SENSITIVITY TO SENTIMENT IN EQUITY MARKETS: A COUNTRY-SPECIFIC PERSPECTIVE

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Abstract

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Key words: International equity market; Investor sentiment; Return predictability; Country-specific characteristics

JEL Classification: G15, G40, G41

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Abstract

This study examines how country-specific factors can modify the predictive power of investor sentiment on stock returns and volatilities. Utilising the data in 52 international equity markets and the consumer confidence index as a proxy for individual investor sentiment, we re-confirm that sentiment negatively (positively) predicts aggregate stock market returns (volatility) on average across nations. We employ 40 country-specific indicators to dissect the divergences between markets with different characteristics. Sentiment exerts more persistent impacts in more established markets but more instant effects in less developed markets. Stronger impacts of sentiment are visible in markets of countries with low institutional holdings, high limits to arbitrage, more gambling opportunities, low internet availability, and more prone to herd-like culture. Further, heterogeneity in sentiment predictive power is also positively correlated with literacy levels, common legal origins, institutional quality, market integrity, and the rates of Catholic, Islamic and Buddhist population. From a cross-sectional perspective, we provide evidence that country-specific factors can rationalise sentiment impacts on the returns of well-documented anomalies.

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1 Introduction

Throughout the history of finance theory, scholars primarily focus on two research streams of traditional and behavioural finance. Initially, conventional finance theory assumes that all market participants are rational economic agents. In other words, people are entirely rational when trading assets in financial markets as they are supposed to observe all available information to form their "rational expectations" about all forthcoming economic events. As such, the financial markets are stable and shift toward the "general equilibrium" as asset prices follow a "random walk" (Cootner, 1964; Fama, 1965). Based on the assumptions of "rational expectations", one of the cornerstones of conventional finance theory - the Efficient Market Hypothesis (EMH) proposes that stock prices immediately and accurately reflect all different forms of information and change without any pattern (Fama, 1965; Samuelson, 1965). Further, Jensen (1978) also specifies the EMH that risk-adjusted profits cannot be systematically gained based on the given information if the financial market set is in its efficient form. In the study of Fama (1970), the efficient market is distinguished into three forms (strong firm, semi-strong form, and weak form) according to the extent to which asset prices promptly reflect a distinct series of publicly available information. As such, finance scholars conventionally construct the financial models or concepts in accordance with the fundamental hypothesis of an efficient market.

One area greatly influenced by psychology is investor sentiment and how it influences asset returns. Employing the concepts of noise traders proposed by Black (1986), De Long et al. (1990) point out that investor sentiment is their realization of beliefs about the future returns and investment risks that are baseless on the current evidence. It can be defined as investors' misinterpretation driven by mood, emotion, and attitude that can potentially cause mispricing. In other words, it is defined as the optimism or pessimism of investors about the financial market in general. Similarly, investor sentiment can be simply described as the opinions about the upcoming cash flows and investment risk of market participants, which is usually shaped by human emotion (Chang et al., 2011) In terms of speculation, Baker and Wurgler (2006) explain investor sentiment as speculative preference driven by optimism or pessimism about the future movement of an asset. That psychological preference of noise traders can lead to mispricing caused by their misperceptions. Further, under- and overreactions theory by Daniel et al. (1998) is proposed based on the well-recognised traders' psychological biases of overconfidence and biased self-attribution. Hence, the under- and overreactions of investors in the financial markets can drive asset prices away from their fundamental values (Schnusenberg and Madura, 2001).

Literature in finance has confirmed the considerable role of country-specific factors on financial decision-making. For instance, nations' cultural values are considered as a driver behind portfolio management (Anderson et al., 2011; Siegel et al., 2011), financial investment behaviour (Eun et al., 2015), or corporate financial policies (Han et al., 2010; Lei et al., 2021; Mohsni et al., 2021). For instance, two cultural dimensions of Hofstede (1980, 2001), individualism and uncertainty avoidance, relate to the willingness to take risk by investors (Beugelsdijk and Frijns, 2010; Shupp and Williams, 2008). A recent study of Han et al. (2020) confirms the difference between beta anomaly between the U.S and Chinese equity markets by attributing to the difference in the markets' feature of institutional and retail investors.

Given the existing literature on cross-countries factors in the financial markets, there is a current lack of evidence on the cross-country structural variances as the crucial factors in the predicting power of sentiment on stock market movements in the current literature. As such, this study is to accomplish clearer findings by how sentiment modifies the trading behaviour of financial market participants in relation to their financial development, market structure, educational quality, gambling prospect, institutional, legal, and cultural, religion backgrounds. By utilising the data of 52 stock markets and the block-bootstrap regression, comprising both developed, emerging and frontier markets across the globe, we initially confirm the negative (positive) predictive power investor sentiment and stock returns (volatility) over different horizons from 1 to 36 months. Our sentiment indicator proxied by the market-specific consumer confidence index (CCI) maintain its power when we consider the different sub-periods and the potential impacts of the business confidence. To consider the divergences between markets with different characteristics, we utilise 40 country-specific indicators in nine groups: *(i) Financial development; (ii) market structure; (iii) Cultural backgrounds; (iv) Religion backgrounds; (v) Legal origin; (vi) Market integrity; (vii) Institutional quality; (viii) Educational backgrounds; and (ix) Gambling opportunity*. We split the entire sample by employing from the 40 aforementioned factors to compare the predictive power of sentiment in markets within upper and lower layers. First, we find that the effects of investor sentiment are more rapid in markets with lower financial development, horizons from 1 to 18 (24) months for frontier (emerging) markets. However, we find that it is more persistent from 2 up to 42 months in developed markets. Further, we also confirm the positive relationship between sentiment and subsequent volatilities across markets, that maintain the persistency up to 3 (2) months in frontier and emerging (developed) markets. Next, we also distinguish the impacts of investor sentiment conditional on different market structure by utilising two indicators of institutional investment and limits to arbitrage. We confirm that sentiment exert stronger (weaker) impacts on the market return (volatility) as in markets with higher rates of institutional holdings. Likewise, the markets with higher limits to arbitrage are more sensitive to changes of investor moods and adverse market events.

We also consider the impacts of culture factors by employing nine culture dimensions that are widely employed in the finance literature. We collect six cultural dimensions developed by Hofstede (2015) and three from Schwartz (2007). Our results provide convincing evidence that markets in countries, which are culturally more prone to herd-like behaviour by lower Individualism, Collectivism, Power Distance and high Embedded, exhibit stronger predictive power of sentiment. Further considering the impacts of national religion beliefs, we sort our sample into different clusters based on the demographic data of Abrahamic religions, including Catholic, Protestant, and Islam, and Indian religions with Hinduism and Buddhism. We find that markets in countries with higher rates Catholic and Buddhist, investors exhibit a stronger propensity to hold lottery-type and high-risk stocks, which are more sensitively to sentiment. Conversely, investors in countries with higher rate of Islamic population exhibit less pronounced impacts on sentiment-return nexus.

Next, we also carry out cross-market investigations to delve into the driving forces of divergences in the impacts of sentiment from the viewpoints of institutional quality and market integrity. As expected, our findings confirm that investor sentiment is less powerful in markets with stronger institutional quality and market integrity than in those with relatively weaker institutions. Evidence also reveals that the impacts of sentiment are less pronounced in freer markets with (positive) negative and significant spreads for returns and volatilities. In other words, better institutions can enhance the information transmission and therefore make financial markets more efficient. In addition, we also explore the influences of legal origins proposed by Porta et al. (1998) on the predictive power of investor sentiment. The result indicates that the investor sentiment effects are less considerable in those markets with a common law legal origin, with better investor protection financial reporting quality, than with the other legal origins. Further, investors with higher education, proxied by Higher education rate and Financial Literacy rate are less subject to hypercritical biases and emotion-driven investment decisions. These findings are also in line with the notion of higher rate of internet availability proxied by internet users, which can minimize the impacts of irrational investment from sentiment. Finally, we broaden the study by contemplating the effects of gambling opportunity, proxied by the ratios of annual lottery sales to national GDP and number of casinos, on the sentiment-return relation. Our results empirical confirm that markets with high levels of gambling display a stronger sentiment impact than those with low corresponding levels.

In the additional analyses, we examine the impact of investor sentiment on stock market returns conditional on bull and bear market regimes for each market and global market. We find that the predictive power of investor sentiment on return and volatility is 1 to 18 months and 1 to 2 months during bull regimes in all markets, respectively, while the impacts are statistically insignificant for the bear regimes. Additionally, we also document empirical evidence on sentiment and cross-section of stock returns. We consider 14 well-documented anomalies in 52 markets and reconfirm that anomaly returns are higher following periods of high investor sentiment that reveals mispricing (Stambaugh et al., 2012). We also carry out cross-market analyses to consider the predictive power of sentiment on the anomaly returns. The impacts of investor sentiment on more straightforward factors of firm age, dividend payment and size are stronger across markets with less financial developed, lower institutional holdings, lower financial literacy level, and herd-like culture. For markets with low quality of accounting standards, we obtain more significant impacts of investor sentiment on return anomalies linked to the accounting information on firms' balance sheets.

This study can contribute to the behavioural finance literature in various ways. First, we provide further evidence on the predictive power of investor sentiment on both future stock returns and volatilities to the global level. Second, we perform various comparative tests based on a wide range set of country specific factors, identifying the similarities and differences in the impact of investor sentiment. This study is the first to provide persuasive evidence on how economic, political, cultural, and social factors can modify the impacts of investor sentiment on predicting the stock market movement. As such, we can deliver a systematic exploration into driving forces of cross-market discrepancies in the power of investor sentiment. Further, this study also extends the literature by considering these interactions by sorting stocks into characteristic-based portfolios. As far as we are aware, this area has not been previously explored as the prior literature only focuses on analysing the raw stock returns. By studying the impacts of investor sentiment on a range of anomalies, this study can postulate perceptions to the current deliberation on the cause of anomalies through the perceptions of market-based characteristics. Therefore, this study can propose several implications for both academics and market participants and a broader paradigm for future research in the investor sentiment literature.

The rest of the paper is structured as follows. The literature review and research question development are presented in Section 2. Section 3 provide the key data descriptions, sources, and baseline method. Section 4 reports the descriptive statistics and conducts preliminary tests. The driving forces of cross-market divergences in the predictive power of investor sentiment are reported in Section 5. Section 6 provides results for the additional analyses. Finally, section 7 concludes the study.

2 Literature Review

2.1 The investor sentiment and stock market performance

From the 1990s, investor sentiment and how it influences asset returns have become one area greatly influenced by psychology in finance literature. Employing the concepts of noise traders proposed by Black (1986) and further developed by De Long et al. (1990), Lee et al. (1991) point out that investor sentiment is their realization of beliefs about the future returns and investment risks that are baseless on the current evidence. It can be defined as investors' misinterpretation driven by mood, emotion, and attitude that can potentially cause mispricing. In other words, it is defined as the optimism or pessimism of investors about the financial market in general. In terms of speculation, Baker and Wurgler (2006) explain investor sentiment as speculative preference driven by optimism or pessimism about the future movement of an asset. That psychological preference of noise traders can lead to mispricing caused by their misperceptions. Further, the under- and overreactions theory by Daniel et al. (1998) is proposed based on the well-recognised traders' psychological biases of overconfidence and biased self-attribution. Hence, the under- and overreactions of investors in the financial markets can drive asset prices away from their fundamental values (Schnusenberg and Madura, 2001). The predictive power of sentiment for returns has been explored in several papers. The results that have been found are mixed.

A large body of finance literature deliberates the roles and influences of investor sentiment on asset returns. From the pioneered contributions proposed to the academic literature that investor sentiment and asset returns by Shiller et al. (1984). The predictive power of sentiment on asset returns has been further confirmed by a rich strand of studies in behavioural finance literature since the 1990s. The study of Lee et al. (1991) provides evidence for the connection between the returns closed-end funds and individual investor sentiment. Using the closed-end fund discounts as a proxy for sentiment, their findings show that optimism of investors leads to lower asset returns as its negative correlation. The noise traders are usually overconfident about the underlying asset values at the beginning of the period, which leads to higher demand. This trading behaviour will drive up the trading prices as well as reduce the realized asset returns. Early empirical studies of Baker and Wurgler (2000); Kothari and Shanken (1997); Shiller (2000); Swaminathan (1996) and Baker and Wurgler (2006); Stambaugh et al. (2012) further encompass the investor sentiment literature and confirm the relationship between sentiment and cross-sectional asset returns. However, Shleifer (2000) conjectures that sentiment imitates the common adjudication mistakes from many investors rather than their ordinary uncorrelated accidental faults.

The pioneered studies of Black (1986) and De Long et al. (1990) also depict the connection between sentiment-driven by noise traders and asset price volatilities. In other words, noise traders' trading activities could substantially impact the stock market in terms of returns and volatilities. The increase of both volatility and return can be explained by the increase in mispricing, which is due to the occurrence of irrational traders' activities (Campbell and Kyle, 1993). Further study by Shleifer and Vishny (1997) suggests that noise traders can systematically affect the asset price by trading non-fundamental information. Trading on noise signals on the market, both bullish and bearish information, this group of traders cap partially to make the market more volatile. Lee et al. (2002) find that investor sentiment can markedly justify stock market volatility, with substantial variations in sentiment associated with high volatility. During the high sentiment periods, the high mispricing is ultimately adjusted through declining stock prices and bubble surges through the sentiment mean-reverting. However, the noise traders shun the market by unwillingness for short selling during this period resulting in higher volatilities on the financial market (Hessary and Hadzikadic, 2017). The study of Verma and Verma (2007) further confirms the role of retail and noise traders in stock price volatility in similar manners.

An empirical study of Verma and Soydemir (2009) also supports the impacts of rational and irrational investors on asset prices. Their evidence indicates that the stock market reactions to volatility are varied depending on the deviations in investor sentiment. Utilising trading volume as a proxy for investor sentiment, Chuang et al. (2010) also reinforce the connection between sentiment and the volatility in the Taiwan financial market. The rise of noise traders' activities during the high sentiment stages pushes up both trading volume and market volatility. This finding is consistent with a study by Yang and Copeland (2014) that investor sentiment has both long-term and short-term asymmetrical effects on market volatility. Investors' bearish sentiment is correlated with lower asset returns than bullish sentiment, indicating the positive (positive) impacts of optimistic feelings on short-term (long-term) volatility.

Qiang and Shu-e (2009) further prove the different impacts of positive and negative sentiment on the asset price variants. Uygur and Taş (2014) also find that investor sentiment can considerably influence the conditional volatilities on seven equity markets. Kumari and Mahakud (2015) posit the effects of investor sentiment on the Indian equity market volatilities. The past sentiment indicator can positively affect the market volatility, consistent with the proposition of noise traders' pessimism and the higher stock markets volatility. This finding is also consistent with findings by Kurov (2010) and Charles et al. (2017) that the positive feedback trading drives the stock prices from the intrinsic values and contributes to the market volatility as its destabilising trends during the high sentiment periods. Exploring the emerging markets, Kumari and Mahakud (2016) and Gong et al. (2022) find pervasive evidence of a positive relationship between sentiment and conditional volatility on the Indian and Chinese equity market. These findings are corroborated by the subsequent studies of Fang et al. (2018) and Liang et al. (2020), who found that sentiment investor is positively correlated with financial market volatility. Given the extend literature, the following research question is raised:

Research Question 1: Can the investor sentiment negatively (positively) predict the subsequent stock returns (volatilities) in the international equity market?

2.2 Financial development, market structure and sentiment in stock markets

Rajan and Zingales (1998) prove that countries with better developed financial systems show superior growth in capital-extensive sectors that rely particularly heavily on external finance. Evidence of Chordia et al. (2011) indicates that secular decreases in trading costs influence the turnover trend in the U.S. market. Further, Chang et al. (2011) show that the sentiment effect has more impact in developed than developing countries. Such insight is difficult to obtain when sample markets exhibit similar economic conditions and exclude those at different stages of development (Huynh et al., 2021)). More recently, Ding et al. (2019) consider the multiple risky assets, which again emphasizes the role of noise traders' misperceptions in influencing stock returns. Because investors in different markets, especially those from different types of markets (developed or emerging), may have different distributions of the misperceptions due to different development levels can partly determine investors' behaviors (Aggarwal and Goodell, 2009; Aggarwal et al., 1999; Chui et al., 2010; Cole et al., 2014; Grinblatt et al., 2012; Kwok and Tadesse, 2006; Zouaoui et al., 2018,1), the impact of investor sentiment on stock returns and volatilities realized by investors' behaviors is also expected to be different. As such, the follow research question is raised:

Research Question 2: Does the level of financial development differentiate the impacts of investor sentiment on returns and volatility?

To compare the two mechanisms, we examine the source of the behavioral biases that Baker and Wurgler (2006) reports by developing tests that examine whether the effects of sentiment extend to institutional investors and security analysts. We study institutional investors because they are often thought to trade on information not available to noise traders (Chakravarty, 2001) and to be less subject to behavioral biases (Sias, 1996). As a result, their trading acts as a countervailing force to stock price movements driven by swings in individual investor (i.e., noise trader) sentiment. Lemmon and Portniaguina (2006), which focuses on small firm stocks and stocks with low institutional ownership, concludes that investor sentiment forecasts returns for such stocks in a manner consistent with the predictions of models based on noise trader sentiment. Consistent with Lemmon and Portniaguina (2006), Brown and Cliff (2005) assume that a subset of investors makes biased asset valuations, and that limits to arbitrage hinder the exploitation of asset mispricing. Related to institutional ownership, Lemmon and Portniaguina (2006) also finds that stocks with low institutional ownership exhibit relatively lower (higher) returns following periods of high (low) sentiment, which is measured using consumer confidence. Lemmon and Portniaguina (2006) concludes that stocks held predominantly by individual investors are more prone to mispricing arising from changes in sentiment. We, in contrast, focus on the change in institutional ownership to determine whether institutional investors mitigate sentiment-related mispricing by trading counter to sentiment. Based on this premise, the following research question is raised:

Research Question 3: To what extent do the levels of institutional holding differentiate the impacts of investor sentiment on returns and volatility?

The current state of the debate in behavioural finance suggests that the majority of returns or cross-sectional patterns of expected returns, could be explained based on two major foundations: investor irrational behaviour and limits on arbitrage, which, in turn, prevent investors from exploiting the mispricing (Barberis and Thaler, 2003; Brav et al., 2010; Jacobs, 2015; Jacobs and Müller, 2020). Recent empirical research suggests this movement away from fundamentals encompasses the influences of investor sentiment on asset valuation (Baker and

Wurgler, 2006,0; Zaremba, 2016). Sentiment-induced asset mispricing arises from a combination of sentiment-driven investor demand and limits to arbitrage. Baker and Wurgler (2006) argue that the debate over whether investor sentiment affects asset prices is over; the question that remains is how to measure sentiment and isolate its effects in environments where significant limits to arbitrage exist. Further, Obaid and Pukthuanthong (2021) and Chiah et al. (2021) hypothesize that the influence of sentiment on stock markets will be more pronounced when faced with greater limits to arbitrage. This is because correction of mispricing will be more difficult. As a result, the following research question is raised:

Research Question 4: To what extent do the levels of limits to arbitrage differentiate the impacts of investor sentiment on returns and volatility?

2.3 Cultural background, religion beliefs and the predictive power of sentiment on stock markets

Classical economists have long ignored the influence of culture in understanding individual decision-making. Literature in finance has confirmed the considerable role of country-specific factors on financial decision-making. For instance, nations' cultural values are considered as a driver behind portfolio management (Andersen et al., 2001; Siegel et al., 2011) or financial investment behaviour (Eun et al., 2015), or . For instance, two cultural dimensions of individualism and uncertainty avoidance, relate to the willingness to take risk by investors (Beugelsdijk and Frijns, 2010; Shupp and Williams, 2008). Considering homogeneous national governance quality and country-specific cultural aspects, Schmeling (2009); Wang (2001) confirmed the modified impacts of those factors on the relation of investor sentiment and financial market movements. Those impacts are relatively more significant in countries with stronger herd-like intentions, more overreaction, and lower levels of institutional and information quality.

