident, with their biased sense of self-attribution prompting overconfidence to change with the realized returns (Daniel et al., 1998; Odean, 1998; Deaves et al., 2009). High realized returns make investors more overconfident due to self-attribution, neglecting the fact that such realized high returns are enjoyed by the entire market (Gervais and Odean, 2001), and therefore, investors' optimism accumulates with overconfidence and is reflected by high trading volume (Odean, 1998; Gervais and Odean, 2001; Statman et al., 2006). It suggests that in bull regimes, the accumulation of optimism enhances the price risk and makes the create-space effect dominate the Friedman effect, leading to higher returns. Pessimism in bull regimes, however, weakens the accumulation of optimism of noise traders' misbelief and makes the Friedman effect dominate, leading to lower returns. In bear regimes, investor sentiment decreases with the declining overconfidence and the accumulation in pessimism enhances the price risk and makes the create-space effect dominate the Friedman effect again, leading to higher returns, and the opposite holds for optimism. While the Friedman effect or the create-space effect remain constant over regimes, their interaction is conditional due to varying investors' behaviors (see, Panel B of Appendix A).

As stocks and investors exhibit disparate characteristics over bull and bear regimes, we test the conditional sentiment impact. Drawing on the discussion above, we propose two testable hypotheses:

Hypothesis 1. For the direct channel, SiIS and stock returns are positively (negatively) related in bull (bear) regimes.

Hypothesis 2. For the indirect channel, SiIS and stock returns are positively (negatively) related in bull (bear) regimes.

3. Data

3.1 Stock markets and sample periods

We incorporate a total of 40 stock markets across the globe. This sample is a diverse combination of global stock markets in both geographic and economic respects.[2] Daily data of stock returns are computed from the DataStream total market equity indices that reflect the overall performance of a specific stock market. The sample size for each market is dictated by data availability and all end

[2] We have 21, 12, 6, and 1 stock markets in Europe, Asia-Pacific, America, and Africa, respectively, and 22 developed and 18 emerging stock markets pursuant to the latest MSCI. Note that three stock markets, including Portugal (from emerging to developed, November 1997), Greece (from emerging to developed, May 2001 and then from developed to emerging, November 2013), and Israel (from emerging to developed, May 2010), have been reclassified over the sample period. In Table 1, we denote developed/emerging based on the classification as of 2015.

on 31 August 2016. Table 1 shows that stock markets yield non-negative average daily excess returns over the sample period except for Greece and Portugal, which is not surprising as both are the most impacted markets in recent financial crises. Excess returns are typically higher and more volatile in emerging than developed stock markets, indicating a rapid but fluctuating trend in the former. The skewness presents some interesting features in that a few markets such as Brazil, Hong Kong, and Russia do not show negatively skewed stock returns that are widely established in literature (Chen et al., 2001). Finally, all markets present leptokurtic stock returns, in line with Lux (1998).

<Table 1>

3.2 Investor sentiment proxy

Investor sentiment is elusive.[3] LJI employ a weekly survey of Investor Intelligence as the proxy for investor sentiment; however, note that Investor Intelligence compiles data from newsletters hiring current or retired *professionals* and thus corresponds to *institutional* rather than individual investor sentiment (Brown and Cliff, 2005; Wang, 2018b & 2020), suggesting that Investor Intelligence should be treated as '*smart money*' rather than '*noise trader risk*' (Schmeling, 2007, p. 143).

[3] Four types of proxies (i.e., direct, indirect, composite, and innovative) are proposed to capture investor sentiment in prior studies. Direct proxies are acquired from surveys asking consumers or investors about their propensity to consume or invest, such as the American Association of Individual Investor (AAII) and consumer confidence (Brown, 1999; Qiu and Welch, 2006; Wang et al., 2021). Indirect proxies are from financial markets and some commonly used indirect proxies include the closed-end fund discount (CEFD), options implied volatility (VIX), initial public offerings (IPO) first day returns and volume, and mutual fund flows (Lee et al., 1991; Swaminathan, 1996; Neal and Wheatley, 1998; Frazzini and Lamont, 2006; Bathia and Bredin, 2013). Composite proxies are constructed based on two or more direct and/or indirect proxies. One important composite proxy is from the seminal paper of Baker and Wurgler (2006) that encompasses six single proxies including the closed-end fund discount, the dividend premium, the equity share in new issues, the NYSE share turnover, the number of IPOs, and average first-day returns on IPOs via the principal component analysis, which is widely adopted and discussed in subsequent studies (Bali et al., 2010; Huang et al., 2015; Chue et al., 2019; Lin et al., 2019). Innovative proxies based on mass media and the Internet surface more in recent studies. Tetlock (2007) compiles an index for media pessimism as the proxy by assembling the content from the Wall Street Journal column. For more details of these sentiment proxies, see, Antweiler and Frank (2004), Kumar and Lee (2006), Bergman and Roychowdhury (2008), Ho and Hung (2009), Fong and Toh (2014), Goetzmann et al. (2015), Lutz (2015), Renault (2017), Behrendt and Schmidt (2018), and Audrino and Tetereva (2019), etc.

Drawing on Baker et al. (2012), we adopt turnover ratio as the investor sentiment proxy.[4] In theory, short-sale constraints make irrational investors tend to trade when they feel optimistic, meaning that irrational investors' optimism (pessimism) is reflected by the ascending (descending) turnover ratio (Baker and Stein, 2004). Beyond turnover ratio, or its companion concept, trading volume, liquidity can be regarded as the sentiment proxy in a much broader manner (Baker and Wurgler, 2007).[5] For instance, applying a battery of liquidity proxies, Boubaker et al. (2019) suggest that liquidity can represent investors' willingness to buy shares. Beyond theoretical underpinnings, there are two further justifications for our adoption of turnover ratio. First, it offers daily data that appropriately fit our GARCH specifications detailed below. As documented in Jacobsen and Dannenburg (2003) and Zhang and Jacobsen (2013), while it is possible to detect volatility clustering in low-frequency financial data (like monthly), the data window should be large enough, such as fifty years. In our global study, we are unable to collect long periods of data for all markets (see, Table 1), suggesting our use of daily data as recourse. Also, the hold-more effect and the price-pressure effect capture the transitory impact of investor sentiment (LJI), and therefore, lower-frequency data such as weekly or monthly may be inappropriate in our global sample. Second, compared with other proxies like implied volatility, mutual fund flows, and close-end fund discounts, etc., turnover ratio explicitly captures sentiment in stock markets rather than options or fund markets. While the choice of the turnover ratio might be cruder than alternative proxies based on microstructure data or brokerage-level data, it is a consistent proxy available with

[4] In their construction of investor sentiment indices for 6 major stock markets, Baker et al. (2012) report factor loadings for the four components (PVOL, NIPO, RIPO, and TURN) for each country. Notably, the factor loadings exhibit variation across the six countries, with min-max values of 0.06–0.36, 0.07–0.45, 0.27–0.49 and 0.35–0.47 for PVOL, NIPO, RIPO, and TURN, respectively. The variation in factor loadings across countries suggests the appropriateness of investor sentiment proxies may vary from one country to the next. With a factor loading spread of only 0.12, turnover (TURN) is the most consistent proxy of those examined in Baker et al. (2012) and has the highest or second highest factor loading in all markets with available data. Thus, given the evidence in Baker et al. (2012) concerning the consistency of turnover across their sample of markets, we select turnover as the proxy of choice in our global study of 40 stock markets.

[5] See, also, Smith et al. (1988); Scheinkman and Xiong (2003); Mei et al. (2009); Baker et al. (2012), etc. Liquidity variables as fine investor sentiment proxies also obtain support from the liquidity literature. In Brennan et al. (1998), a significant and negative relation between expected returns and trading volume is discovered, which aligns with the theoretical analysis on the relation between expected returns and investor sentiment (see, also, Datar et al., 1998; Pan et al., 2016).

plausibly long periods of observations for use in this global analysis requiring daily data in 40 markets.[6, 7]

We employ the daily SiIS, defined as the first-order difference of daily investor sentiment, in following empirical analyses. Table 1 presents the descriptive statistics of SiIS. The mean of the SiIS is small in the vast majority of markets, signifying that optimistic and pessimistic SiIS tend to offset each other during sample periods.[8]

4. Methodology

4.1 Models

As LJI state, the hold-more effect and the price-pressure effect reflect the impact of the *direction* of SiIS on concurrent stock returns; the Friedman effect and the create-space effect capture the lagged impact of *magnitude* of SiIS on conditional volatility. Following LJI, we apply sentiment-augmented return-generating multivariate GARCH-family models, and the mean equation follows:[9]

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[6] As discussed below, we distinguish bull and bear regimes for each market and hence the periods for sample markets should be preferably long to contain at least one cycle.

[7] The global applicability of daily sentiment proxies based on internet data remains unclear. Traffic to stocktwits.com by country shows the US leads the way with 67.85% of traffic, with Canada (9.46%) and the UK (2.75%) a distant second and third, respectively (source: https://www.similarweb.com/website/stocktwits.com/#overview). Likewise, while FEARS uses Google Search Volume Index (SVI) data and has been shown to be an excellent sentiment proxy in the US (Da et al., 2015), Google's share of search traffic is in excess of 80% in the US and many other countries but is also as low as 10% in China (a key financial market in a global study, source: https://www.statista.com/statistics/220534/googles-share-of-search-market-in-selected-countries). Such variation across markets suggests the likes of StockTwits and FEARS are not suitable sentiment proxies in our global study.

[8] In raw data we observe a very high level of volatility in Colombia (the unreported standard deviation is 26.25) that is caused by one extreme turnover value on 26 June 2009, which is also observed from unreported extreme maximum and minimum SiIS values (1,146.84 and –1,147.02, respectively). For quality control, we check this value by looking at the trading volume and the trading value on 26 June 2009 sourced from Refinitiv and both show a dramatic increase on that day. We also check sector by sector and the observed high turnover is mainly driven by the utilities sector. As shown in Section 4, we use SiIS (computed as $s_t - s_{t-1}$) on day t to predict the stock return on day t, and optimistic/pessimistic SiIS on day t to predict conditional volatility on day $t + 1$, and therefore an extreme turnover value on day t would influence estimations on day t, $t + 1$, and $t + 2$, to avoid our results being much affected, we control for these three days (26 June 2009, 30 June 2009, and 1 July 2009) in our analyses. Note, also, that SiIS is defined as the first-order change in investor sentiment proxied by turnover ratio, instead of the percentage change, so results reported in Table 1 are not in percentages. For example, the maximum SiIS for the US stock market, 9.32, occurred on 01 December 2008 when turnover ratio went from 5.34 on 28 November 2008 to 14.67, i.e., a 174.44% change, not a 932.25% change.

[9] For more detail about GARCH-family and other volatility models, see Appendix B.

$$R_t - R_t^f = \alpha_0 + \alpha_1 h_t + \alpha_2 sent_t + \varepsilon_t, \tag{1}$$

where $R_t - R_t^f$ is the daily excess return in the individual stock market at time t; $sent_t$ is the SiIS, i.e., $(s_t - s_{t-1})$, as pointed out in Subsection 3.2, and α_2 accordingly refers to the concurrent impact of SiIS on stock returns, i.e., the direct channel; and h_t is the conditional volatility of stock returns at time t. We employ the parsimonious GARCH (1,1) specification to measure volatility given its wide applicability (Bollerslev et al., 1992; Hansen and Lunde, 2005). The GARCH-M model follows:

$$h_t = \beta_0 + \delta\varepsilon_{t-1}^2 + \beta_1 opt_{t-1}^2 + \beta_2 pes_{t-1}^2 + \lambda h_{t-1} + \xi R_t^f, \tag{2}$$

where we distinguish optimistic (opt_{t-1}, if $sent_{t-1} \geq 0$) and pessimistic (pes_{t-1}, if $sent_{t-1} < 0$) SiIS. We replace the variance of SiIS with the squared terms of opt_{t-1} and pes_{t-1} because the mean of SiIS is close to zero (see, Table 1). In addition, we add the risk-free rate, R_t^f, as volatility is found to be positively related to inflation (Glosten et al., 1993). The GJR-GARCH-M model follows:

$$h_t = \beta_0 + \delta_1\varepsilon_{t-1}^2 + \delta_2\varepsilon_{t-1}^2 I_{t-1} + \beta_1 opt_{t-1}^2 + \beta_2 pes_{t-1}^2 + \lambda h_{t-1} + \xi R_t^f, \tag{3}$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $I_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$. The incorporation of the asymmetric term tests whether investors form expectations of conditional volatility differently to positive and negative innovations. A negative innovation has an impact of $(\delta_1 + \delta_2)$, and a positive innovation has an impact of δ_1. We expect δ_2 to be significantly positive ($\delta_1 + \delta_2 > \delta_1$) since bad news tends to introduce higher volatility than good news, i.e., the leverage effect (Nelson, 1991; Glosten et al., 1993). Finally, the EGARCH-M model follows:

$$h_t = exp\left\{\beta_0 + \delta_1\left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}}\right] + \delta_2\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_1 opt_{t-1}^2 + \beta_2 pes_{t-1}^2 + \lambda\ln(h_{t-1}) + \xi R_t^f\right\}, \tag{4}$$

where δ_2 reflects the leverage effect. A negative innovation has an impact of $(\delta_1 - \delta_2)$ while a positive innovation has an impact of $(\delta_1 + \delta_2)$; hence, we expect δ_2 to be significantly negative (i.e., $\delta_1 - \delta_2 > \delta_1 + \delta_2$).

Linking the models with the two hypotheses provided in Subsection 2.2, we expect α_2 in Eq. (1), reflecting the contemporaneous impact of SiIS on stock returns (the direct channel), to be positive in bull regimes (i.e., that SiIS and stock returns are positively related), while negative in bear regimes (i.e., that SiIS and stock returns are negatively related), and meanwhile, for α_1 in Eq. (1), along with β_1 and β_2 in Eq. (2), (3), and (4), together presenting the lagged impact of magnitude of SiIS on conditional volatility (the indirect channel), we expect α_1 and β_1 to have the same sign, and α_1 and β_2 to have different signs in bull regimes (i.e., that SiIS and stock returns are positively related), while α_1 and β_1 to have different signs, and α_1 and β_2 to have the same sign in bear regimes (i.e., that SiIS and stock returns are negatively related). Finally, to show the predictability of investor sentiment to stock returns, we also estimate a series of base specifications excluding all sentiment variables in Eq. (1), (2), (3), and (4).

