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Investor sentiment and stock market returns: a story of night and day

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ABSTRACT
Some financial relations have been confirmed to be different overnight and intraday due to different clienteles. In this paper, we assess the impact of investor sentiment on stock market returns in 30 international stock markets overnight and intraday. At the global level, empirical evidence reveals a negative sentiment-return relation in both non-trading and trading hours, and the relation is stronger intraday than overnight, indicating that overnight traders are more rational than intraday traders. The separation between developed and emerging markets does not distort the negative relation or the stronger impact intraday. At the individual market level, results reveal a high degree of heterogeneity in the sentiment-return relation, in terms of both influence direction and magnitude. The heterogeneity can be explained by cross-market differences in cultural dimensions and market integrity, and notably, such influence varies across night and day, suggesting that the influence of the two aspects may be more complex than we used to theorize and therefore, future studies applying the cross-market analytical framework may take different clienteles into account.

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1. Introduction

The impact of investor sentiment on asset returns has been widely confirmed in the literature. De Long et al. (1990) and Shleifer and Vishny (1997), among others, posit that sentiment traders' stochastic trading makes asset prices unpredictable, inflicting limitations on arbitrage and leading to a persistent impact on asset returns. Brown and Cliff (2005) argue that high (low) investor sentiment drives stock prices above (below) fundamental values, leading to low (high) subsequent returns due to the mean-reversion property, which suggests a negative sentiment-return relation and is supported by the empirical evidence from the US as well as worldwide (Baker and Wurgler 2006; 2007; Bathia and Bredin 2013; Da, Engelberg, and Gao 2011; Ding, Mazouz, and Wang 2019; Schmeling 2009; Wang, Su, and Duxbury 2021).

Stock markets demonstrate two key differences between overnight (non-trading hours) and intraday (trading hours) as discussed by Lou, Polk, and Skouras (2019). First, the overnight return may reflect more firm-specific information as firms tend to submit important regulatory filings during the non-trading hours. In the US, for example, a large proportion of earnings announcements are issued during non-trading hours. And second, the overnight returns are likely to be driven by the trading of investors who are less concerned with liquidity and price impact.[1] Therefore, non-trading hours and trading hours would introduce investor heterogeneity, i.e. investors may trade in one of the two periods rather than the other. Investor heterogeneity has been widely adopted in explaining various market facts and phenomena such as in Harrison and Kreps (1978), Constantinides and Duffie (1996), Anderson, Ghysels, and Juergens (2005), Basak (2005), Berrada (2006), Weinbaum (2009), Bhamra and Uppal (2014), Chabakauri (2015), Gârleanu and Panageas (2015), Pohl, Schmedders, and Wilms (2021).[2] Of direct relevance, Hendershott, Livdan, and Rösch (2020) suggest that overnight traders are

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long-term investors demanding higher returns for bearing higher market risk, but intraday traders are risk-loving speculators demanding higher market risk, implying that a theorized, positive mean-variance relation is expected to be present overnight, which may be distorted intraday. Empirical evidence of Hendershott, Livdan, and Rösch (2020) and Wang (2021; 2023) supports the theoretical discussion, revealing a positive risk-return relation overnight but not intraday and further confirming the role of the heterogeneous overnight and intraday clienteles.

Combining the two streams of literature, we assess the sentiment-return relation overnight and intraday. Since the sentiment-return relation is realized by investors trading in stock markets and if clienteles are not the same across non-trading and trading hours, the relation might differ as well. Directly testing the sentiment-return relation in the two periods, therefore, helps to present new findings of such a relation and to identify who, overnight or intraday traders, would bring sentiment impact on stock markets. We place our study into a global context containing a total of 30 stock markets for the following considerations.

First, employing a global sample may reveal new evidence. Prior literature confirms the sentiment-return relation to be market-specific, and among various factors, cultures and market integrity hold a strong explanatory power to the divergent patterns across markets (Schmeling 2009; Wang, Su, and Duxbury 2021). Hofstede and Bond (1988) define culture as the collective mind programming that distinguishes one group of people from another and contains values that can shape people's behaviors and perception. The cultural dimension framework has been broadly applied in finance studies, in which cultures have been confirmed to have a significant impact on stock trading decisions (Breuer, Riesener, and Salzmann 2014; Grinblatt and Keloharju 2001; Wang, Su, and Duxbury 2021), stock market participation (Guiso, Sapienza, and Zingales 2008; Rieger 2022), home bias in asset allocation (Aggarwal, Kearney, and Lucey 2012; Anderson et al. 2011; Beugelsdijk and Frijns 2010; Coval and Moskowitz 1999), momentum profits (Chui, Titman, and Wei 2010; Galariotis and Karagiannis 2021), stock price co-movement (Eun, Wang, and Xiao 2015), post earnings announcement drift (Dou, Truong, and Veeraraghavan 2015; Guo and Holmes 2022), and country-level financial systems (Aggarwal and Goodell 2009; Kwok and Tadesse 2006). Market integrity, referring to the overall legal and regulatory level of a market, can influence information circulation and thus have a direct effect on market efficiency that is related to the impact of investor sentiment (Wang and Duxbury 2021; Zouaoui, Nouyrigat, and Beer 2011). With a sample consisting of 30 international stock markets, we anticipate revealing differential patterns of the sentiment-return relation overnight and intraday across markets, and to the extent that differences are detected, we can examine whether cultures and market integrity drive the presented differences, and if so, how, and whether the influence varies across night and day due to different clienteles (Hendershott, Livdan, and Rösch 2020; Lou, Polk, and Skouras 2019).