National culture is regarded as a set of values and beliefs that people within a society pass on relatively unchanged from one generation to the next (Guiso et al., 2009,1). Given the pervasiveness and persistence of culture, many authors have argued that national culture affects economic behavior (Guiso et al., 2009) and financial behavior (Karolyi, 2016). Experimental evidence suggests that culture affects a variety of economic preferences. For example, lab experiments indicate that culture affects people's attitudes towards risk, time preference, and altruism (Benjamin Jr et al., 2010). Large-scale global surveys also show that the degree of risk aversion and time preferences are affected by cultural factors (Rieger et al., 2015; Wang et al., 2016). From an investment perspective, we know that cultural attributes affect stock market participation (Breuer et al., 2014; Rieger, 2020), asset allocation (Anderson et al., 2011; Beugelsdijk and Frijns, 2010), and investment strategies of investors (Cheon and Lee, 2018) among others.

In a similar manner, Chui et al. (2010) also argue that cultural dimensions may be an aspect of investors' behaviour in the financial markets. Proxied by the individualism index developed by Hofstede (2001), Chui et al. (2010) find that momentum returns, volatility, and trading volume are positively correlated with collectivism versus individualism, which is related to investors' overconfidence and self-attribution preference. Likewise, the diversities in cross-country cultural factors regarding uncertainty avoidance are correlated with the predominance of self-attribution preferences, the volume of trading activities, and the extent of momentum in asset pricing (Anderson et al., 2011). Baker et al. (2012) consider several attributes of investor sentiment in different countries by observing its impacts on stock returns. Also providing comparable findings, Chang and Lin (2015) confirm the association between national cultures and investor trading in terms of herding behaviour. Hence, we propose a follow research question:

Research Question 5: Can the cross-country differences in cultural background explain the varying impacts of investor sentiment on asset returns and volatility?

Since the work of Weber (1905), it is recognized that religion affects economic attitudes and the activities of individuals, groups and societies. Authors usually distinguish between the macroeconomic impact of religion on economic growth, international trade, government quality and its microeconomic effect (on individual behaviors towards marriage, suicide, alcohol consumption, risk). At the micro level, recent research has linked individual religiosity to the level of participation in financial markets. Kumar et al. (2011) report that investors located in a Protestant environment are less likely to hold lottery-type stocks (with high firm-specific risk) than those located in a Catholic environment. They invoke social identity and social impact theory (Abrams and Hogg, 1988) to argue that 'the predominant local religion could influence local cultural values and norms and consequently affect the financial and economic decisions of individuals located in that region, even if they do not personally adhere to the dominant local faith' (Kumar et al., 2011). Similarly, Hood et al. (2014) and Kumar and Page (2014) show that investors belonging to different religious denominations will have different portfolio weights in the shares of companies with different social policies (favorable gay/lesbian policies) and companies involved in socially unproductive activities. For instance, they show that Catholic investors are more likely to own sin stocks than Protestant investors. Sin stocks are stocks of publicly traded companies involved in the manufacturing of unethical products such as alcohol and tobacco. Recently, Canepa and Ibnrubbian (2014) show that religious beliefs affect portfolio choices of investors in Saudi Arabia. Further, Religious trading rules lead to variation of the acceptance of gambling among investors with different religions and different levels of religiosity, which leads to heterogeneity in speculative behavior. Several studies relate such heterogeneity in gambling acceptance to heterogeneity in preferences for holding lottery-type stocks (Kumar, 2009; Kumar and Page, 2014; Kumar et al., 2011). Therefore, the following research question is raised:

Research Question 6: Can the cross-country differences in religion belief explain the varying impacts of investor sentiment on asset returns and volatility?

2.4 Institutional quality, market integrity, legal origin, and the predictive power of sentiment on stock markets

The cross-country differences in institutional and legal environments can drive the risk appetite behaviour of the investor (Morck et al., 2000; Porta et al., 1998). Chiou et al. (2010) confirm the significant impacts of legal setting on returns as well as financial risk premiums in 37 stock markets. The authors posit the positive associations between legal system efficiency and financial returns and adverse effect on volatilities. Corredor et al. (2013) consider both different characteristics of cross-country cultural and institutional background to analyse the influences of investor sentiment on European stock markets. Dissecting the role of institutional quality, Shi et al. (2021) suggest that these indicators have substantial negative impacts on volatility in Southeast Asian financial markets. Further, the study of Chang et al. (2012) also confirms the accrediting significance of variations in legal systems and governance quality on the role of sentiment in the financial markets. Considering the differences in economic development levels, Chang et al. (2012) also suggest that investor sentiment has more significant impacts in developed markets than in emerging markets. Market institutions influence the impact of investor sentiment as advanced institutions ameliorate information circulation and thus make stock markets more efficient (Zouaoui et al., 2018,1). In a study providing early motivation for our global examination of the sentiment-return relationship, Schmeling (2009) investigates 18 industrialized countries and reports that cross-country heterogeneity in the relationship can be explained by differences in market institutions across the developed stock markets examined, which is further supported by Wang et al. (2021). The idea behind these variables is that markets with higher institutional quality should have a more developed flow of information and are consequently more efficient. Hence, we propose a follow research question:

Research Question 7: Does the impact of investor sentiment on asset returns vary among different levels of the institutional quality, market integrity and legal origin?

2.5 Literacy, gambling opportunities and the predictive power of sentiment on stock markets

Education is a significant component, which among other factors influences investors' performance, risk-taking and stock market participation. Calvet et al. (2009); Campbell and Kyle (1993) note that educated investors participate more actively on the stock market and they tend to make more rational investment decisions than investors with lower educational level. Besides stock market participation choices, education is considered a key element explaining investors' risk-taking behaviour. Grable (2000) provides empirical evidence that education appears to encourage risk taking and offers a possible explanation that higher level of academic education allows individuals to assess risk and benefits more adequately compared to investors with a lower educational level. Goetzmann and Kumar (2008) find that investors who are younger, have lower income, are less-educated, and less-sophisticated, tend to hold portfolios that are highly volatile and consist of stocks that are more highly correlated compared to stocks, which were chosen randomly. Anderson (2007); Giofré (2017) add to this viewpoint by stating that less-educated investors invest a greater proportion of their wealth in individual stocks, hold more highly concentrated portfolios and have worse trading performance.

Several studies comfirm that besides academic education, real-life trading experience helps to achieve better performance on the stock market. Dhar and Zhu (2006) provide empirical evidence that trading experience helps investors to reduce certain behavioural biases and that investors' trading improves over time. Feng and Seasholes (2005) use the number of trades as a proxy for investor experience and find that investors do learn from their trading experience. Education is considered an important characteristic explaining investors' stock market participation choices, performance and risk-taking decisions on the stock market. Assessing the impact of education on investor trading experience in the form of trading activity, would be important in understanding investors' financial decision-making process. Based on this premise, the following research question is raised:

Research Question 8: Does the impact of investor sentiment on asset returns vary among different levels of literacy?

Gambling and speculation play an important role in financial markets. These and related activities are often associated with high levels of trading volume, high return volatility, and low average returns (Dorn and Sengmueller, 2009; Grinblatt and Keloharju, 2009; Hong et al., 2006; Scheinkman and Xiong, 2003). As gambling attains wider acceptability in society and a "lottery culture" emerges (Dorn and Sengmueller, 2009; Shiller, 2000), the influence of gambling behaviour in financial markets is likely to increase and could have economically significant effects on corporate decisions and stock returns. Specifically, in market settings that superficially resemble actual gambling environments and in which skewness is a salient feature, people's gambling attitudes may influence aggregate market outcomes. Previous studies have emphasized the potential role of gambling in investment decisions (Barberis and Huang, 2008; Kumar, 2009; Shefrin and Statman, 2000; Shiller, 2000). For instance, Barberis and Huang (2008) posit that investors might overweight low probability events and exhibit a preference for stocks with positive skewness.

Research Question 9: To what extent do the levels of gambling opportunity differentiate the impacts of investor sentiment on returns and volatility?

3 Data and method

3.1 Data

The data required in this paper includes financial information and country-specific factors of 52 stock markets to maintain a high level of homogeneity in all country-specific indicators. Overall, the sample is a various collection of international equity markets regarding the geographical[1], economic development[2], cultural levels. The sample periods vary for each stock market depending on the data availability, spanning from January 1980 to September 2022[3]. The major source of data is Refinitiv DataStream that provides monthly and daily stock returns, trading volume, turnover ratio, high, low, closing and opening prices all examined financial markets.

To consider the impacts of country-specific factors on the predictive power of investor sentiment on equity market movements, we collect 40 country-specific indicators in nine groups: *(i) Financial development; (ii) market structure; (iii) Cultural backgrounds; (iv) Religion backgrounds; (v) Legal origin; (vi) Market integrity; (vii) Institutional quality; (viii) Educational backgrounds; and (ix) Gambling opportunity* from several sources. In this study, we follow the MSCI market classification framework to classify the sample into three groups of market according to their financial development levels: developed markets, emerging markets, and frontier markets. According to the 2022 Global Market Accessibility Review[4], the detailed assessment of market accessibility for each equity market include: Openness to foreign ownership, Ease of capital inflows / outflows, Availability of Investment Instruments, Efficiency of the operational framework, Stability of the institutional framework. In addition, we also include other factors regarding the market structure that are possibly modified the predictive power of investor sentiment, include: educational background, institutional investors, and limits to arbitrage levels. The market structure, institutional quality, market integrity and educational levels, religion backgrounds are obtained from the World Bank and other

[1]We have 29, 11, 8, and 4 markets in Europe, Asia-Pacific, Americas, and Africa and Middle East, respectively.

[2]According to the most recent market classification framework of Morgan Stanley Capital International (MSCI), our sample include 22 developed markets, 20 emerging markets, and 10 frontier markets. See https://www.msci.com/our-solutions/indexes/market-classification for the detailed method and criteria for classifying equity market.

[3]See Table 1 for the list and classifications of all market in the sample. For the Ukrainian market, the data is available until February 2022 due to the Russian invasion in March 2022.

[4]For the detailed criteria for market classifications of MSCI, see: https://www.msci.com/documents/1296102/8ae816b1-fa03-bae3-0bb4-1a3b2bf387bf?t=1656972645260

databases. We obtained the legal environment of all country from Porta et al. (1998)[5] and Freedom index from Freedom House database[6]. We also provide a brief explanation and initial processing for all clusters of country-specific factors in each subsection that examined those factors. Table B1 reports the detail descriptions and data sources of all country-specific factor employed in this study.

3.2 Sentiment measures

Given the current literature, there are three two approaches (i.e., direct approach and indirect approach) to capture investor sentiment in the financial markets. The indirect method uses data from financial markets, which can reflect the trading behaviour of the economic agents (Baker and Wurgler, 2006). The direct method mainly utilises surveys data questioning consumers or investors about their predisposition of future economic conditions and investment plans (Qiu and Welch, 2004; Wang et al., 2021). Following prior studies that examine the predictive power in international market, this study adopts a direct approach by using the Consumer confidence indicators (CCI) as the main proxy for investor sentiment. The data for CCI is sourced from Organization for Economic Cooperation and Development (OECD) databases[7].

This approach can solve the issue of data availability for market-based sentiment indicators for all selected market. The CCI is the most appropriate sentiment measure as it is mostly comparable across financial markets (Schmeling, 2009). Most surveys in developed countries have adopted standardized questions to ensure the comparability of this index. These questions are similar to those asked in the survey by the University of Michigan and are structured around three themes: (i) past and future financial situation, (ii) past and future economic situation, and (iii) major purchases of durable goods. To construct this index, information is collected through a monthly survey, including a set of standardized questions about the above themes. Lemmon and Portniaguina (2006) and Ho and Hung (2009) confirmed the positive correlation between consumer confidence and household participation in the stock market. Indeed, when investors are optimistic about the economy, they are also optimistic about the

[5]It may be arguable the score proposed by Porta et al. (1998) is antiquated over years. However, it is undoubtedly the case that in some core areas of law and policies, such as legal procedure, we have found very slow change and a huge amount of persistence (Balas et al., 2009).

[6]See https://freedomhouse.org/sites/default/files/2020-02/Methodology_FIW_2019_for_website.pdf for the methodology.

[7]In case the data is not available for some market, we obtained the sentiment data from several sources such as: national authorities and organizations, and other academic and business research institutes, etc.

stock market. Consumer confidence is shown to be a suitable proxy for investor sentiment in Qiu and Welch (2004), who argue that if investors are bullish (bearish) about the economy, they would also be more (less) likely to invest in stock markets and vice versa, supporting a positive relationship between consumer confidence and investor sentiment—if consumer confidence is high (low), investor confidence would be high (low) accordingly[8].

In addition, the nature of this paper examining multiple stock markets including both developed and emerging markets requires consistency across all sample markets, meaning that one specific proxy should be applied in all 52 markets. The proxy offers such wide availability in all 52 stock markets. This indicator can provide an indication of future developments of households' consumption and saving, based upon answers regarding their expected financial situation, their sentiment about the general economic situation, unemployment, and capability of savings. An indicator above 100 signals a boost in the consumers' confidence towards the future economic situation, as a consequence of which they are less prone to save, and more inclined to spend money on major purchases in the next 12 months. Values below 100 indicate a pessimistic attitude towards future developments in the economy, possibly resulting in a tendency to save more and consume less. As such, this indicator is employed to proxy for investor sentiment in a number of prior studies (Ferrer et al., 2016; Jawadi et al., 2018; Lemmon and Portniaguina, 2006; Schmeling, 2009; Wang et al., 2021). As the consumer confidence indices are gathered from various sources with the discrepancy of neutrality benchmarks[9]. Further, consumer confidence surveys in different countries also naturally differ by the number of participants, which can possibly cause the bias or obvious outliers for smaller sample. To address this issue, we standardize the CCI in each individual market with zero expectation and unit variance.

3.3 Baseline Models

To examine the linear relation between investor sentiment, the univariate analysis is performed for all portfolio returns into groups of high and low sentiment periods. Based on the central prediction theories of investor sentiment in the financial market, which is reversal. In

[8]Empirically, Qiu and Welch (2004) demonstrate the validity of the consumer confidence index as they find a strong correlation between the consumer confidence index and another sentiment proxy, namely the UBS/Gallup Index of Investor Optimism (see, also, Christiansen et al. (2014); Derrien and Kecskés (2009); Greenwood et al. (2016); Lemmon and Portniaguina (2006).

[9]The consumer confidence surveys in different countries naturally differ by the benchmarks to construct the proxies. For instance, the neutral value of survey in the by OEDC countries is "100", while it is "50" for Thailand and Argentina, and "0" for some countries such as Romania or Croatia.

the sentiment models, investors tend to have higher demands for assets that are not indicated by the fundamentals, which pushes the asset prices from the underlying values (Da et al., 2015). As such, when sentiment is high, asset prices is high but later become low. In this study, we utilise the panel regression as follow to examine the impacts of investor sentiment on long-horizons of the market movements. Following Brown and Cliff (2005) and Menkhoff and Rebitzky (2008), we construct a long horizon return regressions as follows:

$$Y_{t+n}^{i} = \alpha_0 + \alpha_1\, Y_{t-1}^{i} + \beta_t^{i} SENT_t^{i} + \epsilon_{i,t} \tag{1}$$

where, Y_{t+n}^{i} is the market returns (*RET*)[10] and volatilities (*VOL*) of market i within different lags from 1, 3, 6, 9, 12, 18, 24, 36, and 48 months after the release of *SENT* (Consumer confidence Index – CCI) in month t. Prior studies usually utilise the average monthly stock returns during n horizon (i.e., the regression of sentiment on month 1 on the average returns of the next 12 months); however, the predictive power of sentiment is faded away over longer horizon (Brown and Cliff, 2005; Menkhoff and Rebitzky, 2008; Schmeling, 2009). Further, the impacts are only strong in first lagged months, the average approach exhibit strong impacts for the whole forecast horizon even when it is in fact not. As such, this study utilises single-period monthly approach to eliminate any permanent impact of sentiment in the following periods.

Prior studies mainly focus on how investor sentiment predict the future returns, this study further consider its impacts on price volatilities[11]. Following prior literature (Christiansen et al., 2012; Mittnik et al., 2015; Paye, 2012; Schwert, 1989; Taylor, 1987; Wang et al., 2016), we utilise the use monthly log realized variance, calculated from daily returns, as proxy for market volatility[12]. For a specific month t, the realized volatility is defined as:

$$VOL_t^{i} = \textstyle\sum_{i=1}^{N_t} RET_{i,t}^{2}$$

Where N_t is the number of trading days in month t, $RET_{i,t}$ is the daily return on the market index on the i^{th} trading day of the t^{th} month. This method is an accurate measure

[10] In this study, we employ the raw returns as Hong et al. (2007) and Schmeling (2009), raw returns are still reliable data for cross-nation regression because data for risk-free rates is hard to obtain outside the U.S.

[11] Volatility is a measurement of the uncertainty of financial asset return. There are several volatility definitions, such as realized volatility (Andersen et al., 2001; Paye, 2012)), absolute return (Ding et al., 1993), daily range (Alizadeh et al., 2002).

[12] This method is widely used in research on stock volatility predictions (Christiansen et al., 2014; Ma et al., 2019; Zhang et al., 2021).

of volatility and contains less noise (Andersen et al., 2001,0). Furthermore, prior literature confirms that several macroeconomics factors can affect market return and volatility (Baker and Wurgler, 2006; Boyd et al., 2005; Chen et al., 1986; Hjalmarsson, 2010; Welch and Goyal, 2008). Following prior studies of Atanasov (2021); Christiansen et al. (2012); Schmeling (2009) and Wang et al. (2021), we include the following six factors to control for the possible impacts of economic cycles and market situations:

- Inflation rate (INF): The proxy is computed from the Consumer price index (CPI) rates (Fama, 1981; Fama and Schwert, 1977).
- Industrial production growth (IDS): the monthly industry production growth (Atanasov et al., 2020).
- Unemployment rate (UNE): The monthly unemployment rate (Atanasov, 2021)
- Economic growth (GDP): The monthly growth rate of the gross domestic product (Fama, 1981).
- Short-term interest (STI): the detrended short-term interest rate (Henry, 2009).
- Global market returns (MSCI): The monthly returns of the MSCI Global Index

As such, we modify Eq. (1) with six additional control variables in the matrix X_t^i as follows:

$$Y_{t+n}^i = \alpha_0 + \alpha_1\, Y_{t-1}^i + \beta_t^i SENT_t^i + \gamma_t^i X_t^i + \epsilon_{i,t} \tag{2}$$

We estimate Eq.(2) with the use of panel fixed-effect regressions across all sample markets. In this model, the intercept is specific for each market; however, slope coefficients are restricted to be equal across countries. In addition, to provide more robust results and to be consistent with prior studies, we also utilise the long-horizon average returns and volatilities in our predictive models as follows:

$$\frac{1}{n}\sum_{n=1}^{n} Y_{t+n}^i = \alpha_0^{i,(n)} + \alpha_1^{i,(n)}\, Y_{t-1}^i + \beta_t^{(n)} SENT_t^i + \gamma_t^{i,(n)} X_t^{i,(n)} + \epsilon_{t+1\to n}^{i,(n)} \tag{3}$$

Where $\frac{1}{n}\sum_{n=1}^{n} Y_{t+n}^i$ is the average n-month returns and volatilities for market i over n months from (1, 3, 6, 9, 12, 18, 24, 36, and 48 months) after the release of SENT (Consumer confidence Index – CCI) in month t. To address the econometric concern of autoregressive forecasting variable and strong correlations between its innovations and return movements[13] (Ang and Bekaert, 2007; Stambaugh, 1999), we follow Schmeling (2009) and Atanasov (2021) to employ the slopes estimated from moving-block bootstrap simulation procedure developed by Gonçalves and White (2005). This approach accounts for the determination of regressors and correlations between stock returns and predictor variations, and consents for common forms of heteroskedasticity, which is valid by the Stambaugh (1999) specification. As such, the finite sample distribution of the estimated coefficient in Eq. (2) and (3) is more accurate and omitted the biased coefficient estimates and standard errors. This approach comprises two steps. Initially, we use of panel fixed-effect regressions across all markets with the original regression model and save all estimated coefficient. Next, the raw data are continually rerun in the moving block-bootstrap with 15 observations for each block length to create 10,000 new time series generated under the null of no predictability for all dependent variables and predictors[14]. Finally, we obtain the bootstrap distribution of all estimated coefficients by utilising the predictive regressions on these 10,000 artificial time series. Overall, we expect that the investor sentiment can positively predict the subsequent returns and heighten the investment risks through causing higher price volatilities.