4.2 Market separation

Studies concerning market separation in the US stock market mainly follow the economic cycle reported by the National Bureau of Economic Research (NBER) that sets the separation principles based on economic indicators such as real GDP, employment, and wholesale-retail sales (Garcia, 2013; McLean and Zhao, 2014; Erdogan et al., 2015; Savaser and Şişli-Ciamarra, 2017). The NBER separation, however, is untenable in our study because first, it is based on the real economy rather than the stock market and recall that the onset of a bullish (bearish) stock market is regarded as a *leading* indicator of economic expansion (recession), and second, the NBER only reflects the US business cycles and so may be inaccurate for other markets, despite the vital role of the US economy and the contagion in real economy.

We employ ‘bull’ and ‘bear’ regimes to substitute economic ‘expansion’ and ‘recession’, respectively. Studies link bull and bear regimes to the periods when stock prices generally increase and decrease (Chauvet and Potter, 2000). We borrow this definition and follow the segregation method proposed by Pagan and Sossounov (2003). Note that Pagan and Sossounov (2003) construct bull and bear regimes from monthly observations while we use daily ones, hence we carry out some minor but necessary modifications in the window length. To elucidate, we do not remove any outliers in the sample and set the window size as 168 trading days, equivalent to eight months set in Pagan and Sossounov (2003). The minimum time for one regime is 84 trading days (i.e., four months) and the minimum time for one cycle is 336 trading days (i.e., 16 months). The settlement of the minimum horizon for each regime helps to avoid frequent conversions between two regimes so that each regime would have a combination of some longer periods instead of numerous shorter periods. Moreover, it allows minor corrections and rebounds within each regime, which are often observed in real markets and meanwhile prevents mistakenly regarding these as new bull or bear regimes. However, to account for some dramatic fluctuations, if the stock price grows (drops) at least by 20% in total within a window of 21 trading days (i.e., one month), the minimum time for one phase is superseded.[10]

5. Empirical results

We first compare results from GARCH-M, GJR-GARCH-M, and EGARCH-M models, identifying EGARCH-M to be most suitable model. We note that these preliminary results from Eq. (1), (2), (3), and (4) above generate rather high and significant Ljung−Box *Q*-statistics (see, Table 2 for brief regression results) in most sample markets, thus suggesting serial correlation in the residuals. To avoid inefficient estimates, we modify our mean equation Eq. (1) by controlling for lagged values of stock returns indicated by the partial correlation. We add as few lags as

[10] In Appendix C, we provide further discussion of the market separation approach employed, along with a table of summary statistics for stock returns and SiIS in bull and bear regimes and a table of plots of market indices with bull and bear periods identified for all the markets in our sample.

possible in order not to lose many observations, and our subsequent discussion is based on the refined specification following:

$$R_t - R_t^f = \alpha_0 + \alpha_1 h_t + \alpha_2 sent_t + \sum_{n=1}^{N} \gamma_n \left(R_{t-k} - R_{t-k}^f\right) + \varepsilon_t. \quad (5)$$

<Table 2>

The unconditional test on the entire sample in Subsection 5.1 reveals that (i) investor sentiment has explanatory power to stock returns as its addition enhances the model predictability; (ii) for the direct channel, SiIS positively affect the stock returns; (iii) for the indirect channel, optimistic (pessimistic) SiIS cause upward (downward) revisions in conditional volatility and then higher (lower) stock returns due to the revealed positive mean-variance relation; (iv) the direct channel overall has a wider impact than the indirect one, but the latter can play a role; and (v) investor sentiment does not affect the observed mean-variance relation and the leverage effect. We then replicate the tests conditional on different market regimes in Subsection 5.2. Results of bull/bear segregation show that optimistic (pessimistic) SiIS increase (decrease) stock returns via both channels in bull regimes but decrease (increase) stock returns via both channels in bear regimes. Subsection 5.3 conducts three robustness tests.

5.1 Unconditional results

Results of market-by-market specifications provide general evidence on the significance of SiIS in explaining stock returns. We only tabulate detailed results of the refined EGARCH-M model regression in Table 3 as it best fits the data, as supported by a comparison of log-likelihood function (LLF) values across models.

5.1.1 Direct channel

Table 3 confirms investor sentiment to be an important explanator of stock returns given its addition enhances model fit as evidenced by higher LLF values (with only one trivial exception: Russia). The SiIS exert significant impact on 29 sample markets, with 21 (eight) presenting a positive (negative) relation.[11] For instance, the estimations for China and France signify that a 1% optimistic (pessimistic) SiIS increases (decreases) daily returns by 0.00163% in China but decreases (increases) daily returns by 0.00073% in France. The results seem to be of limited economic significance, but since SiIS are volatile in nature (see, Table 1), the real impact can be significant. In China and France, a one standard deviation increase in daily SiIS results in a change in daily stock returns by 0.26587% (= 163.1107% × 0.00163) and –0.06473% (= 88.6778% × –0.00074), respectively, while a two standard deviation increase in SiIS (i.e., a large shock), leads to daily stock returns changes of 0.53174% (= 2 × 163.1107% × 0.00163) and –0.12947% (= 2 × 88.6778% × –0.00073), respectively.

<Table 3>

Our finding of a negative relation (α_2 = –0.00033) between SiIS and stock returns in the US is inconsistent with LJI reporting a positive relation, i.e., 0.182, 0.170, and 0.167 for DJIA, S&P500, and NASDAQ, respectively (Table 2, p. 2290). Three main reasons may explain the inconsistency: (i) the sentiment proxy, (ii) data frequency, and (iii) the sample period. For (i), as discussed in Subsection 3.2, Investor Intelligence used in LJI might be thought to proxy institutional, instead of individual, investor sentiment, because it is based on opinions from retired or current market *professionals* (Brown and Cliff, 2005; Wang 2018b & 2020). In contrast, turnover ratio used here, mainly captures individual investor sentiment, with Schmeling (2007) suggesting institutional and individual investor sentiment represent '*smart money*' and '*noise trader risk*', respectively (p. 143). For (ii) and (iii), we conduct a further test on the US by applying a weekly interval and tailoring

[11] In our empirical design for the direct channel, we check a concurrent relation between SiIS and stock returns, which is different from some other papers investigating an intertemporal relation (Schmeling, 2009; Bathia and Bredin, 2013). Therefore, our finding that half our sample markets show a positive relation is not necessarily at odds with other studies reporting a negative sentiment-return relation. In an additional set of tests, we follow Schmeling (2009), among others, by checking an intertemporal relation between investor sentiment and stock returns. In particular, we use turnover, rather than SiIS, as the sentiment proxy, and we only control for the dividend yield and the detrended short-term interest rate due to the data frequency. We find a negative sentiment-return relation in most sample markets, though the negative relation begins to emerge at different forecast horizons.

our sample period from 06 January 1976 to 10 October 1995.[12] The untabulated result shows a significant, positive relation ($\alpha_2 = 0.00083$), in line with LJI, suggesting differences in findings across the two studies are more to do with data frequency and sample period, than sentiment proxy.

5.1.2 Indirect channel

As discussed in Section 2, the indirect channel involves two steps: (i) investor sentiment affects conditional volatility, and (ii) conditional volatility affects returns. Looking at the first step, the magnitude of SiIS has a significant impact on the formation of conditional volatility. Optimistic SiIS cause significant upward revisions in 17 markets, e.g., France ($\beta_1 = 0.01630$) and the US ($\beta_1 = 0.01043$), while no significant downward revision is found following optimistic SiIS. Pessimistic SiIS cause significant downward revisions in eight stock markets, e.g., Austria ($\beta_2 = -0.01731$) and South Korea ($\beta_2 = -0.00536$). Hence, a higher presence of sentiment investors in the market, driven by optimism, is likely to cause stock markets to fluctuate more. Hence, stock markets subject to greater noise trader risk tend to exhibit greater volatility, while those with lower noise traders participation tend to be less volatile, thus supporting DSSW, Sias et al. (1995), Brown (1999), Baker and Stein (2004), Baker and Wurgler (2006 & 2007), etc.

As the second step in the indirect channel, the estimated α_1 in Eq. (5) is positive in most markets. Hence, the risk-return tradeoff is positive, as theorized in traditional asset pricing models, with high (low) risk exposure generating high (low) returns (Merton, 1980; Campbell and Hentschel, 1992; Scruggs, 1998; Ludvigson and Ng, 2007; Rossi and Timmermann, 2015). While the tradeoff is insignificant in many markets, it is partially consistent with prior literature reporting insignificant relation between conditional returns and conditional volatility. Reviewing US studies over the past 50 to 75 years, Lundblad (2007) reveals that the empirical evidence of the risk-return tradeoff '*is ambiguous at best*' (p. 146, see, also, Baillie and DeGennaro, 1990; Lucca and Moench,

[12] The sample period in LJI is from 05 January 1973 to 06 October 1995 while our comparable sample starts in 1976 due to data availability. Overall, our sample period is very close to LJI's.

2015). While overall, the indirect channel provides a relatively weaker influence on the sentiment-return relation then the direct channel, for several markets the indirect one is in fact the leading channel. For example, in the Belgium, South Africa, and UK stock markets, while investor sentiment does not affect stock returns via the direct channel, it does so via the indirect one: Optimistic SiIS can upward shift conditional volatility in Belgium and the UK, leading to higher stock returns, and pessimistic SiIS can downward shift conditional volatility in South Africa, leading to lower stock returns. This finding validates to our research design in which we differentiate between direct and indirect channels: Testing the direct channel only can be misleading, as it neglects the sentiment impact on stock returns via the indirect channel.[13]

5.1.3 Supplementary findings

Table 3 also reveals two interesting findings in addition to the sentiment-return relation. First, the inclusion of investor sentiment does not much distort the mean-variance relation presented in the base model. Second, the incorporation of investor sentiment does not distort the leverage effect. Column (II) of Table 3 shows that our sample markets consistently show the leverage effect, as presented in the base model of Column (I).

5.2 Conditional results

In this subsection we test the impact of investor sentiment on stock returns separately over bull and bear regimes based on the refined EGARCH-M model. Results for both the direct and indirect channels are reported in Table 4.

5.2.1 Direct channel

In the direct channel, SiIS impact stock returns positively over bull regimes but negatively over bear regimes in most markets. Thus, we find support Hypothesis 1. In the UK, for example, the

[13] We also replicate our tests on cross-sectional analyses including small/large and growth/value stocks. Results show that investor sentiment can widely affect returns of stocks of different types. We do not report the results here for the sake of brevity but they are available at shorturl.at/oASV4.

estimations are 0.00028 and –0.00050 in bull and bear regimes, respectively, signifying that an increase (a decrease) in daily SiIS leads to higher (lower) daily returns in bull regimes, but lower (higher) daily returns in bear regimes. For bull regimes, the positive relation between SiIS and stock returns, stemming from (i) optimistic SiIS via the hold-more effect, (ii) pessimistic SiIS via the hold-more effect, and (iii) pessimistic SiIS via the price-pressure effect, dominates the negative relation stemming from optimistic shifts via the price-pressure effect. For bear regimes, the negative relation between SiIS and stock returns stemming from (i) optimistic SiIS via the hold-more effect, (ii) pessimistic SiIS via the hold-more effect, and (iii) optimistic SiIS via the price-pressure effect, dominates the positive relation stemming from pessimistic SiIS via the price-pressure effect. In both regimes, the price-pressure effect is dominated by other three mechanisms.

Table 4 also reports cross-subsample differences in Column (III) that are positive for the direct channel in most markets, further supporting Hypothesis 1. While there are a small number of stock markets (e.g., Canada, France, and the US) where a conditional sentiment impact is not evidenced by a change in sign across bull and bear coefficients, in most cases the sentiment-return relation is statistically more positive (negative) over bull (bear) regimes (see Column (III)) thus still supporting a conditional sentiment impact. For instance, the estimations are –0.00019 and –0.00121 over bull and bear regimes in Canada, respectively, i.e., a consistent negative impact across regimes, but the bull/bear difference is significantly positive, implying a stronger negative impact in bear regimes, in line with most sample markets. Even in such markets, then, the impact of investor sentiment is not constant across bull and bear regimes, thus supporting a form of conditional impact.

<Table 4>

We only find the opposite pattern, i.e., a significantly negative cross-subsample spread, in one out of 40 markets: In China, investor sentiment is positively related to returns across both regimes, with a statistically significant bull/bear difference of –0.00146 revealing a stronger positive impact of investor sentiment on stock market returns in bear than in bull regimes. Such trivial[14] cases, however, do not weaken the validity of Hypothesis 1. It would be extraordinary to obtain perfectly consistent results in a global examination of the impact of investor sentiment, which after all, has been shown to be influenced by various factors such as composition of investor base, culture, and market integrity. Hence, with only one market demonstrating the opposite pattern, we regard our results to be robust and remarkably consistent in this global context.

We conjecture that factors such as culture, market integrity, and market composition might explain the trivial exception in the case of China. To elucidate, a negative (positive) estimation of SiIS in bull (bear) regimes implies a much stronger price-pressure effect caused by optimistic (pessimistic) SiIS so that it drives the net sentiment-return relation to be negative (positive). From DSSW, the price-pressure effect follows $\frac{\mu\rho^*}{r}$, where μ is the proportion of noise traders; ρ^* is the mean misperception measuring noise traders' average bullishness; and r is the fixed real dividend. The price-pressure effect, therefore, is subject to (i) the proportion of noise traders (μ), and (ii) the degree of their bullishness (ρ^*). Indeed, China has a relatively lower level of institutional investors accounting for around 14.3% over 2004 to 2013 (Dyck et al., 2019), indicating a relatively high level of noise traders in the Chinese stock market. Also, Schmeling (2009) documents that sentiment impact tends to be stronger in markets with collectivistic culture and a low level of market integrity. China, as an emerging market, has collectivistic culture leading to overreaction and a relative lower level of market integrity.[15] We find support for this conjecture regardless of

[14] By which we mean both low in frequency and low in statistical significance (10% level only).