Second, a diversified, global sample incorporating both developed and emerging markets would offer additional insights into the sentiment-return relation overnight and intraday that are less likely to be observed if sample markets have similar economic conditions (Ferreira et al. 2012; Machokoto, Gyimah, and Ibrahim 2022). Third, constructing a panel dataset of multiple stock markets can increase the power of statistical analyses (Ang and Bekaert 2007). Fourth, a global sample providing out-of-sample evidence in comparison with the US market is desirable in surveying market anomalies (Ang et al. 2009; Griffin, Ji, and Martin 2003).

We sample 30 international stock markets including 15 developed and 15 emerging markets and spanning America, Asia-Pacific, and Europe. This economically and geographically diversified combination covers a large portion of leading stock markets in the world and is, thus, a representative international sample. We employ the consumer confidence index (CCI) as the sentiment proxy, as consumer confidence and investor sentiment are positively related (Lemmon and Portniaguina 2006; Qiu and Welch 2006) and it is available in all markets. Applying a fixed-effect panel specification pooling all 30 stock markets, we confirm a negative sentiment-return relation for the subsequent 2 to 36 months in global stock markets both overnight and intraday. Notably, for the first time, we document that the impact is significantly stronger intraday than overnight for the subsequent 2 to 36 months, indicating that the widely reported negative sentiment-return relation in the extant studies is mainly driven by intraday traders. A similar pattern is also observed for developed and emerging markets, but meanwhile we report that the impact tends to be more prompt in emerging markets (the subsequent 2 to 12 months for overnight returns and the subsequent 1 to 36 months for intraday returns), while more persistent in developed markets (the subsequent 6 to 36 months for both overnight and intraday returns). These findings are robust to a battery of alternative empirical designs and specifications. The confirmation of the negative sentiment-return relation in non-trading and trading hours reaffirms investor sentiment as a contrarian factor in predicting stock market returns. We, then, survey individual stock markets and report that the sentiment-return relation varies across markets in terms of both influence direction and magnitude, again, across overnight and intraday, indicating that the impact of investor sentiment on stock market returns is not universally consistent across markets, but market-specific.

To the extent that differences in the impact of investor sentiment on stock market returns are revealed, we conduct the cross-market analyses to explore the driving forces of the observed divergences from the perspectives of cultural dimensions and market integrity. For the former, we consider six dimensions, including individualism (IDV), uncertainty avoidance index (UAI), masculinity (MAS), power distance index (PDI), long-term orientation (LTO), and indulgence (IDG). For the latter, we consider seven indicators, including anti-director rights (ADR), government corruption (GVC), accounting standards (ACS), efficiency of judicial systems (EJS), the rule of law (ROL), risk of expropriation (ROE), and risk of contract repudiation (RCR), and construct a composite indicator (MKI) by extracting the common information from the seven individual indicators via the principal component analysis (PCA). Evidence reveals that both cultural dimensions and market integrity induce heterogeneity in the sentiment-return relation, and more importantly, the influence varies across non-trading and trading hours, i.e. that the same indicator may affect overnight and intraday traders in different, or even opposite, ways.

Finally, we follow the anonymous referees' suggestions and conduct three further analyses, showing that (i) the sentiment-return relation largely holds when investor sentiment is measured by a trade-based composite proxy, and its return predictability is comparable with the survey-based CCI; (ii) our finding that investor sentiment affects the intraday stock market returns more than the overnight ones survives the out-of-sample tests; and (iii) the negative sentiment-return relation is also present when daily data are employed.

The remainder of this paper proceeds in the following manner. Sections 2 and 3 discuss data and methodology, respectively. Section 4 presents the sentiment-return relation at both global and market levels. Section 5 explores potential explanations from cultural dimensions and market integrity, followed by Section 6 of additional tests. Section 7 concludes.

2. Sample selection, descriptive statistics, and preliminary tests

We sample a total of 30 stock markets. One of the most important selection criteria is that the sample markets should not contain a large number of zero overnight returns. Our sample is a sound representative for global stock markets, including 15 developed and 15 emerging markets as per Morgan Stanley Capital International (MSCI) and Wang, Su, and Duxbury (2021), and spanning three major areas of the world, including America, Asia-Pacific, and Europe. We source daily market data, including market open and close prices, from Bloomberg, and cross-check them with Refinitiv and the corresponding stock exchanges where possible for quality control. Due to data availability, starting dates vary across markets while the ending dates are at the end of 2018. Following Lou, Polk, and Skouras (2019), Hendershott, Livdan, and Rösch (2020), and Wang (2021), we define the daily intraday return in market i on day s, $r_{i,s}^{intraday}$, as the index appreciation between market close and open indices of the same day s, and impute the overnight return, $r_{i,s}^{overnight}$, based on the daily total return (i.e. the close-to-close return) and this intraday return, following,

$$r_{i,s}^{intraday} = \frac{p_{i,s}^{close}}{p_{i,s}^{open}} - 1 \tag{1}$$

where $p_{i,s}^{close}$ and $p_{i,s}^{open}$ denote the market close and open indices, respectively, and

$$r_{i,s}^{overnight} = \frac{1 + r_{i,s}^{total}}{1 + r_{i,s}^{intraday}} - 1 \tag{2}$$