[13]As stated by Atanasov (2021), the standard errors obtained from Hansen and Hodrick (1980) and Newey and West (1987) approach tend to over reject the null hypothesis of no long-term predictability with persistent predictors.

[14]We also utilize different levels of block length; however, our results remain consistent.

4 Descriptive statistics and preliminary tests

In this section, we provide the descriptive statistics for main variables and conducts several preliminary tests. In table 1, we report the descriptive statistics for market returns, realized volatilities and investor sentiment for all markets in the sample. Regarding the proxy for investor sentiment – Consumer Confidence Index, we also report the first-order autocorrelation ($\rho(1)$) for all sample markets. Overall, the values of $\rho(1)$ are relatively high and uniformly over 0.9, indicating that this sentiment proxy is extremely persistent time-series process. Our regression, therefore, can suffer from the biased estimations of the slope coefficients and standard errors (Ferson et al., 2003). As such, we perform several preliminary tests before proceeding the empirical analyses. First, three panel unit root tests, include Augmented Dickey Fuller (ADF)–Fisher, Im–Pesaran–Shin, and Levin–Lin–Chu tests are employed to test whether our sentiment proxy is unit-root non-stationary. The results are reported in the Appendix A, which indicates that we indeed deal with stationary, but highly persistent, time-series processes. Next, we also utilise the Granger–Causality tests as a simple method to verify for time-series dependencies between our sentiment measures and dependent variables - returns and volatilities. The tests include the simple bivariate test and the block exogeneity test, which are reported in the Appendix A. Overall, our results further confirm the Granger causality, revealing that returns and volatilities depend on investor sentiment, and vice versa, across all markets[15].

– Insert Table 1 about here –

In Table 2, we report the preliminary tests for the panel regression results from the fixed-effect specification, pooling across all sample markets. Overall, we initially confirm the predictive power of investor sentiment on both future stock returns and volatilities. The results for both average and single-period indicators also exhibit consistent results. For market returns, the estimated coefficients are negative and statistically significant in the subsequent 2 to 18 months. In other words, a one standard deviation increase in the SENT causes in a statistically significant decline of 0.57% (p-value = 0.047) and 1.14% (p-value = 0.000) in average monthly returns over the following 1 and 6 months, respectively. For the market volatilities,

[15]Fairly investors are excessively optimistic or pessimistic because of a string of good or bad news, returns, volatility, or macro information (Qiu and Welch, 2004; Schmeling, 2009). Consequently, the conclusion that returns/volatilities can drive sentiment and that sentiment drives subsequent returns/volatilities, seems acceptable.

our results indicate a negative relationship between investor sentiment and future volatilities. The realised average month volatility will increase 0.3% (p-value = 0.000) and 0.19% (p-value = 0.087), over the following 1 and 6 months, respectively in respect to a one standard deviation increase in the SENT. Additionally, it is remarkable to notice that the impacts of sentiment on average future returns reaches the highest level in the following 6 months and progressively decreases when it reaches the horizon of 18 months.

– Insert Table 2 about here –

On the other hand, we obtain the highest coefficient for volatilities during one month after the release of sentiment index, and declines with the forecast horizons up to three months. The negative (positive) impacts of sentiment on return (volatility) lend the support for a proposition that noise traders' optimism can push the stock price away from the equilibrium and make markets highly volatile. As such, our initial findings are in line with Kumari and Mahakud (2015); Lee et al. (2002); Schmeling (2009) and Gong et al. (2022) that higher (lower) market returns are undoubtedly related to the lower (higher) volatility resulting from bullish (bearish) shifts in investor sentiment. The pattern is indicative that a confidence impulse affects aggregate investor behaviour over various time periods, which is consistent with concept that investors endure conservatism. Once investors have made up their mind, their belief is maintained for several months that can affect market outcomes in longer horizons. To the best of our knowledge, the literature does not yield certain references for an accurate time frame for active investors' memory.

In addition, the predictive power of sentiment is also confirmed by the incremental adjusted-R^2 ($\Delta Adj - R^2$) reported under the associated Adj-R^2. The values of the $\Delta Adj - R^2$ are also consistent with the significance of estimated coefficients across difference horizons. The increase in $-R^2$ also shows that investor sentiment improves the goodness of fit of the model relative to the other predictors, particularly for short and medium horizons. This finding has both a statistical and an economic proposition. Theoretically, the declining reliability of investor sentiment suggests the desired estimation technique does not produce spuriously significant findings (Hong et al., 2007). Economically, the declining marginal effect of investor sentiment implies that noise trading effects will be washed out over longer horizons (Brown and Cliff, 2005; Schmeling, 2009). For instance, the limits to arbitrage are more significant in the short to medium run but it becomes undetectable over longer horizons. As such, the predictive power of investor sentiment is supposed to be diminished ultimately over longer horizons Overall, the results of a significantly negative (positive) relation between sentiment and returns (volatilities) is in line with theoretical considerations of the impact of noise traders and earlier empirical findings in prior studies.

– Insert Table 3 about here –

In Table 3, we reported results from robustness tests on the predictive power of sentiment on stock market movements. The first 6 columns, we partition the sample into three equal sub-periods[16] with the key events of the Global Financial Crisis in 2008-2009 by following a study of Jacobs (2015). The sub-period analyses can help to further confirm the robustness of our prior findings by replicating all analyses in Table 2 for each sub-period. Generally, the results remain qualitatively unchanged and confirm the significantly negative (positive) sentiment-return (volatility) correlation. Interestingly, in more recent years, the predictive power of investor sentiment progressively improved. For instance, the impact of investor sentiment is significant up to 6 and 36 months for volatility and returns in the latest period (Feb 2009 - Sep 2022). Also, a standard deviation increase in the SENT initiates in a decline of 0.63% (p-value = 0.035) and 0.37% (p-value = 0.000) in average monthly returns and volatility on a subsequent month, respectively. The significant improvement in the predictive power of investor sentiment overtime can be attributed to the enhancements in quality of the sentiment proxy (i.e., survey quality, construction of the indices, or sample sizes) (Pan, 2020; Zhou and Yang, 2019).

As mentioned in Section 3.2, we expect that our sentiment indicator - CCI measures time-varying beliefs about upcoming economic prospects of the individuals. However, the consumer confidence index only comprises information of basic expectations about individuals' financial position and could not fully represent general expectations of the economy as a whole (Campbell and Kyle, 1993; Møller et al., 2014; Schmeling, 2009). As such, to further confirm the predictive power of investor sentiment, we utilise a further test whether stock market movements driven by anticipated business situations or by the remaining factors beyond these company prospects. In this study, we also collect the business confidence index (BCI)[17] data

[16] Given the longest horizon on sentiment predictive power is up to 48 months, we exclude any markets with less than 48 monthly observations in the first subperiod as the differences in starting months.

[17] Business confidence index (BCI) provides subjective survey-based expectations, just like the CCI, about the qualitative information that has proved useful for monitoring the current economic situation. Typically, they are

from the same sources of consumer confidence data. This indicator is only available for 41 markets (20 developed, 17 emerging, and 4 frontier markets)[18]. Initially, by following Baker and Wurgler (2006); Wang et al. (2021) and Møller et al. (2014), we isolate the independent sentiment elements beyond the expectations of business by regressing the SENT on the BCI in the following model:

$$SENT_{t+n}^{i} = \alpha_0 + \gamma_1 BCI_t^i + SENT_t^{i\perp} \tag{4}$$

In this case, we obtain the orthogonalized term of residual series - $SENT_t^{i\perp}$ as a modified sentiment proxy that excluded the impacts of the business expectations. Then, we apply this indicator in Eq. (2) by replacing the variable of $SENT_t^i$. The results are reported in the last two columns of Table 3. Overall, the results remain consistent with our prior findings reported in Table 2 and 3 that investor sentiment proxied by Consumer confidence index can qualitatively predict future market returns and volatilities.

based on a sample of enterprises and respondents are asked about their assessments of the current situation and expectations for the immediate future. For enterprise surveys this concerns topics such as production, orders, stocks etc. and in the case of consumer surveys their intentions concerning major purposes, economic situation now compared with the recent past and expectations for the immediate future.

[18]We also employ the panel unit-root tests for this indicator and the results indicate that BCI are stationary. The results are not reported here for the sake of brevity, but more detailed descriptive statistics are available upon request.

5 National factors for cross-market differences

To explore the driving forces of the observed cross-market divergences in the impact of investor sentiment on returns and volatilities, we utilise a set of national-specific factors in financial development levels, market structure, cultural and educational background, religions, legal system, institutional quality, and market integrity. For comparability with Schmeling (2009); Wang (2001) and Gong et al. (2022), we focus on the 6-month and 12-month (one- and two-month) forecast horizons to assess the persistent impacts of investor sentiment on stock returns (volatilities)[19].

5.1 Financial development and market structure

In Table 4, we replicate the procedure in Table 2 after separately pooling developed, emerging, and frontier markets[20]. We classify the markets into each group based on the criteria in the MSCI market classification framework (See Appendix B). For brevity, we only report the coefficients and the associated p-value. In similar manners, our results further confirm the market returns are contemporaneously positively correlated with shifts in sentiment. Moreover, the magnitude of bullish changes in sentiment leads to upward in realized volatility in the subsequent months. Despite the general similarities, Table 4 also uncovers three apparent differences in the power of investor sentiment on returns between different groups of financial development. First, the predictive power of sentiment is significantly stronger developed markets, compared to emerging and frontier markets. For instance, one standard deviation surge in investor sentiment drives the average monthly returns down over the subsequent 6 months by 4.26% (-0.71%×6, p-value = 0.000), 3.9% (-0.65%×6, p-value = 0.000), and 3.66% (-0.63%×6, p-value = 0.000) for developed, emerging and frontier markets, respectively. Further, the investor sentiment has a more persistent power of more developed markets, up to 36 months (-0.38, p-value = 0.083) and 24 moths (-0.32, p-value = 0.066) in developed and emerging markets, respectively. For the frontier markets, the adverse impact is statistically up to only 12 months (-0.50, p-value = 0.059) and then completely dissolves afterwards. Thirdly, the impacts of sentiment on market returns are immediate in less developed

[19]The studies of Schmeling (2009) and Wang et al. (2021) only focus on a 12-months forecast horizon to capture longer-term effects. In this study, we provide additional results for 6-month horizon to capture a shorter term of investor sentiment's power.

[20]In the unreported results, we further divide our market sample into by using different classifications, include the International Monetary Fund's (IMF) classification for developed, emerging, and frontier markets. In addition, we all test the sample G7, G20, OECD markets. Overall, our results remain consistent with the findings reported in Section 4 and 5.1. To conserve space, the results are available on request.

markets. Specifically, the estimated coefficient of the SENT for the next-month returns in developed markets is insignificant (-0.24, p-value = 0.121), while it is significant in emerging and frontier markets at the 5% level. Regarding the differences on volatility in Panel B. We obtain consistent predictive horizons for volatility across all markets, which also in line with our findings. Nevertheless, the predictive power of sentiment is significantly stronger less developed markets. For instance, one standard deviation surge in investor sentiment drives the average monthly volatility up over a subsequent month by 0.19% (p-value = 0.031), 0.20% (p-value = 0.016), and 0.21% (p-value = 0.007) for developed, emerging and frontier markets, respectively.

– Insert Table 4 about here –

There are several possible explanations for those discrepancies between different levels of financial development. All markets in our sample are in different economic conditions, quality of information transmission, institutional frameworks, etc, which may affect sentiment investors' behaviours and investment decisions. Our finding on the stronger and more enduring predictive power of sentiment in more developed market are in line with the studies of Chang et al. (2011) and Wang et al. (2021) (emerging versus developed markets). In some ways, our results are also endorsed by prior studies of Jacobs (2015); Jacobs and Müller (2020) and Grinblatt and Keloharju (2009) that mispricing are nonetheless as visible, and sometimes stronger, in more established markets than the others. In addition, less developed markets usually exhibit greater volatility with positive and higher skewness (Aggarwal and Goodell, 2009; Aggarwal et al., 1999; Bekaert et al., 1998). Bartram et al. (2012) also document that the idiosyncratic element of volatility principally initiated by ineffective disclosure, weak accounting standards, more noise trading, higher liquidity risk and political risks. The higher levels of unsophisticated investors in those markets also enhance the predictive power of sentiment on market volatility (Gong et al., 2022; Kumar, 2009), that is empirically evidenced in our findings.

To further confirm the modified impacts of financial market's specific factors on the predictive power of investor sentiment, we utilise two indicators of institutional investment and limits to arbitrage and then tabulate the results in Table 5. The institutional investor is proxied by the proportion of institutional investors as an indicator for market composition. The limit to arbitrage is proxied by the market capitalization, which is computed annually for all available data. It is expected that smaller markets are more likely to face arbitrage constraints such as fundamental risk, short-selling constraint, liquidity risk, and so on (Brav et al., 2010; Chiah et al., 2021). All detailed descriptions and descriptive statistics are reported in Appendix B.1 and B.2. Then, we pool countries according to high or low values of the above discussed determinants and run panel fixed-effects regressions on the resulting subset of countries[21]. Following the approach of Gong et al. (2022); Wang et al. (2021) and Schmeling (2009), we focus on the 6-month and 12-month (1- and 2-month) forecast horizons for the average monthly approach to assess the persistent impacts of investor sentiment on returns and volatilites. In addition, a Wald test is also applied across two sub-samples to compare the estimated bootstrap coefficients. In Panel A, the impacts of sentiment on returns are more significant for markets with lower level of institutional investors and higher limits of arbitrage. For instance, the significant spread of 6-month return is 0.20 (p-value = 0.000) and -0.10 (p-value = 0.042) for factors of institutional investors and limits of arbitrage, respectively. The results are consistent across two return's horizons. As expected, our findings are in line with Kling and Gao (2008); Verma and Verma (2007,0) and Fong and Toh (2014) that sentiment exert stronger impacts on the market return as institutional investors are more rational than individual investors. Likewise, the markets with higher limits to arbitrage are more sensitive to changes of investor moods and adverse market event (Chiah et al., 2021; Smales, 2017; Zaremba, 2016).

– Insert Table 5 about here –

Regarding the volatility, we obtain a significant difference between market with high and low institutional investors (diff = -0.35, p-value = 0.05). This indicates that markets with the dominance of institutional investors are less driven by moody investing or overreactions due to higher levels of sentiment. In other words, market more individual investors exhibit higher volatility due to their irrational reactions. On the other hand, we do not find significant difference for volatility with sub-sample of limits to arbitrage. Hence, our finding can collaborate a study of Bohl and Brzeszczyński (2006) on the negative influences of institutional ownership on volatilities. They found that institutional investors calm down the market by reducing the price volatility after institutional investors turn into primary shareholders (Aitken, 1998; Lakonishok et al., 1992).

[21]Note that markets in the high and low layers based on the median split for the all market-specific factors in subsequent sections do not perfectly reflect the financial development levels (frontier/emerging/developed markets) adopted earlier.

5.2 Cultural background and religions

In this section, we explore how differences in national cultural and religion backgrounds can modify the predictive power of investor sentiment. To consider the impacts of culture factors, we collect nine culture dimensions that are widely employed in the finance literature. We collect six cultural dimensions developed Hofstede (2001) and Hofstede (2015) from Hofstede Insights Database[22]: Individualism (IDV) versus Collectivism (COL), Power Distance Index (PDI), Uncertainty Avoidance Index (UAI), Long-Term Orientation (LTO), Indulgence (IDG), and Masculinity (MAS). We also collect three additional cultural factors Hierarchy (HIC), Embedded (EMB) and Mastery (MAT) from Schwartz (2007). Regarding the religion backgrounds, we utilise data of the World Factbook of the CIA and the U.S. Department of State to cluster the sample into different groups. The markets are classified into each group if by the statistics on the highest proportion of population belong to a specific religion. All detailed descriptions and descriptive statistics for all cultural dimensions and religions are reported in Appendix B.1 and B.3, respectively. Then, we pool countries according to high or low values of the above discussed determinants and run panel fixed-effects regressions on the resulting subset of countries.

– Insert Table 6 about here –

In Table 6, we report the results for return and volatility in different groups of markets classified by the nine cultural backgrounds in Panel A and B, respectively. The 6-month estimated coefficient for return are 0.21 (p-value = 0.076) and 0.45 (p-value = 0.000) for IDV and COL markets, respectively with difference on coefficients is 0.23 (p-value = 0.012). The results indicate that investor sentiment constantly affects subsequent 6-month returns in low IDV markets, but it loses predictability in low COL markets. The impacts of sentiment on volatility are also more significant in low IDV markets with 1-month spread is -0.14 (p-value = 0.025). Our findings could be justified by systematic cross-country variations in herd-like overreaction link to the collectivistic behaviour (Chui et al., 2010). We also obtain similar results when consider the factor of Embedded by Schwartz (2007), which relates to Collectivism. The investor sentiment strongly predicts subsequent 6-month returns in high EMB markets compared to lower EMB markets. Collectivism or Embeddedness assumes that personal in-

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

terest is less valuable than the group's interest, which encourages them to follow each other actions. On the other hand, a high autonomy society, contradict to EMB, reveals the ambition of people to articulate their own preferences and capabilities. Our results here are consistent with Beckmann et al. (2008); Markus and Kitayama (1991); Schmeling (2009) and Chang and Lin (2015) suggesting a positive COL and sentiment impact linked to herding.

Consistent with our anticipation, the spread on the impact of investor sentiment on 6-month returns and volatility for Power Distance Index (PDI) is 0.07 (p-value = 0.062) and 0.14 (p-value = 0.073), implying that trading by investors in low markets has a more noticeable impact on the sentiment predictive power. Power distance reflects the capacity of less powerful people and organizations to accept that the power is distributed unequally, and it is commonly used to identify a stratified society. The equality between each member in the society in low PDI markets lead to more significant herd-like overreaction of market participants, which supports our findings. On the contrary, high Uncertainty Avoidance Index (UAI) and Masculinity (MAS) markets are more suffered from the impacts of investor sentiment as inferred. The masculine societies are identified by competition and material reward for success, and this type of cultures tends to be less emphatic with the weak ones. Uncertainty avoidance involves the perception of people regarding the future, whether they accept that the future can be unpredictable, or they try to control it through beliefs and institutions. As such, our findings on UAI and MAS and predictive power of sentiment are linked to overconfidence hypothesis (Chui et al., 2010; Li et al., 2013). Further, we report a notably stronger prediction by sentiment in low Indulgence (IDG) markets than in high IDG markets. In more indulgent countries, as opposite to restrained, people usually make decisions with more freedom to fulfilling their desires, and are normally more enthusiastic (Hofstede, 2015). As such, the stock markets in countries, which are culturally more prone to herd-like behaviour by lower IDG, exhibit strong predictive power of sentiment. For three factors of Long-Term Orientation (LTO), Hierarchy (HIC), and Mastery (MAS), the results do not clarify divergences between the high and low clusters in general.

In Table 7, we dissect whether the religion beliefs can modify the impacts of sentiment on market movements. By following the classifications of Masuzawa (2005) and Harvey (2000), we sort our sample into different two main clusters of religions: Abrahamic religions, including Catholic, Protestant, and Islam; and Indian religions with Hinduism and Buddhism[23].

[23] In this study, we cannot cover all strands of religions as limited data of the population belong to some religions

Then, we all countries are classified into each group if by the statistics on the highest proportion of population belong to a specific religion by using the data of the World Factbook of the CIA and the U.S. Department of State[24]. In Appendix B, we report descriptive statistics for the religion backgrounds of all countries. Finally, we pool countries according to high or low values of the above discussed determinants and run panel fixed-effects regressions on the resulting subset of countries.

– Insert Table 7 about here –

The differences of the impact of investor sentiment on 6-month return between high and low Catholic and Protestant population are 0.30 (p-value = 0.008) and 0.15 (p-value = 0.017), respectively. The results indicate that investor sentiment persistently impacts subsequent 6-month returns in markets with high Catholic population compared to Protestant. The results exhibit no significant difference between high and low groups for all religions when we consider the impacts on market volatility. Overall, our findings are in line with studies of Kumar et al. (2011) that in regions with higher Catholic–Protestant ratios, investors exhibit a stronger propensity to hold lottery-type and high-risk stocks, which are more sensitively to sentiment.