[15] We are grateful to Prof. Geert Hofstede for making the cultural dimension data available at https://www.hofstede-insights.com. Hofstede et al. (2010) points out that the culture of a market can be defined by six dimensions including individualism (IDV), the uncertainty avoidance index (UAI), masculinity (MAS), the power distance index (PDI), long-term orientation (LTO), and indulgence (IDG). Individualism (IDV) and collectivism (COL) are distinguished as follows: Individuals in high IDV cultures tend to view themselves as autonomous and independent, while those in high COL cultures tend to view themselves more connected with others (Markus and Kitayama, 1991), and thus predicts elevated herding behaviors (Beckmann et al., 2008), meaning that investors in COL cultures tend to trade in concert and induce overreaction. The IDV value ranges from 0 to 100, with 0 denoting the highest level of COL while 100 denoting the highest level of IDV. In our sample markets, the IDV value ranges from 13 (Colombia) to 91 (the US). The IDV value for China is 20, suggesting collectivistic culture.

statistical significance: Of the three markets (Brazil, Chile, and Taiwan) with a non-significant negative cross-subsample difference, all three satisfy (i) and (ii). For example, institutional investors account for 22.5% (2004–2013), 6.1% (2007–2013), and 14.7% (2004–2013) in Brazil, Chile, and Taiwan, respectively, implying a high participation of noise traders in these three markets (Dyck et al., 2019). Also, they are emerging markets, with IDV values of 38, 23, and 17, separately, denoting a collectivistic culture.

To explore this further, following Wang et al. (2021), we examine formally the influence of potential factors on the impact of investor sentiment.[16] We store the significant, estimated bull/bear differences as reported in Table 4 and multiple them by each market's standard deviation to ensure comparability across markets. We then regress the estimates on a series of factors as reported in Wang et al. (2021) and Dyck et al. (2019). In particular, in addition to individualism (IDV) as mentioned above, we also examine five other cultural dimensions including uncertainty avoidance index (UAI), masculinity (MAS), power distance index (PDI), long-term orientation (LTO), and indulgence (IDG).[17] For market integrity, we adopt the following four measures, anti-director rights (ADR), efficiency of judicial system (EJS), government corruption (GC), accounting standard (AS). In addition, we employ the proportion of institutional investors (INS) as an indicator for market composition.

<Table 5>

Results in Table 5 do not provide a great deal further insight. Only one factor, IDG, has significant predictive ability to explain bull/bear differences. Wang et al. (2021) argue that in high IDG markets investors are more prone to engage with stock trading, thereby bringing irrationalities into stock markets. This is in line with our previous discussion that high IDG could lead to the higher

[16] We thank the reviewers for their comments on a cross-market test of the influence of investor sentiment on stock market returns.

[17] See, Wang et al. (2021) for detailed discussion of the potential influence of each cultural dimension on the impact of investor sentiment on stock market returns.

proportion of noise traders (μ) and stronger misperception (ρ^*) and hence to a stronger price-pressure effect. However, a one-unit increase (decrease) in IDG would merely lead to a 0.00003% decrease (increase) in the bull/bear difference and even a one standard deviation increase (decrease) only produces a 0.00060% decrease (increase) in the bull/bear difference. The economic significance of IDG, therefore, is rather limited. All other indicators, including IDV, ADR, EJS, GC, AS, and INS noted above, fail to significantly explain the differences across bull and bear regimes, further supporting the conclusion that cross-market differences are rather limited when allowing for market conditions and estimation specifications.[18]

5.2.2 Indirect channel

In contrast to the direct channel, the indirect channel exhibits both conditional and unconditional features. Optimistic (pessimistic) SiIS invariably cause upward (downward) revisions in conditional volatility in both regimes. However, given the opposite estimated signs of conditional volatility in the mean equation (positive in bull regimes, negative in bear regimes), bearing high risk is rewarded in bull regimes (i.e., a positive mean-variance relation) but penalized in bear regimes (i.e., a negative mean-variance relation). As a result, optimistic SiIS lead to higher returns in bull regimes but lower returns in bear regimes by shifting conditional volatility upward, while pessimistic SiIS result in lower returns in bull regimes but higher returns in bear regimes by

[18] In examining determinants of the impact of investor sentiment on the stock market returns, the empirical approach in studies such as Schmeling (2009), Wang et al. (2021), and Wang and Duxbury (2021) is to separate sample markets into two groups based on the value of each examined determinant (such as individualism and government corruption) and to test the impact of investor sentiment on stock market returns in the two groups. For example, based on individualism, one of the most important cultural dimensions, stock markets are classified as individualistic markets and collectivistic markets, and regressions are run for each group separately to reveal difference in the sentiment impact. Note, however, that such a design relies on panel-level data, but in our main empirical design we use GARCH-family models and the combination of GARCH models and panel data requires a few strong assumptions that negate their use here (see, Lee, 2010). For example, the mean equation assumes no autocorrelations in the disturbance term but in our results, most markets present a persistence process in residuals as reported in Table 2. Also, a consistent balanced dataset would be required for panel GARCH estimations (Valera et al., 2017) but, as shown in Table 1, our sample markets have different starting dates. While some papers such as Schmeling (2009) and Wang et al. (2021) document that the impact of investor sentiment on stock market returns is subject to a wide range of drivers such as cultural dimensions, market integrity, education, and market participation, our results show that with clearly defined market regimes and specifications, the impact can be consistent across markets.

shifting conditional volatility downward. Optimistic (pessimistic) SiIS tend to consistently cause upward (downward) revisions in conditional volatility across bull and bear regimes. However, overall, the impact of the indirect channel is rather limited compared with the direct one, mainly due to the restricted impact of investor sentiment on conditional volatility and the insignificant mean-variance relation.

Looking at the market-by-market results, we can classify the conditional impact of the indirect channel into three different tiers. We classify as the strongest tier, those stock markets exhibiting a significant positive relation over bull regimes and a significant negative relation over the bear regimes, regardless of optimistic or pessimistic SiIS. Such markets include Belgium and France. In a weaker second tier, some stock markets also exhibit a significant positive relation over bull regimes and a significant negative relation over the bear regimes, but the relationship is subject to the direction of SiIS (i.e., optimistic, or pessimistic). This second tier has two sub-patterns. For the first sub-pattern, optimistic SiIS can upward shape conditional volatility that finally leads to increased returns in bull regimes but decreased returns in bear regimes (hence a conditional impact as explained above). While pessimistic SiIS only affect conditional volatility in bull regimes but not in bear regimes, this still represents a form of conditional impact: For pessimistic SiIS, there is a negative sentiment-return relation in bull regimes but no relation in bear regimes. Examples here include the Australia and UK markets. Under the second sub-pattern, for optimistic SiIS there is a positive sentiment-return relation in bull regimes while a negative relation in bear regimes (hence a conditional impact); however, pessimistic SiIS do not significantly shape conditional volatility (hence no conditional impact). Examples here include the US and Indonesia stock markets. In other markets, such as Czech Republic and Singapore, the indirect channel only holds predictability in one regime but not the other, and we regard this as the weakest (third) tier of the conditional impact. As with the direct channel, only one market, in this case India, supports a significant, opposite impact of the indirect channel where optimistic (pessimistic) SiIS lead to lower (higher) returns in bull regimes, while pessimistic SiIS lead to lower returns in bear regimes (but not for optimistic SiIS). With several tiers, our results overall reveal great consistency in the conditional impact of the indirect channel across markets.

As before, there are cases where the indirect channel appears to exert less impact than the direct channel due to the insignificant estimates, either in the first (sentiment-volatility) or the second (mean-variance) steps, in a number of cases. However, similar to our discussion above on the unconditional results, for several markets where investor sentiment does not affect stock returns via the direct channel, we find a significant impact for the indirect one. Examples here include Australia, Brazil, and Spain. In such markets, no sentiment impact on stock returns is detected for the direct channel, but during bull regimes, optimistic and pessimistic SiIS can eventually lead to high and low stock returns, respectively, via the indirect channel. This serves to highlight the necessity of distinguishing the indirect channel from the direct channel.

The observed conditional impact indicates that in bull regimes the space created by noise traders' optimism is substantial to offset their poor market timing, but such space created by their pessimism cannot cover their poor market timing. By contrast, the interaction between the create-space effect and the Friedman effect is reversed in bear regimes. We hence document that neither the Friedman effect nor the create-space effect prevails in general, rather one dominates the other dependent on SiIS and market regimes, thus confirming Hypothesis 2. In particular, the positive relation, stemming from the Friedman effect via pessimistic SiIS and the create-space effect via optimistic SiIS, is stronger than the negative relation, stemming from the Friedman effect via optimistic SiIS and the create-space effect via pessimistic SiIS, in bull regimes, but weaker in bear regimes.

Overall, the market regime plays an important role in the sentiment-return relation via both channels. Combining the two channels produces a consistent influence pattern: In bull regimes, SiIS and stock returns are positively related, while in bear regimes they are negatively related. Our reported unconditional result in Table 3 offers a general picture of the two-channel mechanism for the impact of investor sentiment on stock returns, while the conditional result provides a more nuanced story. As we see from the conditional result, the sentiment-return relation is subject to market regimes (i.e., bull or bear), and so the unconditional result represents a net outcome of bull and bear regimes. The perceived differences, therefore, in the unconditional results across markets reflect in part differences in bull and bear regimes across the markets over our sample period (Appendix C).

5.2.3 Supplementary findings

The mean-variance relation and the leverage effect also exhibit conditional effects over bull and bear regimes as revealed in Table 4. The notion that bearing risk is rewarded in bull regimes but penalized in bear regimes, finds strong support in Yu and Yuan (2011) and Chung et al. (2012). Yu and Yuan (2011) document the risk-return tradeoff over low-sentiment periods, not over high-sentiment periods. Chung et al. (2012) shows that low sentiment appears in economic expansions and high sentiment appears in economic recessions. Together, these papers signify that the risk-return tradeoff presents in economic expansions, in accordance with our finding that bull regimes show a positive mean-variance relation. In addition, the negative mean-variance relation in bear regimes obtains support from Mayfield (2004) and Lundblad (2007) documenting that the risk-return tradeoff is less pronounced during recessions.

Moreover, the leverage effect is much stronger in bear than bull regimes. All markets in bear regimes exhibit a significant leverage effect, while this number drops in bull regimes, which is implicitly supported by Engle and Ng (1993) who find that the leverage effect is more '*dramatic*' (p. 1776) in Japanese stock markets over 1980–1988 than for the same period excluding the October 1987 crash.

5.3 Robustness tests

We conduct three robustness tests in this subsection. First, we select another sentiment proxy, trading volume, to replace turnover ratio. Second, following LJI, we control for the January effect and the October effect by incorporating January and October dummy variables into Eq. (5).[19] Third, in an examination of the global financial crisis (GFC) of 2007–2009, Baur (2012) adopts a global market index to identify the start date and end date of the GFC for all sample markets. Following this, we use the DataStream global market index to re-split our sample. Summary results, reported in Table 6, show highly consistent results; notably, SiIS and stock returns are positively related in bull regimes, but negatively related in bear regimes. Our results are, therefore, robust to the use of an alternative sentiment proxy and alternative regime splits.

<Table 6>

6. A secondary conditional test

In addition to the bull/bear market separation shown above, prior literature also applies up/down sample splits following Cooper et al. (2004). The major difference lies in the fact that the former corresponds to economic expansion and recession defined by the NBER since it describes an *index movement trend*, i.e., growth or decline, while the latter depicts a *relative index level* between the current period and the specific-time-lagged period. We employ one- and three-year lagged price index as reference windows and the up (down) state is defined when the one- or three-year lagged market return is nonnegative (negative).[20]

Results in Table 7 are more mixed, and the conditional impact of investor sentiment reported in Subsection 5.2 is not evident in this analysis. In Austria, for example, the estimations for SiIS are –0.00023 (0.00038) and 0.00055 (0.00027) in up and down states, , respectively, when the market state is identified based on one-year (three-year) lagged index levels, different from the results

[19] Separately controlling for the January effect and the October effect does not affect our results.

[20] We also apply half- and two-year windows. Results are largely consistent with our one- and three-year windows.

based on bull/bear regimes (see, Table 3). The inconsistency is also present in the indirect channel, implying that the reported conditional sentiment-return relation is subject to the classification criteria.

<Table 7>

In an interesting way, however, we note that the impact of investor sentiment seems to be more prevalent in up than down states. In up states, there are 29 and 31 stock markets with a significant impact in the direct channel for the one- and three-year separation, respectively, more than the number of markets in down states (18 and 20, respectively). The same is also found for the indirect channel, which can be regarded as another form of the conditional impact of investor sentiment. Since the impact of investor sentiment on stock returns is transmitted and realized by investors' noise trading (Black, 1986; Baker and Wurgler, 2006; Li and Luo, 2016), we argue that in addition to index movement trends (bull/bear) influencing the interaction between the four sentiment effects specified in the two channels (and thus both the magnitude and direction of the impact on returns), investors also take relative index levels (up/down) into account when making investment decisions, which in turn influences their willingness to trade and hence whether investor sentiment exerts significant influences on returns. This finding supports the argument that investors would prefer staying on the sidelines amid bad times (Antoniou et al., 2016).

7. Conclusion

DSSW discuss two channels, direct and indirect, and four specific effects whereby investor sentiment affects stock returns. While investor sentiment has been shown to have a robust, direct impact on stock returns, the scant literature systematically investigating both channels motivates this study. Extending the prior US-based study by LJI, we examine both direct and indirect channels in 40 global markets. Empirical analyses reveal that in the direct channel, optimistic (pessimistic) SiIS increase (decrease) stock returns, and in the indirect channel, optimistic (pessimistic) SiIS cause upward (downward) revisions in conditional volatility, and then higher (lower) stock returns due to the positive mean-variance relation. Although both channels can affect stock returns, the direct channel is the main driving force. While unconditional results offer a general picture of the two-channel mechanism for the impact of investor sentiment on stock returns, our conditional results provide a more nuanced story, with the sentiment-return relation subject to market regimes (i.e., bull or bear), suggesting heterogeneity across markets in unconditional results may in part reflect differences in bull and bear regimes across markets in the sample period. Conditional results are consistent across markets and the two channels conceptually provide a consistent finding: Optimistic (pessimistic) SiIS lead to higher (lower) stock returns in bull regimes, but lower (higher) stock returns in bear regimes.