Based on daily intraday and overnight returns, we accumulate them in each month t, following,[3]

$$r_{i,t}^{intraday} = \prod_{s \in t} (1 + r_{i,s}^{intraday}) - 1 \tag{3}$$

$$r_{i,t}^{overnight} = \prod_{s \in t} (1 + r_{i,s}^{overnight}) - 1 \tag{4}$$

In Introduction, we discuss two differences across overnight and intraday, as suggested by Lou, Polk, and Skouras (2019). As the two differences persist, the day-to-day differences driven by the heterogeneous clienteles in the two periods can be accumulated in the long term as well. This is further empirically supported by prior studies employing weekly (Aboody et al. 2018; Weißofner and Wessels 2020), monthly (Guo, Li, and Zheng 2019; Lou, Polk, and Skouras 2019; Wang 2023), and even yearly (Guo, Yin, and Zeng 2023) observations.

Descriptive statistics of overnight and intraday returns appear in Table 1. Over sample periods, most stock markets present positive average overnight returns, except for Austria (–0.087%), China (–1.708%), and Luxembourg (–0.215%). This number significantly increases for intraday returns with 21 markets showing negative average intraday returns, accounting for over two-thirds of the sample markets. For the same reason, on average, overnight returns are higher than intraday returns in 23 markets, consistent with Cliff, Cooper, and Gulen (2008), Cai and Qiu (2008), and Kelly and Clark (2011). In total, 22 stock markets show opposite return signs overnight and intraday, suggesting that positive (negative) overnight returns tend to be reversed during the trading hours, as documented in Berkman et al. (2012). Except for Canada and Taiwan showing a similar market return standard deviations overnight and intraday, all other stock markets present a less volatile overnight returns, as in French (1980) and French and Roll (1986).

We employ the consumer confidence index (CCI) as the proxy for investor sentiment. Qiu and Welch (2006) posit that if investors are bullish (bearish) about the economy, they are likely to be bullish (bearish) about stock markets, and vice versa, indicating a positive relation between consumer confidence and investor sentiment. Further, Qiu and Welch (2006) report a strong, positive correlation between the Michigan Consumer Confidence Index and the UBS/Gallup Index of Investor Optimism, confirming consumer confidence as a valid measure of investor sentiment. Consumer confidence has been widely applied in extant studies especially the international studies sampling multiple markets (Bathia and Bredin 2013; Coakley et al. 2014; Derrien and Kecskés 2009; Gao and Süss 2015; Greenwood and Shleifer 2014; Lemmon and Portniaguina 2006; Møller, Nørholm, and Rangvid 2014; Wang, Su, and Duxbury 2021). In addition, CCI is a consistent proxy available in all our 30 sample markets, with plausibly long periods of observations.

We collect CCIs from various sources and two points need highlighting here. The first point is about the data source selection. Many markets have multiple sources providing CCI data, and we follow three main equally important criteria when determining which data source is used for our analyses. First, the CCI data should have a relatively long period so that we can keep a reasonable number of observations for regressions. Second, the selected data sources should fall into the categories of 'key indicators' and/or 'headline' as labeled by Refinitiv to ensure quality, suitability, and accuracy. Third, local sources are preferred to regional or global sources, in that the former can be adaptive surveys to individual markets and therefore, can better reflect the true investor sentiment. Here, we give four examples, including Chile, Germany, Switzerland, and the US, to briefly illustrate how we select data sources based on the three criteria.

For Chile, we identify three CCI sources, including (i) the Chilean Institute of Rational Administration of Enterprises, (ii) the Organisation for Economic Co-operation and Development (OECD), and (iii) the Universidad del Desarrollo. We do not choose (i) or (ii), because (i) has a relatively short period starting from 2011, and (ii) is not a local survey and does not fall into the category of 'key indicators' or 'headline'. For (iii), it is a local survey starting from 2005 and falling into the category of 'headline', and thus is chosen for our analyses. For Germany, we identify two sources, including (i) the Directorate–General for Economic and Financial Affairs (DG ECFIN) and (ii) the OECD, the former, as the regional survey, is preferred to the latter, as the global survey. Also, the DG ECFIN falls into the categories of both 'key indicators' and 'headline' in Refinitiv. For Switzerland, we identify two sources, including (i) State Secretariat for Economic Affairs and (ii) the OECD. The former is a

Table 1. Descriptive statistics.