In line with our prospect, the spread on the impact of sentiment on 6- and 12-month returns for Islam is statistically significant with 0.19 (p-value = 0.01) and 0.22 (p-value = 0.038), respectively. The results suggest that trading behavior of investors in markets with lower rate of Islamic population exhibit more pronounced impacts on sentiment-return nexus. In theory, in Islamic countries, the sharia-compliant stock investment should not have a substantial association with investor sentiment over, at-least, long-run investment horizons (Aloui et al., 2021; Hasan et al., 2021). The sentiment is mainly driven the inclination to speculate of investors (Barberis et al., 1998; Birru, 2018), which is strictly forbidden by the sharia regulations in the Islamic world. As a results, investors with Islamic belief tend to make their investment decisions by using fundamental information rather than depend on optimistic or pessimistic. Further, trusting on rumors or unexpected information is not accepted by the sharia rules (Aloui et al., 2021); therefore, sentiment does exhibit strong impacts on Islamic investors' decisions. As such, our findings on the different between Islamic and non-Islamic

(i.e., Hindu, Sikhism, Taoism or Jewish), which are difficult to classify into our proposed groups.

[24] This approach has been utilized in several prior finance studies (Callen and Fang, 2015; Du, 2014; Jiang et al., 2018; Wang and Lin, 2014).

markets are consistent with prior theories.

Turning to the groups of Indian religions, we do not obtain significant difference between high and low Hinduism countries. However, it does give reasons for divergences across layers, the further split into high and low of Buddhism population with the spread of 6-month return is -0.13 (p-value = 0.044). As such, the sentiment exerts stronger impacts on investment decisions in markets that highly populated by Budish. In theory, investors may recognize the Buddhist philosophy as a positive aspect in nurturing a world that alleviates the probability of being confiscated by moral threats and self-dealing actions (Pace, 2013). Further, the fundamental notion of Buddhism is karma which focuses on the ethical superiority that good moral behaviors can lead to a positive consequence (Jiang et al., 2018; Pace, 2013). Miller (2000) also argues that the levels of risk aversion are driven by belief in Eastern religions (such as Buddhism and Taoism). Hence, those theory on support our findings on the explain divergences across the upper and lower layers of Buddhism population.

5.3 Legal system, institutional quality, and market integrity

In this Section, we consider the modified effects of institutional quality, market integrity, and legal origin on the predictive power of investor sentiment on stock market movements. First, we collect the data of 15 factors including six institutional quality indices, five indices of market integrity, and four groups of legal origins from several sources, which are reported in Appendix B5 and B6. The clustering and test procedures are the same as that used in prior sections. In Table 8, we report the results for 6 institutional quality indices from Worldwide Governance Indicators (WGI) – World Bank. To fully capture the evolution of institutional quality in all countries, we compute a composite score for each factor from the annual data from 1995 to 2020. This score is utilized to pool the countries into high versus low clusters. As expected, our results are consistent across all indices that all spreads of coefficients are positively (negatively) significant for two horizons of returns (volatility). In other words, we find that investor sentiment is less powerful in markets with stronger institutional quality than in those with relatively weaker institutions. As such, our findings are in line with Zouaoui et al. (2011) that better institutions enhance the information transmission and therefore make financial markets more efficient.

– Insert Table 8 about here –

In Table 9, we examine five indicators stock market integrity proposed by Chui et al. (2010). In a similar manner to institutional quality, we expected that markets with better market integrity quality should have a more advanced flow of information and are therefore more efficient. The broad picture here is that better market integrity reduces the predictive power of investor sentiment on return and volatility, which is also consistent with our prior findings in this section. Specifically, our results indicate that the impacts of sentiment are less pronounced in freer markets with (positive) negative and significant spreads for returns and volatilities. This collaborates the findings of Akhter (2004) and Gourinchas and Jeanne (2006) that economic freedom can facilitate international exchange, investment opportunities, financial market efficiency. Overall, our findings propose a policy implication that a market of more comprehensive institutions is vital to reduce the influences of investor sentiment on investment decisions.

– Insert Table 9 about here –

It is plausible that a sound legal context is important for investors (Lamech and Saeed, 2003; Porta et al., 1998), and we believe that the impact of investor sentiment is also affected by the legal origin. In Table 10, we consider the impacts of legal origins proposed by Porta et al. (1998) on the predictive power of investor sentiment. There are four groups of legal origins in our sample, which is statistically reported in Appendix B6. We create binary variables that takes a value of one if the market is under specific legal origin and 0 otherwise. Then we run a regression by adding interaction terms ($SENT_t^i \times D_{Legal,i}$) between sentiment and binary variables in Eq.(3). For brevity, we only report coefficients of the interaction terms in Table 10. We only obtain positive (negative) and significant coefficients for returns and volatilities with Common law origin. In other words, this result indicates that the investor sentiment effects are less significant in those markets with a common law legal origin than with the other legal origins. Financial markets in countries with common law legal origin usually have better investor protection financial reporting quality (Glaum et al., 2013; Knauer and Wöhrmann, 2016; La Porta et al., 1999,9). Further, common-law countries also typically have more liquid markets that offer verifiable market prices, by this means evading subjective evaluations Ball (2006). As such, our findings typically hold notwithstanding the prior literature.

– Insert Table 10 about here –

5.4 Educational and other factors

As a demographic factor, education is widely adopted as an indicator of individuals' potential skills, which possibly affect the investors' behaviour and investment decisions (Dhar and Zhu, 2006; Dwyer et al., 2002). Hence, we consider the impacts of four educational factors, including Overall literacy rate (LR), Higher education rate (HE), Educational expenditure (EE), and Financial Literacy rate (FL), in Table 11. The Appendix B1 and B7 reports the detail description and descriptive statistics for all factors employed in this section. For more robust results, we compute a composite score for each factor from the annual data from 1995 to 2020 according to the data availability. The test procedure is the same as prior section for across the upper- and lower-layer markets. For the LR, the differences between high and low clusters are insignificant. However, we find for HE that in markets with higher rate of bachelor graduates, investor sentiment tends to exert a weaker impact on long-run stock returns and volatility than markets with lower rates. Further, we also obtain similar results for the EE factor. It means stock market with less EE are more affected by investor sentiment than those with low EE. Overall, our findings are in line with Kruger and Dunning (2002); Lichtenstein and Fischhoff (1977) and Dhar and Zhu (2006) that investors with higher education are less subject to hypercritical biases and emotion-driven investment decisions.

– Insert Table 11 about here –

As discussed in Section 2.4, one of important determinant of stock market nonparticipation and investment decisions is information cost, which can be proxied by the technology development (Gürtzgen et al., 2021; Haliassos and Michaelides, 2003). As such, we utilise the rate of Internet users (IU) of national population as an indicator of information flow efficiency. The results conditional on IU reported in Table 9 reveal that high IU supresses the sentiment impact on market return and volatility compared to low IU markets. Higher rate of internet availability can foster the rate of stock market participant, digital literacy, and financial literacy in the market (Choi and Robertson, 2020; Wang et al., 2022). As such, the impacts of irrational investment from sentiment can be lessened.

Finally, we extend the analysis by considering the impacts of gambling opportunity on the sentiment-return relation. As gambling attains wider tolerability in society and a "lottery culture" emerges, the impact of gambling behaviour in the financial markets is therefore expected have reasonably substantial consequences on stock returns (Dorn and Sengmueller, 2009; Shiller, 2000). We utilise two indicators for the gambling opportunity in each market, which collected from two different sources. First, by following the studies of Kumar (2009) and Chiah and Zhong (2020), we collect the data of number of casinos operated in each country from World Casino Directory. We also obtain the ratios of annual lottery sales to national GDP for all available year to compute an average value for each country based on the data availability. From those two indicators, we rank and group all markets into high and low groups of gambling opportunity (GO) .We utilise the same test as prior section and report the results in Table 9. We find that, in low GO markets, the impact of investor sentiment is significantly weaker than in high GO markets for 6-month return (spread = -0.12, p-value = 0.025) and volatility (spread = 0.12, p-value = 0.048). In other words, markets with high levels of gambling display a stronger sentiment impact than those with low corresponding levels. This finding is in line with the "lottery culture" that are often correlated with higher degrees of trading volume, high volatility, and low average returns (Dorn and Sengmueller, 2009; Grinblatt and Keloharju, 2009; Hong et al., 2006; Scheinkman and Xiong, 2003).

6 Additional analyses

6.1 Condition-varying impact of investor sentiment on stock markets

Investors have been shown to exhibit varying behaviour in different market conditions (Gervais and Odean, 2001; Nofsinger, 2005). In this subsection, therefore, we examine the impact of investor sentiment on stock market returns conditional on different economic settings at the global level by adopting two approaches. First, we identify high- and low-sentiment periods as per the neutral value set in the consumer confidence survey in each market. Results in Table 12 show that high sentiment can significantly lead to low stock returns and high volatility in subsequent 1 to 18 months and 1 to 2 months in all markets, respectively. Second, we recognize bull and bear market regimes by utilising returns of each market and global market.

– Insert Table 12 about here –

Prior US studies of the market separation primarily classify regimes based on economic cycle (expansion and recession) described by the National Bureau of Economic Research (NBER), formulating separation principles based on economic indicators such as real GDP, employment, and wholesale-retail sales (Chung et al., 2012; Garcia, 2013; Savaser and Şişli-Ciamarra, 2017). However, due to the data limitation for the global sample, we employ the definitions of 'bull' and 'bear' regimes to substitute economic 'expansion' and 'recession', respectively. The bull and bear regimes represent the intervals when stock prices generally rise and fall, indicating expansion and recession in the real economy as characterised by the NBER (Chauvet and Potter, 2000). Then, we divide the whole sample into bull and bear regimes by following Pagan and Sossounov (2003) and report the results in Table 12. We find that the predictive power of investor sentiment on return and volatility is 1 to 18 months and 1 to 2 months during bull regimes in all markets, respectively. For the bear regimes, the impacts are statistically insignificant. We also obtain similar results for the global market regimes. Overall, there are significant differences in the impact of investor sentiment across bull and bear regimes over short to medium horizons (1 to 18 months), which is consistent with an US study of Chung et al. (2012).

6.2 Cross-sectional impact of investor sentiment on stock returns

In this section, we consider the link sentiment and country factors to high-minus-low return spreads on portfolios constructed by sorting on stock characteristics, which are so-called market anomalies. Follow prior studies in finance literature that consider the factor investing, we obtain 14 well-documented anomalies from the study of Jensen et al. (2021)[25], which is available for all 52 markets. The long–short portfolios are formed based on 14 firm characteristics (X): Age, Asset growth, Book-to-market ratio, Dividend yield, Idiosyncratic volatility, Liquidity, Equity Issuance, Ohlson O-score, Momentum, Gross profit, Quality minus Junk, Return on assets, Firm size, and Total accruals. For each factor, we obtain value-weighted portfolio returns from the long-short strategy using the extreme deciles, 1 and 10, with the long leg being the higher-performing decile (as reported by previous studies and confirmed in our sample period). The descriptions of all long-short returns for all anomalies are reported in Appendix C. By following the studies of Baker and Wurgler (2006) and Stambaugh et al. (2012), we utilise the following predictive regression to consider the impacts of sentiment on returns on long-short strategies:

$$RET^{High,t}_{X_{i,t+n}} - RET^{Low,t}_{X_{i,t+n}} = \alpha_0 + \beta^i_t SENT^i_t + \gamma^i_t Y^i_{t+1} + \epsilon_{i,t} \tag{5}$$

where, $RET^{High,t}_{X_{i,t+n}} - RET^{Low,t}_{X_{i,t+n}}$ is the monthly return on a long-short portfolios (anomaly returns) based on the X firm-characteristics of market i within n lags from 1, 2, 3, 6, 9, and 12 months after the release of SENT in month t. Y^i_{t+1} is the vector of six additional control variables. Then, we further consider the modified impacts of national on the predictive power of sentiment on the factor returns. We create binary variables - $D_{FT,i}$ that takes a value of one if the market is sorted into groups of high specific factor and 0 otherwise. For brevity, we regroup some indicators and only include those with significant results reported in prior sections. We then modify Eq.(5) as follows:

$$RET^{High,t}_{X_{i,t+n}} - RET^{Low,t}_{X_{i,t+n}} = \alpha_0 + \beta^i_t (SENT^i_t \times D_{FT,i}) + \gamma^i_t Y^i_{t+1} + \epsilon_{i,t} \tag{6}$$

[25]The data is available at: https://jkpfactors.com/

– Insert Table 13 about here –

Initially, we report the results from Eq. (5) in Table 12[26]. Overall, the long-short returns for a broad set of cross-sectional factors (anomalies) demonstrate empirical results consistent with a pattern of short-sale impediments and market-wide sentiment. Consistent with Baker and Wurgler (2006) and Stambaugh et al. (2012), we find that the anomaly returns are higher following periods of high investor sentiment, to the magnitude that the factor reveal mispricing. In our sample, there are 10 out of 14 anomalies that exhibit positive coefficients for 1-month lag regression (excluding AG, LIQ, ACC, QMJ). As such, we further explore the modified effects of country specific-indicators on sentiment-return nexus of those ten factors in Table 13. The test procedure is similar to Section 5. For brevity, we only report the results for Wald test between two coefficients when we run the regression for two clusters (high versus low) of markets classified by their specific factors.

– Insert Table 14 about here –

For the financial development levels, we reclassify the markets into two group, developed markets versus emerging and frontier markets[27]. For the factor of financial development, we obtain negative and significant results for five factors of BTM, DIV, MOM, PRO, and ROA. Conversely, three anomalies of AGE, DIV and SIZE exhibit positive coefficients the different between two layers of finanical development. The results for high and low levels of institutional investors are also exhibit similar patterns across all anomalies, but insignificant for groups of Limits to arbitrage. There are two potential reasons that differentiating the predictive power of sentiment between financial development and Institutional investor. First, the factors of firm age, dividend payment and size tend to be more straightforward than distinguishing stocks based on their accounting information on firms' balance sheets, such as IV, EQI or ROA. Hence, that information might be beyond investors in markets with less financial development and lacking in financial literacy (Cole et al., 2011; Grohmann, 2018). Further, institutional investors, who are assumed to be more knowledgeable in related fields (Gharghori

[26] In unreported results, we also run the regression of all factors up to 18 and 24-month lags. The estimated coefficients are all statistically insignificant and are thus not reported to conserve space. However, it is available up on request.

[27] We also maintain the previous classifications (developed, emerging, and frontier markets) and rerun the regression by using the Eq.(4). The Wald test is applied to compare the coefficients between each pair of groups. However, we only obtain the significant results between developed markets and emerging/frontier markets and no difference between emerging and frontier markets. As such, we reclassify the sample into two groups to converse space.

et al., 2008; Venezia et al., 2011), and hence equity markets with more institutional investors are less information asymmetry than other markets with lower rates of institutional holdings.

To consider the impacts of institutional quality, we compute a single index from five individual indicators for each country, which is reported in Appendix B5[28]. We obtain consistently insignificant results for all indicators of institutional quality and market integrity, except Accounting Standards. Negative and statistically differences between markets high and low accounting standards indicate that investor sentiment exhibits stronger impacts on markets with lower quality of accounting guidelines. So, our results here hold notwithstanding the findings of Kaserer and Klingler (2008) and Eisdorfer et al. (2018) that low quality of accounting standards or disclosures makes it more complicated to evaluate firms' value and their financial information. This stimulates an amount of risk to investors and lead to more significant impacts of investor sentiment on return anomalies. Regarding the modified impacts of cultural and religion backgrounds, we find significant distinctions between markets with high and low IDV, EMB. In particular, the positive spreads indicate that the predictive power of sentiment on AGE, DIV, and SIZE is stronger in markets with herd-like culture. This finding is consistent with our findings in section 5.2 that sentiment exerts stronger impacts in country with higher IDV and EMB (Chui et al., 2010). In addition, the results for an indicator of Catholic religion also exhibit a similar pattern, which is possibly explained by the tendency of holding more lottery-type and high-risk stocks by Kumar (2009) that are more sensitively to sentiment.

Finally, we consider two indicators of educational quality and gambling opportunity. As expected, the results indicate that predictive power of sentiment on anomaly returns of SIZE, DIV, and AGE are weaker in markets with greater higher education rates. This finding is linked our explanations for the financial development levels that straightforward anomalies are easier to recognize by investors with lower literacy. With the impacts of financial literacy, the spreads between two layers are positive and significant for five of anomalies that are required analyses of firms' balance sheets. As such, the impacts of sentiment on those anomaly returns are stronger for markets with lower levels of financial literacy. As with more financial knowledge, investors exhibit less involvement with the disposition effect and herding tendency and more connection to mental accounting bias (Anderson, 2007; Baker et al., 2018). Over-

[28] In unreported results, we also test the differences between high and low groups of five institutional quality indices of World Bank. However, the results are economically insignificant, but are available on request.

all, by exploring the heterogeneous nature of investors and anomalies in different markets, we provide further reinforces for the multi-asset model proposed by Ding et al. (2019) that investors' misperception can alter cross-sectional asset prices.

7 Conclusion

In this study, we explore the predictive power of investor sentiment on future stock returns and volatilities by considering the heterogeneity of country-specific factors. Utilising a global dataset of 52 stock markets and 40 different national factors, we document that investor sentiment can negatively (positively) predict future global stock returns (volatilities). Our resutls confirm the predictive power of sentiment on future stock returns and volatilities from the subsequent 1 to 18 and 1 to 2 months, respectively. To the best of our knowledge, this study is the first to encompass the sentiment literature to the international level by examining on returns, volatilities, and a wide range of national indictors. The impacts of sentiment are stronger in advanced markets, but it is more instantaneous in emerging and frontier markets. Variances in the impacts of investor sentiment across markets are also defined by the country-specific factors. Stronger impacts are captured in markets with lower institutional holdings, lower internet accessibility, more limits to arbitrage and opportunities to gambling. Our findings are also supported by prior studies that the power of sentiment is more visible for countries that are culturally more prone to herd-like investment behaviour, which can be elucidated by the cultural and religion backgrounds. Further, heterogeneity in sentiment predictive power is also positively associated with quality of the education, legal origins, national governance, and market integrity. Our study also sheds further light on the impacts of sentiment on cross-sectional returns by utilising the data of 14 well-documented stock market anomalies. From this perspective, we provide novel findings that country-specific characteristics can justify investor sentiment impacts on the returns of stock market anomalies. From the staring points drawn from this study, several practical and policy implications can be propositioned to alleviate the adverse consequences of noise trading in the stock markets.

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Table 1: Summary statistics of stock returns, volatility, and investor sentiment

This table presents descriptive statistics of the sentiment indicators, returns, volatility: mean, standard deviation (S.D), and the first-order autocorrelation ($\rho(1)$) for 52 stock markets. The sample periods vary for all sample markets as the starting month depends on the data availability and the ending month is September 2022. A total of 52 markets in our sample are classified into three groups according to the MSCI market classification framework: 22 developed, 20 emerging, and 10 frontier markets.