Investors' behaviors vary with different market conditions, suggesting the impact of investor sentiment to be varying, too. Distinguishing the entire sample into bull/bear subsamples, we find that the reported sentiment-return relation is conditional on market regimes. In bull regimes, positive (negative) SiIS lead to higher (lower) stock returns in the direct channel and cause upward (downward) revisions in conditional volatility and then higher (lower) stock returns in the indirect channel, which is reversed in bear regimes. This finding is important in that most studies of the sentiment-return relation build upon (i) the theoretical underpinning of a positive concurrent sentiment-return relation and thus a negative intertemporal sentiment-return relation (Brown and Cliff, 2005), and (ii) a constant sentiment-return relation over the sample period. However, both appear not to hold when a conditional context is imposed and therefore it is crucial to distinguish the sentiment impact in different market conditions. While different segregation based on up/down states provides disparate results, as might be expected, by comparing the two sets of results, we argue that investors take both relative index levels and index movement trends into account when deciding investment strategies. The former determines noise traders' willingness to trade and whether they exert significant impact on stock returns, while the latter influences the interaction between the four effects modeled in DSSW and thus the magnitude and direction of the impact.

This paper suggests some potential research avenues. First, given our global perspective, we adopt turnover ratio (and trading volume by way of robustness tests) as the proxy for investor sentiment, because of general availability and applicability to all markets in our global sample (see, Subsection 3.2). We leave it to other studies to further explore the two-channel mechanism using alternative sentiment proxies from either the financial markets or social media and internet use, such as implied volatility index, Twitter, Bloomberg Social Velocity Monitor, Google Search Volume Index, etc. (see, Da et al., 2011 & 2015; Krystyniak and Liu, 2018; Karampatsas et al., 2019). While the use of such proxies would complement our global examination of the two-channel mechanism, they may only be valid for studies of single markets, or a small number of comparable markets, due to issues of data availability and the variable nature of social media and internet adoption across multiple markets. Second, based on our two sets of conditional tests, bull/bear and up/down, we argue that both relative index levels and index movement trends can influence individuals' investment behaviors. This line of reasoning would lend itself to experimental work (Duxbury, 2015a, 2015b), and we leave this endeavor to future studies.

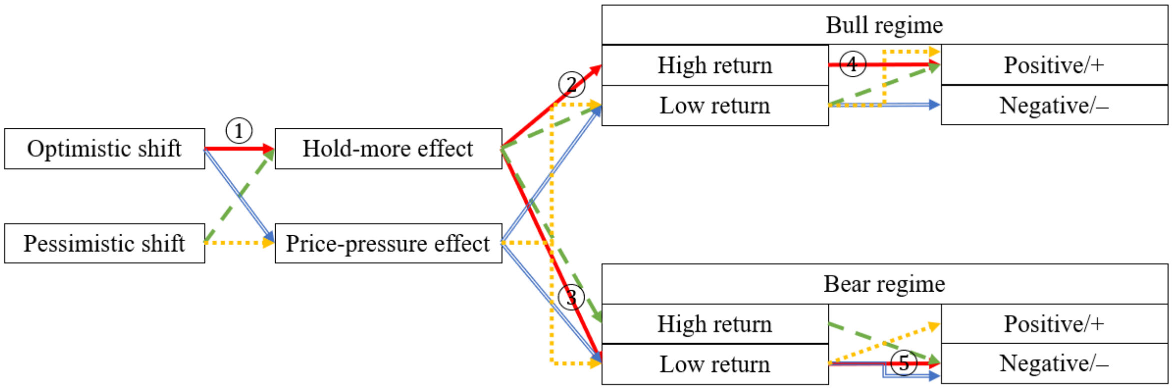
Appendix A. The two-channel influence mechanism in DSSW

As per DSSW, the influence mechanism of investor sentiment can be boiled down to two main channels. First, the direction of SiIS *directly* affects stock returns. Second, the magnitude of SiIS (i.e., the degree of misperceptions) *indirectly* affects stock returns by forming conditional volatility. Each channel has two specific effects: (i) the hold-more effect and the price-pressure effect for the direct channel, and (ii) the Friedman effect and the create-space effect for the indirect channel. The impact of investor sentiment on stock returns is a net outcome of the interaction between these two channels, or four effects. The figure below illustrates this DSSW influence mechanism under two market regimes.

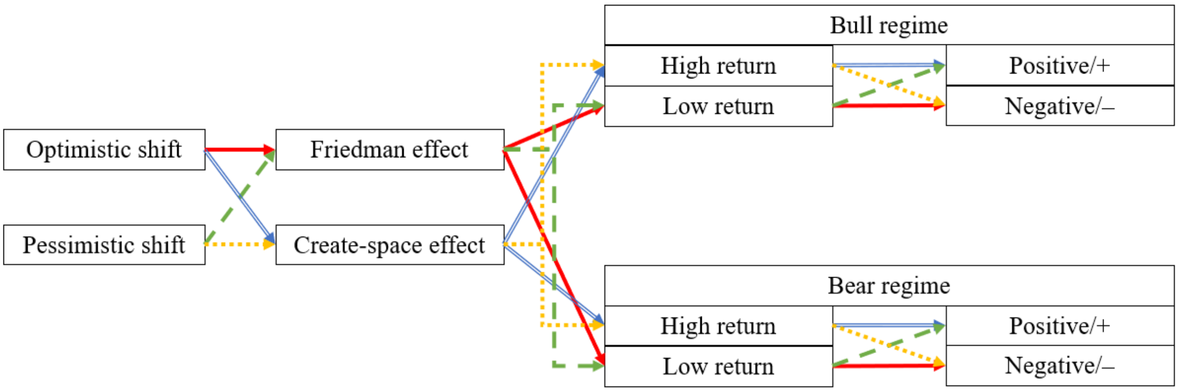
Panel A and B exhibit the direct channel and the indirect channel of the impact of investor sentiment on stock returns, respectively. The direct channel has two effects: the hold-more effect and the price-pressure effect. The indirect channel has two effects: the Friedman effect and the create-space effect. For each specific effect, we consider both optimistic and pessimistic SiIS and how the impact varies across bull and bear regimes. At the end of each route, we denote the relation between SiIS and stock returns (i.e., positive, or negative).

For a better understanding, within each panel, we use the same color to denote the same route. In Panel A, for example, the red route (including ① to ⑤) presents the influence of the hold-more effect, which is driven by optimistic SiIS in investor sentiment, on stock returns in bull and bear regimes. Particularly, the hold-more effect driven by the optimistic SiIS (①) would cause high (②) and low (③) returns and lead to a positive (④) and negative (⑤) SiIS-return relation in bull and bear regimes, respectively.

Panel A The direct channel



Panel B The indirect channel



Appendix B. Volatility models

Volatility prediction in asset pricing studies provokes various approaches for its measurement (for more discussion, see, Ghysels et al., 2005; Yu and Yuan, 2011). The GARCH-type models are extensively applied in modelling stock returns and conditional volatility. LJI employ the asymmetric GARCH-M model to capture the impact of investor sentiment on conditional volatility and the mean-variance relation. Note that, however, the mean-variance relation can be subject to volatility models employed (Turner et al., 1989; Harvey, 2001; Ghysels et al., 2005; Yu and Yuan, 2011; Wang, 2018b; Wang and Duxbury, 2021), indicating that different volatility models may generate different mean-variance relation. With attempts to identify the fittest model and to compare results across multiple models, we adopt three candidates from the GARCH family including GARCH-M, GJR-GARCH-M and EGARCH-M models.

We do not consider other methods measuring volatility like the rolling window (French et al., 1987) and the MIDAS (Ghysels et al., 2005). This is because, the indirect channel specified in DSSW requires sentiment-augmented volatility models. For rolling window and MIDAS models, however, conditional volatility is purely filtered from past stock return series, failing to present the relation between investor sentiment and conditional volatility. Meanwhile, the GARCH-M (Engle et al., 1987) models provide direct specifications to the measure mean-variance relation in the mean equation, corresponding to the second step of the indirect channel.

Appendix C. Descriptive statistics across bull and bear regimes

This appendix reports descriptive statistics of daily stock returns and SiIS over bull and bear regimes. The average excess returns are, by definition, higher in bull than bear markets. Excess returns in the majority of stock markets show higher turbulence in bear regimes, in line with some studies relying on excess volatility when defining crisis periods (Baur, 2012). The widely documented negative skewness of stock returns is mainly driven by bear markets while in bull markets the skewness tends to be positive, indicating the average returns to be lower in bear markets. Returns are leptokurtic in all markets and greater kurtosis statistics are seen in both regimes.

While it is expected to observe the maximum (minimum) daily return in bull (bear) regimes, some dramatic increases (decreases) actually occur in bear (bull) regimes. For example, the highest daily return in the US stock market, 11.52%, is observed on 13, October 2008, amid the global financial crises. As explained, the segregation principles following Pagan and Sossounov (2003) do not exclude all increasing (decreasing) movements in bear (bull) regimes. Some short-lived positive (negative) shocks can still be categorized in a bear (bull) regime especially when the data frequency is high (like daily in our paper) so that such drastic fluctuations cannot be offset over a shorter period.

The average shifts in investor sentiment, reflecting differences in investor sentiment between the initial and the final stages, can be positive, negative, or unchanged over bull and bear regimes, implying that there is no necessary relationship between market regimes and the accumulation of investors' optimism or pessimism. For example, the means of SiIS in Belgium in bull and bear regimes are −0.0010 and 0.0023, respectively. It signifies that optimism gradually fades along with bullish times but accumulates along with bearish times. In particular, at the start of the bull market, Belgian investors are of great optimism that drops at the end of the bull market—that is, the pre-bear market moment. However, the start of the bear market sees a higher degree of pessimism that reduces at the end of the bear market—that is, the pre-bull market moment. In addition, unlike returns, SiIS are not essentially more volatile in bear than bull regimes.

While there is common consensus that bull (bear) regimes denote a period of generally rising (falling) prices, there is no generally accepted formal definition/computation to identify bull and bear markets. We use a daily adaptation of the Pagan and Sossounov (2003) approach, in part because our GARCH-based empirical examination of the sentiment-return relation is based on daily data, but also because the hold-more effect and the price-pressure effect capture the transitory impact of investor sentiment (Lee et al., 2002). Our daily adaptation of the Pagan and Sossounov (2003) identifies the major bear markets during our sample period (the 1987 crash, the dotcom crash of 2000–2002, and the global financial crisis of 2007–2008), thus we are confident it meets our purpose.

To check the consistency of dating bull and bears regimes using higher or lower frequency data, we compare our dating of US bull/bear markets using daily data to that in Pagan and Sossounov (2003) using monthly data. Our daily identification of US bull/bear regimes for comparable periods is very similar to Pagan and Sossounov (2003), with the exception of 1990 and 1994. Looking at 1990, we find that the dates for highest and lowest values are in July and October, so the duration of the bear regime identified in Pagan and Sossounov (2003) is very brief. Specifically, the highest daily value, 302.89, is on 16 July 1990 and the lowest daily value, 245.83, is on 11 October 1990. Since the total number of trading days is 64, we regard it as a correction period in the bull regime and do not count it as a bear regime. The dating remains the same based on S&P 500 as employed in Pagan and Sossounov (2003), with the highest daily value, 368.95, on 16 July 1990 and the lowest daily value, 295.46, on 11 October 1990. If we look at S&P 500 monthly data, the highest value, 361.23, is on 31 May 1990, and the lowest value, 304.00, is on 31 October 1990, which spans five months and therefore can be regarded as a bear regime as per Pagan and Sossounov (2003). A similar situation arises for 1994: From January 1994 to June 1994, it can be classified as a bear regime under monthly frequency, but not under daily frequency (02 February 1994 – 11 May 1994).

If the bull/bear regime is long, then daily and monthly data frequencies generate similar separation results (in 1976–1978, 1980–1982, 1983–1984, where bear regimes were around one year), but if the bull/bear regime is short, daily and monthly data frequencies might produce slightly different results. A notable exception here is the 1987 crash, with associated dramatic market decline, which is identified under both approaches. As seen in the comparison of separation results based on different data frequency, the monthly interval in Pagan and Sossounov (2003) is dependent on the last trading day of that month and neglects the within-month price sequences. While different frequencies result in very similar results and all detect major bear times, we adopt a bull-bear separation based on daily data for consistency with the data used in the GARCH models employed in our main analyses.

Table Appendix C.1 Descriptive statistics of daily excess stock returns and SiIS across bull and bear regimes