Markets	Starting months	CCI (I) Sources	CCI (I) μ	CCI (I) σ	CCI (I) $\rho(1)$	Stock market returns (II) Overnight μ	Overnight σ	Intraday μ	Intraday σ
Argentina	March, 2001	Universidad Torcuato di Tella	46.549	7.744	0.924	1.162	2.143	0.944	10.316
Australia*	July, 2003	Westpac/Melbourne Institute	104.193	9.487	0.843	0.196	1.071	0.133	3.675
Austria*	February, 1997	Oesterreichische Nationalbank	−8.814	5.141	0.915	−0.087	0.365	0.405	6.225
Belgium*	February, 1996	National Bank of Belgium	−5.458	8.075	0.913	1.028	2.988	−0.744	5.300
Brazil	February, 2003	FecomercioSP	129.101	22.225	0.973	0.055	0.258	1.005	7.244
Canada*	October, 2010	Refinitiv/Ipsos	53.425	1.808	0.632	0.875	3.032	−0.649	3.014
Chile	May, 2005	Universidad del Desarrollo	115.712	16.184	0.833	0.531	0.798	0.127	4.527
China	November, 2002	National Bureau of Statistics of China	107.843	5.845	0.932	−1.708	3.549	2.042	6.950
Croatia	August, 2006	DG ECFIN**	−23.440	10.858	0.958	0.043	1.298	−0.246	7.182
Czech Republic	March, 2005	Czech Statistical Office	100.023	10.574	0.971	0.997	2.548	−1.061	6.042
France*	March, 1990	National Institute for Statistics and Economics Studies	99.353	10.436	0.982	0.520	3.183	−0.262	5.175
Germany*	December, 1993	DG ECFIN	−8.573	6.939	0.973	0.859	2.502	−0.307	6.213
Hungary	February, 2001	GKI Economic Research	−30.331	16.661	0.975	0.967	2.669	−0.203	6.397
India	December, 2010	Reserve Bank of India	91.183	19.282	0.860	2.128	2.344	−1.454	3.790
Indonesia	June, 2005	Bank Indonesia	107.849	11.615	0.952	0.127	2.923	0.964	4.980
Ireland*	March, 2005	DG ECFIN	−9.316	14.359	0.971	0.766	1.856	−0.783	6.740
Italy*	June, 2003	National Institute of Statistics	100.045	8.324	0.959	0.990	2.601	−1.161	5.824
Japan*	June, 1988	Cabinet Office	41.920	4.741	0.957	0.695	2.694	−0.783	5.246
Luxembourg*	February, 2006	DG ECFIN	−8.206	5.364	0.867	−0.215	2.191	−0.002	5.869
Mexico	August, 2005	Instituto Nacional de Estadistica, Geografia e Informatica	38.521	3.232	0.945	0.080	0.586	0.562	5.331
Netherlands*	March, 2003	Statistics Netherlands	−6.368	19.751	0.986	0.843	2.482	−0.533	4.948
Philippines	February, 2007	Bangko Sentral ng Pilipinas	−16.576	14.891	0.875	0.965	2.463	−0.376	4.876
Poland	February, 2006	DG ECFIN	−5.906	6.574	0.932	1.239	2.661	−0.980	4.857
Portugal*	February, 2001	DG ECFIN	−20.520	10.911	0.973	0.709	2.331	−1.081	5.049
South Korea	July, 2008	The Bank of Korea	102.973	9.097	0.900	1.303	3.769	−1.151	3.844
Spain*	February, 1996	Ministry of Economy and Finance	−12.238	10.460	0.980	0.705	3.008	−0.383	6.299
Switzerland*	May, 2005	State Secretariat for Economic Affairs	−3.215	7.154	0.766	0.502	2.263	−0.313	3.841
Taiwan	December, 2009	The Research Center for Taiwan Economic Development	80.990	5.119	0.936	1.688	2.873	−1.483	2.849
Thailand	February, 2001	University of the Thai Chamber of Commerce	72.937	10.738	0.982	1.687	3.066	−0.942	4.819
United States*	April, 1982	The Conference Board	94.011	25.306	0.974	0.055	0.645	0.639	4.595

Notes: This table presents descriptive statistics of the consumer confidence index (CCI), as the proxy for investor sentiment, and stock market returns, in Column (I) and (II), respectively. In particular, for CCI, we report sources, mean (μ) standard deviation (σ), and the first-order autocorrelation ($\rho(1)$), and for stock market returns, we report mean (μ) and standard deviation (σ) for both overnight and intraday returns. Starting months vary across markets due to data availability but all end at the end of 2018.

*Represents developed markets following Morgan Stanley Capital International (MSCI) and Wang, Su, and Duxbury (2021).

**Represents the Directorate-General for Economic and Financial Affairs.

local survey and like the DG ECFIN, it also falls into the categories of both 'key indicators' and 'headline'. While it is a quarterly rather than a monthly measure, studies such as Schmeling (2009) and Wang, Su, and Duxbury (2021) provide the approach to convert quarterly observations into monthly ones by applying the last available values for months without data, which we can rely on. And finally for the US, we identify three data sources, including (i) the Conference Board, (ii) the University of Michigan, and (iii) the OECD. The OECD is firstly excluded for the same reasons above. For (ii), it starts from 1952, which is earlier than (i) from 1967. However, (ii) only falls into the category of 'headline', while (i) falls into categories of both 'key indicators' and 'headline'. As the US stock market data are available from 1982, meaning that the sample period is not finally determined by the CCI, and hence, we choose (i) in our paper. Overall, we try seeking balance between consistency (in terms

Table 2. Panel unit root tests.