No	Market	Region	From	Obs	Returns		Volatilities		Sentiment		
					Mean	S.D	Mean	S.D	Mean	S.D	$\rho(1)$
	Developed market			**10,235**	**0.0058**	**0.0652**	**0.0037**	**0.0134**	**100.05**	**1.75**	**0.95**
1	Australia	Asia Pacific	Jan-80	513	0.0067	0.0694	0.0022	0.0054	99.97	1.25	0.92
2	Austria	Europe	Jan-80	513	0.0038	0.0766	0.0047	0.0112	99.99	1.60	0.96
3	Belgium	Europe	Jan-80	513	0.0059	0.0624	0.0035	0.0073	99.93	1.49	0.97
4	Canada	Americas	Jan-80	513	0.0061	0.0579	0.0023	0.0053	99.98	1.75	0.95
5	Denmark	Europe	Jan-80	513	0.0096	0.0568	0.0027	0.0055	100.13	1.40	0.96
6	Finland	Europe	Jan-88	417	0.0055	0.0834	0.0036	0.0056	100.00	2.21	0.93
7	France	Europe	Jan-80	513	0.0064	0.0621	0.0041	0.0070	99.61	1.47	0.94
8	Germany	Europe	Jan-80	513	0.0057	0.0654	0.0041	0.0070	100.03	2.13	0.95
9	Hong Kong	Asia Pacific	Jan-06	513	0.0081	0.0807	0.0054	0.0102	100.18	1.17	0.96
10	Ireland	Europe	Jan-88	417	0.0027	0.0646	0.0047	0.0094	100.82	1.98	0.97
11	Israel	Africa & ME	Mar-11	139	-0.0013	0.0571	0.0023	0.0052	100.00	1.97	0.90
12	Italy	Europe	Jan-80	513	0.0050	0.0728	0.0040	0.0073	100.42	1.70	0.96
13	Japan	Asia Pacific	Apr-82	486	0.0048	0.0588	0.0040	0.0065	100.01	1.43	0.96
14	Norway	Europe	Aug-92	513	0.0055	0.0779	0.0048	0.0107	100.22	1.28	0.97
15	Netherlands	Europe	Jan-80	513	0.0082	0.0567	0.0041	0.0078	99.96	1.55	0.98
16	New Zealand	Asia Pacific	Jun-88	417	0.0036	0.0647	0.0015	0.0036	99.97	1.28	0.95
17	Portugal	Europe	Jan-88	417	0.0012	0.0647	0.0026	0.0050	99.86	2.35	0.98
18	Spain	Europe	Jun-86	436	0.0052	0.0696	0.0046	0.0081	100.01	2.75	0.97
19	Sweden	Europe	Oct-95	324	0.0057	0.0712	0.0047	0.0064	100.03	1.56	0.93
20	Switzerland	Europe	Jan-80	513	0.0075	0.0497	0.0031	0.0057	100.02	1.70	0.95
21	UK	Europe	Jan-80	513	0.0068	0.0526	0.0058	0.0586	100.03	2.13	0.95
22	US	Americas	Jan-80	513	0.0083	0.0445	0.0022	0.0057	99.99	1.53	0.96
	Emerging markets			**5,224**	**0.0105**	**0.1214**	**0.0055**	**0.0147**	**95.03**	**16.61**	**0.93**
1	Brazil	Americas	Jan-95	333	0.0133	0.0829	0.0093	0.0182	100.01	1.85	0.96
2	Chile	Americas	Mar-02	247	0.0072	0.0489	0.0034	0.0073	100.00	2.58	0.95
3	China	Asia Pacific	Jan-91	381	0.0162	0.1495	0.0096	0.0248	100.03	2.41	0.94
4	Colombia	Americas	Nov-01	251	0.1204	0.0658	0.0032	0.0124	100.00	2.61	0.95
5	Czech Rep.	Europe	Jan-95	333	0.0041	0.0621	0.0041	0.0110	100.01	2.14	0.97
6	Greece	Europe	Jan-85	298	0.0198	0.3970	0.0104	0.0159	99.30	2.73	0.98
7	Hungary	Europe	Feb-93	267	0.0063	0.0718	0.0052	0.0150	100.42	1.89	0.96
8	India	Asia Pacific	Aug-12	122	0.0109	0.0479	0.0029	0.0061	99.73	3.77	0.91
9	Indonesia	Asia Pacific	Apr-01	258	0.0131	0.0574	0.0043	0.0083	100.00	1.18	0.94
10	Kuwait	Africa & ME	Jan-11	141	0.0021	0.0468	-0.0039	0.0146	108.16	8.91	0.67
11	Mexico	Americas	Apr-01	258	0.0092	0.0491	0.0035	0.0063	100.00	2.45	0.92
12	Peru	Americas	May-12	357	0.0147	0.0849	0.0041	0.0092	100.13	1.21	0.96
13	Poland	Europe	May-01	257	0.0020	0.0655	0.0054	0.0099	100.01	1.53	0.95
14	Russia	Europe	Nov-98	287	0.0160	0.1082	0.0036	0.0053	99.60	2.77	0.95
15	Saudi Arabia	Africa & ME	Jan-17	69	0.0079	0.0508	0.0022	0.0018	61.23	5.04	0.92
16	South Africa	Africa & ME	Jun-82	327	0.0091	0.0542	0.0053	0.0094	100.27	1.79	0.94
17	South Korea	Asia Pacific	Dec-98	286	0.0077	0.0673	0.0038	0.0056	100.01	1.19	0.86
18	Taiwan	Asia Pacific	Jan-01	261	0.0056	0.0686	0.0037	0.0063	74.98	9.01	0.92
19	Thailand	Asia Pacific	Aug-00	266	0.0083	0.0600	0.0095	0.0120	33.00	12.63	0.91
20	Turkey	Europe	Jan-04	225	0.0156	0.0769	0.0124	0.0351	100.02	3.21	0.96
	Frontier markets			**2,221**	**0.0086**	**0.0834**	**0.0060**	**0.0673**	**53.91**	**53.60**	**0.91**
1	Argentina	Americas	Mar-01	259	0.0289	0.1139	0.0125	0.0173	45.20	7.72	0.88
2	Bulgaria	Europe	Sep-03	229	0.0048	0.0718	0.0184	0.1966	-25.54	5.72	0.76
3	Croatia	Europe	Apr-05	210	0.0021	0.0618	0.0007	0.0003	-20.89	10.88	0.90
4	Estonia	Europe	Jun-02	244	0.0059	0.0856	0.0015	0.0032	101.17	3.11	0.96
5	Lithuania	Europe	Jul-08	171	0.0023	0.0693	0.0006	0.0014	99.16	3.72	0.97
6	Romania	Europe	Jun-02	244	0.0117	0.0762	0.0053	0.0110	-17.29	11.01	0.89
7	Serbia	Europe	Nov-05	203	0.0019	0.0760	0.0001	0.0004	99.68	1.35	0.95
8	Slovenia	Europe	Jun-02	244	0.0044	0.0688	0.0027	0.0047	99.69	2.79	0.96
9	Ukraine	Europe	Mar-2005*	204	0.0073	0.0994	0.0053	0.0116	73.81	16.96	0.91
10	Vietnam	Asia Pacific	Jan-05	213	0.0111	0.0884	0.0060	0.0077	99.64	1.80	0.94
	Global (52 markets)			**17,680**	**0.0076**	**0.0877**	**0.0047**	**0.0280**	**92.77**	**25.81**	

Table 2: The predictive power of sentiment on returns and volatilities

This table presents the panel regression results across all 52 stock markets The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The models for return (volatility) include differences of lags varying from 2 to (12) 48 months after the release of the sentiment proxy. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. The ΔAdj-R^2 denotes the incremental value of $Adj-R^2$ when sentiment indicator is included as an additional regressor in the model. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

PANEL A: Market Returns						
Forecast horizon	**Single-period returns**			**Average returns**		
	SENT	**Adj-R^2**	**Obs**	**SENT**	**Adj-R^2**	**Obs**
1	-0.57	0.08	17,628	-0.57	0.13	17,628
	(0.047)**	(0.01)		(0.047)**	(0.04)	
2	-0.62	0.29	17,576	-0.60	0.14	17,524
	(0.012)**	(0.03)		(0.013)**	(0.05)	
3	-0.63	0.35	17,524	-0.64	0.16	17,472
	(0.000)***	(0.04)		(0.008)**	(0.06)	
4	-0.65	0.36	17,472	-1.03	0.17	17,420
	(0.000)***	(0.04)		(0.000)***	(0.06)	
6	-0.66	0.36	17,368	-1.14	0.27	17,316
	(0.000)***	(0.06)		(0.000)***	(0.06)	
9	-0.66	0.37	17,212	-0.85	0.28	17,160
	(0.004)***	(0.10)		(0.001)***	(0.07)	
12	-0.60	0.36	17,056	-0.52	0.36	17,004
	(0.027)**	(0.07)		(0.058)*	(0.02)	
18	-0.41	0.339	16,744	-0.54	0.29	16,692
	(0.145)	(0.05)		(0.041)**	(0.02)	
24	-0.35	0.305	16,423	-0.27	0.18	16,371
	(0.156)	(0.07)		(0.190)	(0.02)	
36	-0.43	0.244	15,808	-0.18	0.16	15,756
	(0.186)	(0.01)		(0.319)	(0.04)	
42	-0.34	0.25	15,496	-0.07	0.11	15,444
	(0.423)	(0.03)		(0.650)	(0.00)	
48	-0.19	0.25	15,184	0.11	0.11	15,132
	(0.532)	(0.02)		(0.573)	(0.01)	
PANEL B: Volatility						
Forecast horizon	**Single-period volatility**			**Average volatility**		
	SENT	**Adj-R^2**	**Obs**	**SENT**	**Adj-R^2**	**Obs**
1	0.30	0.28	16,744	0.30	0.30	16,744
	(0.000)***	(0.07)		(0.000)***	(0.09)	
2	0.27	0.36	16,423	0.21	0.38	16,371
	(0.006)***	(0.02)		(0.030)**	(0.10)	
3	0.18	0.29	15,808	0.19	0.31	15,756
	(0.067)*	(0.02)		(0.087)*	(0.04)	
4	0.10	0.18	15,496	0.10	0.19	15,444
	(0.242)	(0.02)		(0.199)	(0.03)	
6	0.06	0.16	15,184	0.07	0.17	15,132
	(0.219)	(0.04)		(0.265)	(0.00)	
9	0.02	0.11	14,872	0.05	0.12	14,820
	(0.430)	(0.00)		(0.336)	(0.00)	
12	0.04	0.11	14,560	0.04	0.12	14,508
	(0.433)	(0.01)		(0.447)	(0.01)	

Table 3: Robustness tests on sentiment predictive power

This table presents the panel regression results across all 52 stock markets with three subperiods. The last two columns report the results for the extraction of the business sentiment index (BSI) from the sentiment proxy. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The models for return (volatility) include differences of lags varying from 2 to (12) 48 months after the release of the sentiment proxy. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. The ΔAdj-R^2 denotes the incremental value of $Adj - R^2$ when sentiment indicator is included as an additional regressor in the model. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

PANEL A: Market Returns								
Forecast	**Jan 1980 - Jan 2001**		**Feb 2001 - Dec 2010**		**Jan 2011 - Sep 2022**		**Ex-BCI**	
horizon	**Single-period**	**Average**	**Single-period**	**Average**	**Single-period**	**Average**	**Single-period**	**Average**
1	-0.22	-0.22	-0.35	-0.35	-0.53	-0.53	-0.22	-0.22
	(0.128)	(0.128)	(0.048)**	(0.048)**	(0.035)**	(0.035)**	(0.074)*	(0.074)*
2	-0.25	-0.27	-0.37	-0.39	-0.54	-0.62	-0.27	-0.23
	(0.112)	(0.072)*	(0.043)**	(0.029)**	(0.032)**	(0.010)***	(0.025)**	(0.059)*
3	-0.27	-0.31	-0.38	-0.43	-0.55	-0.63	-0.25	-0.25
	(0.066)*	(0.020)**	(0.009)***	(0.003)***	(0.009)***	(0.008)***	(0.032)**	(0.036)**
4	-0.34	-0.40	-0.40	-0.50	-0.60	-0.71	-0.29	-0.32
	(0.008)***	(0.001)***	(0.006)***	(0.000)***	(0.006)**	(0.001)***	(0.002)***	(0.000)***
6	-0.35	-0.42	-0.48	-0.67	-0.70	-0.83	-0.24	-0.26
	(0.001)***	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.000)***	(0.089)*	(0.001)***
9	-0.40	-0.47	-0.55	-0.78	-0.77	-0.89	-0.26	-0.22
	(0.000)***	(0.004)***	(0.000)***	(0.000)***	(0.000)****	(0.000)***	(0.034)**	(0.044)**
12	-0.31	-0.37	-0.66	-0.36	-0.78	-0.94	-0.17	-0.14
	(0.052)*	(0.027)**	(0.000)***	(0.032)**	(0.000)***	(0.000)***	(0.126)	(0.166)
18	-0.25	-0.30	-0.31	-0.35	-0.50	-0.61	-0.11	-0.09
	(0.087)*	(0.041)**	(0.053)*	(0.035)**	(0.042)**	(0.002)***	(0.286)	(0.336)
24	-0.16	-0.25	-0.25	-0.29	-0.38	-0.49	-0.16	-0.16
	(0.214)	(0.078)*	(0.077)*	(0.037)**	(0.047)**	(0.013)**	(0.584)	(0.644)
36	-0.13	-0.15	-0.11	-0.13	-0.15	-0.22	-0.06	-0.04
	(0.443)	(0.423)	(0.105)	(0.089)*	(0.093)*	(0.049)**	(0.685)	(0.443)
42	-0.10	-0.12	-0.07	-0.08	-0.12	-0.14	0.05	0.04
	(0.462)	(0.562)	(0.368)	(0.432)	(0.162)	(0.108)	(0.474)	(0.422)
48	-0.08	-0.09	-0.06	-0.08	-0.11	-0.13	0.02	0.01
	(0.813)	(0.712)	(0.733)	(0.686)	(0.173)	(0.186)	(0.346)	(0.211)

PANEL B: Volatility								
Forecast	**Jan 1980 - Jan 2001**		**Feb 2008 - Jan 2009**		**Feb 2009 - Sep 2022**		**Ex-BCI**	
horizon	**Single-period**	**Average**	**Single-period**	**Average**	**Single-period**	**Average**	**Single-period**	**Average**
1	0.22	0.22	0.25	0.25	0.37	0.37	0.15	0.15
	(0.041)**	(0.041)**	(0.032)**	(0.032)**	(0.000)***	(0.000)***	(0.002)***	(0.002)***
2	0.21	0.23	0.23	0.24	0.34	0.34	0.14	0.12
	(0.071)*	(0.018)**	(0.045)**	(0.029)**	(0.006)***	(0.005)***	(0.032)**	(0.021)**
3	0.20	0.21	0.19	0.21	0.25	0.26	0.10	0.11
	(0.088)*	(0.087)*	(0.092)*	(0.055)*	(0.031)**	(0.029)**	(0.089)*	(0.076)*
4	0.18	0.19	0.20	0.21	0.21	0.23	0.09	0.09
	(0.136)	(0.122)	(0.116)	(0.065)*	(0.061)*	(0.049)**	(0.124)	(0.152)
6	0.14	0.15	0.16	0.16	0.17	0.18	0.07	0.07
	(0.297)	(0.287)	(0.276)	(0.119)	(0.073)*	(0.066)*	(0.186)	(0.205)
9	0.10	0.12	0.10	0.11	0.09	0.11	0.04	0.03
	(0.682)	(0.512)	(0.532)	(0.324)	(0.372)	(0.224)	(0.226)	(0.357)
12	0.07	0.08	0.08	0.08	0.09	0.09	-0.01	-0.01
	(0.874)	(0.642)	(0.674)	(0.545)	(0.526)	(0.415)	(0.269)	(0.224)

Table 4: The predictive power of sentiment in different levels of market development

This table presents the panel regression results across all 52 stock markets with three subperiods. The last two columns report the results for the extraction of the business sentiment index (BSI) from the sentiment proxy. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The models for return (volatility) include differences of lags varying from 2 to (12) 48 months after the release of the sentiment proxy. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. The ΔAdj-R^2 denotes the incremental value of $Adj-R^2$ when sentiment indicator is included as an additional regressor in the model. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Panel A: Return						
Forecast	**Developed markets**		**Emerging markets**		**Frontier markets**	
horizon	**Single-period**	**Average**	**Single-period**	**Average**	**Single-period**	**Average**
1	-0.24	-0.24	-0.43	-0.43	-0.39	-0.39
	(0.121)	(0.121)	(0.038)**	(0.038)**	(0.047)**	(0.047)**
2	-0.39	-0.51	-0.45	-0.53	-0.41	-0.52
	(0.043)**	(0.024)**	(0.012)**	(0.000)***	(0.024)**	(0.005)***
3	-0.57	-0.68	-0.46	-0.62	-0.53	-0.56
	(0.012)**	(0.002)***	(0.000)***	(0.000)***	(0.012)**	(0.002)***
4	-0.59	-0.69	-0.47	-0.63	-0.62	-0.63
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
6	-0.60	-0.71	-0.48	-0.65	-0.63	-0.63
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
9	-0.61	-0.72	-0.48	-0.48	-0.65	-0.63
	(0.000)***	(0.000)***	(0.004)***	(0.006)**	(0.000)***	(0.000)***
12	-0.61	-0.70	-0.43	-0.43	-0.55	-0.55
	(0.004)***	(0.001)***	(0.027)**	(0.036)**	(0.003)***	(0.002)***
18	-0.55	-0.65	-0.39	-0.37	-0.36	-0.50
	(0.027)**	(0.021)**	(0.041)**	(0.042)**	(0.084)*	(0.059)*
24	-0.50	-0.59	-0.32	-0.28	-0.32	-0.29
	(0.041)**	(0.033)**	(0.066)*	(0.119)	(0.112)	(0.282)
36	-0.40	-0.47	-0.31	-0.26	-0.30	-0.23
	(0.076)*	(0.041)**	(0.186)	(0.192)	(0.375)	(0.286)
42	-0.38	-0.32	-0.25	-0.13	-0.15	-0.18
	(0.083)*	(0.423)	(0.423)	(0.292)	(0.543)	(0.423)
48	-0.17	-0.23	-0.14	-0.02	-0.02	-0.10
	(0.532)	(0.532)	(0.532)	(0.389)	(0.657)	(0.532)
PANEL B: Volatility						
Forecast	**Developed markets**		**Emerging markets**		**Frontier markets**	
horizon	**Single-period**	**Average**	**Single-period**	**Average**	**Single-period**	**Average**
1	0.19	0.19	0.20	0.20	0.21	0.21
	(0.031)**	(0.031)**	(0.016)**	(0.016)**	(0.007)***	(0.007)***
2	0.20	0.21	0.26	0.25	0.38	0.38
	(0.086)*	(0.082)*	(0.000)***	(0.004)***	(0.000)***	(0.000)***
3	0.19	0.20	0.19	0.18	0.19	0.20
	(0.186)	(0.165)	(0.085)*	(0.135)	(0.096)*	(0.089)*
4	0.17	0.18	0.17	0.17	0.17	0.17
	(0.236)	(0.272)	(0.165)	(0.276)	(0.261)	(0.214)
6	0.14	0.14	0.15	0.14	0.14	0.14
	(0.319)	(0.297)	(0.229)	(0.251)	(0.401)	(0.375)
9	0.08	0.10	0.10	0.08	-0.08	0.09
	(0.452)	(0.352)	(0.312)	(0.442)	(0.719)	(0.419)
12	0.06	0.06	0.07	0.07	0.03	-0.29
	(0.617)	(0.542)	(0.488)	(0.518)	(0.478)	(0.918)

Table 5: The predictive power of sentiment in different market structures

This table presents the panel regression results across for different impacts of investor sentiment on return and volatility from the perspectives of market structure. The high and low groups are formed based on the median values of the markets' characteristics. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The coefficients for average return (volatility) are captured from models with 6 and 12-month (1- and 2-month) lags. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Panel A: Return				
Market structure	**6-month**		**12-month**	
	Coef.	**Diff**	**Coef.**	**Diff**
Institutional investor				
High	-0.15		-0.12	
	(0.024)**	**0.20**	(0.082)*	**0.28**
Low	-0.36	**(0.005)***	-0.40	**(0.000)***
	(0.000)***		(0.000)***	
Limits to arbitrage				
High	-0.31		-0.38	
	(0.002)***	**-0.10**	(0.000)***	**-0.20**
Low	-0.21	**(0.042)***	-0.18	**(0.003)***
	(0.032)**		(0.051)*	
PANEL B: Volatility				
Market structure	**1-month**		**2-month**	
	Coef.	**Diff**	**Coef.**	**Diff**
Institutional investor				
High	0.12		0.09	
	(0.024)**	**-0.35**	(0.082)*	**-0.22**
Low	0.46	**(0.005)***	0.31	**(0.000)***
	(0.000)***		(0.000)***	
Limits to arbitrage				
High	0.27		0.18	
	(0.012)**	**0.03**	(0.082)*	**0.02**
Low	0.23	**(0.192)**	0.16	**(0.435)**
	(0.062)*		(0.112)	

