Investor Sentiment and Stock Returns: Global Evidence

Abstract

We assess the impact of investor sentiment on future stock returns in 50 global stock markets. Using the consumer confidence index (CCI) as the sentiment proxy, we document a negative relationship between investor sentiment and future stock returns at the global level. While the separation between developed and emerging markets does not disrupt the negative pattern, investor sentiment has a more instant impact in emerging markets, but a more enduring impact in developed markets. Individual stock markets reveal heterogeneity in the sentiment-return relationship. This heterogeneity can be explained by cross-market differences in culture and institutions, along with intelligence and education, to varying degrees influenced by the extent of individual investor market participation.

***Keywords*:** Consumer confidence index (CCI); Culture; Education; Global; Intelligence; Investor sentiment

***JEL Classification*:** G10; G15; G28; G41

***Declarations of interest*:** None

1. Introduction

Investor sentiment can be conceptualized as the belief concerning risk and returns that is not rationalized by realities (Baker and Wurgler, 2007).[1] Standard financial theories devote scant attention to investor sentiment; however, De Long et al. (1990) and Shleifer and Vishny (1997), among others, posit that sentiment traders' stochastic trading makes asset prices unpredictable, imposing limitations on arbitrage and leading to a persistent impact on stock returns. Brown and Cliff (2005) note that if investor sentiment drives stock prices above (below) fundamental values, future stock returns would be low (high) due to the mean reversion property, suggesting a negative relationship between investor sentiment and future stock returns. Such a relationship is supported by the majority of empirical evidence in the US and some other developed markets (Fisher and Statman, 2000; Brown and Cliff, 2005; Baker and Wurgler, 2006 & 2007; Da et al., 2011; Bathia and Bredin, 2013).[2]

Extant studies mainly explore the sentiment-return relationship in developed stock markets, leaving unanswered the question of how investor sentiment might impact in global markets. This is limiting in the insight provided as we know there are important distinctions between developed and emerging markets, in particular with respect to returns and market efficiency (Bekaert and Harvey, 2002), both of which are fundamental to the sentiment-return relationship. Moreover, in one of the pioneering models of noise traders[3] proposed by De Long et al. (1990, DSSW and henceforth) where informed and noise traders are present together, the pricing rule of an unsafe

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[1] Investor sentiment is defined in different ways, such as "*the propensity to speculate*" (Baker and Wurgler, 2006, p. 1648), investors' expectations relative to the average returns (Brown and Cliff, 2004), and "*synonymous of error*" (Shefrin, 2008, p. 213).

[2] In addition to the general relationship between investor sentiment and stock returns, related studies also include other aspects, such as the cross-sectional impact (Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Bathia and Bredin, 2013), state-varying differences (Yu and Yuan, 2011; Chung et al., 2012; Antoniou et al., 2016), along with institutional investor sentiment (Rangvid et al., 2013; Chelley-Steeley et al., 2017; Wang, 2018b; DeVault et al., 2019).

[3] Noise traders and sentiment investors are often used interchangeably in literature. In Schmeling (2007), for example, individual investor sentiment is found to be a good proxy for noise trader risk.

asset should be dependent on a series of exogenous parameters of the model and noise traders' misperceptions.[4] More recently, Ding et al. (2018) extend the DSSW model by incorporating 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 cultural dimensions, market integrity, and intelligence and education that can partly determine investors' behaviors (e.g., Kwok and Tadesse, 2006; Aggarwal and Goodell, 2009; Chui et al., 2010; Zouaoui et al., 2011; Grinblatt et al., 2011 & 2012; Cole et al., 2014), the impact of investor sentiment on stock returns realized by investors' behaviors is also expected to be different.[5] However, evidence of this is scant. To address this limitation we examine the sentiment-return relationship in a global context spanning 50 stock markets, including 24 developed and 26 emerging markets, and draw comparisons between emerging and developed markets to identify comparative differences in the impact of investor sentiment across market types, thus providing additional insight concerning the sentiment-return relationship.[6] Such insight is difficult to obtain

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[4] The DSSW model presents that in a market with both informed and noise traders, the pricing rule of an unsafe asset follows $p_t = 1 + \frac{\mu(\rho_t - \rho^*)}{1+r} + \frac{\mu\rho^*}{r} - \frac{(2\gamma)\mu^2\sigma_\rho^2}{r(1+r)^2}$, where p_t is the price of unsafe asset u in period t; μ is the fraction of noise traders in the market; r is the dividend paid on a riskless asset (i.e., the risk-free rate); γ is the degree of absolute risk aversion; and finally ρ_t is the misperception of the expected price of the risk asset u, and it is an independent and identically distributed normal random variable, following $\rho_t \sim N(\rho^*, \sigma_\rho^2)$. The DSSW model capturing the influence of noise traders on the price of *one* unsafe asset fits our main empirical analyses sampling the aggregate index for each stock market.

[5] Emerging markets play increasingly important roles in both regional and international economies, due in part to the expanded number of investable markets and global diversification benefits they offer (Goetzmann et al., 2005; Conover, 2011; Fernandes, 2011). For instance, the market capitalization of listed domestic companies in China achieved over eight trillion dollars, putting the country in second place in the world in 2015. According to O'Neill (2011), the GDP in Brazil, India, Russia, and China is projected to rank 4th, 6th, 3rd, and 1st across the world in 2050, respectively, thus supporting the growing importance of such markets in the world economy.

[6] While a study by Chen et al. (2014) examines the impact of investor sentiment on stock returns in an emerging markets context, it mainly focuses on the asymmetric impact of investor sentiment on the different industries and as such does not draw comparisons between emerging and developed markets. Our focus, in contrast, is at the aggregate market level and benefited by this enlarged dataset incorporating both developed and emerging markets, comparisons between two different types of markets become possible. In addition, theory-driven differences in the impact of investor sentiment, as shown above, are expected to be observed and therefore, a further investigation into potential factors driving such differences is justified. Generally, the literature on the role of investor sentiment at the global level remains sparse.

when sample markets exhibit similar economic conditions and exclude those at different stages of development (Ferreira et al., 2012). In addition, our global study allows an empirical examination of drivers of cross-market differences in the sentiment-return relationship. To this end, we investigate the extent to which cross-market differences in culture, market institutions, along with education and intelligence, might help to explain differences in sentiment-return relationships.

The "cultural revolution" under way in finance (Zingales, 2015) documents the important role that cultural differences play in both individual and corporate behaviors. In the context of financial markets and investor behaviors, with which we are concerned in a global study of the sentiment-return relationship, the impact of national culture is evident in investors' stock trading decisions (Grinblatt and Keloharju, 2001), stock market participation (Guiso et al., 2008), and home bias in asset allocation (Beugelsdijk and Frijns, 2010; Aggarwal et al., 2012), as well as playing a crucial role in stock price co-movement (Eun et al., 2015), momentum profits (Chui et al., 2010), post earnings announcement drift (Dou et al., 2015)[7], and country-level financial systems (Kwok and Tadesse, 2006; Aggarwal and Goodell, 2009). A clear and consistent message emanating from such studies is the importance of culture as a determinant of investor behaviors in financial markets. To date, however, we do not understand fully the extent to which culture impacts the sentiment-return relationship in stock markets. 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 cultural dimensions and market institutions[8] across the developed stock markets examined. Such markets, however, tend to share greatly similarities in culture and market

[7] In an examination of momentum profits and post earnings announcement drift, Altanlar et al. (2018) show sentiment and culture interact to affect cognitive dissonance, ultimately impacting momentum profits and post earnings announcement drift.

[8] Institutional settings have long been known to impact financial markets (La Porta et al., 1998) and their importance in the context of the sentiment-return relationship is explored in both Schmeling (2009) and Zouaoui et al. (2011).

institutions (see, Appendix B), thus limiting the potential to examine fully the impact of such potential drivers of heterogeneity in the sentiment-return relationship. A wider dataset including emerging markets provides enhanced variation as developed and emerging markets appear naturally different (Yates et al., 1989; Chen et al., 2007; Truong, 2011), thus providing a more complete examination of the driving forces of divergences in the impact of investor sentiment on stock returns.

The behavioral finance literature documents the importance of investor intelligence and investor sophistication as determinants of the extent to which individual investors succumb to behavioral biases. For example, Grinblatt et al. (2012) find that high-IQ investors exhibit fewer cognitive biases and are better at market timing, stock picking, and trade execution, while the extent to which investors exhibit the disposition effect (Shefrin and Statman, 1985) is shown to be attenuated by investor sophistication (Feng and Seasholes, 2005; Dhar and Zhu, 2006). As an aggregate market phenomenon, the impact of irrational investor sentiment is likely related to the level of individual investor bias present in the market. The extent of investor bias in aggregate might be expected to vary across markets and as such may act as a driver of observed differences in the sentiment-return relationship. In a global study of 50 markets such as ours, it is problematic to obtain individual investor-level measures of intelligence or sophistication, instead we employ market level measures of intelligence and education as proxies. We examine the extent to which such proxies explain sentiment-return relationship differences across markets, including developed and emerging markets.

In this paper, we sample 50 stock markets across the globe, 24 and 26 of which are developed and emerging markets, respectively, as per the Morgan Stanley Capital International (MSCI) market classification framework. This economically and geographically diversified combination covers a large share of leading global markets and thus can be regarded as a representative sample.[9] Given our global focus and the need for a single, comparative proxy of sentiment to be available across all 50 markets examined, we employ the market-specific consumer confidence index (CCI) as our sentiment proxy, noting that consumer confidence and investor sentiment are positively related (Lemmon and Portniaguina, 2006; Qiu and Welch, 2006).

Applying a fixed-effect panel specification pooling all 50 stock markets, we confirm the negative relationship between investor sentiment and stock returns over horizons from 2 to 12 months. We then split the entire sample into developed and emerging markets and find that such separation does not dampen the reported negative relationship. However, we find that the impact of investor sentiment is more instant in emerging markets (horizons from 1 to 12 months), while it is more persistent in developed markets (horizons from 2 to 36 months).[10] The confirmation of the negative relationship between investor sentiment and future stock returns at the global level, along with developed and emerging markets individually, reaffirms investor sentiment as a contrarian factor and so it provides global investors with a useful indicator for global asset allocation decisions. Differences in the impact of investor sentiment across developed and emerging markets are also observed in the cross-section of stock returns. While small stocks and value stocks, rather than large stocks and growth stocks, are more affected by investor sentiment in both developed and emerging markets, we report that investors in emerging markets are likely to distinguish small from large stocks more than value from growth stocks. We also distinguish the impact of investor

[9] Our focus on a global examination of investor sentiment is further warranted from a statistical viewpoint: An enlarged sample across the world serves to enhance the estimation reliability, providing more conclusive evidence on the relationship between investor sentiment and future stock returns (Doukas and Milonas, 2004; Ang and Bekaert, 2007). In addition, an enlarged dataset provides out-of-sample evidence of the impact of investor sentiment on stock returns outside the developed markets, which is essential in studying market anomalies (Griffin et al., 2003; Ang et al., 2009).

[10] Our results in this respect, though seemingly counterintuitive, find support in the work of Griffin et al. (2010), Jacobs (2016), Altanlar et al. (2018), and Cai et al. (2018), demonstrating that anomalies are at least as strong, and sometimes stronger, in mature markets than emerging markets: a phenomenon that Cai et al. (2018) refer to as the global anomaly puzzle.

sentiment conditional on different economic settings, namely, high-/low-sentiment periods and bull/bear regimes, evidencing that the impact tends to be stronger over high-sentiment periods or bull regimes than over low-sentiment periods or bear regimes. Next, we probe individual stock markets and reveal that the negative relationship does not hold universally and is market-specific. Finally, we carry out cross-market analyses to explore the driving forces of divergences in the impact of investor sentiment from the perspectives of cultural dimensions and market institutions, along with intelligence and education. Evidence reveals that all such aspects induce heterogeneity in the sentiment-return relationship, however, as culture is hard to change and the role of intelligence and education is rather mixed, we propose a policy suggestion that a more complete system of market institutions is needed to alleviate the impact of investor sentiment on stock returns.

This paper contributes to the finance literature in three ways. First, we extend the relationship between investor sentiment and future stock returns to the global level by incorporating both developed and emerging markets, whereby we present more complete evidence on the impact of investor sentiment on future stock returns. Second, we conduct comparative tests on developed and emerging markets, identifying the similarities and differences in the impact of investor sentiment, at both aggregate and cross-sectional levels. Third, the global dataset extends the scope of potential drivers that can be examined, including cultural dimensions, market institutions, and intelligence and education, thus providing a systematic investigation into driving forces of cross-market differences in the impact of investor sentiment on stock returns.

The remainder of this paper proceeds in the following manner. Section 2 describes data and conducts preliminary tests. Section 3 illustrates the main methodology, followed by empirical findings and discussions in Section 4. Section 5 explores driving forces of cross-market divergences in the impact of investor sentiment and Section 6 concludes.

2. Sample selection, descriptive statistics, and preliminary tests

We sample a total of 50 stock markets, which are categorized into two comparable groups, i.e., 24 developed markets and 26 emerging markets, under the MSCI market classification framework.[11] We compute monthly stock returns for each market from the DataStream Total Market Equity Index that reflects the overall performance of a specific stock market. The CCI is used as the main proxy for investor sentiment.[12] Monthly CCIs come from various sources, such as national authorities, regional and international organizations, and academic and business research institutes, etc. In several markets such as Hong Kong, Russia, and Switzerland, where consumer confidence surveys are conducted at quarterly intervals, following Baker and Wurgler (2006) and Schmeling (2009), we convert the quarterly CCIs into monthly ones by applying the last available values for months without data to ensure frequency consistency.

<Table 1>

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[11] The Greek stock market was reclassified from developed market to emerging market by the MSCI in November 2013, which is taken into account in the following analyses. In particular, we group the period from March 2004 (i.e., the starting month) to October 2013 to the developed market while the period from November 2013 to December 2015 (i.e., the ending month) to the emerging market, meaning that the Greek stock market appears in both developed and emerging subsamples. In Appendix A and Table 1, the Greek stock market is denoted as developed market given its longer period in our sample.

[12] Consumer confidence is shown to be a suitable proxy for investor sentiment in Qiu and Welch (2006), 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. Empirically, Qiu and Welch (2006) 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, Lemmon and Portniaguina, 2006; Derrien and Kecskés, 2009; Greenwood and Shleifer, 2014; Møller et al., 2014; Gao and Süss, 2015; Kaivanto and Zhang, 2019). 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 50 markets. The CCI offers such wide availability in all 50 stock markets.

Table 1 summarizes descriptive statistics of CCIs in all sample markets.[13] As CCIs are collected from different sources with the application of inconsistent neutrality standards,[14] we standardize the CCI in each individual market with zero expectation and unit variance. The first-order autocorrelations of CCIs range from 0.56 (Nigeria) to 0.98 (Canada, Lithuania, South Africa, and Thailand), with an average of 0.92, suggesting a highly persistent time-series process that might lead to biased estimations of slope coefficients and standard errors (Ferson et al., 2003). To address this issue, we adopt the moving-block bootstrap simulation procedure as suggested by Gonçalves and White (2005) in all regression analyses (see details in Section 3). The observed high level of the first-order autocorrelations also indicates the necessity to check the unit root stationarity of the CCIs. We, therefore, perform three panel unit root tests, i.e., Augmented Dickey Fuller (ADF)–Fisher test, Im–Pesaran–Shin test, and Levin–Lin–Chu test, with results in Table 2 confirming the stationarity of CCIs.[15]

<Table 2>

We also check the pairwise Pearson and Spearman correlations of the CCIs among all markets to ensure that we are effectively employing various sentiment measures for this wide range of sample

[13] While some of our emerging markets have relatively shorter periods, this should not bias our results in a panel framework in which the number of available observations greatly increases (Ang and Bekaert, 2007; Chen et al., 2014). In addition, data from all markets, regardless of whether developed or emerging, are of high quality since they are sourced from national authorities, regional and international organizations, and academic and business research institutes, as mentioned in the main text (see, also, Table 1 for data sources).

[14] To represent investors'/consumers' optimism or pessimism, different consumer confidence surveys apply different applications of neutrality standards. Some surveys, such as Directorate General for Economic and Financial Affairs (the majority of Europe), Bureau for Economic Research (South Africa), and Federal State Statistics Service (Russia), apply "0" as the neutral value, i.e., that a positive (negative) value suggests investors' optimism (pessimism). Some surveys, such as ANZ/Roy Morgan (Australia and New Zealand), National Bureau of Statistics (China), and University of Michigan Consumer Confidence (the US), apply "100" as the neutral value, while in other instances, such as Thomson Reuters/Ipsos (Canada) and Cabinet Office (Japan), "50" is used as the neutral value.