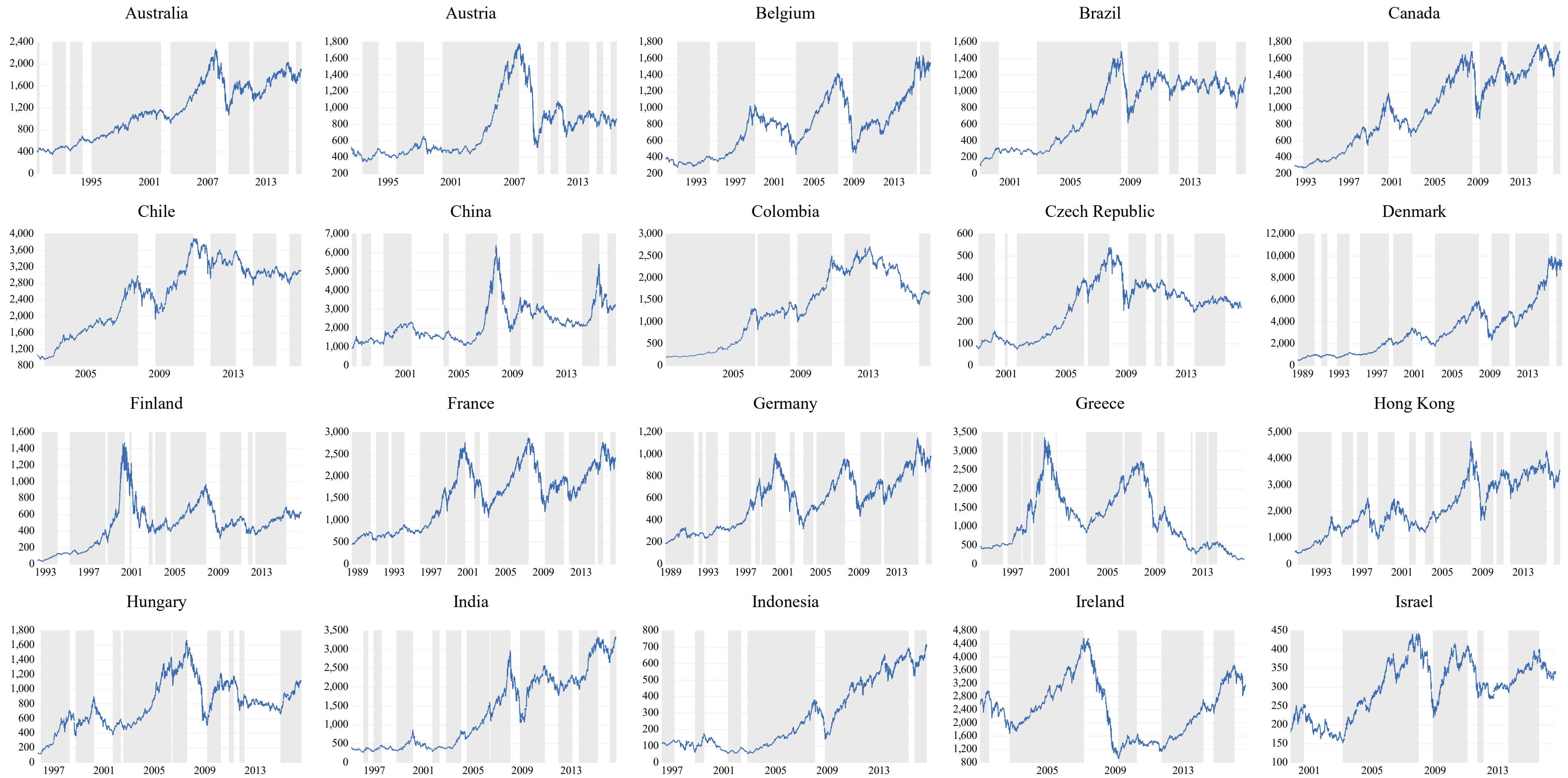
	Bull (I)											Bear (II)										
	Stock returns						SiIS				Obs.	Stock returns						SiIS				Obs.
Markets	*Mean*	*S.D*	*Skew.*	*Kurt.*	*Max.*	*Min.*	*Mean*	*S.D*	*Max.*	*Min.*		*Mean*	*S.D*	*Skew.*	*Kurt.*	*Max.*	*Min.*	*Mean*	*S.D*	*Max.*	*Min.*	
Australia	0.06	0.83	−0.16	3.42	5.92	−6.76	0.07	1.14	15.76	−15.98	5,560	−0.16	1.25	−0.32	4.85	5.70	−8.33	−0.06	1.09	6.60	−6.79	1,339
Austria	0.10	0.88	−0.18	3.98	4.79	−6.44	−0.02	0.90	10.29	−10.52	3,922	−0.19	1.43	−0.09	7.25	10.14	−8.75	0.13	0.90	6.99	−7.00	2,304
Belgium	0.10	0.94	0.30	5.81	8.58	−4.69	−0.10	0.50	7.83	−7.95	4,751	−0.15	1.25	−0.15	5.41	8.28	−7.84	0.23	0.52	4.91	−4.89	2,038
Brazil	0.15	1.49	1.20	18.02	21.49	−6.90	−0.02	0.73	13.79	−14.16	2,774	−0.18	1.50	−0.18	6.06	11.44	−9.50	0.29	0.83	17.64	−17.44	1,597
Canada	0.09	0.81	−0.14	3.67	5.13	−5.99	−0.26	0.76	5.49	−5.68	4,675	−0.17	1.36	−0.40	7.91	9.37	−9.14	0.89	0.91	6.24	−6.58	1,535
Chile	0.11	0.75	0.77	15.03	9.86	−4.99	−0.06	0.43	4.48	−5.89	2,577	−0.16	0.92	−0.51	4.89	5.02	−5.86	0.19	0.53	5.27	−5.38	997
China	0.25	1.57	−0.17	4.38	9.24	−9.03	2.32	0.18	13.66	−12.80	2,225	−0.23	1.75	−0.22	4.61	9.89	−8.92	−2.67	1.34	9.77	−10.87	2,537
Colombia	0.15	0.94	0.76	14.01	12.31	−6.18	−0.00	0.49	7.98	−7.83	2,752	−0.15	1.22	−0.66	9.86	7.99	−8.18	0.06	0.38	5.39	−5.19	1,065
Czech Republic	0.17	1.16	0.06	2.79	8.85	−5.86	−0.46	0.99	8.10	−6.53	2,817	−0.18	1.57	0.08	16.18	16.42	−13.26	0.76	0.74	8.90	−4.30	1,617
Denmark	0.14	0.94	0.10	3.27	6.23	−5.58	−0.02	0.97	19.58	−19.80	4,805	−0.19	1.35	−0.25	6.95	9.84	−10.93	0.19	0.82	14.47	−14.15	2,211
Finland	0.21	1.55	0.35	6.89	16.57	−9.11	0.13	1.86	25.07	−21.74	4,502	−0.28	2.25	−0.20	4.72	10.64	−16.69	−0.14	2.33	38.37	−40.81	2,068
France	0.11	1.07	−0.05	4.00	8.32	−6.95	−0.18	0.83	7.26	−6.00	4,998	−0.19	1.49	0.18	4.34	10.41	−8.10	0.53	1.00	6.56	−7.73	2,158
Germany	0.11	1.03	−0.36	6.34	5.68	−11.45	0.35	3.88	94.89	−91.22	4,951	−0.17	1.44	0.55	13.12	17.39	−8.90	−0.86	4.09	93.83	−95.32	2,194
Greece	0.26	1.58	0.31	3.66	9.68	−7.64	0.31	1.49	15.04	−15.64	2,826	−0.34	2.22	−0.16	7.24	13.26	−19.02	−0.30	1.19	16.47	−16.25	2,727
Hong Kong	0.17	1.32	0.90	10.85	16.78	−8.37	0.06	0.96	32.54	−41.57	4,360	−0.26	1.85	−0.28	6.27	14.39	−12.75	−0.12	0.61	6.58	−3.22	2,125
Hungary	0.18	1.54	−0.19	9.11	11.67	−16.48	−0.31	1.69	21.04	−21.18	3,161	−0.29	1.87	−0.13	8.25	14.03	−12.52	0.64	1.73	29.07	−29.53	2,071
India	0.22	1.40	0.47	7.95	16.26	−6.90	0.10	0.58	6.95	−5.55	3,133	−0.23	1.63	−0.57	5.99	9.09	−11.85	0.06	0.52	3.75	−5.07	2,204
Indonesia	0.17	1.57	0.73	9.67	15.15	−13.07	0.08	0.98	4.59	−3.09	3,704	−0.38	2.12	−0.27	4.45	11.81	−11.83	−0.17	0.58	3.27	−4.06	1,287
Ireland	0.13	1.08	−0.13	2.97	5.11	−6.05	−0.27	1.14	15.40	−15.39	2,428	−0.19	1.77	−0.44	5.54	9.52	−12.52	0.54	1.15	11.71	−12.55	1,533
Israel	0.10	1.06	−0.11	2.56	5.65	−7.73	−0.04	1.00	5.57	−5.94	2,657	−0.17	1.32	−0.39	3.35	7.10	−7.66	0.06	0.98	4.52	−5.93	1,480
Japan	0.13	1.14	0.04	2.95	7.37	−6.77	0.21	1.00	24.97	−9.34	3,080	−0.12	1.48	0.00	5.93	13.08	−9.38	−0.09	0.81	11.34	−11.30	3,091
Mexico	0.12	1.05	0.52	6.28	11.09	−5.08	0.05	0.62	6.57	−5.79	3,859	−0.17	1.44	0.00	5.27	8.84	−9.51	−0.11	0.62	8.76	−9.59	1,316
Netherlands	0.09	1.00	0.13	4.60	7.24	−5.41	−0.17	1.22	17.10	−18.64	5,731	−0.18	1.52	−0.33	6.09	9.73	−10.46	0.37	1.33	8.55	−13.75	2,042
New Zealand	0.06	0.70	0.59	11.16	8.84	−6.88	−0.07	1.17	24.02	−23.05	4,798	−0.12	1.02	−0.61	15.60	9.57	−12.02	0.21	1.98	45.84	−43.29	1,652
Norway	0.14	1.29	0.19	5.93	10.83	−11.05	−0.12	1.71	35.58	−36.71	5,711	−0.33	1.83	−1.01	10.74	10.78	−19.05	0.47	2.37	55.53	−54.46	1,977
Philippines	0.14	1.07	1.19	19.84	15.92	−7.33	0.20	0.35	4.28	−3.35	2,594	−0.22	1.30	−0.75	7.69	8.51	−10.63	−0.49	0.28	2.31	−3.80	1,233
Poland	0.11	1.36	0.17	3.67	7.94	−9.34	−0.01	0.62	7.97	−4.90	3,284	−0.22	1.65	−0.24	2.58	7.88	−9.46	0.01	0.59	5.25	−4.04	1,598
Portugal	0.13	0.86	−0.24	3.59	3.86	−6.59	0.54	1.14	15.90	−10.91	2,101	−0.15	1.33	0.04	5.90	9.95	−10.04	−0.61	1.59	35.22	−35.23	2,388
Russia	0.18	1.82	0.40	7.61	16.58	−11.43	−0.05	0.61	13.01	−12.61	3,440	−0.29	2.38	0.13	22.58	26.02	−18.03	0.21	0.06	5.35	−5.44	336
Singapore	0.13	0.99	0.38	4.22	7.06	−4.77	−0.09	0.72	7.42	−9.59	3,166	−0.15	1.29	−0.04	6.69	9.28	−8.21	0.15	0.54	4.13	−3.66	2,268
South Africa	0.12	1.09	0.15	2.18	5.84	−4.74	−0.11	0.78	7.76	−5.78	3,863	−0.22	1.36	−0.53	3.37	5.61	−8.07	0.58	1.03	9.76	−12.30	527
South Korea	0.19	1.72	0.69	5.47	12.05	−7.82	0.34	1.46	9.56	−11.28	3,790	−0.29	1.95	−0.37	4.05	9.03	−11.93	−0.69	1.58	27.35	−26.63	2,297
Spain	0.13	1.14	−0.30	5.24	6.12	−10.81	−0.20	1.24	16.50	−15.52	4,052	−0.16	1.53	0.28	4.38	12.47	−8.16	0.41	1.21	9.22	−10.27	2,196
Sweden	0.16	1.22	0.59	6.56	11.46	−8.11	−0.15	1.13	9.52	−10.67	5,131	−0.28	1.82	0.03	2.42	8.92	−8.16	0.48	1.34	18.14	−15.07	2,311
Switzerland	0.12	0.86	−0.16	6.22	6.64	−8.48	−0.19	0.87	14.09	−7.83	5,152	−0.17	1.35	−0.19	5.36	10.31	−8.90	0.53	0.98	4.85	−6.59	1,788
Taiwan	0.17	1.40	0.35	3.23	8.51	−6.85	1.19	1.66	8.34	−9.85	3,783	−0.24	1.77	−0.01	1.85	6.76	−9.80	−2.18	1.48	15.66	−9.52	2,422
Thailand	0.14	1.26	0.29	4.00	8.84	−5.50	−0.39	0.87	4.53	−4.51	1,938	−0.21	1.69	−1.13	17.15	12.44	−16.32	0.74	1.02	14.37	−6.34	907
Turkey	0.16	1.47	0.07	2.67	9.39	−6.00	−0.61	1.48	8.89	−8.34	1,668	−0.27	1.86	−0.05	4.64	12.38	−9.99	1.38	1.55	7.46	−6.86	889
UK	0.08	0.86	0.12	3.18	5.54	−4.31	−0.03	0.82	9.81	−4.55	5,490	−0.13	1.39	−0.38	7.48	9.26	−12.22	0.03	0.98	5.87	−9.20	2,008
US	0.07	0.91	−0.05	4.02	6.93	−6.80	−0.06	0.95	8.13	−9.58	8,197	−0.13	1.49	−0.78	17.63	11.52	−18.72	0.46	1.22	9.32	−12.80	2,064

(*continued*)

(*continued*)

This table displays summary statistics of daily excess stock returns and SiIS over bull and bear regimes in Column I and II, respectively, including the mean (*Mean*), the standard deviation (*S.D.*), the skewness (*Skew.*), the kurtosis (*Kurt.*), the maximum value (*Max.*), and the minimum value (*Min.*). For SiIS, the reported mean has been multiplied by 100. The segregation criterion borrows from Pagan and Sossounov (2003); however, we make minor but necessary modifications since Pagan and Sossounov (2003) adopt monthly observations while we employ daily ones.