Table 6: The predictive power of sentiment in different cultural backgrounds

This table presents the panel regression results across for different impacts of investor sentiment on return and volatility from the perspectives of national cultural backgrounds. The high and low groups are formed based on the median values of the markets' characteristics. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The coefficients for average return (volatility) are captured from models with 6 and 12-month (1- and 2-month) lags. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Cultural factors	Panel A: Return				PANEL B: Volatility			
	6-month		12-month		1-month		2-month	
	Coef.	Diff	Coef.	Diff	Coef.	Diff	Coef.	Diff
Individualism								
High	-0.21		-0.12		0.12		0.15	
	(0.076)*	**0.23**	(0.087)*	**0.28**	(0.024)**	**-0.14**	(0.082)*	**-0.08**
Low	-0.45	**(0.012)****	-0.40	**(0.008)*****	0.26	**(0.025)****	0.23	**(0.000)*****
	(0.000)***		(0.000)***		(0.000)***		(0.000)***	
Power Distance Index								
High	-0.27		-0.17		0.12		0.15	
	(0.032)**	**0.07**	(0.051)*	**0.14**	(0.189)	**0.14**	(0.572)	**0.02**
Low	-0.34	**(0.062)***	-0.30	**(0.012)****	0.26	**(0.073)***	0.17	**(0.286)**
	(0.002)***		(0.000)***		(0.021)**		(0.224)	
Masculinity								
High	-0.42		-0.42		0.23		0.29	
	(0.000)***	**-0.18**	(0.000)***	**-0.21**	(0.012)**	**0.05**	(0.042)**	**0.15**
Low	-0.24	**(0.032)****	-0.21	**(0.003)*****	0.19	**(0.062)***	0.14	**(0.035)****
	(0.053)*		(0.011)**		(0.117)		(0.261)	
Uncertainty Avoidance								
High	-0.36		-0.34		0.28		0.21	
	(0.000)***	**-0.19**	(0.002)***	**-0.15**	(0.038)**	**0.13**	(0.082)*	**0.01**
Low	-0.17	**(0.012)****	-0.19	**(0.043)****	0.14	**(0.042)****	0.20	**(0.338)**
	(0.069)*		(0.033)**		(0.277)		(0.126)	
Long-Term Orientation								
High	-0.25		-0.19		0.19		0.21	
	(0.054)*	**0.02**	(0.094)*	**0.02**	(0.188)	**-0.03**	(0.082)*	**-0.04**
Low	-0.26	**(0.867)**	-0.21	**(0.643)**	0.23	**(0.375)**	0.26	**(0.833)**
	(0.024)**		(0.063)*		(0.077)*		(0.026)**	
Indulgence								
High	-0.18		-0.16		0.16		0.17	
	(0.087)*	**0.11**	(0.051)*	**0.13**	(0.119)	**0.03**	(0.072)*	**0.03**
Low	-0.29	**(0.047)****	-0.29	**(0.017)****	0.19	**(0.683)**	0.20	**(0.515)**
	(0.002)***		(0.000)***		(0.081)*		(0.041)**	
Hierarchy								
High	-0.29		-0.29		0.18		0.20	
	(0.004)***	**0.02**	(0.002)***	**0.02**	(0.088)*	**-0.02**	(0.052)*	**0.01**
Low	-0.31	**(0.277)**	-0.32	**(0.393)**	0.20	**(0.635)**	0.19	**(0.716)**
	(0.000)***		(0.003)***		(0.047)**		(0.096)*	
Mastery								
High	-0.31		-0.32		0.17		0.20	
	(0.000)***	**-0.01**	(0.000)***	**-0.02**	(0.008)***	**0.00**	(0.002)***	**0.02**
Low	-0.30	**(0.267)**	-0.30	**(0.353)**	0.17	**(0.597)**	0.18	**(0.528)**
	(0.004)***		(0.000)***		(0.047)**		(0.016)**	
Embedded								
High	-0.40		-0.49		0.29		0.20	
	(0.006)***	**-0.19**	(0.000)***	**-0.29**	(0.003)***	**0.11**	(0.058)*	**0.07**
Low	-0.21	**(0.002)*****	-0.20	**(0.000)*****	0.19	**(0.005)*****	0.13	**(0.397)**
	(0.070)*		(0.080)*		(0.036)**		(0.172)	

Table 7: The predictive power of sentiment in different religion backgrounds

This table presents the panel regression results across for different impacts of investor sentiment on return and volatility from the perspectives of national religion backgrounds. The high and low groups are formed based on the median values of the markets' characteristics. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The coefficients for average return (volatility) are captured from models with 6 and 12-month (1- and 2-month) lags. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Religion background	**Panel A: Return**				**PANEL B: Volatility**			
	6-month		**12-month**		**1-month**		**2-month**	
Abrahamic religions	**Coef.**	**Diff**	**Coef.**	**Diff**	**Coef.**	**Diff**	**Coef.**	**Diff**
Catholic								
High	-0.53		-0.44		0.40		0.37	
	(0.003)***	**0.30**	(0.009)***	**0.14**	(0.002)***	**0.01**	(0.012)**	**0.01**
Low	-0.23	**(0.008)*****	-0.30	**(0.058)***	0.39	**(0.575)**	0.36	**(0.893)**
	(0.086)*		(0.072)*		(0.004)***		(0.027)**	
Protestant								
High	-0.28		-0.34		0.18		0.17	
	(0.065)*	**0.15**	(0.065)*	**0.18**	(0.077)*	**-0.05**	(0.077)*	**-0.07**
Low	-0.43	**(0.017)****	-0.51	**(0.008)****	0.23	**(0.675)**	0.24	**(0.583)**
	(0.002)***		(0.002)***		(0.037)**		(0.037)**	
Islam								
High	-0.29		-0.40		0.25		0.18	
	(0.039)**	**0.19**	(0.021)**	**0.22**	(0.021)**	**0.02**	(0.122)	**-0.01**
Low	-0.48	**(0.010)****	-0.62	**(0.019)****	0.27	**(0.292)**	0.19	**(0.535)**
	(0.000)***		(0.000)***		(0.008)***		(0.086)*	
Indian Religions								
Hinduism								
High	-0.36		-0.35		0.22		0.20	
	(0.048)**	**0.03**	(0.062)*	**0.01**	(0.058)*	**-0.06**	(0.042)**	**0.02**
Low	-0.39	**(0.276)**	-0.36	**(0.585)**	0.28	**(0.542)**	0.19	**(0.294)**
	(0.039)**		(0.037)**		(0.017)**		(0.072)*	
Buddhism								
High	-0.42		-0.57		0.24		0.15	
	(0.000)***	**-0.13**	(0.000)***	**-0.26**	(0.035)**	**0.03**	(0.122)	**-0.04**
Low	-0.32	**(0.044)****	-0.31	**(0.038)****	0.21	**(0.485)**	0.19	**(0.183)**
	(0.024)**		(0.032)**		(0.037)**		(0.056)*	

Table 8: The predictive power of sentiment in different institutional quality

This table presents the panel regression results across for different impacts of investor sentiment on return and volatility from the perspectives of institutional quality. The high and low groups are formed based on the median values of the markets' characteristics. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The coefficients for average return (volatility) are captured from models with 6 and 12-month (1- and 2-month) lags. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Institutional quality	**Panel A: Return**				**PANEL B: Volatility**			
	6-month		**12-month**		**1-month**		**2-month**	
WDI factors	**Coef.**	**Diff**	**Coef.**	**Diff**	**Coef.**	**Diff**	**Coef.**	**Diff**
Control of corruption								
High	-0.30		-0.26		0.14		0.13	
	(0.012)**	**0.19**	(0.051)*	**0.16**	(0.161)	**-0.08**	(0.219)	**-0.04**
Low	-0.49	**(0.002)***	-0.42	**(0.005)***	0.22	**(0.048)**	0.17	**(0.466)**
	(0.000)***		(0.000)***		(0.009)***		(0.095)*	
Government effectiveness								
High	-0.22		-0.20		0.17		0.15	
	(0.073)*	**0.21**	(0.075)*	**0.17**	(0.389)	**-0.10**	(0.109)	**-0.40**
Low	-0.42	**(0.000)***	-0.37	**(0.015)**	0.28	**(0.008)***	0.55	**(0.398)**
	(0.000)***		(0.000)***		(0.017)**		(0.065)*	
Political stability								
High	-0.24		-0.17		0.18		0.17	
	(0.035)**	**0.22**	(0.051)*	**0.29**	(0.116)	**-0.07**	(0.103)	**-0.05**
Low	-0.45	**(0.001)***	-0.45	**(0.000)***	0.25	**(0.078)***	0.22	**(0.146)**
	(0.000)***		(0.000)***		(0.001)***		(0.037)**	
Rule of law								
High	-0.26		-0.25		0.18		0.14	
	(0.032)**	**0.13**	(0.051)*	**0.10**	(0.095)*	**-0.05**	(0.119)	**-0.08**
Low	-0.39	**(0.012)**	-0.35	**(0.000)***	0.23	**(0.086)***	0.22	**(0.075)***
	(0.003)***		(0.000)***		(0.000)***		(0.038)**	
Regulatory Quality								
High	-0.37		-0.31		0.19		0.16	
	(0.000)***	**-0.05**	(0.008)***	**-0.02**	(0.086)*	**0.01**	(0.097)*	**0.02**
Low	-0.32	**(0.191)**	-0.29	**(0.148)**	0.18	**(0.137)**	0.14	**(0.544)**
	(0.006)***		(0.087)*		(0.093)*		(0.183)	
Voice & accountability								
High	-0.28		-0.28		0.16		0.16	
	(0.051)*	**0.12**	(0.044)**	**0.12**	(0.122)	**-0.09**	(0.274)	**-0.01**
Low	-0.40	**(0.045)**	-0.40	**(0.048)**	0.25	**(0.046)**	0.17	**(0.036)**
	(0.006)***		(0.009)***		(0.012)**		(0.018)**	

Table 9: The predictive power of sentiment in different market integrity

This table presents the panel regression results across for different impacts of investor sentiment on return and volatility from the perspectives of stock market integrity. The high and low groups are formed based on the median values of the markets' characteristics. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The coefficients for average return (volatility) are captured from models with 6 and 12-month (1- and 2-month) lags. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Market integrity	**Panel A: Return**				**PANEL B: Volatility**			
	6-month		**12-month**		**1-month**		**2-month**	
	Coef.	**Diff**	**Coef.**	**Diff**	**Coef.**	**Diff**	**Coef.**	**Diff**
Anti-self -dealing								
High	-0.27		-0.26		0.13		0.10	
	(0.044)**	**0.25**	(0.052)*	**0.21**	(0.114)	**0.11**	(0.289)	**0.13**
Low	-0.53	**(0.000)****	-0.47	**(0.003)*****	0.24	**(0.032)****	0.23	**(0.236)**
	(0.000)***		(0.000)***		(0.011)**		(0.035)**	
Anti-director rights								
High	-0.24		-0.22		0.18		0.17	
	(0.021)**	**0.23**	(0.036)**	**0.19**	(0.061)*	**-0.12**	(0.109)	**-0.06**
Low	-0.47	**(0.002)*****	-0.40	**(0.013)****	0.30	**(0.028)****	0.23	**(0.163)**
	(0.000)***		(0.001)***		(0.004)***		(0.045)**	
Democracy index								
High	-0.19		-0.21		0.14		0.14	
	(0.089)*	**0.19**	(0.071)*	**0.19**	(0.084)*	**-0.23**	(0.093)*	**-0.16**
Low	-0.38	**(0.058)****	-0.40	**(0.062)****	0.37	**(0.000)*****	0.29	**(0.023)****
	(0.004)***		(0.003)***		(0.000)***		(0.031)**	
Accounting standards								
High	-0.21		-0.21		0.14		0.14	
	(0.038)**	**0.25**	(0.045)**	**0.23**	(0.092)*	**-0.23**	(0.274)	**-0.11**
Low	-0.47	**(0.000)*****	-0.44	**(0.000)*****	0.37	**(0.000)*****	0.25	**(0.041)****
	(0.000)***		(0.000)***		(0.009)***		(0.048)**	
Freedom index								
High	-0.41		-0.39		0.26		0.20	
	(0.000)***	**-0.16**	(0.002)***	**-0.18**	(0.018)**	**0.10**	(0.068)*	**0.04**
Low	-0.25	**(0.012)****	-0.21	**(0.007)*****	0.17	**(0.075)***	0.16	**-0.20**
	(0.033)**		(0.041)**		(0.081)*		(0.094)*	

Table 10: The predictive power of sentiment in different legal origins

This table presents the panel regression results across for different impacts of investor sentiment on return and volatility from the perspectives of legal origin by using the interaction term with dummy variables. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The coefficients for average return (volatility) are captured from models with 6 and 12-month (1- and 2-month) lags. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Legal Origins	**Panel A: Return**		**PANEL B: Volatility**	
	6-month	**12-month**	**1-month**	**2-month**
Common law	0.17	0.19	-0.06	-0.18
	(0.072)*	(0.041)**	(0.316)	(0.078)*
French Civil Law	0.08	0.03	0.02	0.02
	(0.391)	(0.586)	(0.219)	(0.316)
German Civil Law	0.07	-0.09	-0.02	0.03
	(0.423)	(0.329)	(0.286)	(0.322)
Scandinavian Civil Law	-0.06	0.05	0.02	-0.01
	(0.532)	(0.752)	(0.413)	(0.152)

Table 11: The predictive power of sentiment in different educational backgrounds and other factors

This table presents the panel regression results across for different impacts of investor sentiment on return and volatility from the perspectives of educational backgrounds, internet users, and gambling opportunities. The high and low groups are formed based on the median values of the markets' characteristics. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The coefficients for average return (volatility) are captured from models with 6 and 12-month (1- and 2-month) lags. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Educational background	**Panel A: Return**				**PANEL B: Volatility**			
	6-month		**12-month**		**1-month**		**2-month**	
	Coef.	**Diff**	**Coef.**	**Diff**	**Coef.**	**Diff**	**Coef.**	**Diff**
Overall Literacy rate								
High	-0.32		-0.30		0.20		0.17	
	(0.004)***	**0.02**	(0.018)**	**0.02**	(0.078)*	**0.00**	(0.094)*	**0.02**
Low	-0.34	**(0.276)**	-0.32	**(0.273)**	0.20	**(0.377)**	0.15	**(0.394)**
	(0.003)***		(0.003)*		(0.091)*		(0.213)	
Higher education rate								
High	-0.26		-0.26		0.13		0.13	
	(0.031)**	**0.20**	(0.041)**	**0.20**	(0.161)	**-0.11**	(0.203)	**-0.11**
Low	-0.46	**(0.001)*****	-0.45	**(0.002)*****	0.24	**(0.031)****	0.24	**(0.046)****
	(0.000)***		(0.000)***		(0.005)***		(0.015)**	
Educational expenditure								
High	-0.23		-0.25		0.21		0.17	
	(0.028)**	**0.05**	(0.022)**	**0.04**	(0.069)*	**-0.01**	(0.152)	**-0.03**
Low	-0.29	**(0.641)**	-0.29	**(0.332)**	0.21	**(0.435)**	0.19	**(0.738)**
	(0.020)**		(0.014)**		(0.047)**		(0.075)*	
Financial Literacy rate								
High	-0.21		-0.23		0.14		0.13	
	(0.033)**	**0.20**	(0.021)**	**0.22**	(0.011)**	**-0.13**	(0.059)*	**-0.14**
Low	-0.41	**(0.000)*****	-0.46	**(0.000)*****	0.27	**(0.048)****	0.27	**(0.026)****
	(0.000)***		(0.000)***		(0.004)***		(0.005)***	
Internet users								
High	-0.25		-0.28		0.16		0.16	
	(0.048)**	**0.20**	(0.043)**	**0.13**	(0.119)	**-0.08**	(0.147)	**-0.09**
Low	-0.45	**(0.000)*****	-0.41	**(0.022)****	0.25	**(0.385)**	0.25	**(0.418)**
	(0.000)***		(0.001)***		(0.024)**		(0.015)**	
Gambling Opportunity								
High	-0.41		-0.40		0.28		0.28	
	(0.000)***	**-0.13**	(0.002)***	**-0.17**	(0.009)***	**0.12**	(0.021)**	**0.10**
Low	-0.28	**(0.025)****	-0.23	**(0.008)*****	0.16	**(0.048)****	0.17	**(0.076)***
	(0.030)**		(0.047)**		(0.091)*		(0.075)*	

Table 12: Condition-varying impact of investor sentiment on stock returns and volatilities

This table presents the panel regression results across for different impacts of investor sentiment on return and volatility from the perspectives of market regime separation. The predictive model includes the sentiment factor and a set of six macroeconomic indicators to explain the single-period and average monthly returns/volatilities in Panel A & B, respectively. The coefficients for average return (volatility) are captured from models with 6 and 12-month (1- and 2-month) lags. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Panel A: Returns

Forecast	Sentiment regime			Single market regime			Global market regime		
horizon	High	Low	Diff	Bull	Bear	Diff	Bull	Bear	Diff
1	-0.56	-0.15	**-0.42**	-0.69	-0.15	**-0.54**	-0.56	-0.18	**-0.38**
	(0.012)**	(0.621)	**(0.348)**	(0.038)**	(0.683)	**(0.048)****	(0.042)**	(0.348)	**(0.387)**
2	-0.65	-0.18	**-0.47**	-0.73	-0.25	**-0.48**	-0.65	-0.22	**-0.43**
	(0.002)***	(0.521)	**(0.213)**	(0.004)***	(0.544)	**(0.087)***	(0.011)**	(0.316)	**(0.253)**
3	-0.75	-0.23	**-0.51**	-0.84	-0.29	**-0.55**	-0.75	-0.29	**-0.46**
	(0.000)***	(0.475)	**(0.162)**	(0.000)***	(0.435)	**(0.052)***	(0.000)***	(0.291)	**(0.332)**
4	-0.86	-0.31	**-0.55**	-0.97	-0.32	**-0.65**	-0.87	-0.38	**-0.49**
	(0.000)***	(0.255)	**(0.132)**	(0.000)***	(0.340)	**(0.035)****	(0.000)***	(0.221)	**(0.098)***
6	-0.77	-0.28	**-0.49**	-1.12	-0.36	**-0.75**	-0.78	-0.46	**-0.32**
	(0.000)***	(0.128)	**(0.095)***	(0.000)***	(0.198)	**(0.005)*****	(0.000)***	(0.125)	**(0.165)**
9	-0.61	-0.25	**-0.36**	-0.89	-0.33	**-0.56**	-0.62	-0.53	**-0.08**
	(0.044)**	(0.257)	**(0.054)***	(0.000)***	(0.278)	**(0.000)*****	(0.034)**	(0.063)*	**(0.252)**
12	-0.53	-0.20	**-0.33**	-0.54	-0.30	**-0.25**	-0.53	-0.58	**0.04**
	(0.041)**	(0.455)	**(0.138)**	(0.034)**	(0.496)	**(0.000)*****	(0.063)*	(0.043)**	**(0.238)**
18	-0.49	-0.15	**-0.33**	-0.46	-0.23	**-0.23**	-0.42	-0.46	**0.03**
	(0.078)*	(0.636)	**(0.197)**	(0.069)*	(0.575)	**(0.049)****	(0.299)	(0.147)	**(0.517)**
24	-0.42	-0.12	**-0.30**	-0.37	-0.18	**-0.19**	-0.49	-0.36	**-0.13**
	(0.329)	(0.738)	**(0.435)**	(0.246)	(0.656)	**(0.337)**	(0.148)	(0.395)	**(0.505)**
36	-0.25	-0.10	**-0.14**	-0.17	-0.15	**-0.02**	-0.25	-0.28	**0.03**
	(0.391)	(0.786)	**(0.797)**	(0.354)	(0.722)	**(0.954)**	(0.357)	(0.588)	**(0.949)**