[15] Both ADF–Fisher test and Im–Pesaran–Shin test employ the null hypothesis of a unit root and assume that the autocorrelation across cross-sections are *heterogeneous*, while Levin–Lin–Chu test employs the null hypothesis of a unit root and assumes that the autocorrelation across cross-sections are *homogeneous* (see, Choi, 2001; Levin et al., 2002; Im et al., 2003).

markets.[16] Two approaches generate very similar results: The pairwise Pearson and Spearman correlation coefficients range from −0.765 (between Ireland and Turkey) to 0.883 (between Czech Republic and Portugal) with an average of 0.263, and from –0.731 (between Ireland and Turkey) to 0.887 (between Lithuania and the US) with an average of 0.247, respectively, signaling that the correlations of the CCIs among sample markets are not prohibitively high. Also, we note that CCIs are not necessarily geographically- nor trade-related. For instance, the correlation coefficients of the CCIs between Japan and its three Asia-Pacific neighboring markets are 0.343 (Hong Kong), 0.320 (New Zealand), 0.123 (South Korea), and the correlation coefficients between the US and its three major trading partners are 0.508 (China), 0.263 (Germany), and 0.018 (South Korea).

<Table 3>

Finally, we conduct two panel Granger causality tests—the simple bivariate test and the block exogeneity test—to provide some preliminary results on the interdependency between the CCI (cci_t) and stock returns (r_t).[17] Table 3 confirms the Granger causality, revealing that stock returns depend on investor sentiment, and vice versa, across all, developed, and emerging markets.

3. Methodology

To examine the impact of investor sentiment on future stock returns, the basic predictive specification is to regress future stock returns (r_{t+1}) on the CCI (cci_t),

$$r^i_{t+\tau} = \alpha + \beta cci^i_t + \varepsilon^i_{t+1}. \quad (1)$$

[16] This generates two large correlation tables, each having 1,225 ($= C^2_{50}$) correlation coefficients. The full pairwise Pearson and Spearman correlation coefficients of the CCIs among all sample markets are hence not presented here for the sake of brevity, but are available at https://goo.gl/iktbWU.

[17] While the simple bivariate test and the block exogeneity test employ the null hypothesis of no Granger causation, the former tests the Granger causality between stock returns and investor sentiment, and the latter is based on a vector autoregression (VAR) specification including a matrix of six macroeconomic variables that are defined in Eq. (2).

A number of studies confirm the predictability of macroeconomic variables to stock returns (e.g., Chen et al., 1986; Lamont, 2001; Boyd et al., 2005; Hjalmarsson, 2010), and previous sentiment research also accounts for a wide range of macroeconomic factors in attempts to disentangle the effect of business cycle components on stock returns (e.g., Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Bathia and Bredin, 2013). Given the nature of this global study, we identify six macroeconomic and market factors, including (i) the inflation rate computed from the consumer price index (*cpi*), (ii) the industrial production growth (*ip*), (iii) the dividend yield (*dy*), (iv) the unemployment rate growth (*unem*), (v) the gross domestic production growth (*gdp*), and (vi) the detrended short-term interest rate (*ir*), to control for the potential influence of business cycles and market conditions. Like CCIs, these six macroeconomic variables are also standardized with zero expectation and unit variance. Therefore, Eq. (2) includes an additional combination of six macroeconomic variables in matrix ψ_{t+1},

$$r_{t+\tau}^{i} = \alpha + \beta cci_{t}^{i} + \gamma \Psi_{t+1}^{i} + \varepsilon_{t+1}^{i}. \tag{2}$$

As the impact of investor sentiment is subject to the length of forecast horizons, following Brown and Cliff (2005) and Menkhoff and Rebitzky (2008), we test its impact at various forecast horizons up to 36 months after the release of the CCI, with the following model,

$$\frac{1}{T}\sum_{\tau=1}^{T} r_{t+\tau}^{i} = \alpha^{(T)} + \beta^{(T)} cci_{t}^{i} + \gamma^{(T)} \Psi_{t}^{i,(T)} + \varepsilon_{t+1\to T}^{i,(T)}, \tag{3}$$

where $\frac{1}{T}\sum_{\tau=1}^{T} r_{t+\tau}^{i}$ represents the average monthly return for market *i* over *T* months (T = 1, 2, 3, 6, 9, 12, 24, and 36) after the release of the CCI at month *t*.

We estimate Eq. (3) with the use of panel fixed-effect regressions across all sample markets. Also, we replicate the above procedure after separately pooling developed and emerging markets. We construct a quasi-weakly-balanced dataset starting from January 2001 to December 2015 to ensure our results are not driven by markets with considerably longer periods of observations (see, Table 1). A moving-block bootstrap simulation procedure suggested by Gonçalves and White (2005) is employed in all regression analyses to account for biased coefficient estimates and standard errors. Specifically, we estimate original regressions and save all coefficients. Then we repeatedly bootstrap the raw data in blocks with a block length of 15 and generate 10,000 new time series under the null of no predictability for all dependent and independent variables.[18] Finally, we generate the bootstrap distribution of coefficient estimates by estimating the predictive model on the 10,000 artificial time series.

4. Empirical results

Subsection 4.1 reports a negative relationship between investor sentiment and future stock returns at the global market level. The negative relationship holds separately in developed and emerging markets. Notably, investor sentiment has a more enduring impact on stock returns in developed markets, but a more instant impact in emerging markets. Subsection 4.2 shows that our results are robust to various alternative tests. Subsection 4.3 extends the survey to the cross-section of stock returns, documenting that the impact of investor sentiment tends to be concentrated in small stocks and value stocks, rather than large stocks and growth stocks. However, in emerging markets, such distinction is observed more strongly in small/large stocks than in growth/value stocks, while this is not so clearly the case in developed counterparts. Subsection 4.4 distinguishes the impact of investor sentiment conditional on different economic settings, i.e., high-/low-sentiment periods and bull/bear regimes. The results indicate the impact tends to be stronger over high-sentiment periods or bull regimes than over low-sentiment periods or bear regimes, while in bear regimes the ability to short-sell prompts differences across developed and emerging markets , with the impact

[18] The use of different block lengths does not alter our results.

significant in the former but not the latter. Finally, Subsection 4.5 provides additional results showing that at the individual market level, the observed negative relationship is market-specific.

4.1. Panel regression results

4.1.1. Preliminaries

Table 4 presents the panel regression results from the fixed-effect specification, pooling across all sample markets, showing a negative relationship between investor sentiment and future stock returns. In particular, the estimated coefficients of the CCI—the proxy for investor sentiment—are significantly negative in the subsequent 2 to 12 months. For example, a one standard deviation increase in the CCI results in a statistically significant decline of 0.67% (*p*-value = 0.001) and 0.57% (*p*-value = 0.001) in average monthly returns over the following 6 and 9 months, respectively. Moreover, the negative impact of investor sentiment fluctuates with the length of forecast horizons: It reaches the highest level in the subsequent 6 months and gradually declines afterwards. The reported declining trend over longer forecast horizons is not surprising and can be explained from statistical and economic perspectives. Statistically, the declining predictability of investor sentiment suggests the chosen estimation method does not generate spuriously significant results (Hong et al., 2007).[19] Economically, the impact of investor sentiment is expected to be mitigated eventually over longer horizons (Brown and Cliff, 2005). Even so, a one standard deviation increase in the CCI can still have a negative impact of 5.28% (–0.44% × 12, *p*-value = 0.006) on stock returns over the following 12 months. The impact of investor sentiment on future stock

[19] Hong et al. (2007) argue that it would be "*comforting*" if predictability is found at shorter horizons but not at longer horizons (p. 383). The applied regression here is, therefore, informative and not subject to bias that may lead to significant results at longer forecast horizons.

returns is also supported by the incremental adjusted R^2 values reported in Table 4. It seems clear that the addition of investor sentiment enhances the goodness of fit of the model.[20]

<Table 4>

In addition, the observed significantly negative relationship between investor sentiment and future stock returns holds in both developed and emerging markets. For example, a one standard deviation increase in investor sentiment drives the returns down over the following 12 months by 5.64% (–0.47% × 12, p-value = 0.000) and 4.68% (–0.39% × 12, p-value = 0.061) in developed and emerging markets, respectively. Overall, our results confirm investor sentiment as a contrarian indicator in predicting future stock returns at global, developed, and emerging market levels.

Notwithstanding the general similarities, Table 4 reveals two noticeable differences in the impact of investor sentiment between developed and emerging markets. First, the estimated coefficient of the CCI for the next-month stock returns in developed markets is insignificant ($cci_1 = -0.22$, p-value = 0.113), while it is significant in emerging markets at the 5% level ($cci_1 = -0.68$, p-value = 0.022), indicating that the impact of investor sentiment is more instant in emerging markets. Second, investor sentiment has a more enduring impact of up to 36 months in developed markets ($cci_{36} = -0.25$, p-value = 0.000), while the negative impact is statistically negative up to only 12 months ($cci_{12} = -0.39$, p-value = 0.061) and then disappears afterwards in emerging markets ($cci_{24} = -0.19$, p-value = 0.489; $cci_{36} = -0.11$, p-value = 0.620). Since markets in different economic conditions (developed or emerging) have different cultures, market institutions, as well as intelligence and education,[21] all of which may influence sentiment investors' behaviors, these two

[20] Table 4 also indicates that the adjusted R^2 rises with the forecast horizon from the following 1 to 12 months, in line with Cochrane (2011). However, with further increases in the forecast horizon, the adjusted R^2 declines due to the decreasing statistical and economic significance of investor sentiment. While the adjusted R^2 and the incremental adjusted R^2 appear to be low across all forecast horizons, this is typical in stock return forecasts (Schmeling, 2009; Bathia and Bredin, 2013).

[21] See, Appendix B, for more details.

differences in the impact of investor sentiment on stock market returns provide some direct empirical support, in a comparative sense, to De Long et al. (1990) documenting that unsafe asset prices are partly influenced by noise traders' misperceptions.

While the latter finding appears at odds with perceptions that developed markets are more efficient, and hence are expected to be less impacted by behavioral anomalies, our results here find support in the work of Griffin et al. (2010) and Jacobs (2016) demonstrating that anomalies are at least as strong, and sometimes stronger, in mature markets than emerging ones. In the context of reversal, momentum, and earnings surprise anomalies, Griffin et al. (2010) report returns spreads for emerging markets that are similar or smaller than those of developed markets, thus supporting the view that the former markets are no less efficient than the latter markets. Jacobs (2016) finds that mispricing, based on 11 long/short market anomalies, is no more prevalent in emerging markets than it is in developed ones, further corroborating the findings in Griffin et al. (2010). We add to this body of evidence by documenting a more enduring impact of investor sentiment on stock returns in developed markets than emerging markets.

4.1.2. Comparisons with previous studies

The majority of the previous literature examines the relationship between investor sentiment and stock returns in the US market (e.g., Brown and Cliff, 2005; Lemmon and Portniaguina, 2006; Baker and Wurgler, 2006 & 2007). For example, Brown and Cliff (2005) report that a one standard deviation increase in investor sentiment affects the average monthly stock returns by around −0.15% (−0.0067 × 22%), −0.24% (−0.0110 × 22%), −0.19% (−0.0088 × 22%), and −0.20% (−0.0092 × 22%) in the subsequent 6, 12, 24, and 36 months, respectively.[22] Estimating exclusively for the US market, we find a one standard deviation increase in investor sentiment gives rise to −0.71%,

[22] The impact of one standard deviation increase in investor sentiment on average monthly stock returns is computed by multiplying the estimated coefficient of the CCI by the standard deviation of investor sentiment, i.e., 22%, as per Table 3 in Brown and Cliff (2005).

−0.42%, −0.14%, and −0.25%, in the following 6, 12, 24, and 36 month (see, Table 4), separately, qualitatively in line with Brown and Cliff (2005).

Two recent studies by Schmeling (2009) and Bathia and Bredin (2013) explore a wider range of developed markets, namely 18 industrialized countries and the G7 countries, respectively. Both studies document a significantly negative impact of investor sentiment on the next-month stock returns, contrary to our results for all markets and for developed markets (see, Table 4). While it is not surprising to observe the insignificant predictability of investor sentiment in our near-term future returns (e.g., in the following month), since Brown and Cliff (2005, p. 407) argue that if that is the case "*there would be a potentially profitable trading strategy*", we conjecture that differences across studies might arise from the different sample markets examined. To rule out the potential influence of sample differences, we further estimate Eq. (3) using the same sample markets as included in Schmeling (2009) and Bathia and Bredin (2013). Table 4 shows results remain consistent, thus supporting the significantly negative impact of the CCI on the next-month stock returns. It is highly likely, therefore, that sample selection makes the difference. We interpret this evidence as strong support for our premise that a global examination of investor sentiment is warranted and that results based on a smaller number of developed markets might not hold generally.

4.2. Robustness tests

In light of the limitations associated with emerging market data and the associated need for robustness tests (Bekaert and Harvey, 2002), this subsection examines the robustness of our results by undertaking three main alternative tests: (i) the separation of the entire sample period into two subperiods; (ii) the extraction of the economic expectations from the CCI; and (iii) the use of the *single-period* monthly returns to replace the *average* monthly returns as the dependent variable.

4.2.1. Two subperiods

Following other studies, such as Jacobs (2016), we divide the entire sample period into two equal subperiods, i.e., from January 2001 to June 2008 and from July 2008 to December 2015. Such an approach allows consideration of whether our results hold in different sample periods or, if not, reveals potential changes in the sentiment-return relationship across sample periods. We replicate all analyses in Subsection 4.1.1 for each subperiod and results appear in Panel A of Table 5.[23] Overall, our reported panel regression results, i.e., a significantly negative sentiment-return relationship, remain qualitatively unchanged. Still, investor sentiment has more instant impact in emerging markets and more enduring impact in developed markets over the first subperiod, similar to that observed in Table 4. For example, investor sentiment has a statistically significant and more enduring impact up to 24 months in developed markets (cci_{24} = –0.20, p-value = 0.032), while the impact is only up to 12 months in emerging markets (cci_{12} = –0.71, p-value = 0.025).

<Table 5>

However, in more recent years, the negative impact of investor sentiment in emerging markets progressively approaches that observed in developed markets, as evidenced over the second subperiod: The impact of investor sentiment is significant up to 36 months in both developed markets (cci_{36} = –0.16, p-value = 0.030) and emerging markets (cci_{36} = –0.42, p-value = 0.000). The implications are twofold. First, the divergences in the impact of investor sentiment on stock returns revealed between developed and emerging markets are mainly driven by earlier data than more recent data. Second, more recently, as emerging markets continue their development, the impact of investor sentiment on stock returns in such markets more closely resembles that observed in developed markets. In this regard, our results are in line both with findings from early studies

[23] Given our interest in the sentiment-return relationship over horizons from 1 to 36 months, we exclude markets with observations less than 36 months in each subperiod, including Estonia, Greece, Hong Kong, Indonesia, Israel, Lithuania, Luxembourg, Mexico, New Zealand, Nigeria, Philippine, Poland, Romania, Slovakia, Taiwan, and Turkey.

based on contemporary samples of their day, such as Bekaert and Harvey (2002), evidencing large differences between developed and emerging markets, and also with more recent studies documenting an increased integration of emerging markets with developed markets, in part due to financial liberalization (e.g., Rejeb and Boughrara, 2013), though the process remains incomplete (Bekaert et al., 2011).

4.2.2. The extraction of the ESI from the CCI

Campbell and Diebold (2009, p.266) document that "*expected business conditions consistently affect expected excess returns in a statistically and economically significant counter-cyclical fashion*" (see, also, Møller et al., 2014). As investor sentiment carries the basic elements of expected business conditions, it is unknown whether our reported negative relationship between investor sentiment and future stock returns is driven by expected business conditions or by the remaining component beyond these business expectations. In Eq. (3), we already include a series of macroeconomic and market indicators as independent variables to account for the potential impact of economic conditions. Here, we further control for the expected business conditions represented by the economic sentiment index (ESI) which, in contrast to such *objective* factors as macroeconomic and market indicators, provides *subjective* survey-based expectations, just like the CCI. The ESI is accessible for 34 markets, though this reduced sample remains a representative collection of international markets as it includes 17 developed markets and 17 emerging markets (see, Appendix A).

We adopt another approach to incorporate the ESI into Eq. (3). To remove the influence of macroeconomic and market factors, Baker and Wurgler (2006) replace the original investor sentiment proxy with the residual series obtained from regressing investor sentiment on macroeconomic indicators (see, also, Sibley et al., 2016; Zheng et al., 2018). Inspired by this, we extract the independent sentiment component beyond the expected economic conditions by regressing the CCI on the ESI:

$$cci_t^i = \upsilon + \varphi^i esi_t^i + cci_t^{i,\perp}, \tag{4}$$

where the orthogonalized term $cci_t^{i,\perp}$ is the residual series that captures the investor sentiment not justified by the business or economic expectations. We thus use $cci_t^{i,\perp}$ to replace cci_t^i in Eq. (3). If the CCI does not contain information beyond the expected economic conditions (i.e., ESI), or this component does not hold any predictive power, $cci_t^{i,\perp}$ would not have a statistically significant impact on future stock returns.[24] Panel B of Table 5 shows that our results are qualitatively similar to those in Table 4, confirming the predictability of investor sentiment to future stock returns.

4.2.3. The use of single-period monthly returns

As evidenced in Table 4, the impact of investor sentiment fades away over longer forecast horizons. Note that the application of the average monthly returns may inflate the persistence of the impact of investor sentiment. For example, if the impact is strong in the first coming month, after averaging stock returns in a period of subsequent 12 months, the 'average' impact might still be strong even when it is in fact not. Therefore, the previously employed average monthly stock returns ($\frac{1}{T}\sum_{\tau=1}^{T} r_{t+\tau}^i$) are replaced with the single-period monthly stock returns ($r_{t+\tau}^i$), so as to remove any persistent effect of investor sentiment in the immediately subsequent months.[25] Panel C of Table 5 clearly shows that our previous conclusions do not alter.