Panel unit root and stationarity tests	All	Developed	Emerging
ADF–Fisher χ^2	94.515[a]	59.349[a]	46.555[b]
Im–Pesaran–Shin W	−2.542[a]	−2.843[a]	−1.937[b]
Breitung t	−2.994[a]	−3.304[a]	−2.734[a]

Notes: This table presents the results of panel unit root tests for the monthly consumer confidence index (CCI), as the proxy for investor sentiment, in all, developed, and emerging markets. Three panel unit root and stationarity tests, including Augmented Dickey Fuller (ADF)–Fisher test, Im–Pesaran–Shin test, and Breitung test, are used. Individual intercepts are included, and the Schwarz information criterion (SIC) is adopted in determining the lag length.
[a]and [b] represent statistical significance at the 1% and 5% level, respectively.

of the application of our selection criteria) and flexibility (when two or more candidates are closely competitive, like the US) when choosing the data sources for each market. In one of the robustness tests, we use the world-wide OECD data, where available, as an alternative, and results are not qualitatively affected.

The second point is about the release dates. One possibility is that different data sources can have different CCI release dates, and hence, there might exist a cross-market discrepancy in investor sentiment information carried by CCIs. While some markets do not provide clear information on the specific release schedule, from the information available we note that the CCI is more likely to be released in the middle or at the end of the month. For example, in Belgium the CCI is published around 21st of each month by National Bank of Belgium. In some European markets including Croatia, Germany, Ireland, Luxembourg, Poland, and Portugal, the CCI is usually released at the end of each month by the DG ECFIN. In Argentina, the CCI is normally released on the last Thursday of each month by Universidad Torcuato di Tella.

For the survey-based investor sentiment proxies, like the CCIs employed in our paper or some others such as the American Association of Individual Investors (AAII) and sentix (Brown and Cliff 2004; Fisher and Statman 2000; Schmeling 2007; Wang and Duxbury 2021), the best situation is to track and reflect the whole-month investor sentiment from the start to the end, but it would be very difficult, if not impossible, to achieve this in practice, and this seems to be inherently borne by such survey-based proxies. However, as per the data compilation methodology, particularly the data collection window, the CCI is a representative investor sentiment proxy that can well reflect investor sentiment in a specific month. For example, the DG ECFIN collects consumer confidence information from 1st of the month until the day just before the release date that is at the end of the month as mentioned above, it largely tracks investor sentiment of the whole month. The Cabinet Office in Japan collects consumer confidence information on 15th of each month, and as the temporal midpoint, it appears to be the best in representing investor sentiment of the whole month compared with other dates such as 1st and 30th. Therefore, while different markets have different release dates, the released CCI can still be a representative measure for specific months, making it comparable across markets.

Table 1 summarizes descriptive statistics of CCIs. Consumer confidence surveys across markets apply different neutrality values and calibrations,[4] we, hence, standardize the CCI in each individual market with zero expectation and unit variance. The first-order autocorrelations of CCIs range from 0.632 (Canada) to 0.986 (Netherlands), with an average of 0.921, suggesting (i) a highly persistent time-series process that might lead to biased estimates of slope coefficients and standard errors (Ferson, Sarkissian, and Simin 2003), and (ii) a potential concern of unit-root nonstationary CCIs. To deal with the potential biased estimates of slope coefficients and standard errors, following Bathia and Bredin (2013) and Wang, Su, and Duxbury (2021), we employ the moving-block bootstrap simulation as suggested by Gonçalves and White (2005).[5] And for the potential nonstationary CCIs, we conduct three panel unit root tests, including Augmented Dickey Fuller (ADF)–Fisher test, Im–Pesaran–Shin test, and Breitung test. Results in Table 2 confirm the CCIs to be stationary. The two approaches, therefore, could keep the potential issues due to the persistent investor sentiment to the minimum.

Finally, we conduct two panel Granger causality tests, including the simple bivariate test and the block exogeneity test based on a vector autoregression incorporating a total of five macroeconomic and market variables as specified in Equation (6), to present the interdependency between the CCI (cci_t) and stock returns (r_t). Table 3

Table 3. Panel Granger causality tests.

		All		Developed		Emerging	
Panel Granger causality tests		Overnight	Intraday	Overnight	Intraday	Overnight	Intraday
Simple bivariate test	$cci_t \rightarrow r_t$	4.920[a]	5.454[a]	2.789[c]	2.888[c]	3.583[b]	3.312[b]
	$r_t \rightarrow cci_t$	12.952[a]	67.690[a]	10.147[a]	66.362[a]	4.664[a]	12.919[a]
Block exogeneity test	$cci_t \rightarrow r_t$	5.430[a]	3.881[b]	3.550[b]	2.733[c]	3.596[a]	2.827[c]
	$r_t \rightarrow cci_t$	12.130[a]	50.622[a]	9.491[a]	53.523[a]	5.156[a]	12.055[a]

Notes: 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 market returns, across all, developed, and emerging markets, overnight and intraday. The former tests the Granger causality between investor sentiment and stock market returns, and the latter is based on the vector autoregression specification including five macroeconomic variables as defined in Equation (6), including (i) the inflation rate computed from the consumer price index, (ii) the industrial production growth, (iii) the dividend yield, (iv) the unemployment rate growth, and (v) the detrended short-term interest rate (ir).