Panel B: Volatility

Forecast	Sentiment regime			Single market regime			Global market regime		
horizon	High	Low	Diff	Bull	Bear	Diff	Bull	Bear	Diff
1	0.22	0.13	**0.09**	0.26	0.16	**0.11**	0.25	0.20	**0.06**
	(0.046)**	(0.240)	**(0.197)**	(0.012)**	(0.150)	**(0.037)****	(0.024)**	(0.127)	**(0.153)**
2	0.21	0.13	**0.08**	0.25	0.14	**0.11**	0.23	0.18	**0.05**
	(0.080)*	(0.389)	**(0.532)**	(0.030)**	(0.249)	**(0.053)***	(0.039)**	(0.313)	**(0.296)**
3	0.20	0.12	**0.07**	0.21	0.13	**0.07**	0.19	0.17	**0.03**
	(0.210)	(0.522)	**(0.812)**	(0.178)	(0.486)	**(0.341)**	(0.135)	(0.377)	**(0.741)**
4	0.18	0.14	**0.05**	0.15	0.15	**0.01**	0.14	0.18	**-0.04**
	(0.398)	(0.478)	**(0.337)**	(0.653)	(0.568)	**(0.867)**	(0.437)	(0.388)	**(0.326)**
6	0.17	0.15	**0.02**	0.15	0.14	**0.01**	0.14	0.17	**-0.03**
	(0.469)	(0.456)	**(0.733)**	(0.764)	(0.483)	**(0.540)**	(0.554)	(0.343)	**(0.940)**

Table 13: Cross-sectional impact of investor sentiment on stock returns

This table presents the panel regression results across for different impacts of investor sentiment on anomaly returns of 14 long-short portfolios. The descriptions of all long-short portfolios are reported in Appendix C. The predictive model includes the sentiment factor and a set of six macroeconomic indicators. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Factor	**Abbr**	**Horizons**					
		1	**2**	**3**	**6**	**9**	**12**
(1) Age	AGE	0.68	0.29	0.12	.09	0.09	-0.05
		(0.002)***	(0.078)*	(0.219)	(0.676)	(0.872)	(0.356)
(2) Asset growth	AG	0.32	0.22	0.15	0.10	-0.11	-0.10
		(0.113)	(0.387)	(0.407)	(0.977)	(0.473)	(0.537)
(3) Book-to-market equity	BTM	0.29	0.14	0.11	-0.12	-0.11	0.07
		(0.005)***	(0.218)	(0.457)	(0.274)	(0.544)	(0.832)
(4) Dividend yield	DIV	0.77	0.52	0.25	0.25	0.15	-0.07
		(0.021)**	(0.078)*	(0.329)	(0.586)	(0.752)	(0.276)
(5) Idiosyncratic volatility	IV	0.67	0.45	0.31	0.11	0.08	-0.07
		(0.032)**	(0.082)*	(0.156)	(0.453)	(0.854)	(0.397)
(6) Liquidity	LIQ	0.15	0.10	0.07	0.03	0.02	-0.02
		(0.186)	(0.407)	(0.757)	(0.895)	(0.933)	(0.156)
(7) Equity issuance	EQI	0.41	0.25	0.17	0.11	-0.12	-0.11
		(0.084)*	(0.387)	(0.407)	(0.977)	(0.473)	(0.537)
(8) Ohlson O-score	OS	0.38	0.18	0.14	0.15	0.08	-0.05
		(0.019)**	(0.289)	(0.356)	(0.421)	(0.778)	(0.453)
(9) Momentum	MOM	0.37	0.30	0.17	0.06	0.05	-0.04
		(0.043)**	(0.089)*	(0.286)	(0.493)	(0.537)	(0.195)
(10) Profitability	PRO	0.32	0.18	0.10	0.11	0.08	0.04
		(0.066)*	(0.287)	(0.366)	(0.319)	(0.597)	(0.975)
(11) Quality minus Junk	QMJ	0.20	0.14	0.09	0.10	0.10	-0.04
		(0.389)	(0.455)	(0.742)	(0.635)	(0.703)	(0.356)
(12) Return on Assets	ROA	0.55	0.26	0.17	0.19	0.19	-0.07
		(0.091)*	(0.455)	(0.742)	(0.635)	(0.703)	(0.356)
(13) Size	SIZE	0.49	0.23	0.19	0.20	0.10	-0.07
		(0.009)***	(0.121)	(0.317)	(0.263)	(0.821)	(0.531)
(14) Total accruals	ACC	0.22	0.15	0.05	0.06	0.06	0.02
		(0.165)	(0.267)	(0.826)	(0.737)	(0.693)	(0.957)

Table 14: Cross-sectional impact of sentiment on factor returns by national factors

This table presents the panel regression results across for different impacts of investor sentiment on anomaly returns of 14 long-short portfolios, which is controlled by the country-specific factors from Eq.(6). The descriptions of all long-short portfolios are reported in Appendix C. The predictive model includes the sentiment factor and a set of six macroeconomic indicators. All independents and control variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation technique with fixed-effect specification is utilized to deal with the possible problem of a highly continual time-series process. The bootstrap model is generated with a block length of 15 to generate 10,000 new time series generated under the null of no predictability for all dependent and explanatory variables. Then, the predictive regressions are then estimated on these 10,000 artificial time series to obtain the bootstrap distribution of coefficient estimates. The p-values are reported under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Factor	**AGE**	**BMT**	**DIV**	**IV**	**EQI**	**OS**	**MOM**	**PRO**	**ROA**	**SIZE**
Financial development and structure										
Financial development	0.24	-0.34	0.19	0.22	-0.02	0.04	-0.49	-0.29	-0.12	0.49
	(0.098)*	(0.035)**	(0.042)**	(0.187)	(0.756)	(0.443)	(0.037)**	(0.078)*	(0.069)*	(0.012)**
Institutional investor	0.62	-0.57	0.09	-0.11	-0.28	-0.06	-0.37	-0.13	-0.24	0.35
	(0.005)***	(0.012)**	(0.336)	(0.286)	(0.034)**	(0.685)	(0.62)*	(0.079)*	(0.012)**	(0.045)**
Limits to arbitrage	-0.15	0.05	0.04	-0.11	-0.02	0.01	0.17	0.10	0.07	0.13
	(0.097)*	(0.474)	(0.422)	(0.173)	(0.573)	(0.211)	(0.407)	(0.156)	(0.346)	(0.186)
Governance quality & market integrity										
Institutional quality	-0.39	0.19	0.14	-0.03	0.01	0.15	0.18	0.05	0.07	-0.18
	(0.121)	(0.135)	(0.483)	(0.940)	(0.540)	(0.653)	(0.388)	(0.337)	(0.812)	(0.344)
Anti-director right	-0.33	0.18	0.17	0.09	-0.01	0.13	0.12	0.10	0.11	0.09
	(0.088)*	(0.272)	(0.469)	(0.415)	(0.269)	(0.486)	(0.512)	(0.532)	(0.324)	(0.372)
Democracy index	-0.18	0.14	-0.14	-0.01	0.15	0.15	-0.29	0.21	0.21	-0.12
	(0.584)	(0.251)	(0.108)	(0.224)	(0.229)	(0.568)	(0.092)*	(0.274)	(0.274)	(0.162)
Political rights index	0.14	0.17	0.18	0.19	0.14	0.07	0.21	0.15	-0.08	0.09
	(0.554)	(0.343)	(0.136)	(0.122)	(0.297)	(0.341)	(0.065)*	(0.287)	(0.719)	(0.419)
Accounting standards	0.07	-0.23	-0.20	-0.19	-0.29	-0.42	0.16	-0.59	-0.34	-0.12
	(0.205)	(0.049)**	(0.089)*	(0.085)*	(0.012)**	(0.001)***	(0.276)	(0.000)***	(0.020)**	(0.178)

Table 14: Cross-sectional impact of sentiment on factor returns by national factors (Cont)

Factor	**AGE**	**BMT**	**DIV**	**IV**	**EQI**	**OS**	**MOM**	**PRO**	**ROA**	**SIZE**
Cultural background										
Individualism	0.11	-0.04	0.36	-0.04	0.14	0.17	0.26	0.02	-0.07	0.40
	(0.076)*	(0.326)	(0.012)**	(0.226)	(0.165)	(0.276)	(0.029)**	(0.733)	(0.874)	(0.005)***
Masculinity	0.17	0.10	0.20	0.03	0.07	0.09	0.36	0.40	0.19	0.20
	(0.236)	(0.312)	(0.210)	(0.478)	(0.488)	(0.152)	(0.261)	(0.624)	(0.186)	(0.165)
Uncertainty Avoidance	0.14	0.08	0.07	0.16	-0.17	0.18	0.07	0.21	-0.10	0.06
	(0.297)	(0.674)	(0.518)	(0.119)	(0.073)*	(0.357)	(0.186)	(0.095)*	(0.166)	(0.867)
Indulgence	0.10	0.19	0.08	0.14	0.39	0.17	0.03	-0.11	0.06	0.12
	(0.682)	(0.088)*	(0.545)	(0.375)	(0.326)	(0.377)	(0.741)	(0.224)	(0.542)	(0.522)
Embedded	0.50	0.13	0.71	0.08	0.10	0.14	0.68	0.20	0.06	0.38
	(0.042)**	(0.437)	(0.000)***	(0.452)	(0.695)	(0.319)	(0.002)***	(0.089)*	(0.617)	(0.047)**
Religion background										
Islam	0.23	0.16	0.69	0.15	-0.07	0.09	0.58	0.08	0.01	-0.35
	(0.018)**	(0.214)	(0.002)***	(0.764)	(0.368)	(0.124)	(0.002)***	(0.442)	(0.211)	(0.035)**
Hinduism	0.14	0.15	0.38	-0.15	-0.06	-0.08	0.02	0.04	-0.08	0.19
	(0.478)	(0.456)	(0.098)*	(0.186)	(0.733)	(0.686)	(0.746)	(0.801)	(0.813)	(0.096)*
Education and other factors										
Higher education	0.49	0.12	0.23	-0.15	-0.11	0.02	-0.04	-0.11	-0.13	0.39
	(0.000)***	(0.116)	(0.045)**	(0.423)	(0.105)	(0.685)	(0.443)	(0.173)	(0.186)	(0.007)***
Financial Literacy	0.43	-0.15	0.19	-0.09	-0.13	-0.25	0.05	-0.25	-0.29	0.60
	(0.006)***	(0.093)*	(0.092)*	(0.712)	(0.089)*	(0.078)*	(0.474)	(0.077)*	(0.037)**	(0.000)***
Gambling Opportunity	-0.16	-0.25	-0.09	-0.19	-0.08	-0.12	-0.14	-0.16	0.04	-0.17
	(0.644)	(0.166)	(0.336)	(0.562)	(0.432)	(0.162)	(0.108)	(0.584)	(0.422)	(0.126)

APPENDIX

Appendix A – Preliminary Tests

Table A1: Panel unit root tests and Granger causality tests.

This table shows panel unit-root tests for CCI and the pairwise Granger-causality tests for sentiment and returns and tests for block-exogeneity. The latter are obtained from VAR models which include returns, sentiment, and pre-determined control variables. The test by Levin, Lin, and Chu tests the null of a unit root assuming a common unit root process. The other two procedures test the null of a unit root assuming individual unit root processes. The lag length selection is based on SIC and the test equation contains individual intercepts. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Panel unit root & stationarity tests		All markets	Developed markets	Emerging markets	Frontier markets
Levin–Lin–Chu t		-39.86	-12.05	-20.25	-6.88
		(0.000)***	(0.000)**	(0.000)***	(0.000)**
ADF–Fisher 2		348.1	226.27	200.24	190.23
		(0.000)***	(0.000)***	(0.000)***	(0.000)***
Im–Pesaran–Shin W		-83.7	-25.66	-46.59	-14.44
		(0.000)***	(0.000)***	(0.000)***	(0.000)***
Panel Granger causality tests		All markets	Developed markets	Emerging markets	Frontier markets
Returns	χ^2				
Simple bivariate	SENT → RET	21.72***	117.23***	45.48***	48.46***
	RET→ SENT	33.16***	102.47***	85.24***	20.79**
Block exogeneity	SENT → RET	75.73***	74.21***	40.07***	14.02***
	RET→ SENT	53.11***	84.71***	45.74***	20.58***
Volatility	χ^2				
Simple bivariate	SENT → VOL	105.66***	19.30***	46.96***	20.20***
	VOL → SENT	41.30**	9.12**	17.98***	7.46**
Block exogeneity	SENT → VOL	45.78***	50.26***	52.27***	39.20***
	VOL → SENT	35.70***	39.20***	40.77***	30.58***

Appendix B. National factors

Table B1: Descriptions of national factors

Factors	Description	Source
Economic development levels		
Developed market (DM)	The markets with high levels of institutional investors, capital flow flexibility, efficiency of regulation and oversight, market exchange, and good liquidity and stability of the institutional framework.	MSCI
Emerging market (EM)	These markets maintain relatively good quality of market accessibility that become more engaged with global markets. They are mainly characterised by the dependable regulatory system, accessibility by foreign investors, higher risks due to lower liquidity, and investment volatility.	MSCI
Frontier market (FM)	Those market are more established than markets in least developed countries (LDCs) but still less established than the emerging markets.They are mainly characterised by smaller, less accessible, and to some extent riskier than more established markets due to political instability, poor liquidity, inadequate regulation, substandard financial reporting, and higher fluctuations.	MSCI
Market structure		
Institutional investor	The proportion of institutional investors as an indicator for market composition. For each market, we collect all available annual data of institutional ownership and compute an average value.	Refinitiv & Factset
Limits to arbitrage	The country sample are divided into large and small markets based on the median market capitalization. It is expected that smaller markets are more likely to face arbitrage constraints such as fundamental risk, short-selling constraint, liquidity risk, and so on (Chiah et al., 2021). For each market, we collect all available annual data of market capitalization and compute an average value.	Refinitiv & World Bank
Cultural factors		
Individualism (IDV)	Hofstede's cultural index related to the interdependent relationships within a society. Higher values imply the higher importance of personal interest even at the cost of the others.	Hofstede (2015)
Power Distance Index (PDI)	Hofstede's cultural index related to the acceptance of the human inequality. Higher values imply greater acceptance of human inequality.	Hofstede (2015)
Masculinity (MAS)	Hofstede's cultural index related to the fundamentals of success. Higher values reflect increased competition and personal achievement.	Hofstede (2015)
Uncertainty Avoidance (UAI)	Hofstede's cultural index related to the society's tolerance for unknown. Higher values imply the acceptance of unpredictability within the society.	Hofstede (2015)
Long-Term Orientation (LTO)	Hofstede's cultural index related to the fostering of virtues oriented towards future rewards perseverance and thrift.	Hofstede (2015)
Indulgence (IDG)	Hofstede's cultural index related to the society that allows relatively free gratification of basic and natural human drives related to enjoying life and having fun. Restraint stands for a society that suppresses gratification of needs and regulates it by means of strict social norms.	Hofstede (2015)
Hierarchy (HIC)	Schwartz's cultural index related to inequality of responsibilities and resources. Higher values imply that the important decisions within society are taken by the high-ranking individuals.	Schwartz (2007)
Mastery (MAT)	Schwartz's cultural index related to self-assertion. Higher values imply the achievement of personal interests by changing the social world.	Schwartz (2007)
Embedded (EMB)	Schwartz's cultural index related to affectively positive experiences. Higher Embedded values indicate sustaining the social order, of avoiding change and retaining tradition that is significant where people are living or working closely with others and where conformance with group norms is important.	Schwartz (2007)

Table B1: Descriptions of national factors (cont)

Factors	Description	Source
	Legal system	
Common law	Dummy = 0 if no, = 1 if yes	Porta et al. (1998)
French Civil Law	Dummy = 0 if no, = 1 if yes	Porta et al. (1998)
German Civil Law	Dummy = 0 if no, = 1 if yes	Porta et al. (1998)
Scandinavian Civil Law	Dummy = 0 if no, = 1 if yes	Porta et al. (1998)
	Market integrity	
Anti-self-dealing index (ASD)	The Anti-self-dealing index proposed by Djankov et al. (2008) captures the legal protection of minority shareholders against expropriation.	Djankov et al. (2008)
Anti-director right (ADR)	Revised anti-director rights index of Djankov et al. (2008)	Djankov et al. (2008)
Democracy index (DI)	An index that measures the quality of democracies, especially related to voter participation, perception of human rights protection and freedom to form organizations and parties.	Database of Economist Intelligence Unit
Freedom index (FI)	An index that measures the extent to which the political and civil rights of society's members are respected	Freedom House
Accounting standards (AS)	The scores for each country based on the differences in accounting standards.	Porta et al. (1998)
	Governance quality	
Control of corruption (COC)	An index that captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption. Higher values imply a greater importance of the public gain and the avoidance of authorities to achieve private gain.	World Bank - WGI
Government effectiveness (GE)	An index that captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies	World Bank - WGI
Political stability (PS)	An index that captures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism.	World Bank - WGI
Rule of law (ROL)	An index that captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, the likelihood of crime and violence	World Bank - WGI
Regulatory quality (RQ)	Regulatory Quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	World Bank - WGI

Table B1: Descriptions of national factors (cont)

Factors	Description	Source
Religion	Classification by highest proportion of population belong religion	
Abrahamic religions		
Catholic	Dummy = 0 if no, =1 if yes	The World Factbook of the CIA and the U.S. Department of State.
Protestant	Dummy = 0 if no, =1 if yes	
Islam	Dummy = 0 if no, =1 if yes	
Indian religions		
Hinduism	Dummy = 0 if no, =1 if yes	
Buddhism	Dummy = 0 if no, =1 if yes	
Educational levels and other factors		
Overall Literacy rate (LR)	Literacy rate, adult total (% of people ages 15 and above): the percentage of the population aged 15 and above who can write and read a short and simple report about their daily life, with understanding.	World Bank
Higher education rate (HE)	Educational attainment, at least Bachelor's or equivalent, population 25+, total (%) (cumulative): The ration of population over 25 years old with at least a bachelor's degree.	World Bank
Internet users (IU)	Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc. (% of population)	World Bank
Educational expenditure (EE)	The total spending on schools, universities, and public and private educational institutions and is denoted as a percentage of GDP.	World Bank
Financial Literacy (FL)	This proxy measures individuals' understanding of financial concepts including basic numeracy, interesting compounding, inflation, and risk diversification.	2014 Financial Literacy Survey Standard & Poor's Ratings Services Global
Gambling Opportunity (GO)		
Number of Casino	The number of casinos for countries/regions in our sample. Casino information is downloaded from the website of the Word Casino Directory.	World Casino Directory
Lottery Sale (% GDP)	The annual lottery sales as a percentage of GDP by country (%)	The LaFleur's Annual World Lottery Almanac (2000 - 2019)

Table B2: Descriptive statistics of financial development and market structure

Market	**MSCI group**	**Institutional holdings**	**Limit to arbitrage**	**Market**	**MSCI group**	**Institutional holdings**	**Limit to arbitrage**
Argentina	FM	Low	High	Kuwait	EM	Low	High
Australia	DM	High	Low	Lithuania	FM	Low	High
Austria	DM	High	High	Mexico	EM	Low	High
Belgium	DM	Low	High	Netherlands	DM	High	Low
Brazil	EM	Low	Low	New Zealand	DM	High	High
Bulgaria	FM	Low	High	Norway	DM	High	High
Canada	DM	High	Low	Peru	EM	Low	High
Chile	EM	Low	High	Poland	EM	High	High
China	EM	Low	Low	Portugal	DM	High	High
Colombia	EM	Low	High	Romania	FM	Low	High
Croatia	FM	Low	High	Russia	EM	Low	Low
Czech Republic	EM	High	High	Saudi Arabia	EM	Low	Low
Denmark	DM	High	High	Serbia	FM	Low	High
Estonia	FM	Low	High	Slovenia	FM	Low	High
Finland	DM	High	High	South Africa	EM	High	Low
France	DM	Low	Low	South Korea	EM	Low	Low
Germany	DM	High	Low	Spain	DM	High	Low
Greece	EM	Low	High	Sweden	DM	High	Low
Hong Kong	DM	Low	Low	Switzerland	DM	High	Low
Hungary	EM	Low	High	Taiwan	EM	High	High
India	EM	Low	Low	Thailand	EM	Low	High
Indonesia	EM	Low	High	Turkey	EM	Low	High
Ireland	DM	High	High	UK	DM	High	Low
Israel	DM	Low	High	Ukraine	FM	Low	High
Italy	DM	Low	Low	US	DM	High	Low
Japan	DM	High	Low	Vietnam	FM	Low	High