[24] The panel unit root tests confirm ESIs to be stationary. The results are not reported here for the sake of brevity but are available on request.

[25] For example, r_{t+1}^i, r_{t+6}^i, and r_{t+12}^i represent returns in the following first, sixth, and twelfth months, respectively.

4.2.4. More robustness tests

We also carry out three additional robustness tests: (i) using trading volume as an alternative proxy for investor sentiment (see, Baker and Stein, 2004; Baker and Wurgler, 2007; Baker et al., 2012); (ii) adopting the commonly employed market index in each individual market to compute stock returns; and (iii) applying the FTSE Annual Country Classification Review to reclassify developed and emerging stock markets. Our conclusions remain well supported across these three additional robustness tests.[26]

4.3. Cross-sectional impact of investor sentiment on stock returns

Ding et al. (2018) extend the DSSW model by incorporating multiple risky assets, showing that hard-to-value and difficult-to-arbitrage stocks tend to be more affected by investor sentiment, consistent with prior empirical findings (e.g., Brown and Cliff, 2005; Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Joseph et al., 2011). Like the DSSW model, this new model also emphasizes the importance of noise traders' misperceptions in influencing the cross-section of stock returns, necessitating a further check based on a global sample incorporating naturally different noise traders in this regard (see, Appendix B, and also, Yates et al., 1989; Chen et al., 2007; Truong, 2011).

We, thus, re-examine Eq. (3), but for each market, with aggregate market returns replaced by returns of small, large, growth, and value stocks,[27] as well as two long-short portfolios constructed by using size premium (small minus large stocks) and value premium (value minus growth stocks). Results appear in Table 6.

<Table 6>

[26] Results are not reported here for the sake of brevity but are available in the Supplementary Materials.

[27] Data are sourced from the MSCI. Note that, for some markets, data are not balanced across small, large, growth, and value due to the availability.

At the global level, despite the differences in the impact of investor sentiment on separate categories of stocks, we do not observe any statistically significant differences in the two long-short portfolios. For developed markets, investor sentiment consistently affects small and large stocks over 2 to 36 months, but with significantly higher economic magnitude for small relative to large stocks over medium and long forecast horizons (i.e. from 6 to 12, and 36 months). In addition, investor sentiment affects both growth and value stocks over 2 to 36 months, with value stocks being affected more than growth stocks over medium forecast horizons (i.e. from 6 to 12 months). For emerging markets, the negative relationship between investor sentiment and small stock returns is observed immediately in the first ensuing month (cci_1 = –0.66, p-value = 0.020) and can be persistent for 3 years (cci_{36} = –0.41, p-value = 0.004). By contrast, investor sentiment only significantly affects large stock returns over 2 to 12 months. Results from the long-short portfolio confirms this significant difference in the sentiment impact on small and large stocks from 9 to 36 months. Likewise, compared with value stocks, growth stocks appear to be less influenced by investor sentiment in terms of both persistence and economic impact.

Results from developed and emerging markets collectively support two consistent findings. First, all categories of stocks are negatively affected by investor sentiment, suggesting that the observed negative relationship is not driven by a specific type of stock, rather it is quite pervasive in markets. Second, compared with large stocks and growth stocks, small stocks and value stocks are more affected by investor sentiment, both with respect to persistence and economic significance. [28]

[28] Note that findings of the cross-sectional impact of investor sentiment drawn from prior literature of a single US market are not completely consistent with each other. For example, Baker and Wurgler (2006 & 2007), Lemmon and Portniaguina (2006), and Qiu and Welch (2006) find small stocks to be more affected by investor sentiment while, Brown and Cliff (2005) show that the impact of investor sentiment is concentrated in large stocks, instead. Likewise, Kumar and Lee (2006) find that value stocks are more affected by investor sentiment, while Brown and Cliff (2005) find otherwise, and Baker and Wurgler (2006) document a 'U'-shape pattern with both growth and value stocks, rather than those in the middle, more sensitive to investor sentiment. Hence, our results can support one stream of prior findings, but not another.

One difference across developed and emerging markets reported in Table 6 is that investors in emerging markets are likely to distinguish small from large stocks more than value from growth stocks given the higher estimations of investor sentiment for the long-short portfolios S – L than V – G, while those in developed markets do not clearly exhibit this distinction. One potential reason is that differentiating small from large stocks tends to be more straightforward than differentiating value from growth stocks, in that the former is simply based on market capitalization, while the latter involves analyses of firms' balance sheets, which might be beyond investors in emerging markets lacking in financial literacy.[29] Considering the heterogeneous nature of investors in different markets, this divergence also supports the more recent multi-asset model of Ding et al. (2018) showing that investors' misperception can affect cross-sectional asset prices.

4.4. Condition-varying impact of investor sentiment on stock returns

Investors have been shown to exhibit varying behavior in different market conditions (e.g., Gervais and Odean, 2001; Nofsinger, 2005; Li and Luo, 2017). 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 (i.e., 0, 100, or 50, see, Footnote 14). Results in Table 7 show that high sentiment can significantly lead to low stock returns in subsequent 2 to 12 months, 2 to 36 months, and 1 to 12 months in all, developed, and emerging markets, respectively, thus confirming results obtained from the entire sample in Table 4. By contrast, low sentiment does not hold significant predictive power to future stock returns in all cases. However, broadly in line with

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[29] See, Appendix B, for more details. While in Subsection 5.3, we do not provide evidence that the impact of investor sentiment on stock returns is more pronounced in markets with a lower level of financial literacy than in markets with a higher level of financial literacy, this does not negate our conjecture here as its focus is on the cross-sectional stock selection.

Baker and Wurgler (2006), we find no significant difference in the impact of high and low investor sentiment on stock returns in all and emerging markets, and only two trivial significant cases for developed markets (i.e., subsequent 6 and 9 months).

<Table 7>

Second, we identify bull and bear market regimes. Prior US studies of the market separation mainly identify regimes based on economic cycle (expansion and recession) reported by the National Bureau of Economic Research (NBER), formulating separation principles based on economic indicators such as real GDP, employment, and wholesale-retail sales (e.g., Chung et al., 2012; Garcia, 2013; McLean and Zhao, 2014; Erdogan et al., 2015; Savaser and Şişli-Ciamarra, 2017). This NBER separation, however, is untenable in our study since, first, it is based on the real economy rather than the stock market, and recall that the onset of a growing (declining) stock market is regarded as a *leading* indicator of economic expansion (recession), and second, it only represents US business cycles that can be inaccurate for other markets. We thus employ the twin definitions of 'bull' and 'bear' regimes to substitute economic 'expansion' and 'recession', respectively, whereby bull and bear regimes refer to the periods when stock prices generally increase and decrease, reflecting expansion and recession in the real economy as defined by the NBER (Chauvet and Potter, 2000).

We split the entire sample into bull and bear regimes as in Pagan and Sossounov (2003). Results show that investor sentiment significantly and negatively affects stock returns over the following 1 to 12 months (all markets), 2 to 36 months (developed markets), and 1 to 12 months (emerging markets) during bull regimes, while the impact is only significant for developed markets in subsequent 2 to 36 months during bear regimes. Contrary to the results revealed by the high- and low-sentiment separation above, significant differences in the impact of investor sentiment across bull and bear regimes are widely observed in all, developed, and emerging markets, especially over short and medium forecast horizons (2 to 12 months), providing global support to Chung et al. (2012) reporting a stronger impact of investor sentiment on the US market during periods of economic expansion.

While in theory investors can purchase stocks when they are optimistic or when the market is in an upward trend (Baker and Wurgler, 2006; Chung et al., 2012), and conversely short sell when pessimistic or the market is in a downward trend,[30] in practice, purchasing and short selling are unbalanced in the presence of short-sale constraints and investors tend to be unsophisticated (see, Shleifer and Vishny, 1997; Jones and Lamont, 2002; Ofek et al., 2004; Chang et al., 2007; Gabaix et al., 2007; Lewellen, 2011; Lam and Wei, 2011; Yu and Yuan, 2011; Wang, 2018a). As a consequence, investors are more likely to trade and thus to bring a stronger impact on stock markets during periods of high-sentiment or bull regimes, as shown in Table 7. In developed markets, however, investor sentiment can affect stock returns during bear regimes (Panel B.2, Table 7), which can be ascribed to the fact that developed markets tend to have looser short-sale constraints (De Roon et al., 2001; Bris et al., 2007; Charoenrook and Daouk, 2009; Griffin et al., 2010; Saffi and Sigurdsson, 2011; Feng et al., 2017)[31] and higher levels of investor financial literacy (see, Appendix B). However, the short-sale constraints still impede sizable bearish trading and so we note a significant difference in the sentiment impact across bull and bear regimes in more scenarios than not.

[30] In terms of trading strategies, our finding in Table 7, however, suggests otherwise. Given the negative sentiment-return relationship, investors might purchase stocks amid low-sentiment periods while short selling over high-sentiment periods. We do not specify trading strategies for bull/bear regimes, however, as such designations applied in our tests rely on future realized prices and thus are not implementable (Pagan and Sossounov, 2003).

[31] In an extensive study of global short-sale constraints, Charoenrook and Daouk (2009) report that short-sale was legal in 22 out of 23 developed markets (around 95.65%), but only in 25 out of 88 emerging markets (around 28.41%), while it was feasible in 20 out of 23 developed markets (around 86.96%), but only in 9 out of 88 emerging markets (around 10.22%), explicitly signalling that short-sale is more prevalent in developed than emerging markets. A similar conclusion is also drawn in Bris et al. (2007), documenting that short-sales were allowed and practiced in most developed markets, but not emerging markets.

4.5. *Individual market results*

Thus far, we run the fixed-effect panel regression with the assumption of identical slope coefficients across all sample markets and across the two separate groups of developed and emerging markets, hence the role of investor sentiment in each individual stock market is not addressed. This subsection examines the impact of investor sentiment on future stock returns at the market level based on an eight-equation system with different forecast horizons. Since the results are correlated across various forecast horizons, a joint test for predictability is more reasonable than tests at individual forecast horizons (Ang and Bekaert, 2007). Specifically, we jointly estimate Eq. (4) for T months (T = 1, 2, 3, 6, 9, 12, 24, and 36) in a system of eight regression equations using the generalized method of moments (GMM) to test whether there exists the jointly significant impact of investor sentiment on stock returns—that is, we test the form of $\beta^{i,(1)} = 0$, $\beta^{i,(2)} = 0$, $\beta^{i,(3)} = 0$, $\beta^{i,(6)} = 0$, $\beta^{i,(9)} = 0$, $\beta^{i,(12)} = 0$, $\beta^{i,(24)} = 0$, and $\beta^{i,(36)} = 0$. The eight-equation system is jointly estimated for each individual market i as follows,

$$
\begin{aligned}
r_{t+1}^{i} &= \alpha^{i,(1)} + \beta^{i,(1)} cci_t^i + \gamma^{i,(1)} \Psi_t^{i,(1)} + \varepsilon_{t+1}^{i,(1)}, \\
\frac{1}{2}\sum_{\tau=1}^{2} r_{t+\tau}^{i} &= \alpha^{i,(2)} + \beta^{i,(2)} cci_t^i + \gamma^{i,(2)} \Psi_t^{i,(2)} + \varepsilon_{t+1\to 2}^{i,(2)}, \\
\frac{1}{3}\sum_{\tau=1}^{3} r_{t+\tau}^{i} &= \alpha^{i,(3)} + \beta^{i,(3)} cci_t^i + \gamma^{i,(3)} \Psi_t^{i,(3)} + \varepsilon_{t+1\to 3}^{i,(3)}, \\
\frac{1}{6}\sum_{\tau=1}^{6} r_{t+\tau}^{i} &= \alpha^{i,(6)} + \beta^{i,(6)} cci_t^i + \gamma^{i,(6)} \Psi_t^{i,(6)} + \varepsilon_{t+1\to 6}^{i,(6)}, \\
\frac{1}{9}\sum_{\tau=1}^{9} r_{t+\tau}^{i} &= \alpha^{i,(9)} + \beta^{i,(9)} cci_t^i + \gamma^{i,(9)} \Psi_t^{i,(9)} + \varepsilon_{t+1\to 9}^{i,(9)}, \\
\frac{1}{12}\sum_{\tau=1}^{12} r_{t+\tau}^{i} &= \alpha^{i,(12)} + \beta^{i,(12)} cci_t^i + \gamma^{i,(12)} \Psi_t^{i,(12)} + \varepsilon_{t+1\to 12}^{i,(12)}, \\
\frac{1}{24}\sum_{\tau=1}^{24} r_{t+\tau}^{i} &= \alpha^{i,(24)} + \beta^{i,(24)} cci_t^i + \gamma^{i,(24)} \Psi_t^{i,(24)} + \varepsilon_{t+1\to 24}^{i,(24)}, \\
\frac{1}{36}\sum_{\tau=1}^{36} r_{t+\tau}^{i} &= \alpha^{i,(36)} + \beta^{i,(36)} cci_t^i + \gamma^{i,(36)} \Psi_t^{i,(36)} + \varepsilon_{t+1\to 36}^{i,(36)}.
\end{aligned}
\tag{5}
$$

Contrary to the previous panel approach in which all observations before January 2001 are removed so as to ensure markets with considerably longer observation periods do not drive our results, here we retain the full sample as shown in Table 1 for each individual market. Table 8 reports the average predictive coefficients of the CCIs over the subsequent 1, 2, 3, 6, 9, 12, 24, and 36 months. We find the impact of investor sentiment to be market-specific, which is reasonable given the wide variety of the attributes of sentiment investors across different markets. The coefficients of the CCIs are significantly positive or negative in 28 markets over the subsequent 36 months at least at the 10% significance level. In particular, the varying relationship between investor sentiment and future stock returns exists among both developed and emerging markets, unrelated to the location or size of a specific market. For example, the impact of investor sentiment is strong in China (*cci* = –1.18, *p*-value = 0.002), France (*cci* = –1.49, *p*-value = 0.002), and Spain (*cci* = –1.42, *p*-value = 0.042), but relatively weak in Australia (*cci* = –0.41, *p*-value = 0.012), Japan (*cci* = –0.06, *p*-value = 0.088), and Malta (*cci* = –0.26, *p*-value = 0.066). However, a significantly positive impact of investor sentiment on future stock returns is found in markets such as Romania (*cci* = 0.75, *p*-value = 0.027) and Slovakia (*cci* = 0.09, *p*-value = 0.003). We return to these differences in Section 5.

<Table 8>

Finally, we examine the correlation between unexpected returns (ε_{t+1}^{i}) and innovations in investor sentiment (ξ_{t+1}^{i}) based on the predictive model as follows,

$$\begin{aligned} r_{t+1}^{i} &= \alpha^{i} + \beta^{i} cci_{t}^{i} + \gamma^{i} \Psi_{t}^{i} + \varepsilon_{t+1}^{i}, \\ cci_{t+1}^{i} &= \eta^{i} + \lambda^{i} cci_{t}^{i} + \xi_{t+1}^{i}. \end{aligned} \tag{6}$$

The rational framework for estimating stock returns predicts a negative correlation between unexpected returns and innovations in discount factors (e.g., Campbell and Shiller, 1988). A positive correlation, however, is expected under the behavioral framework, in which excessive optimism (pessimism), i.e., innovations in investor sentiment, should unexpectedly drive stock prices above (below) fundamental values (De Long et al, 1990; Subrahmanyam, 2007), signifying a positive correlation ($\rho_{\varepsilon,\xi}$) between ε_{t+1} and ξ_{t+1}. Table 8 reveals the positive correlations between unexpected returns and the innovation in investor sentiment in the majority of our sample markets, consistent with the expectation of the behavioral framework.

5. Driving forces of cross-market divergences

This section explores driving forces of the observed cross-market divergences in the impact of investor sentiment shown in Section 4. Subsection 5.1 probes cultural dimensions, including individualism (IDV), the uncertainty avoidance index (UAI), masculinity (MAS), the power distance index (PDI), long-term orientation (LTO), and indulgence (IDG). Subsection 5.2 explores market institutions, including the antidirector right (ADR), government corruption (GC), the accounting standard (AS), and efficiency of judicial system (EJS), while Subsection 5.3 assesses intelligence and education, including the intelligence quotient (IQ), adult general literacy (AGL), financial literacy (FL), the student test average (STA), tertiary education graduation (TEG), and education expenditure (EE).

5.1. Cultural dimensions

We examine six cultural dimensions in total, including IDV, UAI, MAS, PDI, LTO, and IDG. While the first two are explored in some prior sentiment literature, the last four are largely unexamined in this literature.