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

confirms a bidirectional Granger causality, showing that stock market returns depend on investor sentiment, and vice versa, both overnight and intraday and across all, developed, and emerging markets.

3. Methodology

The basic predictive specification to examine the impact of investor sentiment on future stock returns in stock market i in month t is to regress future stock returns (r^i_{t+1}, overnight or intraday) on investor sentiment (cci^i_t), following,

$$r^i_{t+1} = \alpha + \beta cci^i_t + \varepsilon^i_{t+1} \tag{5}$$

Studies confirm the predictability of macroeconomic and market variables to stock market returns and a wide range of such factors are included in the sentiment-return relation to disentangle the impact of the macroeconomic and market factors (Bathia and Bredin 2018; Bathia, Bredin, and Nitzsche 2016; Boyd, Jagannathan, and Hu 2005; Chelley-Steeley, Lambertides, and Savva 2019; Chen, Roll, and Ross 1986; Ding, Mazouz, and Wang 2021; Hjalmarsson 2010; Huang et al. 2015; Keiber and Samyschew 2019; Kräussl and Mirgorodskaya 2017; Lamont 2001; Lemmon and Portniaguina 2006). Considering data availability, we select five macroeconomic and market factors, including (i) the inflation rate computed from the consumer price index, (ii) the industrial production growth, (iii) the dividend yield, (iv) the unemployment rate growth, and (v) the detrended short-term interest rate, and they are included in matrix ψ_{t+1} as below,

$$r^i_{t+1} = \alpha + \beta cci^i_t + \gamma \Psi^i_{t+1} + \varepsilon^i_{t+1} \tag{6}$$

Finally, as the impact of investor sentiment on stock market returns can persist (Bathia and Bredin 2013; Brown and Cliff 2005; Da, Engelberg, and Gao 2011; Ding, Mazouz, and Wang 2019), we test it at various forecast horizons up to 36 months, following,

$$\frac{1}{T}\sum_{\tau=1}^{\mathrm{T}} r^i_{t+\tau} = \alpha^{(T)} + \beta^{(T)} cci^i_t + \gamma^{(T)} \Psi^{i,(T)}_t + \varepsilon^{i,(T)}_{t+T} \tag{7}$$

where $\frac{1}{T}\sum_{\tau=1}^{T} r^i_{t+\tau}$ denotes the average monthly return for market i over T months ($T = 1, 2, 3, 6, 12, 24$, and 36) following CCI at month t. We estimate Equation (7) with the use of panel fixed-effect regressions across all, developed, and emerging markets. Our equations are in the same spirit as the prior studies examining the sentiment-return relation, such as Brown and Cliff (2005), Schmeling (2009), Bathia and Bredin (2013), Ding, Mazouz, and Wang (2019), Kaivanto and Zhang (2019), Wang, Su, and Duxbury (2021), and Ung, Gebka, and Anderson (2023).

There are two potential issues associated with Equation (7). First, the inclusion of the persistent independent variable, CCIs as shown in Table 1, can bias the coefficient estimates as they are 'predetermined but not strictly exogenous' (Brown and Cliff 2005, 418; see, also, Stambaugh 1999). Second, estimating regressions with overlapping dependent variables generates strong serial correlation in the residuals (Boudoukh, Isarel, and Richardson 2019; 2022; Britten-Jones, Neuberger, and Nolte 2011; Hodrick 1992; Kostakis, Magdalinos, and Stamatogiannis 2015; Richardson and Smith 1991; Richardson and Stock 1989; Valkanov 2003), and such an issue still exists even when the independent variable has no persistence (Boudoukh, Richardson, and Whitelaw 2008). To circumvent the two problems, we adopt a moving-block bootstrap simulation suggested by Gonçalves and White (2005) and applied in Schmeling (2009), Bathia and Bredin (2013), and Kaivanto and Zhang (2019; 2023).[6] To elucidate, first, Equation (7) is estimated and coefficient estimate ($\widehat{\beta^{(T)}}$), constant ($\widehat{\alpha^{(T)}}$), residuals ($\widehat{\varepsilon_{t+T}^{i,(T)}}$), and t-statistics $\hat{t}$ are stored. Second, residuals are repeatedly drawn in a block with the block length of 8 to generate an artificial bootstrap series, and the bootstrapped residuals are denoted as $\overline{\varepsilon_{t+T}^{i,(T)}}$. Third, a series of the dependent variable, $\overline{\frac{1}{T}\sum_{\tau=1}^{\mathrm{T}} r_{t+\tau}^{i}}$, is generated under the null hypothesis of no predictability for all independent variables, following, $\overline{\frac{1}{T}\sum_{\tau=1}^{\mathrm{T}} r_{t+\tau}^{i}} = \widehat{\alpha^{(T)}} + \overline{\varepsilon_{t+T}^{i,(T)}}$. Fourth, the generated dependent variable is regressed on the estimated constant, $\widehat{\alpha^{(T)}}$, and the independent variables, cci_t^i and $\Psi_t^{i,(T)}$, following, $\overline{\frac{1}{T}\sum_{\tau=1}^{\mathrm{T}} r_{t+\tau}^{i}} = \widehat{\alpha^{(T)}} + \beta^{(T)} cci_t^i + \gamma^{(T)}\Psi_t^{i,(T)} + \eta_{t+T}^{i,(T)}$, and coefficient estimate ($\widetilde{\beta^{(T)}}$) and the corresponding t-statistics are stored. Fifth, the above steps are repeated 10,000 times and the bootstrap distribution of coefficient estimates and t-statistics are obtained.[7] Sixth, the bias-adjusted coefficient estimates are obtained by subtracting the mean of the 10,000 bootstrap coefficient estimates from the original estimate ($\widehat{\beta^{(T)}}$), and p-values are based on the share of bootstrapped t-statistics exceeding the estimated t-statistic from the original regression.[8]