Table B3: Descriptive statistics of cultural dimensions

Market	Hofstede's demensions						Schwartz's dimensions		
	IDV	PDI	MAS	UAI	LTO	IDG	HIC	EMB	MAS
Argentina	46	49	56	86	20	62	2.1	3.5	3.9
Australia	90	36	61	51	21	71	2.3	3.6	4.0
Austria	55	11	79	70	60	63	1.8	3.1	3.9
Belgium	75	65	54	94	82	57	1.7	3.3	3.8
Brazil	38	69	49	76	44	59	2.4	3.6	3.9
Bulgaria	30	70	40	5	69	16	2.7	3.9	4.0
Canada	80	39	52	48	36	68	2.1	3.5	4.1
Chile	23	63	28	86	31	68	2.3	3.6	3.8
China	20	80	66	30	87	24	3.5	3.7	4.4
Colombia	13	67	64	80	13	83	2.9	3.9	4.0
Croatia	27	73	40	80	58	33	2.6	4.0	4.1
Czech Republic	58	57	57	74	70	29	2.2	3.6	3.8
Denmark	74	18	16	23	35	70	1.9	3.2	3.9
Estonia	60	40	30	60	82	16	2.0	3.8	3.8
Finland	63	33	26	59	38	57	1.8	3.4	3.7
France	71	68	43	86	63	48	2.2	3.2	3.7
Germany	67	35	66	65	83	40	1.9	3.0	3.9
Greece	35	60	57	100	45	50	1.8	3.4	4.3
Hong Kong	25	68	57	29	61	17	2.9	3.8	4.1
Hungary	80	46	88	82	58	31	1.9	3.6	3.7
India	48	77	56	40	51	26	3.1	4.0	4.3
Indonesia	14	78	46	48	62	38	2.6	4.3	3.8
Ireland	70	28	68	35	24	65	2.1	3.4	4.0
Israel	54	13	47	81	38	–	2.5	3.6	4.0
Italy	76	50	70	75	61	30	1.6	3.5	3.8
Japan	46	54	95	92	88	42	2.7	3.5	4.1
Kuwait	-	-	-	-	-	-	-	-	-
Lithuania	60	42	19	65	82	16	-	-	-
Mexico	30	81	69	82	24	97	2.1	3.9	3.9
Netherlands	80	38	14	53	67	68	1.9	3.2	4.0
New Zealand	79	22	58	49	33	75	2.3	3.3	4.1
Norway	69	31	8	50	35	55	1.5	3.5	3.9
Peru	16	64	42	87	25	46	2.8	3.9	4.1
Poland	60	68	64	93	38	29	2.5	3.9	3.8
Portugal	27	63	31	99	28	33	1.9	3.4	4.1
Romania	30	90	42	90	52	20	2.0	3.8	4.1
Russia	39	93	36	95	81	20	2.7	3.8	4.0
Saudi Arabia	48	72	43	65	27	14	-	-	-
Serbia	25	86	43	92	52	28	1.6	3.6	4.0
Slovenia	27	71	19	88	49	48	1.6	3.7	3.7
South Africa	65	49	63	49	34	63	2.6	4.0	3.9
South Korea	18	60	39	85	100	29	2.9	3.7	4.2
Spain	51	57	42	86	48	44	1.8	3.3	3.8
Sweden	71	31	5	29	53	78	1.8	3.1	3.8
Switzerland	68	34	70	58	74	66	2.1	3.0	3.7
Taiwan	17	58	45	69	93	49	2.7	3.8	4.0
Thailand	20	64	34	64	32	45	3.2	4.0	3.9
Turkey	37	66	45	85	46	49	3.0	3.8	4.0
UK	89	35	66	35	51	69	2.3	3.3	4.0
Ukraine	25	92	27	95	86	14	2.6	3.9	4.0
US	91	40	62	46	26	68	2.4	3.7	4.1
Vietnam	20	70	40	30	57	35	-	-	-
Median	**48.0**	**60.0**	**46.0**	**70.0**	**51.0**	**47.1**	**2.2**	**3.6**	**4.0**

Table B4: Descriptive statistics religion backgrounds

Market	**Abrahamic religions**			**Indian religions**	
	Catholic	**Protestant**	**Islam**	**Hinduism**	**Buddhism**
Argentina	x				
Australia		x			
Austria	x				
Belgium	x				
Brazil	x				
Bulgaria		x			
Canada	x				
Chile	x				
China					x
Colombia	x				
Croatia	x				
Czech Republic	x				
Denmark		x			
Estonia		x			
Finland		x			
France	x				
Germany		x			
Greece		x			
Hong Kong					x
Hungary	x				
India				x	
Indonesia			x		
Ireland	x				
Israel		x			
Italy	x				
Japan					x
Kuwait			x		
Lithuania	x				
Mexico	x				
Netherlands	x				
New Zealand		x			
Norway		x			
Peru	x				
Poland	x				
Portugal	x				
Romania		x			
Russia		x			
Saudi Arabia			x		
Serbia		x			
Slovenia	x				
South Africa		x			
South Korea					x
Spain	x				
Sweden		x			
Switzerland	x				
Taiwan					x
Thailand					x
Turkey			x		
UK		x			
Ukraine		x			
US		x			
Vietnam					x

Table B5: Descriptive statistics of institutional quality

Market	Insitutional Quality						
	COC	**GE**	**PS**	**ROL**	**VAA**	**RQ**	**Average**
Argentina	-0.3	-0.1	-0.1	0.4	-0.5	-0.5	-0.2
Australia	1.9	1.7	1.0	1.4	1.7	1.7	1.6
Austria	1.7	1.7	1.1	1.4	1.8	1.5	1.5
Belgium	1.4	1.6	0.8	1.4	1.4	1.3	1.3
Brazil	-0.2	-0.2	-0.2	0.4	-0.2	0.1	-0.1
Bulgaria	-0.2	0.0	0.3	0.5	-0.1	0.5	0.2
Canada	1.9	1.8	1.1	1.5	1.7	1.6	1.6
Chile	1.3	1.0	0.5	1.0	1.2	1.4	1.1
China	-0.4	0.2	-0.4	-1.6	-0.4	-0.3	-0.5
Colombia	-0.3	-0.1	-1.5	-0.1	-0.5	0.2	-0.4
Croatia	0.0	0.5	0.6	0.5	0.1	0.3	0.3
Czech Republic	0.4	0.9	1.0	1.0	1.0	1.1	0.9
Denmark	2.3	2.0	1.1	1.6	1.9	1.8	1.8
Estonia	1.1	1.0	0.7	1.1	1.1	1.4	1.1
Finland	2.3	2.1	1.3	1.6	2.0	1.8	1.8
France	1.3	1.5	0.4	1.2	1.4	1.2	1.2
Germany	1.8	1.6	0.9	1.4	1.7	1.6	1.5
Greece	0.2	0.5	0.2	0.9	0.6	0.6	0.5
Hong Kong	1.7	1.7	0.8	0.4	1.5	1.9	1.3
Hungary	0.4	0.7	0.8	0.8	0.7	0.9	0.7
India	-0.4	0.0	-1.1	0.4	0.0	-0.3	-0.2
Indonesia	-0.7	-0.2	-1.0	-0.1	-0.6	-0.2	-0.5
Ireland	1.6	1.5	1.1	1.4	1.6	1.7	1.5
Israel	0.9	1.2	-1.2	0.7	1.0	1.1	0.6
Italy	0.3	0.5	0.5	1.0	0.5	0.8	0.6
Japan	1.4	1.4	1.0	1.0	1.4	1.1	1.2
Kuwait	0.2	0.0	0.3	-0.5	0.4	0.1	0.1
Lithuania	0.4	0.8	0.8	0.9	0.8	1.1	0.8
Mexico	-0.6	0.1	-0.6	0.1	-0.5	0.2	-0.2
Netherlands	2.0	1.9	1.1	1.5	1.8	1.8	1.7
New Zealand	2.3	1.7	1.4	1.6	1.9	1.8	1.8
Norway	2.1	1.9	1.3	1.6	1.9	1.5	1.7
Peru	-0.4	-0.3	-0.7	0.1	-0.6	0.3	-0.3
Poland	0.5	0.5	0.7	0.9	0.6	0.9	0.7
Portugal	1.0	1.1	1.0	1.2	1.1	1.0	1.1
Romania	-0.3	-0.2	0.2	0.4	0.1	0.4	0.1
Russia	-1.0	-0.4	-0.9	-0.8	-0.9	-0.4	-0.7
Saudi Arabia	0.0	0.0	-0.4	-1.7	0.1	0.0	-0.3
Serbia	-0.5	-0.3	-0.4	0.0	-0.5	-0.3	-0.3
Slovenia	0.9	1.0	1.0	1.0	1.0	0.8	1.0
South Africa	0.2	0.3	-0.2	0.7	0.0	0.4	0.2
South Korea	0.4	0.7	1.0	1.0	0.5	0.9	0.7
Spain	1.0	1.2	0.1	1.1	1.1	1.1	0.9
Sweden	2.2	1.9	1.2	1.6	1.9	1.7	1.7
Switzerland	2.1	2.0	1.3	1.5	1.9	1.7	1.7
Taiwan	0.8	1.1	0.8	0.9	1.0	1.1	1.0
Thailand	-0.4	0.2	-0.7	-0.4	0.0	0.1	-0.2
Turkey	-0.1	0.1	-1.1	-0.3	-0.1	0.2	-0.2
UK	1.8	1.6	0.5	1.3	1.7	1.7	1.4
Ukraine	-1.0	-0.6	-0.7	-0.2	-0.8	-0.5	-0.6
US	1.4	1.5	0.4	1.1	1.5	1.5	1.3
Vietnam	-0.5	-0.2	0.2	-1.4	-0.4	-0.6	-0.5
Median	**0.5**	**0.8**	**0.5**	**0.9**	**0.9**	**0.9**	**0.8**

Table B6: Descriptive statistics of market integrity and legal system

Market	Market integrity					Legal system
	ASD	ADR	DI	FI	AS	
Argentina	0.3	4.0	6.9	84	45	French Civil Law
Australia	0.8	4.0	9.1	95	75	Common law
Austria	0.2	2.0	8.4	93	54	German Civil Law
Belgium	0.5	0.0	7.9	96	61	French Civil Law
Brazil	0.3	3.0	7.1	73	54	French Civil Law
Bulgaria	0.7	–	6.9	79	–	French Civil Law
Canada	0.6	4.0	9.1	98	74	Common law
Chile	0.6	3.0	7.8	94	52	French Civil Law
China	0.8	–	2.9	9	–	German Civil Law
Colombia	0.6	1.0	6.7	64	50	French Civil Law
Croatia	0.2	–	6.8	85	–	German Civil Law
Czech Republic	0.3	–	7.9	91	–	German Civil Law
Denmark	0.5	3.0	9.3	97	62	Scandinavian Civil Law
Estonia	–	–	7.8	94	–	German Civil Law
Finland	0.5	2.0	9.1	100	77	Scandinavian Civil Law
France	0.4	2.0	7.9	89	69	French Civil Law
Germany	0.3	1.0	8.6	94	62	German Civil Law
Greece	0.2	1.0	7.6	87	55	French Civil Law
Hong Kong	1.0	4.0	6.1	43	69	Common law
Hungary	0.2	–	6.9	69	–	German Civil Law
India	0.6	5.0	7.4	66	57	Common law
Indonesia	0.7	2.0	6.6	59	–	French Civil Law
Ireland	0.8	3.0	8.9	97	–	Common law
Israel	0.7	3.0	7.7	76	64	Common law
Italy	0.4	0.0	7.8	90	62	French Civil Law
Japan	0.5	3.0	8.1	96	65	German Civil Law
Kuwait	–	–	3.7	37	–	French Civil Law
Lithuania	0.4	–	7.4	89	–	–
Mexico	0.2	0.0	6.5	60	60	French Civil Law
Netherlands	0.2	2.0	9.0	97	64	French Civil Law
New Zealand	1.0	4.0	9.2	99	70	Common law
Norway	0.4	3.0	9.8	100	74	Scandinavian Civil Law
Peru	0.5	3.0	6.5	72	59	French Civil Law
Poland	0.3	–	7.0	81	–	German Civil Law
Portugal	0.4	2.0	7.9	95	36	French Civil Law
Romania	0.4	–	6.6	83	–	–
Russia	0.4	–	3.6	19	–	–
Saudi Arabia	–	–	1.9	7	–	–
Serbia	–	–	6.5	62	–	French Civil Law
Slovenia	–	–	7.7	90	–	German Civil Law
South Africa	0.8	4.0	7.6	79	70	Common law
South Korea	0.5	2.0	8.0	83	62	German Civil Law
Spain	0.4	2.0	8.2	90	64	French Civil Law
Sweden	0.3	2.0	9.5	100	83	Scandinavian Civil Law
Switzerland	0.3	1.0	9.0	96	68	German Civil Law
Taiwan	0.6	3.0	7.9	94	65	German Civil Law
Thailand	0.8	3.0	5.8	29	64	Common law
Turkey	0.4	2.0	5.1	32	51	French Civil Law
UK	1.0	4.0	8.3	93	78	Common law
Ukraine	0.1	2.0	6.0	61	–	German Civil Law
US	0.7	5.0	8.1	83	71	Common law
Vietnam	0.1	–	3.1	19	–	French Civil Law
Median	**0.4**	**3.0**	**7.7**	**86.0**	**64.0**	–

Table B7: Descriptive statistics of market integrity and legal system

Market	**LR**	**HE**	**IU**	**EE**	**FL**	**Casino**	**Lottery Sale (% GDP)**	**GO**
Argentina	98.9	19.1	38.3	13.1	28	146	0.87	High
Australia	99.0	30.8	69.4	18.7	64	82	0.64	High
Austria	98.0	13.6	62.8	23.2	53	54	0.69	High
Belgium	99.0	32.6	62.0	22.2	55	150	0.54	High
Brazil	90.8	15.9	35.8	16.2	35	1	0.38	Low
Bulgaria	98.3	22.0	35.9	18.9	35	15	0.07	Low
Canada	99.0	25.8	72.3	17.6	68	222	0.74	High
Chile	96.8	12.5	44.7	14.3	41	31	0.73	High
China	94.3	3.6	27.9	5.9	28	3	0.13	Low
Colombia	93.8	10.4	30.8	15.2	32	90	0.22	Low
Croatia	98.6	8.9	44.2	8.9	44	153	0.62	High
Czech Republic	99.8	20.0	51.2	12.8	58	421	0.33	Low
Denmark	99.0	31.2	76.6	24.8	71	44	0.62	High
Estonia	99.8	30.8	62.1	21.2	54	49	0.21	Low
Finland	100.0	23.1	72.4	18.7	63	16	0.92	Low
France	99.0	17.8	56.4	17.7	52	190	0.47	Low
Germany	99.0	24.9	65.8	16.8	66	88	0.50	High
Greece	95.4	22.8	40.2	20.2	45	8	1.51	Low
Hong Kong	93.5	27.5	62.1	14.0	43	6	0.67	Low
Hungary	99.1	20.9	49.3	20.5	54	12	0.66	Low
India	66.9	9.1	9.3	10.6	24	20	0.07	Low
Indonesia	93.7	9.0	13.8	11.9	32	0	0.00	Low
Ireland	99.0	30.4	56.3	14.5	55	31	0.77	High
Israel	97.1	32.5	50.1	21.0	68	0	1.21	Low
Italy	98.9	16.5	43.8	22.3	37	38	0.96	High
Japan	99.0	19.9	66.6	22.4	43	26	0.16	Low
Kuwait	94.9	9.2	49.1	17.1	44	0	0.00	Low
Lithuania	99.7	32.9	47.5	17.7	39	60	0.54	High
Mexico	93.3	14.9	31.0	12.9	32	209	0.49	High
Netherlands	99.0	29.9	75.1	15.9	66	190	0.23	Low
New Zealand	99.0	28.1	69.3	18.7	61	6	0.76	Low
Norway	100.0	27.4	79.9	20.9	71	7	0.68	Low
Peru	92.1	91.1	28.3	9.0	28	41	0.00	Low
Poland	98.7	24.8	46.9	24.6	42	17	0.57	Low
Portugal	98.2	13.0	34.1	14.0	26	11	1.34	Low
Romania	99.6	59.3	39.3	9.5	22	454	0.49	High
Russia	89.9	23.0	40.1	17.7	38	18	0.00	Low
Saudi Arabia	98.2	12.8	50.7	50.2	31	0	0.00	Low
Serbia	98.2	12.8	50.7	50.2	38	4	0.05	Low
Slovenia	99.7	19.8	53.4	27.6	44	39	1.02	High
South Africa	92.4	7.4	26.7	15.3	42	60	0.03	Low
South Korea	98.0	26.5	71.5	20.4	33	32	0.27	Low
Spain	97.9	22.1	53.8	18.5	49	69	2.16	High
Sweden	99.0	23.3	78.3	23.0	71	5	0.91	Low
Switzerland	99.0	44.0	72.0	22.6	57	24	0.39	Low
Taiwan	96.1	28.8	67.5	22.0	37	0	0.01	Low
Thailand	93.8	14.6	25.4	19.7	27	2	0.22	Low
Turkey	92.9	28.0	33.7	13.7	24	9	0.26	Low
UK	99.0	32.2	69.2	19.1	67	309	1.05	High
Ukraine	99.7	16.7	24.9	34.5	40	3	0.00	Low
US	96.8	33.7	66.6	20.4	57	2128	0.56	High
Vietnam	92.4	10.2	27.6	19.4	24	40	1.04	High
Median	**98.5**	**22.5**	**50.4**	**18.7**	**43.0**	**31**	**0.48**	**-**

Appendix C. Cross-sectional asset pricing factors

Table C1: Definition of cross-sectional factors - anomalies

No	Anomalies	Abbr	Description
1	Age	AGE	Age is the number of years between the firm's first appearance and time t. Jiang et al. (2005) find that young firms earn lower returns compared to older ones.
2	Asset growth	AG	Asset growth is measured following the methodology of McLean and Pontiff (2016). Cooper et al. (2008) find companies that grow their total assets more earn lower subsequent returns.
3	Book-to-market equity	BTM	Book-to-market is measured following the methodology of Hou et al. (2015). Pontiff and Schall (1998) confirm that BTM is positively and significantly related to futher retuns.
4	Dividend yield	DIV	Dividends is a dummy variable that takes a value of one for dividend-paying firms. Dividend-paying firms are those for which the dividend yield is greater than zero. Hodrick (1992) finds that dividend can postitively predict expected future returns
5	Idiosyncratic volatility	IV	Following Ang et al. (2006), idiosyncratic volatility is measured as the standard deviation of the residuals from a regression of a stock's excess return on the Fama and French (1993) three-factor model. Portfolios are rebalanced monthly. Ang et al. (2006) and Bali et al. (2016) document a negative relation between IV and stock returns.
6	Liquidity	LIQ	The Amihud (2002) illiquidity measure is computed by taking the ratio of the absolute daily return to the daily monetary trading volume. Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) confirm that return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities.
7	Net equity issuance	EQI	Loughran and Ritter (1995) find a negative relation between net stock issues and subsequent stock returns.
8	O-score	OS	Ohlson (1980) finds firms with high bankruptcy risk earn lower than average returns.
9	Momentum	MOM	Price momentum t-12 to t-1: Jegadeesh and Titman (1993) find that high (low) past recent returns forecast high (low) future returns.
10	Profitability	PRO	Novy-Marx (2013) discovers that sorting on gross profit-to-assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones.
11	Quality minus Junk	QMJ	The quality-minus-junk (QMJ) factor proposed by Asness et al. (2019) that find that high-quality stocks do have higher high risk-adjusted returns than low-quality stocks.
12	Return on Assets	ROA	Following Hou et al. (2015), return on assets is measured as income before extraordinary items divided by one-quarter-lagged total assets. Fama and French (2006) and Haugen and Baker (1996) find that more profitable firms have higher expected returns than less profitable firms.
13	Size	SIZE	Size is measured as market equity from June of month t and is calculated as price times shares outstanding. Banz (1981) document that small stocks outperform big stocks.
14	Total accruals	ACC	Sloan (1996) and Richardson et al. (2005) show that firms with high accruals earn lower average returns compared to firms with low accruals.