5.1.1. IDV and UAI

Researchers distinguish between IDV and its opposite, collectivism (COL), as follows: Individuals in high IDV cultures tend to view themselves as autonomous and independent, while those in high COL cultures tend to view themselves more connected with others (Markus and Kitayama, 1991). A body of evidence reveals that individuals in high IDV cultures tend to be overconfident and thus commit cognitive biases (e.g., Heine et al., 1999; Chui et al., 2010; Li et al., 2013). For example, Chui et al. (2010) report a positive relationship between IDV and momentum profits, and due to the mean reversion property, they further document a positive relationship between IDV and stock price reversals, implying that the impact of investor sentiment would be positively related to IDV. On the other hand, IDV predicts reduced herding behavior relative to COL (e.g., Markus and Kitayama, 1991; Beckmann et al., 2008), meaning that investors in COL cultures tend to trade in concert and induce overreaction. As a result, it seems inconclusive whether IDV or COL leads to more evident impact of investor sentiment on stock returns.

The UAI measures the extent to which people react to uncertain situations (Hofstede, 2001). High uncertainty avoidance indicates low risk tolerance so that individuals in high UAI cultures generally react less rationally to uncertain circumstances (Hofstede, 2001), and as a consequence, investors in these markets are more likely to overreact to market fluctuations, causing a stronger impact of investor sentiment. By contrast, investors in low uncertainty-avoiding markets tend to be more comfortable with unexpected market changes.

5.1.2. MAS, PDI, LTO, and IDG

These four factors are not as present in the sentiment literature as IDV and UAI; thus, in the discussion to follow we make inferences based on existing evidence from studies of examining the influence of culture on financial behavior more generally.

MAS represents the pursuit of heroism, assertiveness, and competitiveness, more related to males, while its opposite, femininity (FEM), represents modesty and cooperation, more related to females (Hofstede, 2001). As males appear more overconfident and less rational in stock trading (e.g., Lundeberg et al., 1994; Barber and Odean, 2001), high MAS may imply a more pronounced impact of investor sentiment.

The PDI refers to the degree to which less powerful individuals expect and accept power to be unequally distributed (Hofstede, 2001). High PDI denotes centralized control by authorities (Hofstede et al., 2010), indicating stock markets to be more administered.[32] Hence, investor sentiment in high PDI markets may be less influential in that fluctuations, particularly dramatic ones, caused by investor sentiment, among other things, could be restrained by authorities. LTO reflects whether the focus of individuals' efforts is on the present and past, or on the future (Hofstede and Bond, 1988). Individuals in LTO markets prefer family business and real estate while those in short-term orientation (STO) markets prefer shares and mutual funds (Hofstede et al., 2010). Hence, we would expect individual investors to trade more in STO than LTO markets. Recall that individual investors are normally uninformed noise traders and as such they tend to overreact and to trade in concert (Lee and Swaminathan, 2000; Kumar and Lee, 2006; Grinblatt and Keloharju, 2000; Dimpfl and Jank, 2016); therefore, stock returns in STO markets may be more affected by investor sentiment because of the higher participation of individual investors. Finally, IDG refers to the restraints on gratification and basic human desires in relation to enjoying life (Hofstede et al., 2010). Compared with consumers in high IDG markets, those in low IDG markets would purchase goods only when they need (Minkov, 2011), from which we infer that investors in high IDG markets may be more prone to engage with stock trading, thus imparting a stronger sentiment impact. For both LTO and IDG, our arguments associated with culture-driven

[32] For instance, the Shanghai Stock Exchange (SSE) in China underwent a dramatic decrease in the middle of 2015. The market index plummeted from 5,178.19 the highest on Friday, 12 June 2015 to the closing point of 3,877.80 on Friday, 10 July 2015. Over this month, the Chinese authority adopted a series of approaches to prevent the stock prices from further plunging. On Saturday, 27 June 2015, the Chinese central bank announced the cut in the reserve requirement ratio and the interest rate enforced from Sunday, 28 June 2015. On Wednesday, 1 July 2015, the stock exchange announced lower transaction costs. On Friday, 3 July 2015, the China Security Regulatory Commission (CSRC) reiterated a desire to reduce the number of the initial public offering (IPO) and on the same day, the CSRC declared that Central Huijin Investment Ltd., a state-owned investment company, had begun trading in the stock market, etc. The administration is also observed when the stock market shows signs of overheating. More recently, trading of one ChiNext board listed stock, Xinjiang Tianshan Animal Husbandry Bio-engineering, has been halted twice since August 2020, after the stock price surged around sixfold in only three weeks. Note that, however, the stock price escalation was not performance-supporting but due to the eased trading restrictions that stocks listed on the ChiNext can rise or fall by 20%, doubling the previous 10%, which created speculative opportunities for investors pursuing profits from greater price swings. The PDI in China is 80, among the top markets in Hofstede et al. (2010).

differences in the influence of investor sentiment are rooted in differences in market participation (MP). To isolate these culture-driven differences in the sentiment impact, our primary subject matter, we control for MP in the following analyses.[33]

5.1.3. *Results*

All six cultural dimensions are collected from Hofstede's website where scores ranging from 0 to 100 are given to different markets,[34] and thus the culture of a market is described and determined by these six dimensions. For a given market, each cultural dimension is time-invariant, so rather than including these dimensions in the predictive regression Eq. (3), we rank markets by score in a descending order and separate them into upper (above-median) and lower (below-median) layers.[35] Regressions are then run for both layers to test the impact of investor sentiment in markets with different cultural dimensions. Note that classifications of markets in the upper and lower layers based on the median split for the six cultural measures do not mimic directly the emerging/developed market classification adopted earlier, thus the analysis to follow addresses different issues to those examined earlier. For LTO and IDG, we control for MP by further dividing high and low LTO (IDG) layers into four smaller samples conditional on high/low MP sourced from Lu et al. (2020), giving high MP/high LTO (IDG), high MP/low LTO (IDG), low MP/high

[33] We thank the anonymous reviewer for drawing our attention to the need to control for MP in our analyses, specifically in the context of IQ (see Subsection 5.3 below) and also more generally, to ensure the negative sentiment relationship we examine is driven by such differences as IQ and culture, and does not merely reflect differences in individual trading, i.e., MP. See, Conlin et al. (2015) and Bamiatzi et al. (2016), for further discussion relating to MP.

[34] We are grateful to Prof. Geert Hofstede for making the data available at https://www.hofstede-insights.com. Data are presented in Appendix B and the pairwise correlations are presented in Appendix C. While there appear critiques of Hofstede's framework (McSweeney, 2002; Ailon, 2008), it is arguably the most comprehensive dealing with national culture, as evidenced by its cumulative impact on research generally and in finance specifically (see, Karolyi, 2016, for a critical review in the context of finance).

[35] For example, markets classified in the upper IDV layer are individualistic markets while those classified in the lower IDV layer are collectivistic markets. Likewise, markets grouped in the upper UAI layer are high uncertainty-avoiding markets while those grouped in the lower UAI layer are low uncertainty-avoiding markets. The same case also applies to the other four cultural dimensions including MAS, PDI, LTO, and IDG. While, for instance, markets in an upper (lower) IDV layer may not necessarily exhibit an absolute level of individualism (collectivism), a clear distinction between two subsamples is present due to the different cultural scores. The same procedure is also replicated for market institutions and intelligence and education, as shown below.

LTO (IDG), and low MP/low LTO (IDG).[36] For comparability with Schmeling (2009), we focus on the 12-month forecast horizon to assess the persistent impact of investor sentiment. The results are reported in Panel A of Table 9.

The estimations of the impact of investor sentiment are −0.51 (p-value = 0.001) and −0.37 (p-value = 0.243) for IDV and COL markets, respectively, showing that investor sentiment persistently affects subsequent 12-month returns in high IDV markets, but it loses predictability in high COL markets. The significant spread (–0.14, p-value = 0.019) confirms the impact of investor sentiment to be stronger in IDV markets, supporting one line of evidence suggesting a positive IDV and sentiment impact linked to overconfidence etc. (e.g., Heine et al., 1999; Chui et al., 2010; Li et al., 2013), over another suggesting a positive COL and sentiment impact linked to herding (e.g., Markus and Kitayama, 1991; Beckmann et al., 2008).

Our results here are contrary to Schmeling (2009) in which a stronger impact of investor sentiment on stock returns in collectivistic than individualistic cultures is reported, thus demonstrating the importance of a global study of investor sentiment, based on an enlarged market sample and importantly an extended IDV scale. Note, the values of IDV in Schmeling (2009) vary from 46 (Japan) to 91 (the US), whereas ours range from 13 (Colombia) to 91 (the US), evidently extending the IDV scale to the left end. Such extension brings a large degree of variation into the IDV measure. Untabulated tests show that the standard deviation of IDV in our sample (23.057) is nearly double that of Schmeling's (2009) sample (12.491), while equality statistics from the F-test, Levene's test, and Brown-Forsythe test are 3.407, 15.788, and 12.880, with p-values of 0.008, 0.000, and 0.001, respectively, show a robustly significant difference in the variation of the two samples. IDV data in emerging markets are generally low, i.e. emerging markets tend to be

[36] While MP data from Lu et al. (2020) provides good coverage of our global sample, not all markets are included, hence the four smaller sub-samples have fewer markets compared with the two upper/lower layers. Due to limitations in the cross-sectional variation in our data, in this section we employ univariate or bivariate sorting approaches, hence it is conceivable that potential interaction effects are missed. We acknowledge this as a potential caveat in our paper.

culturally collectivistic. Indeed, the lower-layer group consists of a large number of emerging markets: There are 18 emerging markets in the lower layer, accounting for 75% of the entire group (see, Appendix B).

<Table 9>

Consistent with our expectation, the spread on the impact of investor sentiment on stock returns for UAI is –0.21 (*p*-value = 0.001), suggesting that trading by investors in high UAI markets has a more pronounced impact on the sentiment-return relationship. Conversely, high PDI markets suffer less impact of investor sentiment (0.15, *p*-value = 0.005) as conjectured. Turning to LTO, while it does not explain divergences across the upper and lower layers in general, the further split into high and low MP is informative. We observe a significantly stronger sentiment impact in low LTO markets than in high LTO markets conditional on low MP (spread = 0.50, *p*-value = 0.000) but not high MP (spread = 0.08, *p*-value = 0.168), thus confirming the role of MP in this mechanism. For the remaining two dimensions, MAS and IDG, however, we find no significant differences across the upper and lower layers, even after accounting for MP in the case of the latter.

5.2. Market institutions

Market institutions influence the impact of investor sentiment as advanced institutions ameliorate information circulation and thus make stock markets more efficient (e.g., Zouaoui et al., 2011). Therefore, investor sentiment might be expected to be less influential in markets with stronger market institutions than in those with relatively weaker market institutions. We examine four indicators, including ADR, GC, AS, and EJS, and all four scores are collected from La Porta et al.

(1998), in which markets with more advanced institutions are given higher scores (see, Appendix B).[37] The test procedure is the same as that used in Subsection 5.1.

Regression results appear in Panel B of Table 9, evidencing that stock returns in markets with higher antidirector rights, less government corruption, more complete accounting standards, and more efficient judicial systems are less affected by investor sentiment, in line with Schmeling (2009) and Zouaoui et al. (2011). Note that markets in the upper and lower layers based on the median split for the four market institution measures do not perfectly reflect the emerging/developed market classification adopted earlier (see, Appendix B) and so our results here hold notwithstanding the findings of Griffin et al. (2010) and Jacobs (2016) discussed in the context of emerging versus developed markets. These results imply the policy suggestion that a system of more complete market institutions is needed to lessen the impact of investor sentiment on stock returns, and based on our findings, a set of more complete market institution refers to more antidirector rights, stricter measures to prevent government corruption, the adoption of more complete accounting standards, and establishment of more efficient judicial systems.

5.3. Intelligence and education

5.3.1. Intelligence

Intelligence reflects the totality of cognitive abilities and partially determines people's behaviors (Rindermann et al., 2014). Applying Finnish Armed Forces (FAF) intelligence data, Grinblatt et al. (2012) report that high-IQ investors exhibit fewer cognitive biases and are better at market timing, stock picking, and trade execution and as such are rewarded with higher returns, thus

[37] One potential concern relating to the application of data in La Porta et al. (1998) is that market institutions in some markets, especially emerging markets, have developed in recent years and as such data from pre-1998 may seem inappropriate to represent the more recent situation. Note, however, that we employ the market institution data as a grouping criterion only. Arguably, markets with relatively weak market institutions before 1998 would be expected to remain *relatively* weak compared with those with more advanced market institutions, i.e. the rank among markets is not expected to change dramatically. Note also, the La Porta et al. (1998) data continue to be used in recent studies (see, Bilinski et al., 2013; Ahern et al., 2015; Scharfstein, 2018), justifying this adoption.

indicating a smart-trading effect. Despite this, high-IQ investors could still succumb to irrational sentiment in that noise traders can also earn higher returns by bearing more of the risk that they create in markets (De Long et al., 1990). Burson et al. (2006) find that good performers and bad performers tend to make equally noisy judgment and, for difficult tasks, good performers are more miscalibrated (see, also, Krueger and Mueller, 2002). It is possible, therefore, that while high-IQ investors perform better in stock markets, they can still bring noise and a more pronounced sentiment impact to stock markets. Using the same FAF dataset, Grinblatt et al. (2011) reveal that high-IQ investors prefer value stocks and small stocks. In an unreported test based on the Finnish stock market, we find that value stocks and small stocks are more affected by investor sentiment than growth stocks and large stocks, in line with our cross-sectional results for developed markets (Panel B, Table 6), and also with Schmeling (2009), showing that high-IQ investors' participation can lead to a stronger sentiment impact, thus implying a noise-trading effect. In light of such opposing views, high-IQ investors and sentiment-free investors need not be one and the same, and so a priori it appears inconclusive how the impact of investor sentiment on stock returns is related to IQ. Furthermore, as Grinblatt et al. (2011) show that high-IQ investors participate more in stock trading than low-IQ investors, it is of interest to examine whether and how the effects of MP and IQ interact in their influence on the sentiment-return relationship.

5.3.2. Education

While intelligence and education represent distinct constructs, they are closely entwined (Mayer, 2000), necessitating a comparable examination of the impact of the latter on the sentiment-return relationship. In theory, education helps to explain differences in national IQs in as much as it is a secondary determinant of IQs, along with other environmental factors (Hunt, 2011; Lynn and Vanhanen, 2012). In practice, education is also applied to reflect IQs. For instance, the FAF intelligence data employed in Grinblatt et al. (2011 & 2012) is computed from 120 questions covering mathematical, verbal, and logical skills, which effectively captures education.

As one demographic factor, education is widely adopted as an indicator of individuals' potential skills. There is little doubt that education affects investors' behavior,[38] whereas, similar to IQ, evidence on the relationship between investors' education and rationality are, at best, mixed. On the one hand, investors with higher education are less subject to judgmental biases and heuristics (e.g., Lichtenstein and Fischhoff, 1977; Kruger and Dunning, 1999 & 2002; Dhar and Zhu, 2006). On the other hand, like high-IQ individuals, those with higher education level can be more miscalibrated in the face of difficult tasks and so might be associated with a stronger sentiment impact (Krueger and Mueller, 2002; Burson et al., 2006). Again, we take MP into consideration as prior research reveals a positive relationship between stock market participation and education or financial literacy (e.g., Guiso and Jappelli, 2005; Lusardi and Mitchell, 2008; van Rooij et al., 2011; Cole et al., 2014).[39]

5.3.3. Results

We compile six indicators reflecting intelligence and education at the market level including intelligence quotient (IQ), adult general literacy (AGL), financial literacy (FL), the student test average (STA), tertiary education graduation (TEG), and educational expenditure (EE), from

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[38] Extant literature adopts variations in education (i.e., high and low education levels) to explain social, economic, and financial phenomena. In an experimental study, Heath and Tversky (1991) reveal that when people are more knowledgeable or competent in a specific area, they tend to bet on their own judgment instead of the matched-probability lottery, known as "*competence effect*". Graham et al. (2009) demonstrate that investors with higher education levels would trade more frequently than those with lower education levels. Similar to this, Warren et al. (1990) show that investors with higher education tend to be "*heavy investors*" (p. 75) with over $30,000 investment holdings, while those with lower education are likely to be "*light investors*" (p. 75). Likewise, Riley and Chow (1992) and Dwyer et al. (2002) both report that higher-educated investors are likely to assume more risk.

[39] Lusardi and Mitchell (2011) conclude that, while higher educational attainment correlates well with financial knowledge/literacy, education is not a perfect proxy for financial literacy, hence our focus here on education generally as opposed to financial literacy alone.

various sources.[40] Specifically, IQ, AGL, FL, and STA are collected from Lynn and Vanhanen (2012),[41] the World Bank (2015), the Standard & Poor's Ratings Services Global Financial Literacy Survey (S&P Global FinLit Survey, 2014), and the Program for International Student Assessment (PISA, 2015), separately; TEG and EE are collected from the latest OECD reports available (2014 and 2013, respectively). The test procedure is the same as Subsection 5.1, while additionally here we control for MP for all six factors.[42] Results appear in Panel C of Table 9.

Drawing comparison across the upper- and lower-layer markets, we find for AGL that in markets with higher education, investor sentiment tends to exert a weaker impact on long-run stock returns than markets with lower education. In contrast, however, stock markets with high TEG and EE are more affected by investor sentiment than those with low TEG and EE, and notably for TEG, the result remains consistent across high/low MP splits.