4. Empirical results

This section presents empirical results on the sentiment-return relation overnight and intraday. Subsection 4.1 is based on the global level and examines the sentiment-return relation in all, developed, and emerging markets, followed by a series of robustness tests in Subsection 4.2. Subsection 4.3 focuses on the sentiment-return relation in individual markets.

4.1. Global evidence

Table 4 presents the panel regression results from the fixed-effect specification, pooling all, developed, and emerging markets. For all markets, investor sentiment has a significantly negative impact on overnight and intraday returns in the subsequent 2 to 36 months. A one-standard-deviation increase (decrease) in investor sentiment, for example, results in a significant decline (rise) of 0.195% and 0.265% in average monthly returns over the following 3 months overnight and intraday, respectively. The negative impact fluctuates with the forecast horizons: For overnight returns, the impact reaches the peak in the subsequent 3 months, while for intraday returns, it reaches the highest level in the subsequent 24 months, both of which are followed by a gradual decline afterwards. The declining trend over longer forecast horizons is expected in both economic and statistical aspects. Economically, the impact of investor sentiment is supposed to be weakened over longer horizons (Brown and Cliff 2005), and statistically, the declining predictability of investor sentiment suggests that the estimation method does not generate spuriously significant results (Hong, Torous, and Valkanov 2007). Despite this, a one-standard-deviation increase (decrease) in investor sentiment would still lead to a decline (rise) of 1.296% (–0.036% × 36) and 7.128% (–0.198% × 36) on overnight and intraday returns, respectively, over the following 36 months. The impact of investor sentiment on stock market returns is also reflected by the incremental change in adjusted R^2s as the addition of investor sentiment enhances the goodness of fit of the model in most of the cases. Our results are in line with the mainstream findings that there is a negative impact of investor

Table 4. Panel regression results.

Months	1	2	3	6	12	24	36
Panel A. All markets							
Overnight	−0.083	−0.122[c]	−0.195[b]	−0.172[a]	−0.147[a]	−0.110[a]	−0.036[b]
$\Delta adj.\ R^2$	0.00	0.00	0.01	0.03	0.03	0.02	0.01
Intraday	−0.134	−0.191[b]	−0.265[a]	−0.280[a]	−0.277[a]	−0.287[a]	−0.198[a]
$\Delta adj.\ R^2$	0.00	0.01	0.02	0.04	0.04	0.04	0.03
Difference (O – I)	0.052	0.070[c]	0.070[c]	0.108[a]	0.130[a]	0.178[a]	0.162[a]
Panel B. Developed markets							
Overnight	−0.054	−0.092	−0.168	−0.154[b]	−0.152[a]	−0.157[a]	−0.084[a]
$\Delta adj.\ R^2$	0.00	0.00	0.00	0.02	0.03	0.03	0.02
Intraday	−0.076	−0.135	−0.208	−0.230[a]	−0.261[a]	−0.296[a]	−0.212[a]
$\Delta adj.\ R^2$	0.00	0.00	0.01	0.04	0.06	0.07	0.06
Difference (O – I)	0.024	0.043	0.040	0.076[c]	0.108[a]	0.139[a]	0.128[a]
Panel C. Emerging markets							
Overnight	−0.126	−0.166[b]	−0.236[b]	−0.200[a]	−0.140[a]	−0.031	0.035
$\Delta adj.\ R^2$	0.00	0.01	0.02	0.03	0.02	0.01	0.00
Intraday	−0.219[c]	−0.274[b]	−0.348[b]	−0.355[a]	−0.303[a]	−0.281[a]	−0.189[a]
$\Delta adj.\ R^2$	0.01	0.01	0.02	0.03	0.04	0.03	0.02
Difference (O – I)	0.093	0.108[c]	0.112[b]	0.155[b]	0.163[a]	0.242[a]	0.223[a]

Notes: This table presents the panel regression results across all, developed, and emerging markets, overnight and intraday. The predictive model includes the CCI, as the proxy for investor sentiment, and a matrix of five macroeconomic variables to explain the average monthly return for market i over T months ($T = 1, 2, 3, 6, 12, 24$, and 36). The set of macroeconomic factors includes (i) the inflation rate computed from the consumer price index, (ii) the industrial production growth, (iii) the dividend yield, (iv) the unemployment rate growth, and (v) the detrended short-term interest rate (ir). The CCIs and the five macroeconomic variables are standardized with zero expectation and unit variance. The fixed-effect specification allows each individual market to have different regression constants when all markets enter the regressions jointly. A moving-block bootstrap simulation suggested by Gonçalves and White (2005) and applied empirically in Bathia and Bredin (2013), Kaivanto and Zhang (2019), and Wang, Su, and Duxbury (2021) is adopted to account for biased coefficient estimates and standard errors due to the highly persistent time-series process of CCIs. $\Delta adj.\ R^2$ is 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.

sentiment on stock market returns and the impact can be persistent for years in the US stock market (Baker and Wurgler 2006; Brown and Cliff 2005), the developed stock markets (Bathia and Bredin 2013; Schmeling 2009), and the global stock markets (Wang, Su, and Duxbury 2021). And notably, we supplement the finding with new overnight and intraday evidence.