Table Appendix C.2 Plots of market indices



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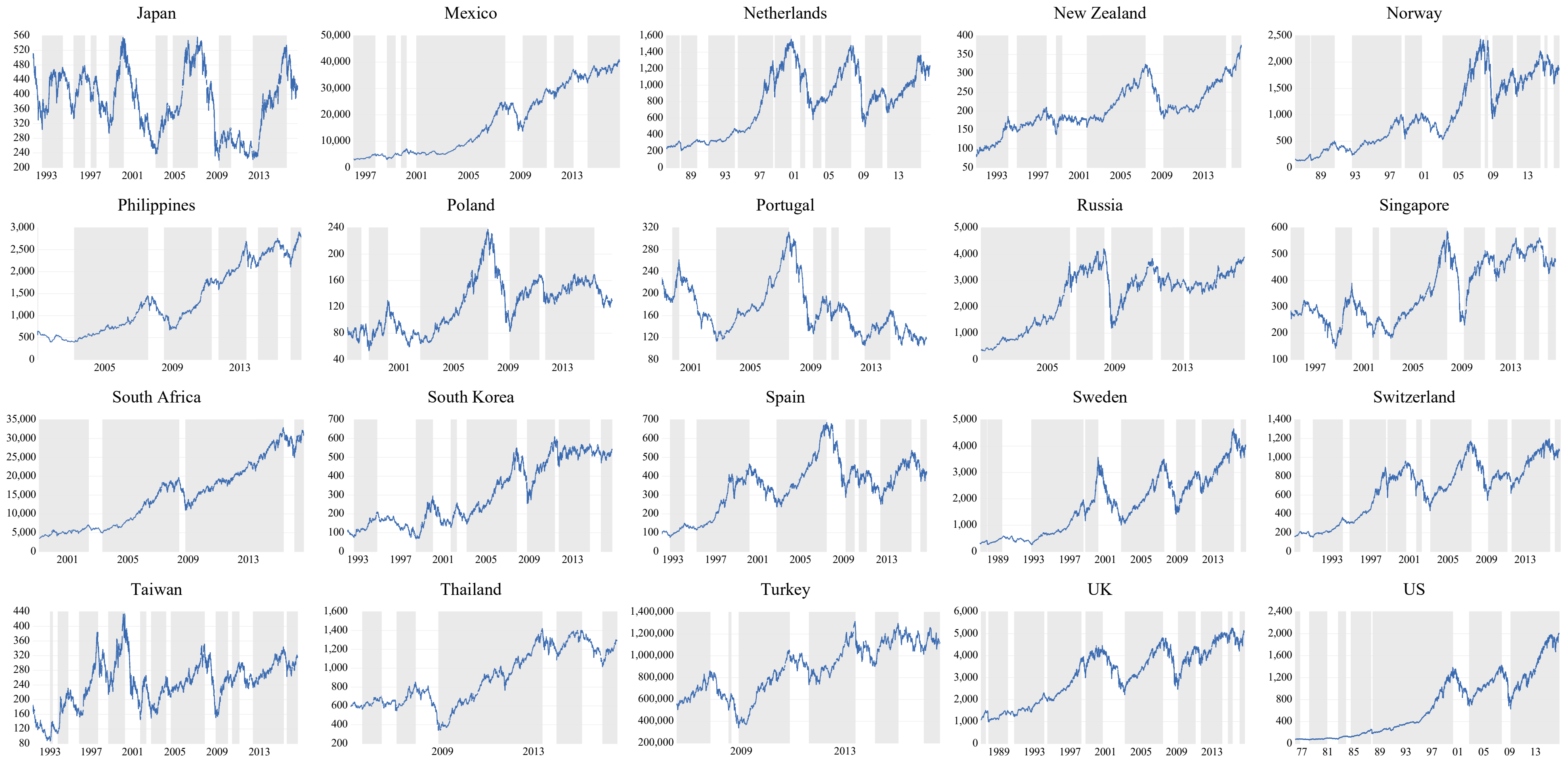
(*continued*)



This figure plots market indices for all sample markets. Shaded areas denote bull regimes.

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Table 1. Summary statistics of daily excess stock returns and shifts in investor sentiment

		Daily excess stock returns (I)						Shifts in investor sentiment (II)			
Market	**Starting**	***Mean***	***S.D***	***Skew.***	***Kurt.***	***Max.***	***Min.***	***Mean***	***S.D***	***Max.***	***Min.***
Australia*	02 June 1990	0.01	0.95	−0.37	5.49	5.92	−8.33	0.04	1.13	15.76	−15.98
Austria*	11 June 1991	0.01	1.10	−0.31	8.66	10.14	−8.75	0.02	0.90	10.29	−10.52
Belgium*	19 October 1989	0.02	1.06	−0.03	6.27	8.58	−7.84	0.01	0.51	7.83	−7.95
Brazil	04 January 1999	0.02	1.49	0.67	13.37	21.49	−9.50	0.05	0.77	17.64	−17.44
Canada*	03 January 1992	0.02	0.99	−0.51	9.62	9.37	−9.14	0.04	0.81	6.24	−6.58
Chile	09 May 2002	0.03	0.81	0.11	10.46	9.86	−5.86	0.02	0.46	5.27	−5.89
China	03 January 1997	0.03	1.67	−0.23	4.44	9.89	−9.03	0.04	1.63	13.66	−12.80
Colombia	03 January 2001	0.05	1.06	−0.12	12.45	12.31	−8.18	0.02	0.45	7.98	−7.83
Czech Republic	05 January 1998	0.03	1.35	−0.04	13.01	16.42	−13.26	0.02	0.90	8.90	−6.53
Denmark*	05 July 1988	0.04	1.10	−0.26	6.76	9.84	−10.93	0.04	0.93	19.58	−19.80
Finland*	02 April 1992	0.05	1.82	−0.13	6.57	16.57	−16.69	0.05	2.03	38.37	−40.81
France*	01 June 1988	0.02	1.22	−0.04	4.86	10.41	−8.10	0.03	0.89	7.26	−7.73
Germany*	14 June 1988	0.02	1.19	0.05	11.82	17.39	−11.45	–0.04	3.95	94.89	−95.32
Greece	12 April 1994	−0.02	1.92	−0.17	7.26	13.26	−19.02	0.03	1.36	16.47	−16.25
Hong Kong*	05 June 1990	0.03	1.52	0.10	9.13	16.78	−12.75	0.00	0.88	32.54	−41.57
Hungary	08 September 1995	0.03	1.67	−0.24	8.80	14.03	−16.48	–0.00	1.70	29.06	−29.53
India	03 January 1995	0.03	1.53	−0.14	6.98	16.26	−11.85	0.09	0.56	6.95	−5.55
Indonesia	26 March 1996	0.02	1.76	0.12	7.58	15.15	−13.07	0.01	0.56	4.59	−4.06
Ireland*	15 January 2001	0.01	1.39	−0.55	7.09	9.52	−12.52	0.04	1.15	15.40	−15.39
Israel*	02 November 1999	0.01	1.15	−0.31	3.30	7.10	−7.73	–0.01	0.99	5.57	−5.94
Japan*	11 October 1991	0.00	1.33	−0.06	5.59	13.07	−9.38	0.06	0.91	24.97	−11.30
Mexico	01 February 1996	0.03	1.18	0.14	6.48	11.09	−9.51	0.00	0.63	8.76	−9.59
Netherlands*	05 February 1986	0.02	1.17	−0.27	7.21	9.73	−10.46	–0.02	1.25	17.10	−18.64
New Zealand*	04 January 1990	0.01	0.81	−0.21	16.65	9.57	−12.02	0.01	1.45	45.84	−43.29
Norway*	03 January 1986	0.03	1.45	−0.53	10.23	10.83	−19.05	0.02	1.89	55.53	−54.46
Philippines	17 January 2001	0.03	1.16	0.23	14.33	15.92	−10.63	–0.02	0.33	4.28	−3.80
Poland	01 March 1997	0.00	1.47	−0.08	3.36	7.94	−9.46	–0.00	0.61	7.97	−4.90
Portugal*	05 January 1999	−0.01	1.14	−0.16	6.69	9.95	−10.04	–0.06	1.39	35.22	−35.23
Russia	29 January 2001	0.06	1.99	0.20	16.19	26.02	−18.03	–0.02	0.61	13.01	−12.61
Singapore*	04 January 1995	0.01	1.14	0.02	6.42	9.28	−8.21	0.02	0.65	7.42	−9.59
South Africa	02 February 1999	0.03	1.18	−0.21	3.09	5.84	−8.07	0.07	0.86	9.76	−12.30
South Korea	06 January 1992	0.02	1.82	0.17	5.02	12.05	−11.93	–0.02	1.50	27.35	−26.63
Spain*	20 December 1991	0.02	1.30	−0.06	5.10	12.47	−10.81	0.02	1.23	16.50	−15.52
Sweden*	05 January 1987	0.03	1.45	0.10	4.79	11.46	−8.16	0.04	1.20	18.14	−15.07
Switzerland*	18 January 1989	0.03	1.04	−0.37	7.34	10.31	−8.90	0.03	0.90	14.09	−7.83
Taiwan	01 May 1991	0.01	1.56	0.06	2.68	8.51	−9.80	–0.08	1.60	15.66	−9.85
Thailand	05 January 2005	0.03	1.42	−0.55	13.14	12.44	−16.32	–0.04	0.92	14.37	−6.34
Turkey	04 July 2006	0.01	1.63	−0.09	4.11	12.38	−9.99	0.09	1.50	8.89	−8.34
UK*	05 January 1987	0.01	1.07	−0.37	8.81	9.26	−12.22	–0.01	0.88	9.81	−9.20
US*	02 January 1976	0.03	1.07	−0.61	17.47	11.52	−18.72	0.06	1.01	9.32	−12.80

This table displays summary statistics of daily excess stock returns and SiIS over bull and bear regimes in Column I and II, respectively, including the mean (*Mean*), the standard deviation (*S.D.*), the skewness (*Skew.*), the kurtosis (*Kurt.*), the maximum value (*Max.*), and the minimum value (*Min.*). For SiIS, the reported mean has been multiplied by 100.

* Developed stock markets pursuant to the Morgan Stanley Capital International (MSCI).

Table 2. Counts from the GARCH-M, GJR-GARCH-M, and refined EGARCH-M models

Market	Base (I)					Sentiment-augmented GARCH-M model (II)												
	h		δ_2		LLF	*h*		*Sent*		*Opt*		*Pes*		δ_2		LLF		*Q*
	+	–	+	–	Max.	+	–	+	–	+	–	+	–	+	–	Max.	↑	Sig.
Panel A Count: the GARCH-M model																		
Africa	1	0			0	1	0	0	0	1	0	0	1			0	1	1
America	4	0			0	3	0	3	1	3	0	0	1			0	4	6
Asia-Pacific	2	0			0	6	0	9	0	3	3	2	3			0	11	8
Europe	7	0			0	8	0	10	5	7	2	0	9			0	18	16
Developed	8	0			0	11	0	9	5	8	2	1	8			0	19	18
Emerging	6	0			0	7	0	13	1	6	3	1	6			0	15	13
World	14	0			0	18	0	22	6	14	5	2	14			0	34	31
Panel B Count: the GJR-GARCH-M model																		
Africa	0	0	1	0	1	0	0	0	0	1	0	0	1	1	0	1	2	1
America	3	0	6	0	3	2	0	3	2	3	1	0	2	6	0	2	3	6
Asia-Pacific	2	0	12	0	5	4	0	9	0	6	1	0	3	12	0	6	12	9
Europe	1	0	21	0	8	1	0	12	3	7	0	0	6	21	0	7	22	18
Developed	3	0	22	0	15	3	0	8	5	9	0	0	8	22	0	4	21	20
Emerging	3	0	18	0	2	4	0	14	0	8	2	0	4	18	0	12	18	14
World	6	0	40	0	17	7	0	22	5	17	2	0	12	40	0	16	39	34
Panel C Count: the EGARCH-M model																		
Africa	0	0	0	1	0	0	0	0	0	1	0	0	1	0	1	0	1	1
America	3	0	0	6	3	3	0	3	2	2	0	0	0	0	6	4	6	6
Asia-Pacific	4	1	0	12	7	4	1	9	1	5	0	1	4	0	12	6	12	9
Europe	5	0	0	21	13	3	0	9	4	7	0	0	5	0	21	14	20	17
Developed	6	0	0	22	18	6	0	8	6	8	0	0	5	0	22	18	22	19
Emerging	6	1	0	18	5	4	1	13	1	7	0	1	5	0	18	6	17	14
World	12	1	0	40	23	10	1	21	7	15	0	1	10	0	40	24	39	33

This table reports the counts from GARCH-M, GJR-GARCH-M, and the EGARCH-M models. In particular, we report the number of positive (+) and negative (–) estimations for each estimated parameter that are significant at least at the 10% significance level. For LLF, we present the number of highest values across all GARCH models (Max.) and the number of increased LLF values after adding investor sentiment variables (↑). For *Q*-statistics, we present the number of significant statistics (Sig.).