While IQ does not predict the difference in the sentiment impact on its own, the results conditional on MP reveal that high IQ promotes a significantly stronger sentiment impact in high MP markets, but a significantly weaker sentiment impact in low MP markets. As explained above, high-IQ investors are not necessarily sentiment-free, and the influence of IQ on the impact of investor sentiment depends on the smart-trading effect and the noise-trading effect. In low MP markets where individual investor participation is not high, the impact of investor sentiment is significantly weaker in high IQ markets than in low IQ markets (spread = 0.64, *p*-value = 0.000), suggesting a

[40] AGL measures 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. FL measures individuals' understanding of financial concepts including basic numeracy, interesting compounding, inflation, and risk diversification. STA is the average score from student mathematics, reading, and science tests evaluating the skills and knowledge of students aged 15. TEG and EE reflect the aggregate education level. TEG estimates the percentage of people who will graduate at the tertiary level over their lifetime. EE is the total spending on schools, universities, and public and private educational institutions and is denoted as a percentage of GDP.

[41] The IQs compiled by Lynn and Vanhanen (2012), the compilation approach of which follows Lynn and Vanhanen (2002). Despite critiques from several aspects (see, Barnett and Williams, 2004; Hunt, 2011); however, their measures afford a high level of suitability via comparison with educational attainment (e.g., Lynn and Mikk, 2007; Lynn and Meisenberg, 2010).

[42] Again, we thank the anonymous reviewer for noting the tension in our motivation, in particular in the context of IQ, and suggesting the need to control for MP to isolate the effect of IQ, along with other variables of interest.

stronger smart-trading effect. On the contrary, in high MP markets the impact is significantly stronger in high IQ markets than in low IQ markets (spread = –0.28, *p*-value = 0.000), thus supporting a noise-trading effect, which could be due to high-IQ investors' miscalibration (Burson et al., 2006).[43] FL shows a similar pattern to IQ, in as much as FL does not explain the difference in the sentiment impact on its own, but high FL significantly strengthens the sentiment impact in high MP markets while weakens the sentiment impact in low MP markets. Such opposing influences for both IQ and FL across high and low MP accounts for their null net influence on the impact of investor sentiment on stock returns, thus supporting the inclusion of the role of MP in the earlier motivating discussion.[44] For STA, however, we find no statistical differences in the strength of the negative sentiment-return relationship across the upper- and lower-layer markets.

We note a number of intriguing insights suggested by these results. First, it might initially appear that educational measures that may be deemed to be more basic or less direct, such as adult general literacy (i.e. basic reading comprehension) and educational expenditure (a proxy based on percentage of GDP spent on education), respectively, provide better explanation of the heterogeneity in the sentiment-return relationship than measures that might be deemed more sophisticated or of direct relevance, such as intelligence quotient and financial literacy, respectively. However, the basic or less direct measures seem to be picking up differences in market participation, while, after accounting for such differences, the influence of intelligence quotient and financial literacy become clearer, with high IQ and high FL associated with stronger/weaker sentiment impact in markets with high/low levels of market participation by individual investors. Our findings, therefore, align more closely with those of Grinblatt et al. (2011) than those of Grinblatt et al. (2012), in as much as high IQ (and FL) in conjunction with higher

[43] It is conceivable that other factors discussed in this section may also interact with IQ. However, as explained in Footnote 36, we adopt only univariate or bivariate sorting approaches due to limitations in the cross-sectional variation in our data.

[44] In Appendix D, we explore further the entwined roles of IQ and MP on the impact of investor sentiment.

levels of individual investor market participation exacerbates the negative sentiment-return relationship, as opposed to high IQ being indicative of individual investors exhibiting fewer cognitive biases and so diminishing the negative relationship, though the reverse is true under low market participation. Second, markets with high levels of tertiary education graduation display a stronger sentiment impact than those with low corresponding levels and this holds in general, irrespective of market participation. While the stronger negative sentiment-return relationship observed in markets with higher levels of tertiary education graduation might be unexpected, evidence that investors with higher education levels tend to be more overconfident in their abilities (Bhandari and Deaves, 2006) is suggestive of a potential link between overconfidence and the extent to which investor sentiment is observed in a market. We leave it to further studies to examine these issues more closely with purposely collected data thus allowing greater insight to be obtained.

6. Conclusion

Investors are rational under the standard financial framework and therefore are not subject to sentiment (e.g., Fama, 1965). However, a growing number of studies find that investors are irrational and, further, their irrational trading can exert persistent impact on asset prices and returns (e.g., De Long et al., 1990; Shleifer and Vishny, 1997; Ding et al., 2018). Despite the large amount of theoretical and empirical research in the US and some other markets, the limited number of studies on the impact of investor sentiment at the global level makes it unclear whether investor sentiment holds predictability under a wider scope.

This paper, to the best of our knowledge, is the first to extend the sentiment literature to the global level by investigating both developed and emerging markets. We document that investor sentiment negatively predicts future global stock returns from the subsequent 2 to 12 months. In addition, while we show that the negative pattern holds for both developed and emerging markets, we are also the first to document a negative sentiment-return relationship that exerts a more immediate impact in emerging markets, but a more enduring impact in developed markets, and in doing so contribute to the recent literature demonstrating that anomalies are at least as strong, and sometimes stronger, in developed than emerging markets (Griffin et al., 2010; Jacobs, 2016). Our results hold true under an array of alternative robustness tests. Differences in the impact of investor sentiment across developed and emerging markets are also revealed from cross-sectional tests, showing that investors in emerging markets tend to distinguish small from large stocks more than value from growth stocks: a phenomenon not so clear in developed markets. Moreover, we report that the cross-market differences in the impact of investor sentiment on stock returns are present in both developed and emerging markets, with small stocks and value stocks being more affected. A series of tests on the condition-varying impact of investor sentiment on stock returns evidence that the impact is more pronounced over high-sentiment periods and bull regimes, than low-sentiment periods and bear regimes. Furthermore, we document heterogeneity in the sentiment-return relationship at the individual market level and find that disparate cultural dimensions and market institutions, along with intelligence and education, can explain such differences to varying degrees influenced by the extent of individual investor market participation. Drawing on this, we propose that a system of more complete market institution is needed to weaken the impact of investor sentiment on stock returns.

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Appendix A: Descriptive statistics of the ESIs

Markets	Starting month	Sources	μ	σ	$\rho(1)$
Australia*	2001.01	National Australia Bank, Business Confidence Index	12.64	10.14	0.83
Austria*	2001.01	Directorate-General for Economic and Financial Affairs (DG ECFIN), Economic Sentiment Indicator (ESI)	99.65	9.40	0.96
Belgium*	2001.01	DG ECFIN, ESI	99.88	9.62	0.96
Bulgaria	2001.01	DG ECFIN, ESI	102.38	8.48	0.96
China	2007.04	MNI China Business Sentiment Indicator (BSI)	57.92	7.21	0.84
Croatia	2008.05	DG ECFIN, ESI	95.25	8.59	0.96
Cyprus	2004.06	DG ECFIN, ESI	99.31	9.94	0.94
Czech Republic	2005.02	DG ECFIN, ESI	100.82	9.89	0.98
Denmark*	2001.01	DG ECFIN, ESI	101.47	9.35	0.93
Estonia	2011.01	DG ECFIN, ESI	102.08	3.86	0.93
Finland*	2001.01	DG ECFIN, ESI	100.28	8.41	0.93
France*	2001.01	DG ECFIN, ESI	100.44	8.97	0.97
Germany*	2001.01	DG ECFIN, ESI	98.28	9.70	0.98
Greece*	2004.02	DG ECFIN, ESI	94.38	11.11	0.98
Hungary	2001.01	DG ECFIN, ESI	100.33	9.91	0.96
Italy*	2001.01	DG ECFIN, ESI	99.09	8.63	0.96
Japan*	2001.01	Bank of Japan, TANKAN Business Conditions	–9.55	16.04	0.94
Lithuania	2006.01	DG ECFIN, ESI	101.41	11.73	0.98
Luxembourg*	2006.01	DG ECFIN, ESI	96.00	9.87	0.93
Malta	2002.11	DG ECFIN, ESI	99.28	9.98	0.87
Netherlands*	2003.02	DG ECFIN, ESI	97.64	11.11	0.98
Nigeria	2014.03	MNI Nigeria BSI	62.58	3.08	0.01
Poland	2006.01	DG ECFIN, ESI	99.15	9.81	0.98
Portugal*	2001.01	DG ECFIN, ESI	96.51	9.35	0.96
Romania	2006.01	DG ECFIN, ESI	97.69	9.32	0.98
Russia	2013.03	MNI Russia BSI	80.07	15.26	0.92
Slovakia	2006.04	DG ECFIN, ESI	100.00	10.41	0.98
Slovenia	2003.09	DG ECFIN, ESI	100.34	11.50	0.97
South Korea	2001.01	Korean Economic Research Institute, Business Survey Index	99.63	12.74	0.71
Spain*	2001.01	DG ECFIN, ESI	98.82	9.13	0.98
Sweden*	2001.01	DG ECFIN, ESI	101.93	8.44	0.96
Thailand	2001.01	Bank of Thailand, Business Sentiment Index	47.50	3.98	0.79
United Kingdom*	2001.01	DG ECFIN, ESI	100.48	10.37	0.96
United States*	2001.01	Institute for Supply Management, Purchasing Manager Index	52.05	5.31	0.94

This appendix presents descriptive statistics of the economic/business sentiment index (ESI) for each individual market: mean (μ), standard deviation (σ), and the first-order autocorrelation ($\rho(1)$). The monthly ESIs are obtained from various sources including national authorities, regional and international organizations, and academic and business research institutes. For Australia and Japan where business surveys are conducted at quarterly intervals, the quarterly ESIs are converted into monthly. The starting month of the ESI for each individual market depends on the data availability, but the ending month is uniformly December 2015. A total of 34 markets with available ESI data can be categorized into two groups: 17 developed markets and 17 emerging markets, based on the criteria set forth in the MSCI market classification framework. The Greek stock market is classified as the developed market before November 2013 and as the emerging market afterwards due to the recent Greek government-debt crisis.

* represents developed markets as defined under the MSCI market classification framework.

Appendix B: Descriptive statistics of cultural dimensions, market institutions, and intelligence and education

	Cultural dimensions						Market institutions				Intelligence and education					
Market	**IDV**	**UAI**	**MAS**	**PDI**	**LTO**	**IDG**	**ADR**	**GC**	**AS**	**EJS**	**IQ**	**AGL**	**FL**	**STA**	**TEG**	**EE**
Australia*	90	51	61	36	21	71	4	8.52	75	10.00	99.2	—	64	502.26	75.21	1.7
Austria*	55	70	79	11	60	63	2	8.57	54	9.50	99.0	—	53	492.22	50.45	1.7
Belgium*	75	94	54	65	82	57	0	8.82	61	9.50	99.3	—	55	502.50	—	1.4
Brazil	38	76	49	69	44	59	3	6.32	54	5.75	85.6	92.59	35	395.03	—	0.9
Bulgaria	30	85	40	70	69	16	—	—	—	—	93.3	98.39	35	439.56	—	—
Canada*	80	48	52	39	36	68	4	10.00	74	9.25	100.4	—	68	523.34	—	—
Chile	23	86	28	63	31	68	3	5.30	52	7.25	89.8	96.63	41	442.73	50.76	2.4
China	20	30	66	80	87	24	—	—	—	—	105.8	96.36	28	514.34	23.47	—
Colombia	13	80	64	67	13	83	1	5.00	50	7.25	83.1	94.58	32	410.09	—	2.2
Croatia	27	80	40	73	58	33	—	—	—	—	97.8	99.27	44	475.43	—	—
Cyprus	—	—	—	—	—	—	—	—	—	—	91.8	99.06	35	437.51	—	—
Czech	58	74	57	57	70	29	—	—	—	—	98.9	—	58	490.80	—	1.3
Denmark*	74	23	16	18	35	70	3	10.00	62	10.00	97.2	—	71	504.28	64.33	1.7
Estonia	60	60	30	40	82	16	—	—	—	—	99.7	98.82	54	524.29	—	2.0
Finland*	63	59	26	33	38	57	2	10.00	77	10.00	100.9	—	63	522.72	48.91	1.8
France*	71	86	43	68	63	48	2	9.05	69	8.00	98.1	—	52	495.74	—	1.5
Germany*	67	65	66	35	83	40	1	8.93	62	9.00	98.8	—	66	508.07	37.78	1.2
Greece*	35	100	57	60	45	50	1	7.27	55	7.00	93.2	95.29	45	458.50	—	—
Hong Kong*	25	29	57	68	61	17	4	8.52	69	10.00	105.7	—	43	532.63	—	—
Hungary	80	82	88	46	58	31	—	—	—	—	98.1	99.38	54	474.37	36.14	1.3
Indonesia	14	48	46	78	62	38	2	2.15	—	—	85.8	95.44	32	395.49	23.56	0.5
Ireland*	70	35	68	28	24	65	3	8.52	—	8.75	94.9	—	55	509.04	—	1.2
Israel*	54	81	47	13	38	—	3	8.33	64	10.00	94.6	—	68	471.73	—	1.7
Italy*	76	75	70	50	61	30	0	6.13	62	6.75	96.1	99.02	37	485.01	34.12	1.0
Japan*	46	92	95	54	88	42	3	8.52	65	10.00	104.2	—	43	528.93	71.10	1.6
Lithuania	60	65	19	42	82	16	—	—	—	—	94.3	99.81	39	475.40	52.08	1.7
Luxembourg*	60	70	50	40	64	56	—	—	—	—	95.0	—	53	483.34	21.64	0.5
Malta	59	96	47	56	47	66	—	—	—	—	95.3	—	44	463.36	—	—
Mexico	30	82	69	81	24	97	0	4.77	60	6.00	87.8	94.55	32	415.67	25.05	1.3
Netherlands*	80	53	14	38	67	68	2	10.00	64	10.00	100.4	—	66	507.93	46.06	1.7
New Zealand*	79	49	58	22	33	75	4	10.00	70	10.00	98.9	—	61	505.93	75.60	1.8
Nigeria	30	55	60	80	13	84	3	3.03	59	7.25	70.0	59.57	26	—	—	—
Norway*	69	50	8	31	35	55	3	10.00	74	10.00	97.2	—	71	504.47	46.89	1.6
Philippine	32	44	64	94	27	42	4	2.92	65	4.75	86.1	96.62	25	—	—	—
Poland	60	93	64	68	38	29	—	—	—	—	96.1	99.79	42	503.87	—	1.4
Portugal*	27	99	31	63	28	33	2	7.38	36	5.50	94.4	95.43	26	496.95	41.90	1.4
Romania	30	90	42	90	52	20	—	—	—	—	91.0	98.76	22	437.48	—	—
Russia	39	95	36	93	81	20	—	—	—	—	96.6	99.72	38	491.77	—	1.4

(*continued*)

Appendix B: (*continued*)

	Cultural dimensions						Market institutions				Intelligence and education					
Market	**IDV**	**UAI**	**MAS**	**PDI**	**LTO**	**IDG**	**ADR**	**GC**	**AS**	**EJS**	**IQ**	**AGL**	**FL**	**STA**	**TEG**	**EE**
Slovakia	52	51	100	100	77	28	—	—	—	—	98.0	—	48	462.84	42.75	1.1
Slovenia	27	88	19	71	49	48	—	—	—	—	97.6	99.71	44	509.33	56.15	1.2
South Africa	65	49	63	49	34	63	4	8.92	70	6.00	71.6	94.60	42	—	—	—
South Korea	18	85	39	60	100	29	2	5.30	62	6.00	104.6	—	33	526.64	—	2.3
Spain*	51	86	42	57	48	44	2	7.38	64	6.25	96.6	98.11	49	491.40	59.30	1.3
Sweden*	71	29	5	31	53	78	2	10.00	83	10.00	98.6	—	71	495.83	41.10	1.7
Switzerland*	68	58	70	34	74	66	1	10.00	68	10.00	100.2	—	57	506.32	49.63	1.2
Taiwan	17	69	45	58	93	49	3	6.85	65	6.75	104.6	—	37	523.92	—	—
Thailand	20	64	34	64	32	45	3	5.18	64	3.25	89.9	93.98	27	—	—	—
Turkey	37	85	45	66	46	49	2	5.18	51	4.00	89.4	95.69	24	424.76	55.80	1.7
United Kingdom*	89	35	66	35	51	69	4	9.10	78	10.00	99.1	—	67	499.89	47.71	1.8
United States*	91	46	62	40	26	68	5	8.63	71	10.00	97.5	—	57	487.60	54.17	2.6
Median value (*Med*)	55	70	50	57	51	49	3	8.52	64	8.88	97.2	96.63	44	493.98	48.31	1.6

This appendix presents the statistics of cultural dimensions, market institutions, and intelligence and education for each individual market. Cultural dimensions include individualism (IDV), the uncertainty avoidance index (UAI), masculinity (MAS), the power distance index (PDI), long-term orientation (LTO), and indulgence (IDG), collected from Hofstede et al. (2010) and the companion website at: https://www.hofstede-insights.com. Market institutions include the antidirector right (ADR), government corruption (GC), the accounting standard (AS), and efficiency of judicial system (EJS), obtained from La Porta et al. (1998). Intelligence and education include intelligence quotient (IQ), adult general literacy (AGL), financial literacy (FL), the student test average (STA), tertiary education graduation (TEG), and educational expenditure (EE). We compile data of intelligence and education from various sources—IQ from Lynn and Vanhanen (2012), AGL from the World Bank (2015), FL from the Standard & Poor's Ratings Services Global Financial Literacy Survey (S&P Global FinLit Survey, 2014), STA from the Program for International Student Assessment (PISA, 2015), and TEG and EE from the latest Organization for Economic Co-operation and Development (OECD) reports (2014 and 2013, respectively). We also report the median split value (*Med*) for each factor.

* represents developed markets as defined under the MSCI market classification framework.

Appendix C: Pairwise correlations

Panel A: Cultural dimensions

	IDV	UAI	MAS	PDI	LTO	IDG
IDV						
UAI	–0.312					
	(0.029)[b]					
MAS	0.085	0.027				
	(0.560)	(0.857)				
PDI	–0.651	0.328	0.149			
	(0.000)[a]	(0.022)[b]	(0.308)			
LTO	–0.073	0.141	0.050	0.100		
	(0.616)	(0.335)	(0.731)	(0.494)		
IDG	0.277	–0.237	0.010	–0.376	–0.601	
	(0.056)[c]	(0.105)	(0.947)	(0.008)[a]	(0.000)[a]	

Panel B: Market institutions

	ADR	GC	AS	EJS
ADR				
GC	0.150			
	(0.388)			
AS	0.375	0.552		
	(0.031)[b]	(0.001)[a]		
EJS	0.164	0.781	0.571	
	(0.354)	(0.000)[a]	(0.001)[a]	

Panel C: Intelligence and education

	IQ	AGL	FL	STA	TEG	EE
IQ						
AGL	0.671					
	(0.000)[a]					
FL	0.447	0.342				
	(0.001)[a]	(0.094)[c]				
STA	0.914	0.631	0.502			
	(0.000)[a]	(0.002)[a]	(0.000)[a]			
TEG	0.292	0.433	0.332	0.407		
	(0.148)	(0.184)	(0.098)[c]	(0.039)[b]		
EE	0.195	0.071	0.137	0.221	0.578	
	(0.254)	(0.801)	(0.427)	(0.194)	(0.003)[a]	

This table presents the pairwise correlations of each pair in cultural dimensions, market institutions, and intelligence and education along with the according *p*-values. Cultural dimensions include individualism (IDV), the uncertainty avoidance index (UAI), masculinity (MAS), the power distance index (PDI), long-term orientation (LTO), and indulgence (IDG), collected from Hofstede et al. (2010) and the companion website at: https://www.hofstede-insights.com. Market institutions include the antidirector right (ADR), government corruption (GC), the accounting standard (AS), and efficiency of judicial system (EJS), obtained from La Porta et al. (1998). Intelligence and education include intelligence quotient (IQ), adult general literacy (AGL), financial literacy (FL), the student test average (STA), tertiary education graduation (TEG), and educational expenditure (EE). We compile data of intelligence and education from various sources—IQ from Lynn and Vanhanen (2012), AGL from the World Bank (2015), FL from the Standard & Poor's Ratings Services Global Financial Literacy Survey (S&P Global FinLit Survey, 2014), STA from the Program for International Student Assessment (PISA, 2015), and TEG and EE from the latest Organization for Economic Co-operation and Development (OECD) reports (2014 and 2013, respectively). [a], [b], and [c] represent statistical significance at the 1%, 5%, and 10% level, respectively.

Appendix D. A discussion on market participation

We provide some additional insights into the role of MP and IQ in the impact of investor sentiment in this appendix.

We source individual MP from Lu et al. (2020) due to the larger coverage of our global sample. We regress the market-level 12-month estimated sentiment-return relationship, obtained from Eq. (5),[45] on standardized IQ, standardized MP, along with their interaction term. We report results in Table D.1 and Figure D.1. Panel A.1 of Figure D.1, with IQ as the dependent variable, reveals that high (low) IQ leads to an insignificantly stronger (weaker) sentiment impact for high MP markets (slope = –0.385, *p*-value = 0.148)[46], but a significantly weaker (stronger) impact for low MP markets (slope = 0.352, *p*-value = 0.011), thus implying that the influence of the IQ on the impact of investor sentiment is in part moderated by MP. Likewise, Panel A.2 shows the influence of MP on the sentiment impact is partially moderated by IQ, with high (low) MP associated with a significantly weaker (stronger) sentiment impact for low IQ markets (slope = 0.487, *p*-value = 0.036), but an insignificantly stronger (weaker) impact for high IQ markets (slope = –0.250, *p*-value = 0.133). The 3D graph in Panel A.3 maps out the relationship between IQ and MP and how they combine to influence the sentiment-return relationship. These findings, based on the use of continuous IQ and MP variables, are supported by results using dichotomous splits of IQ and MP (i.e., high/low, based on the median), as depicted in Panel B of Figure 1.

We investigate the relationship further by examining partial differential equations (PDEs) based on estimated results, as follows,

$$\frac{\partial}{\partial IQ}(-0.633545 - 0.016347IQ + 0.118163MP - 0.368491IQ \times MP) = -0.016347 - 0.368491MP, \qquad (7)$$

[45] While Eq. (5) is a system with eight equations and is jointly estimated, we can store the 12-month estimate for investor sentiment from line 6 of Eq. (5).

[46] The significance of the slope is obtained as suggested in Holmbeck (2002).

$$\frac{\partial}{\partial MP}(-0.633545 - 0.016347IQ + 0.118163MP - 0.368491IQ \times MP) = 0.118163 - 0.368491IQ. \quad (8)$$

Solving the two equations, we have MP = –0.04 and IQ = 0.32, indicating that high IQ would reduce (intensify) the negative impact of investor sentiment when MP is lower (greater) than –0.04 (equivalent to the actual value of 15.06 in our dataset), and high MP would reduce (intensify) the negative impact when IQ is lower (greater) than 0.32 (equivalent to the actual value of 98.50 in our dataset). We present interpretation and implications for the four combinations of PDE with IQ and MP in Table D.2.

Overall, the results above suggest that MP could be a potential confounding factor that plays a role in the influence of IQ on the impact of investor sentiment.

Table D.1: Regression results

	Constant	**IQ**	**MP**	**IQ × MP**
Coefficients	–0.633545 (0.000)[a]	–0.016347 (0.017)[b]	0.118163 (0.001)[a]	–0.368491 (0.046)[b]

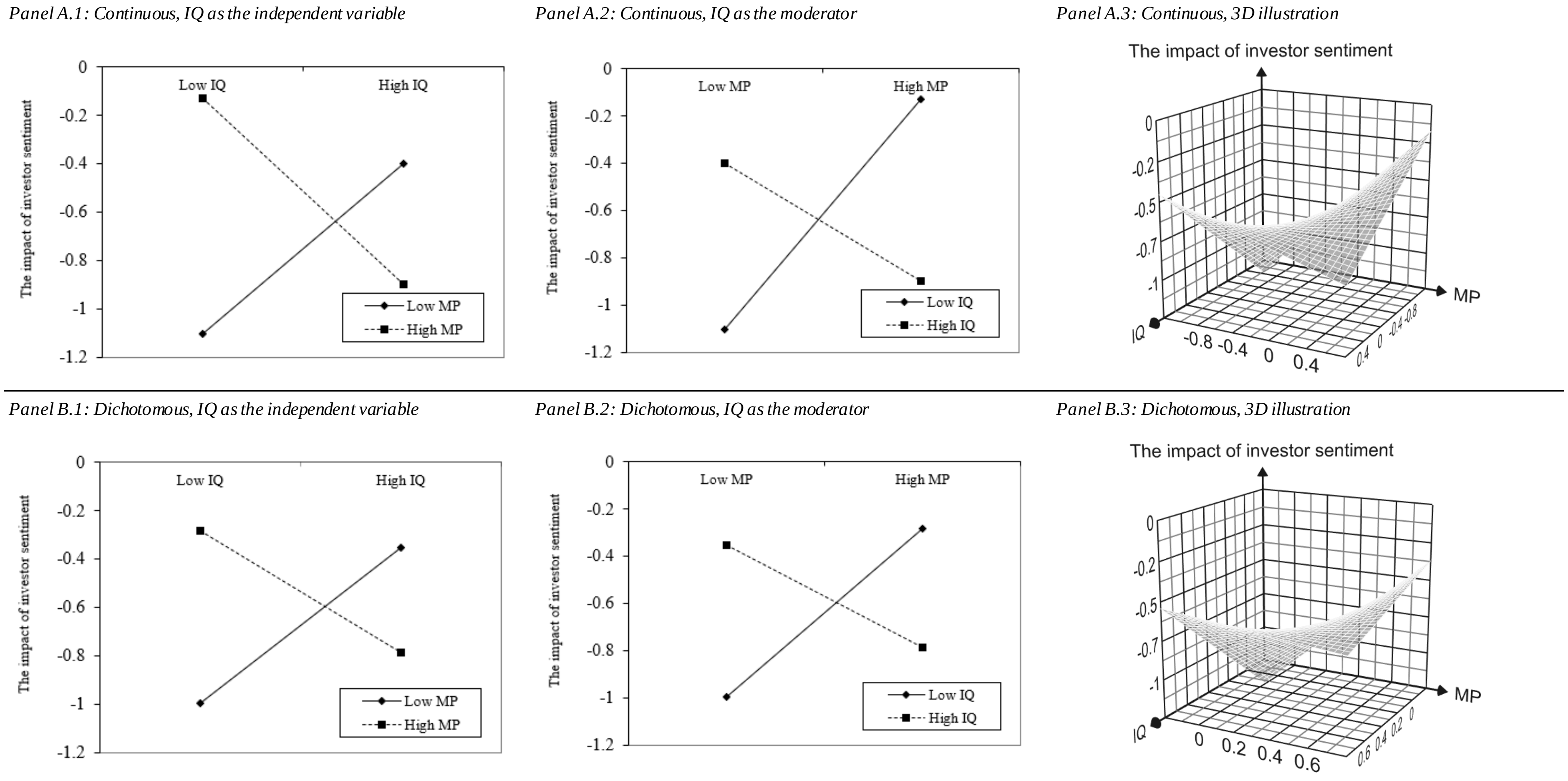
This table presents the results from regressing the market-level 12-month estimated sentiment-return relationship, obtained from Eq. (5), on standardized IQ, standardized MP, along with their interaction term.
[a] and [b] represent statistical significance at the 1% and 5% level, respectively.

Table D.2: PDE analysis

	PDE	**Solutions**	**Interpretation**	**Implication**
Eq. (7)	PDE < 0	MP > –0.04	IQ and the sentiment impact are negatively related	Higher (Lower) IQ causes a stronger (weaker) sentiment impact
	PDE > 0	MP < –0.04	IQ and the sentiment impact are positively related	Higher (Lower) IQ causes a weaker (stronger) sentiment impact
Eq. (8)	PDE < 0	IQ > 0.32	MP and the sentiment impact are negatively related	Higher (Lower) MP causes a stronger (weaker) sentiment impact
	PDE > 0	IQ < 0.32	MP and the sentiment impact are positively related	Higher (Lower) MP causes a weaker (stronger) sentiment impact

This table presents PDE analysis based on Eq. (7) and (8).

Figure D.1: The interaction effects of IQ and MP on the impact of investor sentiment



This figure presents the interaction effects of IQ and MP on the impact of investor sentiment. In particular, we report results from continuous and dichotomous IQ and MP, along with 3D illustrations. IQ and MP are sourced from Lynn and Vanhanen (2012) and Lu et al. (2020), respectively.

Table 1: Descriptive statistics of the CCIs

Markets	Starting month	Sources	μ	σ	$\rho(1)$
Australia*	1980.02	ANZ/Roy Morgan Research	108.91	13.24	0.93
Austria*	1997.02	Oesterreichische Nationalbank (Austrian Nationalbank)	−1.48	8.04	0.94
Belgium*	1996.02	National Bank of Belgium	−5.99	8.40	0.91
Brazil	2003.02	Federation of Goods, Services and Tourism of the State of Sao Paulo	134.65	20.75	0.97
Bulgaria	2001.05	Directorate-General for Economic and Financial Affairs (DG ECFIN)	−33.86	7.29	0.91
Canada*	1998.02	Organization for Economic Co-operation and Development (OECD)	100.14	1.00	0.98
Chile	2005.05	University del Desarrollo (UDD)	119.01	16.26	0.83
China	2002.11	National Bureau of Statistics of China	106.50	4.34	0.88
Colombia	2003.11	Foundation for Higher Education and Development, Colombia	19.23	9.84	0.85
Croatia	2005.05	DG ECFIN	−32.28	10.08	0.95
Cyprus	2004.07	DG ECFIN	−36.30	10.11	0.90
Czech Republic	2005.03	Czech Statistical Office	92.31	10.77	0.96
Denmark*	2001.02	DG ECFIN	10.41	6.03	0.90
Estonia	2011.02	Estonian Institute of Economic Research	−6.23	4.26	0.82
Finland*	1995.11	DG ECFIN	12.88	5.79	0.92
France*	1985.01	DG ECFIN	−19.03	8.31	0.92
Germany*	1992.01	DG ECFIN	−8.44	9.75	0.97
Greece*	2004.03	DG ECFIN	−50.18	17.99	0.97
Hong Kong*	2006.01	Chinese University of Hong Kong	86.85	17.06	0.88
Hungary	2001.02	GKI Economic Research Co., Hungry	−39.74	15.26	0.96
Indonesia	2005.06	Bank Indonesia	104.56	10.79	0.94
Ireland*	1998.03	DG ECFIN	−12.35	19.46	0.97
Israel*	2011.03	Central Bureau of Statistics, Israel	−23.54	5.49	0.74
Italy*	1997.02	Italian National Institute of Statistics	100.50	8.24	0.96
Japan*	1982.06	Cabinet Office, Government of Japan	42.66	4.88	0.97
Lithuania	2006.01	Statistics Lithuania	−16.96	15.83	0.98
Luxembourg*	2006.02	DG ECFIN	−2.54	6.85	0.91
Malta	2002.11	DG ECFIN	−21.92	13.48	0.97
Mexico	2005.08	National Institute of Statistics and Geography, Mexico	94.04	8.52	0.97
Netherlands*	2003.03	DG ECFIN	−3.89	12.07	0.94
New Zealand*	2009.09	ANZ/Roy Morgan Research	112.20	11.11	0.90
Nigeria	2011.01	Central Bank of Nigeria	−4.80	5.17	0.56
Norway*	1992.08	TNS Gallup	18.53	13.24	0.94
Philippine	2007.02	Bangko Sentral ng Pilipinas	−22.58	11.10	0.92
Poland	2006.02	DG ECFIN	−18.67	8.39	0.93
Portugal*	2001.02	DG ECFIN	−32.65	12.52	0.97
Romania	2006.02	DG ECFIN	−31.48	13.62	0.97
Russia	2004.02	Federal State Statistics Service, Russia	−11.20	8.16	0.78
Slovakia	2006.05	Statistical Office of the Slovak Republic	−18.90	11.99	0.94
Slovenia	2003.10	DG ECFIN	−21.64	8.87	0.87
South Africa	2001.03	OECD	100.40	1.35	0.98
South Korea	1999.08	Bank of Korea	99.99	1.30	0.97
Spain*	1996.02	Ministry of Economy and Finance, Spain	−12.48	11.47	0.97
Sweden*	2001.02	National Institute of Economic Research, Sweden	99.96	8.52	0.93
Switzerland*	2005.05	Swiss State Secretariat for Economic Affairs	−5.67	14.44	0.95
Taiwan	2009.12	Research Centre for Taiwan Economic Development	80.87	5.82	0.94
Thailand	2001.02	University of the Thai Chamber of Commerce	74.60	11.01	0.98
Turkey	2010.06	Turkish Statistical Institute	74.23	5.24	0.84
United Kingdom*	1989.02	DG ECFIN	−8.95	8.96	0.95
United States*	1973.04	University of Michigan	77.53	13.52	0.94

This table presents descriptive statistics of the consumer confidence index (CCI): mean (μ), standard deviation (σ), and the first-order autocorrelation ($\rho(1)$), for each individual market. The monthly CCIs are obtained from various sources, e.g., national authorities, regional and international organizations, and academic and business research institutes. For some markets, including Hong Kong, Nigeria, Norway, Russia, Switzerland, and Philippine, where consumer confidence surveys are conducted at quarterly intervals, the quarterly CCIs are converted into monthly. The sample periods vary for all sample markets as the starting month depends on the data availability, but the ending month is uniformly December 2015. A total of 50 markets in our sample are categorized into two groups: 24 developed markets and 26 emerging markets, based on the criteria set forth in the Morgan Stanley Capital International (MSCI) market classification framework. The Greek stock market is classified as the developed market before November 2013 and as the emerging market afterwards due to the recent Greek government-debt crisis.

* represents developed markets as defined under the MSCI market classification framework.