Table 3. Results from the refined EGARCH-M model

Market	Base (I) *h*	Base (I) δ_2	Base (I) LLF	EGARCH-M (II) *h*	EGARCH-M (II) *Sent*	EGARCH-M (II) *Opt*	EGARCH-M (II) *Pes*	EGARCH-M (II) δ_2	EGARCH-M (II) LLF	EGARCH-M (II) *Q*
Panel A Market-by-market results										
Australia	2.33^{c}	–0.08^{a}	–8,458.34	2.46^{c}	–0.13^{c}	2.59	1.58	–0.08^{a}	–8,454.40	36.21
Austria	1.81	–0.07^{a}	–7,945.94	1.92	0.31^{a}	16.84^{b}	–17.31^{b}	–0.07^{a}	–7,937.82	36.16
Belgium	2.82^{c}	–0.09^{a}	–8,432.01	2.67^{c}	0.09	33.99^{c}	–21.46	–0.09^{a}	–8,429.79	33.51
Brazil	3.59^{b}	–0.06^{a}	–7,336.63	3.59^{b}	–0.04	2.40	–3.54	–0.06^{a}	–7,336.22	39.04
Canada	2.84^{c}	–0.07^{a}	–7,200.28	2.30	–0.35^{a}	22.79^{b}	–5.83	–0.07^{a}	–7,190.72	28.87
Chile	9.22^{a}	–0.09^{a}	–3,670.82	9.97^{a}	0.52^{b}	36.09^{b}	–6.36	–0.09^{a}	–3,664.34	35.10
China	4.60^{a}	–0.04^{a}	–8,355.87	5.87^{a}	1.63^{a}	4.33^{c}	–2.87	–0.03^{a}	–8,310.73	39.15
Colombia	4.42^{b}	–0.04^{a}	–4,723.71	4.74^{b}	0.82^{a}	–2.42	–12.43	–0.05^{a}	–4,661.86	38.65
Czech Republic	0.21	–0.06^{a}	–6,863.57	0.32	–0.40^{b}	11.07	0.21	–0.05^{a}	–6,857.89	38.20
Denmark	2.23	–0.05^{a}	–9,335.31	2.47	0.25^{a}	1.91	–0.92	–0.05^{a}	–9,332.78	37.26
Finland	–0.31	–0.05^{a}	–11,080.49	–0.12	–0.21^{a}	–0.75	–0.40	–0.05^{a}	–11,069.88	34.90
France	3.57^{b}	–0.10^{a}	–10,406.13	3.23^{b}	–0.73^{a}	16.30^{b}	–16.64^{b}	–0.10^{a}	–10,388.69	38.22
Germany	2.23^{c}	–0.08^{a}	–10,001.59	2.59^{b}	0.19^{a}	0.25	–0.28	–0.08^{a}	–9,981.19	35.95
Greece	–0.33	–0.05^{a}	–10,230.61	–0.34	0.16	–3.16	2.38	–0.05^{a}	–10,228.73	37.75
Hong Kong	0.44	–0.07^{a}	–10,536.56	0.88	1.19^{a}	0.65	–0.79	–0.08^{a}	–10,525.63	36.35
Hungary	2.22^{c}	–0.06^{a}	–9,156.43	2.47^{b}	0.32^{a}	1.45	–1.39	–0.06^{a}	–9,152.02	38.49
India	2.91^{b}	–0.09^{a}	–8,819.98	2.55^{b}	–0.62^{b}	–3.66	24.40	–0.09^{a}	–8,815.05	39.87
Indonesia	–1.27	–0.07^{a}	–8,800.35	0.81	5.97^{a}	64.89^{b}	–34.18	–0.09^{a}	–8,696.95	37.27
Ireland	–1.71	–0.08^{a}	–6,073.50	–1.74	0.08	4.25	–2.29	–0.08^{a}	–6,072.28	26.30
Israel	2.49	–0.07^{a}	–5,983.52	2.40	–0.27^{c}	50.16^{a}	–32.15^{a}	–0.07^{a}	–5,973.02	39.64
Japan	4.13^{a}	–0.10^{a}	–9,627.44	4.17^{a}	0.46^{a}	1.46	–0.22	–0.10^{a}	–9,622.25	33.08
Mexico	0.86	–0.09^{a}	–7,167.70	1.53	0.73^{a}	9.69	–10.37	–0.09^{a}	–6,917.35	25.82
Netherlands	1.68	–0.08^{a}	–10,337.69	1.31	0.03	9.95^{a}	–7.60^{a}	–0.08^{a}	–10,332.03	38.62
New Zealand	–3.64	–0.03^{a}	–6,554.28	–3.59	0.01	0.33	–0.57	–0.03^{a}	–6,554.05	39.36
Norway	0.53	–0.08^{a}	–12,246.49	0.73	0.20^{a}	0.39	–0.27	–0.08^{a}	–12,241.10	37.31
Philippines	6.18^{b}	–0.07^{a}	–5,373.94	8.21^{a}	3.10^{a}	225.26^{a}	–231.69^{a}	–0.08^{a}	–5,354.10	36.69
Poland	0.06	–0.05^{a}	–8,089.04	0.23	1.03^{a}	–13.36	7.47	–0.05^{a}	–8,080.25	28.33
Portugal	–0.02	–0.09^{a}	–6,024.24	1.59	0.40^{a}	2.01	–2.17	–0.09^{a}	–6,014.34	38.17
Russia	1.14	–0.04^{a}	–7,233.18	1.33	1.20^{a}	4.17	–9.35	–0.04^{a}	–7,299.67	27.87
Singapore	0.57	–0.05^{a}	–7,251.12	1.12	1.03^{a}	8.37	–0.26	–0.06^{a}	–7,235.19	43.04
South Africa	4.51^{b}	–0.09^{a}	–6,378.22	4.65^{b}	0.06	8.80	–13.59^{a}	–0.09^{a}	–6,375.08	23.83
South Korea	0.73	–0.04^{a}	–10,865.93	1.21	1.47^{a}	5.26^{a}	–5.36^{a}	–0.04^{a}	–10,816.05	39.20
Spain	0.41	–0.08^{a}	–9,564.50	0.31	–0.04	7.53^{b}	–4.73	–0.07^{a}	–9,562.63	26.69
Sweden	–1.20	–0.09^{a}	–11,854.28	–1.20	0.04	3.20	–2.50	–0.09^{a}	–11,853.68	28.38
Switzerland	2.94^{c}	–0.12^{a}	–8,706.21	2.93^{c}	0.05	1.28	–6.48	–0.12^{a}	–8,705.22	39.81
Taiwan	–1.85	–0.05^{a}	–10,671.83	2.04	2.15^{a}	12.27^{a}	–7.25^{a}	–0.07^{a}	–10,529.70	36.19
Thailand	–0.25	–0.08^{a}	–4,516.27	0.40	1.25^{a}	–2.19	–16.50	–0.08^{a}	–4,503.81	37.79
Turkey	–1.94	–0.09^{a}	–4,606.81	–1.85	0.57^{a}	1.73	4.30	–0.10^{a}	–4,599.74	31.63
UK	3.25^{b}	–0.09^{a}	–9,612.90	3.16^{b}	0.13	8.38^{a}	–4.07	–0.09^{a}	–9,610.38	43.71
US	3.62^{a}	–0.08^{a}	–12,992.21	2.24^{c}	–0.33^{a}	10.43^{a}	–1.09	–0.07^{a}	–12,971.54	40.97

Panel B Count

Market	Base (I) *h* +	Base (I) *h* –	Base (I) δ_2 +	Base (I) δ_2 –	EGARCH-M (II) *h* +	EGARCH-M (II) *h* –	*Sent* +	*Sent* –	*Opt* +	*Opt* –	*Pes* +	*Pes* –	δ_2 +	δ_2 –	LLF ↑	*Q* Sig.
Africa	1	0	0	1	1	0	1	0	0	0	0	1	0	1	1	0
America	5	0	0	6	4	0	3	2	3	0	0	0	0	6	6	0
Asia-Pacific	5	0	0	12	5	0	9	2	5	0	0	3	0	12	12	0
Europe	6	0	0	21	6	0	8	4	8	0	0	4	0	21	20	0
Developed	9	0	0	22	8	0	8	6	9	0	0	4	0	22	22	0
Emerging	8	0	0	18	8	0	13	2	8	0	0	4	0	18	17	0
World	17	0	0	40	16	0	21	8	17	0	0	8	0	40	39	0

This table reports the results from the refined EGARCH-M model. Column (I) and (II) display the results from the refined EGARCH-M base model and the sentiment-augmented EGARCH-M model as specified in Eq. (4) and (5). In Panel A, the estimations of SiIS (α_2), *Sent,* and optimistic and pessimistic shifts (β_1 and β_2), *Opt* and *Pes*, are multiplied by 1,000. The estimation of conditional volatility (α_1) in Eq. (1) is *h*. The estimation of the leverage effect is δ_2. The *Q*-statistic (*Q*) tests for serial correlation in residuals for lags up to 30. In attempts to find the most suitable model and compare between base and sentiment-augmented models, we also report the log-likelihood function values, LLF. In Panel B, we report the count. In particular, we report the number of positive (+) and negative (–) estimations for each estimated parameter that are significant at least at the 10% significance level. For LLF, we present the number of increased LLF values after adding investor sentiment variables (↑). For *Q*-statistics, we present the number of significant statistics (Sig.).

^{a}, ^{b}, and ^{c} represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4. Results from the refined EGARCH-M model, conditional on bull and bear regimes

	Bull regime (I)					Bear regime (II)					Bull/bear differences (III)		
Market	***h***	***Sent***	***Opt***	***Pes***	δ_2	***h***	***Sent***	***Opt***	***Pes***	δ_2	***Sent***	***Opt***	***Pes***
Panel A Market-by-market results													
Australia	12.61[a]	–0.09	8.16[c]	–5.67[c]	–0.08[a]	–10.07[a]	–0.77[a]	21.07[a]	3.46	–0.10[a]	0.68[a]	–12.91	–9.13
Austria	13.36[b]	0.60[b]	6.86[c]	–19.23[c]	–0.07[a]	–1.99	–0.88[b]	39.58[a]	–37.94[a]	–0.07[a]	1.48[a]	–32.71	18.73[c]
Belgium	10.76[a]	0.46[b]	43.16[a]	–28.25[b]	–0.06[a]	–11.71[a]	–1.22[a]	46.16[a]	–50.23[a]	–0.11[a]	1.66[a]	–3.01	21.99
Brazil	9.44[a]	0.21	2.14[a]	–5.39[a]	–0.02[a]	–10.67[a]	1.80	–35.82	15.46	–0.11[a]	–1.59	37.97[a]	–20.86[a]
Canada	5.96[a]	–0.19	24.87[a]	–11.61	–0.05[a]	–12.44[b]	–1.21[a]	28.46[a]	–4.84	–0.11[a]	1.01[a]	–3.59	–6.77
Chile	16.00[a]	0.74[a]	38.60[b]	–13.63	–0.04[a]	–22.84[a]	0.86[a]	–87.89[a]	85.25[a]	–0.15[a]	–0.12	126.50	–98.87
China	5.06[a]	0.81[a]	–0.52	0.30	0.05[a]	–1.49	2.27[a]	5.59[b]	–4.73[c]	–0.11[a]	–1.46[a]	–6.11	5.03
Colombia	4.38	1.22[a]	15.37	–32.23	0.04[c]	2.47	0.46	12.35	22.98	–0.14[a]	0.77[a]	3.02	–55.21
Czech Republic	7.25[a]	–0.01	2.52	1.72	–0.02	–12.50[a]	–3.01[a]	54.52[a]	11.90	–0.10[a]	3.00[a]	–52.00[b]	–10.18
Denmark	8.60[a]	0.14	1.05	–0.13	–0.04[a]	–12.33[a]	–0.09	–7.31[b]	5.19	–0.04[a]	0.23	8.36	–5.32
Finland	11.32[a]	–0.07	0.89	–3.81[b]	–0.07[a]	–11.96[a]	–2.10[a]	0.78	–2.06[a]	–0.13[a]	2.03[a]	0.11	–1.75
France	9.34[a]	–0.72[a]	14.18[b]	–20.56[a]	–0.07[a]	–6.30[a]	–1.44[a]	39.80[a]	–29.48[a]	–0.13[a]	0.72[a]	–25.62[c]	8.92
Germany	10.71[a]	0.22[a]	0.18	–0.27[b]	–0.08[a]	4.48[a]	0.07	0.25[c]	–0.25	–0.09[a]	0.15[b]	–0.07	–0.02
Greece	8.98[a]	0.07	–6.15[a]	4.05[a]	0.00	–7.25[a]	0.05	–2.03	1.82	–0.10[a]	0.02	–4.12	2.23
Hong Kong	8.31[a]	1.55[a]	–14.82[a]	9.56[a]	–0.02[a]	–10.03[a]	–3.96[a]	17.25[a]	2.47	–0.15[a]	5.51[a]	–32.07	7.09
Hungary	7.10[a]	0.74[a]	0.64	–3.05	–0.01[b]	–9.80[a]	–1.26[a]	1.20	–1.63	–0.16[a]	2.01[a]	–0.56	–1.41
India	9.48[a]	0.01	–21.05[a]	37.48[a]	–0.03[a]	–12.93[a]	–1.48[a]	16.11	22.15[b]	–0.13[a]	1.48[b]	–37.15	15.33
Indonesia	4.01[a]	4.92[a]	2.67[a]	3.89	–0.05[a]	–8.98[a]	1.57[a]	21.83[a]	–10.53	–0.17[a]	3.35[a]	–19.16	14.43
Ireland	2.91	0.20	0.28	0.98	–0.06[a]	–10.27[a]	–0.80[a]	5.51	–3.31	–0.11[a]	1.01[a]	–5.23	4.30
Israel	9.23	–0.40[a]	25.80[a]	–15.57[a]	–0.02[b]	–3.22	–0.48[c]	82.25[a]	–59.31[a]	–0.12[a]	0.09	–56.44[c]	43.73[b]
Japan	11.67[b]	0.91[a]	–1.12	5.27	–0.07[a]	3.06	–0.21	27.10[a]	–27.44[a]	–0.09[a]	1.13[a]	–28.21[a]	32.70[a]
Mexico	6.61[a]	0.91[a]	11.75[b]	–19.13[b]	–0.07[a]	–9.99[a]	–0.13	1.41	–0.25	–0.12[a]	1.04[b]	10.34	–18.87
Netherlands	7.30[a]	0.18[b]	11.41[a]	–9.17[a]	–0.05[a]	–7.10[a]	–1.13[a]	4.79	–6.52[a]	–0.14[a]	1.31[a]	6.63	–2.65
New Zealand	6.80[c]	0.05	6.55[a]	–6.99[a]	0.00	–4.04	–0.16[c]	–2.13[b]	2.64[a]	–0.12[a]	0.21[b]	8.69[a]	–9.63[a]
Norway	4.22[b]	0.21[a]	0.99	–1.14	–0.05[a]	–12.42[a]	–0.33[a]	0.21	–0.03	–0.14[a]	0.54[b]	0.78	–1.11
Philippines	12.93[a]	3.16[a]	178.90[a]	–165.44[a]	–0.02[c]	9.20[b]	–1.52[c]	76.90[a]	–232.53[a]	–0.07[a]	4.68[a]	101.99	67.08
Poland	4.50[a]	1.05[a]	–14.45	–10.41	–0.03[a]	–10.21[a]	0.86[b]	–35.75[b]	64.61[a]	–0.11[a]	0.19	21.29	–75.03
Portugal	9.36[b]	0.73[a]	0.75	4.21	–0.03[a]	–12.43[a]	0.05	1.94	–2.83	–0.14[a]	0.68[a]	–1.20[c]	7.04[c]
Russia	2.60	2.88[a]	11.46	–17.59	–0.00	–1.54	–4.51[a]	23.19[b]	–67.55[a]	–0.10[a]	7.39[a]	–11.73	49.97[b]
Singapore	12.04[a]	1.05[a]	–22.42	15.63	–0.03[a]	–11.55[a]	0.29	48.59[a]	–20.23	–0.09[a]	0.76[c]	–71.00[b]	35.87
South Africa	10.10[a]	0.36[b]	10.34[a]	–14.95[c]	–0.06[a]	–11.69[a]	–0.57[a]	–12.81	–1.18	–0.15[a]	0.94[a]	23.15	–13.77
South Korea	6.69[a]	1.94[a]	12.34[a]	–4.22[b]	–0.03	–5.11[a]	–0.00	–0.71[a]	0.78	–0.10[a]	1.93[a]	13.05[a]	–5.01[b]
Spain	7.05[a]	0.10	5.32[a]	–3.61[b]	–0.04[a]	0.55	–1.27[a]	26.51[a]	–16.89[a]	–0.12[a]	1.38[a]	–21.19[a]	13.29[c]
Sweden	7.65[a]	0.39[a]	1.83[a]	–0.30	–0.06[a]	–9.94[a]	–1.89[a]	10.22[a]	–6.19[a]	–0.08[a]	2.28[a]	–8.38	5.90
Switzerland	17.01[a]	0.30[a]	0.72[a]	–4.67	–0.10[a]	–1.50	–1.47[a]	27.92[b]	–9.00	–0.10[a]	1.76[a]	–27.20[b]	4.32
Taiwan	9.32[a]	2.14[a]	17.01[a]	–13.02[a]	–0.06[a]	3.34	2.43[a]	1.19[a]	0.18	–0.09[a]	–0.30	15.81[c]	–13.20[a]
Thailand	5.03	1.80[a]	67.93[a]	–23.29[c]	–0.04[b]	–6.53[a]	–2.40[a]	4.63[b]	–51.47[a]	–0.15[a]	4.20[a]	63.29[a]	28.17
Turkey	7.28[c]	1.07[a]	7.32	–3.61	–0.03[a]	–11.40[a]	–0.38[c]	–1.14	14.91	–0.19[a]	1.46[a]	8.46	–18.51
UK	10.90[a]	0.28[a]	24.07[b]	–37.17[a]	–0.05[a]	–7.15[a]	–0.50[a]	14.75[a]	3.47	–0.12[a]	0.78[a]	9.31	–40.64[b]
US	8.51[a]	–0.29	8.02[a]	–2.54	–0.08[a]	–5.42[a]	–0.81[a]	16.84[a]	–2.24	–0.13[a]	0.52[a]	–8.81	–0.31