Table 2: Panel unit root tests

	All sample markets		Developed markets		Emerging markets	
Panel unit root and stationarity tests	**Test statistic**	***p*-value**	**Test statistic**	***p*-value**	**Test statistic**	***p*-value**
ADF–Fisher χ^2	205.61	(0.000)[a]	141.20	(0.000)[a]	102.49	(0.000)[a]
Im–Pesaran–Shin W	−6.22	(0.000)[a]	−6.89	(0.000)[a]	−4.04	(0.000)[a]
Levin–Lin–Chu t	−2.93	(0.002)[a]	−3.87	(0.000)[a]	−2.14	(0.016)[b]

This table presents the results of panel unit root tests for the monthly investor sentiment across all sample markets. Three panel unit root and stationarity tests, i.e., Augmented Dickey Fuller (ADF)–Fisher test, Levin–Lin–Chu test, and Im–Pesaran–Shin test, are employed to examine whether the CCIs are unit root non-stationary. ADF–Fisher test and Im–Pesaran–Shin test employ the null hypothesis of a unit root and assume the autocorrelation across cross-sections to be heterogeneous, while Levin–Lin–Chu test employs the null hypothesis of a unit root and assume the autocorrelation across cross-sections to be homogeneous (Choi, 2001; Levin et al., 2002; Im et al., 2003). The Schwarz information criterion (SIC) is chosen in determining the lag length and individual intercepts are included in the test.

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

Table 3: Panel Granger causality tests

Panel Granger causality tests		All sample markets χ^2	All sample markets *p*-value	Developed markets χ^2	Developed markets *p*-value	Emerging markets χ^2	Emerging markets *p*-value
Simple bivariate test	$cci_t \rightarrow r_t$	61.58	(0.000)[a]	24.13	(0.000)[a]	63.01	(0.000)[a]
	$r_t \rightarrow cci_t$	112.35	(0.000)[a]	286.83	(0.000)[a]	80.86	(0.000)[a]
Block exogeneity test	$cci_t \rightarrow r_t$	60.72	(0.000)[a]	61.71	(0.000)[a]	17.78	(0.000)[a]
	$r_t \rightarrow cci_t$	40.39	(0.000)[a]	173.52	(0.000)[a]	39.80	(0.000)[a]

This table presents the results of two panel Granger causality tests: the simple bivariate test and the block exogeneity test, to examine the interdependency between investor sentiment and stock returns, across all sample markets and across developed and emerging markets, separately. Although both tests employ the null hypothesis of no Granger causation, the former is to simply test the Granger causality between stock returns and investor sentiment, while the latter is based on the vector autoregression (VAR) specification and includes six macroeconomic variables as defined in Eq. (2).

[a] represents statistical significance at the 1% level.

Table 4: Panel regression results at various forecast horizons

	All sample markets				Developed markets				Emerging markets			
Months	***cci_t***	***p*-value**	***adj. R^2***	***Δadj. R^2***	***cci_t***	***p*-value**	***adj. R^2***	***Δadj. R^2***	***cci_t***	***p*-value**	***adj. R^2***	***Δadj. R^2***
1	−0.37	(0.157)	0.06	0.00	−0.22	(0.113)	0.09	0.00	−0.68	(0.022)[b]	0.05	0.01
2	−0.55	(0.023)[b]	0.12	0.01	−0.50	(0.007)[a]	0.17	0.01	−0.66	(0.011)[b]	0.10	0.01
3	−0.62	(0.006)[a]	0.17	0.02	−0.60	(0.000)[a]	0.24	0.02	−0.66	(0.012)[b]	0.14	0.02
6	−0.67	(0.001)[a]	0.27	0.04	−0.69	(0.000)[a]	0.40	0.06	−0.65	(0.008)[a]	0.21	0.02
9	−0.57	(0.001)[a]	0.33	0.05	−0.58	(0.000)[a]	0.48	0.08	−0.50	(0.026)[b]	0.27	0.03
12	−0.44	(0.006)[a]	0.37	0.04	−0.47	(0.000)[a]	0.53	0.09	−0.39	(0.061)[c]	0.31	0.01
24	−0.21	(0.283)	0.31	0.04	−0.27	(0.000)[a]	0.48	0.11	−0.19	(0.489)	0.28	0.01
36	−0.17	(0.312)	0.20	0.02	−0.25	(0.000)[a]	0.44	0.10	−0.11	(0.620)	0.19	0.00

	The US market				18 industrialized countries				G7 industrialized countries			
Months	***cci_t***	***p*-value**	***adj. R^2***	***Δadj. R^2***	***cci_t***	***p*-value**	***adj. R^2***	***Δadj. R^2***	***cci_t***	***p*-value**	***adj. R^2***	***Δadj. R^2***
1	−0.71	(0.025)[b]	0.03	0.01	−0.38	(0.089)[c]	0.10	0.01	−0.41	(0.039)[b]	0.04	0.00
2	−0.77	(0.000)[a]	0.07	0.02	−0.60	(0.012)[b]	0.18	0.02	−0.61	(0.011)[b]	0.10	0.02
3	−0.78	(0.000)[a]	0.11	0.05	−0.73	(0.000)[a]	0.25	0.03	−0.80	(0.009)[a]	0.17	0.05
6	−0.66	(0.000)[a]	0.21	0.07	−0.74	(0.000)[a]	0.40	0.07	−0.86	(0.000)[a]	0.33	0.13
9	−0.52	(0.000)[a]	0.29	0.07	−0.61	(0.000)[a]	0.48	0.09	−0.70	(0.000)[a]	0.43	0.17
12	−0.42	(0.005)[a]	0.36	0.07	−0.50	(0.000)[a]	0.52	0.10	−0.53	(0.000)[a]	0.50	0.13
24	−0.14	(0.000)[a]	0.35	0.05	−0.36	(0.000)[a]	0.49	0.13	−0.35	(0.000)[a]	0.54	0.13
36	−0.25	(0.019)[b]	0.33	0.00	−0.34	(0.000)[a]	0.45	0.12	−0.28	(0.000)[a]	0.55	0.12

Table 4 presents the panel regression results across all sample markets and across developed and emerging market, separately. Also, this table presents regression results from the US stock market, the 18 industrialized countries, and the G7 countries, separately, to compare with previous related studies. The predictive model includes the CCI and a matrix of six macroeconomic variables to explain the average monthly return for market i over T months (T = 1, 2, 3, 6, 9, 12, 24, and 36) after the release of the CCI at month t. The set of macroeconomic factors includes (i) the inflation rate computed from the consumer price index (*cpi*), (ii) the industrial production growth (*ip*), (iii) the dividend yield (*dy*), (iv) the unemployment rate growth (*unem*), (v) the gross domestic production growth (*gdp*), and (vi) the detrended short-term interest rate (*ir*). The CCIs and the six macroeconomic variables are standardized with zero expectation and unit variance. We construct the quasi-weakly-balanced dataset starting from January 2001 to December 2015. The fixed-effect specification allows each individual market to have different regression constants when all markets enter the regressions jointly. The moving-block bootstrap simulation procedure is employed to address the potential issue of a highly persistent time-series process. Specifically, we initially estimate the panel regression and save all coefficients. We then repeatedly bootstrap the raw data in blocks with a block length of 15 to generate 10,000 new time series under the null of no predictability for all dependent and explanatory variables, though different block lengths do not seem to alter our results. We finally generate the bootstrap distribution of coefficient estimates by estimating the predicative model on the 10,000 artificial time series. $\Delta adj.\ R^2$ represents the incremental adjusted R^2 when the CCI is included as an additional regressor in the predictive model.

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

Table 5: Robustness test results

	All sample markets		Developed markets		Emerging markets	
Months	cci_t	***p*-value**	cci_t	***p*-value**	cci_t	***p*-value**
Panel A: Two subperiods						
A.1 The first subperiod January 2001 to June 2008						
1	–0.59	(0.123)	–0.52	(0.131)	–0.90	(0.012)[b]
2	–0.68	(0.044)[b]	–0.64	(0.053)[c]	–0.94	(0.002)[a]
3	–0.77	(0.013)[b]	–0.69	(0.000)[a]	–0.92	(0.003)[a]
6	–0.66	(0.019)[b]	–0.60	(0.023)[b]	–0.92	(0.005)[a]
9	–0.47	(0.067)[c]	–0.51	(0.013)[b]	–0.69	(0.015)[b]
12	–0.36	(0.058)[c]	–0.30	(0.012)[b]	–0.71	(0.025)[b]
24	–0.23	(0.143)	–0.20	(0.032)[b]	–0.38	(0.187)
36	–0.06	(0.281)	–0.05	(0.379)	–0.22	(0.417)
A.2 The second subperiod July 2008 to December 2015						
1	–0.70	(0.049)[b]	–0.26	(0.295)	–1.46	(0.006)[a]
2	–0.93	(0.009)[a]	–0.61	(0.002)[a]	–1.31	(0.005)[a]
3	–0.94	(0.002)[a]	–0.72	(0.000)[a]	–1.26	(0.001)[a]
6	–0.93	(0.000)[a]	–0.73	(0.000)[a]	–1.15	(0.000)[a]
9	–0.76	(0.000)[a]	–0.71	(0.000)[a]	–0.82	(0.000)[a]
12	–0.64	(0.000)[a]	–0.60	(0.000)[a]	–0.68	(0.000)[a]
24	–0.40	(0.001)[a]	–0.21	(0.055)[c]	–0.62	(0.000)[a]
36	–0.24	(0.001)[a]	–0.16	(0.030)[b]	–0.42	(0.000)[a]
Panel B: The extraction of the ESI from the CCI						
1	–0.27	(0.069)[c]	–0.24	(0.113)	–0.43	(0.074)[c]
2	–0.31	(0.007)[a]	–0.29	(0.010)[b]	–0.36	(0.048)[b]
3	–0.29	(0.001)[a]	–0.32	(0.000)[a]	–0.25	(0.089)[c]
6	–0.26	(0.000)[a]	–0.33	(0.000)[a]	–0.19	(0.052)[c]
9	–0.22	(0.000)[a]	–0.36	(0.000)[a]	–0.11	(0.404)
12	–0.31	(0.000)[a]	–0.41	(0.000)[a]	–0.05	(0.611)
24	–0.06	(0.606)	–0.23	(0.000)[a]	0.03	(0.228)
36	–0.01	(0.985)	–0.19	(0.000)[a]	0.06	(0.148)
Panel C: The use of the single-period monthly returns to replace average monthly returns as the dependent variable						
1	−0.37	(0.157)	−0.22	(0.113)	−0.68	(0.022)[b]
2	−0.64	(0.016)[b]	−0.64	(0.001)[a]	−0.66	(0.011)[b]
3	−0.67	(0.004)[a]	−0.71	(0.000)[a]	−0.59	(0.029)[a]
6	−0.49	(0.005)[a]	−0.51	(0.002)[a]	−0.42	(0.062)[c]
9	−0.21	(0.244)	−0.21	(0.044)[b]	−0.31	(0.139)
12	−0.20	(0.285)	−0.20	(0.045)[b]	−0.17	(0.383)
24	0.12	(0.581)	0.14	(0.316)	0.09	(0.525)
36	0.02	(0.879)	−0.01	(0.939)	0.05	(0.744)

This table presents the panel regression results across all sample markets and across developed and emerging market, separately, by undertaking three alternative tests: (i) the separation of the entire sample into two equivalent subperiods (in Panel A); (ii) the extraction of the economic sentiment index (ESI) from the CCI (in Panel B); and (iii) the use of single-period monthly returns to replace average monthly returns as the dependent variable (in Panel C). For the results presented in Panels A and B, the predictive model includes the CCI, but for the results presented in Panel C, the predictive model includes the orthogonalized CCI that is obtained by restoring the residuals after regressing the CCIs on the ESIs. Also, the predictive model includes a matrix of six macroeconomic variables to explain the monthly return for market i over T months (T = 1, 2, 3, 6, 9, 12, 24, and 36) after the release of the CCI at month t. The set of macroeconomic factors includes (i) the inflation rate computed from the consumer price index (*cpi*), (ii) the industrial production growth (*ip*), (iii) the dividend yield (*dy*), (iv) the unemployment rate growth (*unem*), (v) the gross domestic production growth (*gdp*), and (vi) the detrended short-term interest rate (*ir*). We construct the quasi-weakly-balanced dataset over various sample periods. The fixed-effect specification allows each individual market to have different regression constants when all markets enter the regressions jointly. The moving-block bootstrap simulation procedure is employed to address the potential issue of a highly persistent time-series process. Specifically, we initially estimate the panel regression and save all coefficients. We then repeatedly bootstrap the raw data in blocks with a block length of 15 to generate 10,000 new time series under the null of no predictability for all dependent and explanatory variables, though different block lengths do not seem to alter our results. We finally generate the bootstrap distribution of coefficient estimates by estimating the predicative model on the 10,000 artificial time series.

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

Table 6: Cross-sectional impact of investor sentiment

Months	1	2	3	6	9	12	24	36
Panel A: All sample markets								
Small	−0.24	−0.59	−0.76	−0.93	−0.85	−0.70	−0.48	−0.40
	(0.402)	(0.046)[b]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.001)[a]	(0.000)[a]
Large	−0.65	−0.78	−0.87	−0.92	−0.74	−0.56	−0.39	−0.35
	(0.348)	(0.127)	(0.076)[c]	(0.055)[c]	(0.048)[b]	(0.056)[c]	(0.083)[c]	(0.088)[c]
S – L	0.40	0.16	0.08	−0.05	−0.14	−0.16	−0.12	−0.07
	(0.597)	(0.762)	(0.868)	(0.931)	(0.720)	(0.615)	(0.611)	(0.678)
Growth	−0.23	−0.46	−0.58	−0.65	−0.55	−0.42	−0.25	−0.21
	(0.375)	(0.077)[c]	(0.016)[b]	(0.001)[a]	(0.000)[a]	(0.001)[a]	(0.023)[b]	(0.102)
Value	−0.23	−0.51	−0.63	−0.74	−0.65	−0.52	−0.29	−0.25
	(0.367)	(0.036)[b]	(0.005)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.002)[a]	(0.009)[a]
V – G	0.00	−0.05	−0.05	−0.09	−0.11	−0.10	−0.04	−0.04
	(0.983)	(0.712)	(0.675)	(0.429)	(0.297)	(0.260)	(0.601)	(0.542)
Panel B: Developed markets								
Small	0.04	−0.40	−0.62	−0.81	−0.76	−0.62	−0.41	−0.40
	(0.869)	(0.059)[c]	(0.001)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]
Large	−0.30	−0.54	−0.65	−0.68	−0.56	−0.45	−0.33	−0.32
	(0.304)	(0.021)[b]	(0.001)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]
S – L	0.34	0.13	0.01	−0.20	−0.26	−0.22	−0.10	−0.11
	(0.122)	(0.453)	(0.955)	(0.096)[c]	(0.002)[a]	(0.002)[a]	(0.214)	(0.075)[c]
Growth	−0.15	−0.40	−0.54	−0.57	−0.49	−0.39	−0.26	−0.27
	(0.577)	(0.099)[c]	(0.008)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.002)[a]	(0.000)[a]
Value	−0.18	−0.50	−0.65	−0.75	−0.67	−0.53	−0.29	−0.28
	(0.409)	(0.012)[b]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.004)[a]	(0.000)[a]
V – G	−0.04	−0.10	−0.11	−0.18	−0.18	−0.14	−0.02	−0.02
	(0.668)	(0.411)	(0.318)	(0.056)[c]	(0.060)[c]	(0.091)[c]	(0.753)	(0.741)
Panel C: Emerging markets								
Small	−0.66	−0.90	−1.00	−1.14	−0.98	−0.83	−0.71	−0.41
	(0.020)[b]	(0.007)[a]	(0.005)[a]	(0.001)[a]	(0.001)[a]	(0.003)[a]	(0.005)[a]	(0.004)[a]
Large	−0.71	−0.66	−0.69	−0.68	−0.53	−0.35	−0.19	−0.05
	(0.245)	(0.066)[c]	(0.021)[b]	(0.004)[a]	(0.013)[b]	(0.047)[b]	(0.101)	(0.693)
S – L	0.05	−0.24	−0.32	−0.45	−0.46	−0.48	−0.51	−0.36
	(0.933)	(0.297)	(0.310)	(0.108)	(0.083)[c]	(0.067)[c]	(0.008)[a]	(0.000)[a]
Growth	−0.38	−0.54	−0.63	−0.70	−0.57	−0.42	−0.24	−0.06
	(0.112)	(0.023)[b]	(0.009)[a]	(0.001)[a]	(0.002)[a]	(0.005)[a]	(0.104)	(0.699)
Value	−0.37	−0.57	−0.66	−0.72	−0.61	−0.48	−0.39	−0.25
	(0.081)[c]	(0.008)[a]	(0.002)[a]	(0.000)[a]	(0.001)[a]	(0.005)[a]	(0.000)[a]	(0.030)[b]
V – G	0.01	−0.03	−0.03	−0.02	−0.04	−0.06	−0.15	−0.19
	(0.954)	(0.733)	(0.764)	(0.837)	(0.711)	(0.593)	(0.203)	(0.012)[b]

This table presents the panel regression results across all, developed, and emerging markets in Panel A, B, and C, separately. The dependent variables are returns for small, large, growth, and value stocks. In addition, the long-short portfolios are constructed by using size premium (small minus large stocks, S – L) and value premium (value minus growth stocks, V – G). The predictive model includes the CCI and a matrix of six macroeconomic variables to explain the average monthly return for market i over T months (T = 1, 2, 3, 6, 9, 12, 24, and 36) after the release of the CCI at month t. The set of macroeconomic factors includes (i) the inflation rate computed from the consumer price index (*cpi*), (ii) the industrial production growth (*ip*), (iii) the dividend yield (*dy*), (iv) the unemployment rate growth (*unem*), (v) the gross domestic production growth (*gdp*), and (vi) the detrended short-term interest rate (*ir*). The CCIs and the six macroeconomic variables are standardized with zero expectation and unit variance. We construct the quasi-weakly-balanced dataset starting from January 2001 to December 2015. The fixed-effect specification allows each individual market to have different regression constants when all markets enter the regressions jointly. The moving-block bootstrap simulation procedure is employed to address the potential issue of a highly persistent time-series process. Specifically, we initially estimate the panel regression and save all coefficients. We then repeatedly bootstrap the raw data in blocks with a block length of 15 to generate 10,000 new time series under the null of no predictability for all dependent and explanatory variables, though different block lengths do not seem to alter our results. We finally generate the bootstrap distribution of coefficient estimates by estimating the predicative model on the 10,000 artificial time series.