(continued)

Table 4. *(continued)*

	Bull regime (I)										Bear regime (II)										Bull/bear differences (III)					
Market	***h***		***Sent***		***Opt***		***Pes***		***δ_2***		***h***		***Sent***		***Opt***		***Pes***		***δ_2***		***Sent***		***Opt***		***Pes***	
Panel B Count																										
	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
Africa	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0	0
America	5	0	3	0	5	0	0	2	1	5	0	5	1	2	2	1	1	0	0	6	3	0	1	0	0	1
Asia-Pacific	11	0	9	0	7	2	2	6	1	9	1	7	3	6	9	2	2	4	0	12	11	1	4	2	1	3
Europe	19	0	13	2	9	1	1	9	0	18	1	15	1	16	11	2	1	9	0	21	17	0	0	6	5	1
Developed	20	0	12	2	14	1	1	11	1	21	1	15	0	17	15	2	1	9	0	22	20	0	1	7	5	2
Emerging	16	0	14	0	8	2	2	7	1	12	1	13	5	8	7	3	3	4	0	18	12	1	4	1	1	3
World	36	0	26	2	22	3	3	18	2	33	2	28	5	25	22	5	4	13	0	40	32	1	5	8	6	5

This table reports market-by-market results from the refined EGARCH-M model conditional on two subsamples, i.e., bull regimes (in Column I) and bear regimes (in Column II). The segregation criterion borrows from Pagan and Sossounov (2003); however, we make minor but necessary modifications since Pagan and Sossounov (2003) adopt monthly observations while we employ daily ones. Column III reports differences between estimations across bull and bear regimes. In Panel A, the estimations of SiIS (α_2), *Sent,* and optimistic and pessimistic shifts (β_1 and β_2), *Opt* and *Pes*, are multiplied by 1,000. The estimation of conditional volatility (α_1) in Eq. (1) is *h*. The EGARCH-M model takes the leverage effect into consideration, and we thus present this estimation (δ_2). In Panel B, we report the count. In particular, we report the number of positive (+) and negative (–) estimations for each estimated parameter that are significant at least at the 10% significance level.

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

Table 5: Cross-market differences

	IDV	UAI	MAS	PDI	LTO	IDG	ADR	EJS	GC	AS	INS
Australia	90	51	61	36	21	71	4	10	8.52	75	10.8
Austria	55	70	79	11	60	63	2	9.5	8.57	54	18.4
Belgium	75	94	54	65	82	57	0	9.5	8.82	61	16.4
Canada	80	48	52	39	36	68	4	9.25	10	74	42
China	20	30	66	80	87	24	–	–	–	–	14.3
Colombia	13	80	64	67	13	83	1	7.25	5	50	4.1
Czech Republic	58	74	57	57	70	29	–	–	–	–	–
Finland	63	59	26	33	38	57	2	10	10	77	31.4
France	71	86	43	68	63	48	2	8	9.05	69	25.6
Germany	67	65	66	35	83	40	1	9	8.93	62	27.9
Hong Kong	25	29	57	68	61	17	4	10	8.52	69	16.7
Hungary	80	82	88	46	58	31	–	–	–	–	–
Indonesia	14	48	46	78	62	38	–	–	–	–	10.9
Ireland	70	35	68	28	24	65	3	8.52	—	8.75	39.6
Japan	46	92	95	54	88	42	3	10	8.52	65	13.5
Mexico	30	82	69	81	24	97	0	6	4.77	60	18.6
Netherlands	80	53	14	38	67	68	2	10	10	64	35.7
New Zealand	79	49	58	22	33	75	4	10	10	70	14
Norway	69	50	8	31	35	55	3	10	10	74	35.6
Philippines	32	44	64	94	27	42	4	4.75	2.92	65	12.6
Portugal	27	99	31	63	28	33	2	5.5	7.38	36	10.6
Russia	39	95	36	93	81	20	–	–	–	–	14.4
South Africa	65	49	63	49	34	63	4	6	8.92	70	21.4
South Korea	18	85	39	60	100	29	2	6	5.3	62	11.6
Spain	51	86	42	57	48	44	2	6.25	7.38	64	13.4
Sweden	71	29	5	31	53	78	2	10	10	83	39.4
Switzerland	68	58	70	34	74	66	1	10	10	68	26.8
Thailand	20	64	34	64	32	45	3	3.25	5.18	64	13.6
Turkey	37	85	45	66	46	49	2	4	5.18	51	14
UK	89	35	66	35	51	69	4	10	9.1	78	34.3
US	91	46	62	40	26	68	5	10	8.63	71	–
Coefficients	–0.01	0.01	–0.02	0.01	0.01	–0.03[b]	0.04	–0.08	–0.06	0.02	0.00

This table reports statistics of cultural dimension, market integrity, and market composition used in the cross-market tests as well as results. In particular, we regress the significant, estimated bull/bear difference as reported in Table 4 (to ensure consistency across markets, for each market, we multiply the estimate by the standard deviation) on a series of factors as reported in Wang et al. (2021) and Dyck et al. (2019), including individualism (IDV), uncertainty avoidance index (UAI), masculinity (MAS), power distance index (PDI), long-term orientation (LTO), indulgence (IDG), anti-director rights (ADR), efficiency of judicial system (EJS), government corruption (GC), accounting standard (AS), and the proportion of institutional investors (INS). The estimates are multiplied by 1,000.

[b] represents statistical significance at the 5% level.

Table 6. Robustness tests

Market	Bull (I)										Bear (II)										Bull/bear differences (III)					
	h		*Sent*		*Opt*		*Pes*		δ_2		*h*		*Sent*		*Opt*		*Pes*		δ_2		*Sent*		*Opt*		*Pes*	
	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
Panel A Count: trading volume as the sentiment proxy																										
Africa	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0	0
America	3	0	3	0	3	0	0	3	0	5	0	3	1	2	2	0	0	0	0	6	3	0	1	0	0	0
Asia-Pacific	10	0	9	0	7	1	1	5	1	7	2	6	2	5	5	0	0	3	0	12	9	1	3	1	0	2
Europe	20	0	13	2	10	1	0	10	0	18	1	12	0	14	11	1	1	10	0	21	17	0	0	4	6	0
Developed	21	0	11	2	13	1	1	9	0	20	2	9	0	15	15	0	0	11	0	22	20	0	1	5	6	0
Emerging	13	0	15	0	8	1	0	10	1	11	1	13	3	7	3	1	1	2	0	18	10	1	3	0	0	2
World	34	0	26	2	21	2	1	19	1	31	3	20	3	22	18	1	1	13	0	40	30	1	5	5	6	2
Panel B Count: controlling for the January effect and the October effect																										
Africa	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	1	0	0	0	1	1	0	0	0	0	0
America	5	0	2	1	5	0	0	3	0	6	0	5	2	2	1	1	0	0	0	6	3	0	1	0	0	1
Asia-Pacific	11	0	9	0	7	1	1	7	1	9	1	7	1	6	9	2	1	4	0	12	10	1	4	2	1	2
Europe	19	0	13	1	9	1	1	9	0	18	1	15	1	16	11	2	0	9	0	21	17	0	0	6	4	1
Developed	20	0	12	1	14	1	1	13	1	21	1	15	0	17	14	2	0	9	0	22	20	0	1	7	4	2
Emerging	16	0	13	1	8	1	1	7	0	13	1	13	4	8	7	4	1	4	0	18	11	1	4	1	1	2
World	36	0	25	2	22	2	2	20	1	34	2	28	4	25	21	6	1	13	0	40	31	1	5	8	5	4
Panel C Count: using the global market index for bull/bear splits																										
Africa	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0	0
America	5	0	3	0	5	0	0	2	1	5	0	4	2	1	1	1	2	0	0	6	2	1	1	0	0	1
Asia-Pacific	6	0	5	1	5	2	1	7	1	9	2	3	2	4	6	1	1	4	0	12	8	0	3	1	1	1
Europe	19	0	12	2	9	1	2	9	0	18	1	14	1	16	12	0	1	9	0	21	17	0	0	5	2	1
Developed	20	0	10	2	14	1	2	12	1	21	2	14	0	16	13	0	2	9	0	22	20	0	1	5	2	1
Emerging	8	0	11	1	6	2	1	7	1	12	1	7	5	6	6	2	2	4	0	18	9	1	3	1	1	2
World	28	0	21	3	20	3	3	19	2	33	3	21	5	22	19	2	4	13	0	40	29	1	4	6	3	3

This table reports the counts from the refined EGARCH-M model conditional on two subsamples, i.e., bull regimes (in Column I) and bear regimes (in Column II). In particular, we report the number of positive (+) and negative (–) estimations for each estimated parameter that are significant at least at the 10% significance level. The segregation criterion borrows from Pagan and Sossounov (2003); however, we make minor but necessary modifications since Pagan and Sossounov (2003) adopt monthly observations while we employ daily ones. Column III reports differences between estimations across bull and bear regimes. Panel A employs trading volume as the sentiment proxy; Panel B controls for the January effect and the October effect; and Panel C uses the global market index for bull/bear regime designation.

Table 7. Results from the refined EGARCH-M model in up and down states

Market	Up (I)										Down (II)										Up/down differences (III)					
	h		*Sent*		*Opt*		*Pes*		δ_2		*h*		*Sent*		*Opt*		*Pes*		δ_2		*Sent*		*Opt*		*Pes*	
	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
Panel A Count: one-year lagged returns																										
Africa	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0
America	3	0	2	4	4	0	0	3	0	6	2	2	0	0	3	0	0	0	0	5	1	2	0	0	0	2
Asia-Pacific	8	0	9	3	6	2	5	3	0	12	3	1	8	0	4	2	3	2	0	12	1	6	3	3	1	1
Europe	10	2	4	7	10	2	1	12	0	20	6	6	4	6	9	1	2	4	0	21	4	5	2	3	0	6
Developed	13	2	5	10	13	1	2	12	0	21	7	5	7	5	9	2	2	3	0	22	4	8	2	5	1	6
Emerging	9	0	10	4	7	4	3	6	0	18	4	4	5	1	8	1	3	3	0	17	2	5	3	2	1	3
World	22	2	15	14	20	5	5	18	0	39	11	9	12	6	17	3	5	6	0	39	6	13	5	7	2	9
Panel B Count: three-year lagged returns																										
Africa	1	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0	1	1	0
America	3	0	1	3	4	0	0	3	0	6	2	1	2	1	2	0	0	1	0	6	1	1	1	0	1	5
Asia-Pacific	7	0	9	3	8	2	1	7	0	12	3	0	7	0	6	1	1	4	0	12	1	6	4	1	2	4
Europe	5	3	9	6	12	1	1	11	0	21	2	2	3	7	9	0	1	7	0	21	10	3	4	3	2	5
Developed	9	3	9	9	14	2	1	13	0	22	4	1	5	6	11	0	0	7	0	22	7	5	4	4	3	5
Emerging	7	0	10	3	11	1	1	8	0	18	2	2	7	2	7	1	2	6	0	18	5	5	5	1	3	6
World	16	3	19	12	25	3	2	21	0	40	6	3	12	8	18	1	2	13	0	40	12	10	9	5	6	11
Panel C Count: half-year lagged returns																										
Africa	1	0	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0
America	3	0	2	3	3	1	0	2	0	6	2	0	2	2	3	0	0	1	0	5	0	2	1	1	0	1
Asia-Pacific	7	1	9	0	8	0	0	6	0	12	3	1	8	0	2	1	1	0	0	12	3	3	4	0	0	3
Europe	4	1	12	3	7	0	0	8	0	20	1	1	3	7	8	0	1	6	0	21	7	4	1	2	0	3
Developed	10	2	11	4	10	0	0	9	0	21	3	2	5	7	10	1	1	6	0	22	6	5	3	2	0	4
Emerging	5	0	12	2	8	2	0	7	0	18	4	0	8	2	4	0	1	1	0	17	4	4	3	2	0	3
World	15	2	23	6	18	2	0	16	0	39	7	2	13	9	14	1	2	7	0	39	10	9	6	4	0	7
Panel D Count: two-year lagged returns																										
Africa	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
America	2	0	1	3	4	0	1	4	0	5	2	0	2	2	3	1	2	1	0	6	1	2	0	0	1	1
Asia-Pacific	6	1	9	3	7	0	0	6	0	12	3	0	8	1	4	0	1	1	0	12	1	6	3	1	1	3
Europe	7	1	8	4	9	0	0	11	0	21	2	0	4	7	9	1	1	5	0	21	7	4	4	3	1	5
Developed	11	2	8	6	11	0	0	14	0	22	4	0	7	7	11	1	1	5	0	22	6	5	5	4	1	3
Emerging	5	0	10	4	9	0	1	7	0	17	3	0	7	3	5	1	3	2	0	18	3	7	2	0	2	6
World	16	2	18	10	20	0	1	21	0	39	7	0	14	10	16	2	4	7	0	40	9	12	7	4	3	8

This table reports the counts from the EGARCH-M specification based on two subsamples, i.e., the up market (Column I) and the down market (Column II). This segregation borrows from Cooper et al. (2004). The separation of up and down states depends on one-, three-, half-, and two-year lagged returns and the count of the results are given in Panel A–D, respectively. In particular, we report the number of positive (+) and negative (–) estimations for each estimated parameter that are significant at least at the 10% significance level.