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

Table 7: Condition-varying impact of investor sentiment

Months	**1**	**2**	**3**	**6**	**9**	**12**	**24**	**36**
Panel A.1: High/low sentiment, all sample markets								
High	–0.66	–0.95	–1.01	–0.98	–0.77	–0.56	–0.24	–0.20
	(0.104)	(0.041)[b]	(0.011)[b]	(0.001)[a]	(0.000)[a]	(0.011)[c]	(0.332)	(0.407)
Low	–0.06	–0.12	–0.23	–0.30	–0.28	–0.29	–0.19	–0.16
	(0.873)	(0.736)	(0.622)	(0.502)	(0.402)	(0.285)	(0.341)	(0.445)
H – L	–0.59	–0.83	–0.78	–0.69	–0.49	–0.28	–0.05	–0.04
	(0.384)	(0.213)	(0.163)	(0.136)	(0.168)	(0.413)	(0.795)	(0.485)
Panel A.2: High/low sentiment, developed markets								
High	–0.43	–0.87	–1.00	–0.95	–0.78	–0.58	–0.32	–0.31
	(0.098)[c]	(0.027)[b]	(0.002)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.017)[b]
Low	0.01	–0.08	–0.22	–0.34	–0.30	–0.29	–0.20	–0.17
	(0.972)	(0.792)	(0.430)	(0.111)	(0.154)	(0.162)	(0.218)	(0.203)
H – L	–0.44	–0.78	–0.78	–0.61	–0.47	–0.28	–0.13	–0.14
	(0.518)	(0.181)	(0.123)	(0.036)[b]	(0.063)[c]	(0.274)	(0.543)	(0.502)
Panel A.3: High/low sentiment, emerging markets								
High	–1.00	–1.03	–1.03	–1.02	–0.68	–0.41	–0.19	0.00
	(0.097)[c]	(0.049)[a]	(0.029)[b]	(0.011)[b]	(0.037)[b]	(0.058)[c]	(0.495)	(0.973)
Low	–0.35	–0.29	–0.25	–0.25	–0.25	–0.37	–0.19	–0.14
	(0.429)	(0.464)	(0.515)	(0.436)	(0.261)	(0.302)	(0.557)	(0.641)
H – L	–0.65	–0.74	–0.77	–0.77	–0.43	–0.04	0.00	0.14
	(0.453)	(0.333)	(0.256)	(0.163)	(0.235)	(0.919)	(0.995)	(0.300)
Panel B.1: Bull/bear regime, all sample markets								
High	–0.73	–0.99	–1.08	–1.10	–0.85	–0.59	–0.25	–0.19
	(0.081)[c]	(0.009)[a]	(0.002)[a]	(0.000)[a]	(0.000)[a]	(0.001)[a]	(0.326)	(0.257)
Low	–0.09	–0.20	–0.27	–0.28	–0.26	–0.27	–0.17	–0.16
	(0.722)	(0.383)	(0.244)	(0.235)	(0.240)	(0.198)	(0.398)	(0.486)
H – L	–0.63	–0.79	–0.81	–0.83	–0.59	–0.33	–0.08	–0.03
	(0.092)[c]	(0.021)[b]	(0.013)[b]	(0.003)[a]	(0.006)[a]	(0.091)[c]	(0.663)	(0.872)
Panel B.2: Bull/bear regime, developed markets								
High	–0.30	–0.86	–1.12	–1.14	–0.92	–0.60	–0.30	–0.29
	(0.109)	(0.031)[b]	(0.002)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.003)[a]	(0.000)[a]
Low	–0.07	–0.22	–0.36	–0.37	–0.31	–0.29	–0.22	–0.21
	(0.299)	(0.064)[c]	(0.007)[a]	(0.005)[a]	(0.012)[b]	(0.015)[b]	(0.007)[a]	(0.004)[a]
H – L	–0.22	–0.53	–0.75	–0.78	–0.62	–0.31	–0.07	–0.08
	(0.588)	(0.097)[c]	(0.044)[b]	(0.002)[a]	(0.001)[a]	(0.045)[b]	(0.510)	(0.304)
Panel B.3: Bull/bear regime, emerging markets								
High	–1.04	–1.01	–1.01	–0.97	–0.63	–0.46	–0.21	–0.17
	(0.005)[a]	(0.002)[a]	(0.001)[a]	(0.000)	(0.002)[a]	(0.027)[b]	(0.471)	(0.557)
Low	–0.22	–0.17	–0.19	–0.18	–0.18	–0.26	–0.17	0.02
	(0.268)	(0.434)	(0.319)	(0.334)	(0.295)	(0.199)	(0.453)	(0.794)
H – L	–0.83	–0.75	–0.81	–0.79	–0.45	–0.20	–0.05	–0.18
	(0.017)[b]	(0.022)[b]	(0.016)[b]	(0.009)[a]	(0.045)[b]	(0.186)	(0.793)	(0.207)

(*continued*)

Table 7: (*continued*)

This table presents the panel regression results of the condition-varying impact of investor sentiment on all, developed, and emerging markets. The entire sample for each market is classified into high-/low-sentiment periods (Panel A), or bull/bear regimes (Panel B). In addition, a Wald test is applied across two periods (H – L). The predictive model includes the CCI and a matrix of six macroeconomic variables to explain the average monthly return for market i over T months (T = 1, 2, 3, 6, 9, 12, 24, and 36) after the release of the CCI at month t. The set of macroeconomic factors includes (i) the inflation rate computed from the consumer price index (cpi), (ii) the industrial production growth (ip), (iii) the dividend yield (dy), (iv) the unemployment rate growth ($unem$), (v) the gross domestic production growth (gdp), and (vi) the detrended short-term interest rate (ir). The CCIs and the six macroeconomic variables are standardized with zero expectation and unit variance. We construct the quasi-weakly-balanced dataset starting from January 2001 to December 2015. The fixed-effect specification allows each individual market to have different regression constants when all markets enter the regressions jointly. The moving-block bootstrap simulation procedure is employed to address the potential issue of a highly persistent time-series process. Specifically, we initially estimate the panel regression and save all coefficients. We then repeatedly bootstrap the raw data in blocks with a block length of 15 to generate 10,000 new time series under the null of no predictability for all dependent and explanatory variables, though different block lengths do not seem to alter our results. We finally generate the bootstrap distribution of coefficient estimates by estimating the predicative model on the 10,000 artificial time series.

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

Table 8: Regression results and correlations in each individual market

Developed markets					Emerging markets				
Markets	cci_t	p-value	$\rho_{\varepsilon,\xi}$	p-value	**Markets**	cci_t	p-value	$\rho_{\varepsilon,\xi}$	p-value
Australia	–0.41	(0.012)[b]	0.17	(0.001)[a]	Brazil	2.14	(0.903)	0.09	(0.279)
Austria	–0.85	(0.006)[a]	0.29	(0.000)[a]	Bulgaria	–0.25	(0.890)	0.01	(0.932)
Belgium	–0.97	(0.000)[a]	0.27	(0.000)[a]	Chile	–0.05	(0.447)	0.06	(0.534)
Canada	–0.29	(0.138)	0.26	(0.000)[a]	China	–1.18	(0.002)[a]	0.09	(0.257)
Denmark	–1.17	(0.757)	0.11	(0.140)	Colombia	–0.45	(0.422)	0.01	(0.933)
Finland	–1.05	(0.109)	0.06	(0.349)	Croatia	–1.58	(0.032)[b]	0.04	(0.686)
France	–1.49	(0.002)[a]	0.18	(0.001)[a]	Cyprus	–1.13	(0.645)	0.11	(0.208)
Germany	–0.67	(0.008)[a]	0.15	(0.013)[a]	Czech Republic	–1.64	(0.161)	0.01	(0.904)
Greece	–3.06	(0.045)[b]	0.17	(0.049)[b]	Estonia	–0.39	(0.472)	0.04	(0.742)
Hong Kong	–4.27	(0.120)	0.09	(0.320)	Hungary	–0.70	(0.057)[c]	0.26	(0.001)[a]
Ireland	–0.51	(0.181)	0.21	(0.002)[a]	Indonesia	–0.42	(0.004)[a]	0.04	(0.698)
Israel	–0.91	(0.178)	0.15	(0.285)	Lithuania	2.05	(0.059)[c]	0.21	(0.023)[b]
Italy	–1.47	(0.005)[a]	0.14	(0.039)[b]	Malta	–0.26	(0.066)[c]	0.16	(0.046)[b]
Japan	–0.06	(0.088)[c]	0.18	(0.000)[a]	Mexico	2.82	(0.177)	0.07	(0.449)
Luxembourg	–0.96	(0.576)	0.12	(0.201)	Nigeria	–1.06	(0.036)[b]	0.07	(0.598)
Netherlands	–1.41	(0.051)[c]	0.31	(0.000)[a]	Philippine	0.89	(0.090)[c]	0.00	(0.967)
New Zealand	–0.08	(0.327)	0.14	(0.043)[b]	Poland	–5.61	(0.003)[a]	0.20	(0.029)[b]
Norway	–0.47	(0.023)[b]	0.15	(0.011)[b]	Romania	0.75	(0.027)[b]	0.23	(0.011)[b]
Portugal	0.19	(0.755)	0.13	(0.083)[c]	Russia	–7.65	(0.002)[a]	0.05	(0.534)
Spain	–1.42	(0.042)[b]	0.16	(0.014)[b]	Slovakia	0.09	(0.003)[a]	0.14	(0.136)
Sweden	–0.40	(0.033)[b]	0.26	(0.001)[a]	Slovenia	–0.10	(0.502)	0.01	(0.911)
Switzerland	–0.63	(0.063)[c]	0.11	(0.233)	South Africa	–1.06	(0.810)	–0.14	(0.069)[c]
United Kingdom	–0.27	(0.145)	0.20	(0.000)[a]	South Korea	–0.97	(0.007)[a]	0.35	(0.000)[a]
United States	–0.42	(0.030)[b]	0.36	(0.000)[a]	Taiwan	–0.72	(0.590)	0.15	(0.211)
					Thailand	–0.42	(0.003)[a]	0.06	(0.461)
					Turkey	–0.22	(0.697)	–0.02	(0.873)

This table presents the regression results in each individual market based on an eight-equation system with different forecast horizons. Specifically, we jointly estimate the eight-equation system for T months (T = 1, 2, 3, 6, 9, 12, 24, and 36) in a system of regression equations using the generalized method of moments (GMM) to test whether there exists a jointly significant impact in the following T months. The predictive model includes the CCI and a matrix of six macroeconomic variables to explain the average monthly return for market i over T months after the release of the CCI at month t. The set of macroeconomic factors includes (i) the inflation rate computed from the consumer price index (cpi), (ii) the industrial production growth (ip), (iii) the dividend yield (dy), (iv) the unemployment rate growth ($unem$), (v) the gross domestic production growth (gdp), and (vi) the detrended short-term interest rate (ir). The CCIs and the six macroeconomic variables are standardized with zero expectation and unit variance. The moving-block bootstrap simulation procedure is employed to address the potential issue of a highly persistent time-series process. Specifically, we initially estimate the panel regression and save all coefficients. We then repeatedly bootstrap the raw data in blocks with a block length of 15 to generate 10,000 new time series under the null of no predictability for all dependent and explanatory variables, though different block lengths do not seem to alter our results. We finally generate the bootstrap distribution of coefficient estimates by estimating the predicative model on the 10,000 artificial time series. This table also reports the correlation between unexpected returns and the innovation in expected returns ($\rho_{\varepsilon,\xi}$).

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

Table 9: Cross-market analyses

	Upper	*p*-value	Lower	*p*-value	Spread	*p*-value
Panel A: Cultural dimensions						
Individualism vs Collectivism (IDV)	–0.51	(0.001)[a]	–0.37	(0.243)	–0.14	(0.019)[b]
Uncertainty avoidance index (UAI)	–0.57	(0.023)[b]	–0.36	(0.020)[b]	–0.21	(0.000)[a]
Masculinity vs Femininity (MAS)	–0.44	(0.017)[b]	–0.49	(0.040)[b]	0.05	(0.317)
Power distance index (PDI)	–0.33	(0.297)	–0.48	(0.001)[a]	0.15	(0.005)[a]
Long-term vs Short-term orientation (LTO)	–0.40	(0.161)	–0.44	(0.041)[b]	0.04	(0.934)
High MP markets	–0.62	(0.000)[a]	–0.70	(0.003)[a]	0.08	(0.168)
Low MP markets	–0.39	(0.216)	–0.88	(0.000)[a]	0.50	(0.000)[a]
Indulgence vs Restraints (IDG)	–0.45	(0.012)[b]	–0.41	(0.177)	–0.04	(0.642)
High MP markets	–0.67	(0.000)[a]	–0.57	(0.000)[a]	–0.10	(0.191)
Low MP markets	–0.47	(0.222)	–0.65	(0.004)[a]	0.17	(0.332)
Panel B: Market institutions						
Antidirector right (ADR)	–0.34	(0.038)[b]	–0.63	(0.001)[a]	0.29	(0.000)[a]
Government corruption (GC)	–0.46	(0.001)[a]	–0.60	(0.014)[b]	0.14	(0.016)[b]
Accounting standard (AS)	–0.39	(0.008)[a]	–0.56	(0.018)[b]	0.17	(0.001)[a]
Efficiency of judicial system (EJS)	–0.42	(0.003)[a]	–0.61	(0.008)[a]	0.19	(0.000)[a]
Panel C: Intelligence and education						
Intelligence quotient (IQ)	–0.43	(0.002)[a]	–0.42	(0.172)	–0.01	(0.936)
High MP markets	–0.61	(0.000)[a]	–0.33	(0.000)[a]	–0.28	(0.000)[a]
Low MP markets	–0.44	(0.109)	–1.08	(0.000)[a]	0.64	(0.000)[a]
Adult general literacy (AGL)	–0.37	(0.115)	–0.77	(0.031)[b]	0.40	(0.000)[a]
High MP markets	–0.76	(0.109)	–0.87	(0.000)[a]	0.10	(0.504)
Low MP markets	–1.02	(0.041)[b]	–0.81	(0.033)[b]	–0.20	(0.589)
Financial literacy (FL)	–0.48	(0.001)[a]	–0.47	(0.160)	–0.01	(0.843)
High MP markets	–0.59	(0.000)[a]	–0.28	(0.233)	–0.31	(0.044)[b]
Low MP markets	–0.56	(0.018)[b]	–0.88	(0.001)[a]	0.32	(0.011)[b]
Student test average (STA)	–0.48	(0.001)[a]	–0.54	(0.093)[c]	0.06	(0.109)
High MP markets	–0.66	(0.000)[a]	–0.67	(0.000)[a]	0.01	(0.870)
Low MP markets	–0.70	(0.000)[a]	–0.86	(0.035)[b]	0.15	(0.232)
Tertiary education graduation (TEG)	–0.57	(0.001)[a]	–0.37	(0.060)[c]	–0.20	(0.001)[a]
High MP markets	–0.72	(0.007)[a]	–0.49	(0.000)[a]	–0.24	(0.014)[b]
Low MP markets	–1.08	(0.000)[a]	–0.55	(0.175)	–0.52	(0.000)[a]
Educational expenditure (EE)	–0.67	(0.000)[a]	–0.53	(0.004)[a]	–0.14	(0.004)[a]
High MP markets	–0.74	(0.001)[a]	–0.60	(0.004)[a]	–0.13	(0.096)[c]
Low MP markets	–1.00	(0.000)[a]	–0.85	(0.003)[a]	–0.14	(0.236)

This table presents the results for differences in the impact of investor sentiment on stock returns over the subsequent 12 months, from the perspectives of cultural dimensions, market institutions, and intelligence and education. The upper- and lower-layer portfolios are constructed based on whether the score of each factor is above or below the median value. For factors related to MP, including LTO, IDG, IQ, AGL, FL, STA, TEG, and EE, we further divide the upper- and lower-layer portfolios into four smaller samples conditional on high/low MP. The results are generated from the fixed-effect panel regression. The statistical significance for the spread (the difference of the estimated coefficient of the CCI between the upper the lower layers) is based on the *p*-value obtained from the Wald test.

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