Looking at the sentiment-return relation across overnight and intraday, we find that the impact is negative across most of forecast horizons, meaning that high (low) investor sentiment would be followed by low (high) overnight and intraday returns. More importantly, we note a significant difference in the magnitude and in particular, the impact of investor sentiment on stock market returns is stronger intraday than overnight over the subsequent 2 to 36 months. For example, a one-standard-deviation increase (decrease) in investor sentiment would bring about a decline (rise) of 2.640% (–0.110% × 24) and 6.888% (–0.287% × 24) on overnight and intraday returns, and the difference is as high as 4.272% (–0.178% × 24) in a two-year forecast horizon. A large shock, like a two-standard-deviation change, will double the difference to 8.544% that is of greater economic significance.

The reported negative sentiment-return relation both overnight and intraday, is somewhat expected in the literature of investor sentiment. More importantly, our findings provide strong assurance that the widely documented negative impact of investor sentiment on stock market returns, such as in Brown and Cliff (2005), Baker and Wurgler (2006; 2007), Schmeling (2009), Bathia and Bredin (2013), and Wang, Su, and Duxbury (2021), is jointly driven by both overnight and intraday returns. However, embedding our paper in the literature of financial relations across overnight and intraday, such as Lou, Polk, and Skouras (2019), Hendershott, Livdan, and Rösch (2020), and Wang (2021; 2023), our consistent findings are surprising since the prior literature mainly documents different or even opposing relations overnight and intraday. For example, Hendershott, Livdan, and Rösch (2020) evidence that stock returns are positively related to beta overnight, while negatively related to beta intraday. Our results, however, suggest a consistent, negative sentiment-return relation both overnight and intraday, adding some surprising results to this literature.

Note, however, that by comparing the relations overnight and intraday, we further document that the negative relation is stronger intraday than overnight, which can be viewed as another form of 'different' relations. Therefore, our empirical findings present a feature of duality: First, looking at the sentiment-return relations overnight and intraday separately, the consistent, negative relation is not in line with the prior studies revealing different or opposite financial relations, such as the beta-return relation and the mean-variance relation, overnight and intraday (Hendershott, Livdan, and Rösch 2020; Wang 2021), while second, looking at the two relations jointly, the significant differences in the relation confirm different relations overnight and intraday.

Recall that the impact of investor sentiment on stock market returns is realized by investors trading in stock markets and largely determined by investor rationality. Hendershott, Livdan, and Rösch (2020) argue that overnight traders are long-term investors demanding higher returns for bearing higher market risk, but intraday traders are risk-loving speculators demanding higher market risk, implying the former to be more rational than the latter. This is confirmed in their empirical results showing a positive beta-return relation, as theorized in the traditional finance framework, overnight, but not intraday due to irrational trading, which is further confirmed at the market level in the US as well as in the international markets, i.e. a positive mean-variance relation overnight but not intraday (Wang 2021; 2023). Our results are consistent with the findings above: The weaker sentiment-return relation overnight and the stronger one intraday suggests that overnight traders tend to be more rational than the intraday counterparts so that the impact of investor sentiment brought by overnight traders is not as stronger as that brought by intraday traders. Also, we further document that the difference is not transitory but persistent until the following 36 months.

Results of developed and emerging markets are largely in line with the above from the all-market sample. A negative sentiment-return relation is found overnight and intraday, and such impact, again, tends to be stronger intraday. Beyond the similarities, Table 4 reveals a noticeable difference in the impact of investor sentiment between developed and emerging markets: The impact appears to be more enduring in developed markets (the subsequent 6 to 36 months for both overnight and intraday) while more immediate in emerging markets (the subsequent 2 to 12 months and 1 to 36 months for overnight and intraday, respectively). While the impact is significant until 36 months for intraday returns in emerging markets, we still state that the impact in emerging markets is less persistent due to much weakened impact overnight.[9]

The results seem to be at odds with conventional perceptions that developed markets are more efficient, and thus should be less affected by financial anomalies or irrationalities, such as investor sentiment, compared with emerging markets. We find support in Griffin, Kelly, and Nardari (2010), Jacobs (2016), Cai et al. (2018), Altanlar, Guo, and Holmes (2019), and Wang, Su, and Duxbury (2021) documenting that anomalies are at least as strong, and sometimes stronger, in developed markets than emerging markets. Of direct relevance, Wang, Su, and Duxbury (2021) report that the impact of investor sentiment on stock market returns is more persistent in developed markets (up to 36 months) than in emerging markets (up to 12 months), and we add further evidence by separately investigating overnight and intraday, and meanwhile, reveal that the less enduring impact in emerging markets is mainly due to non-trading hours.

4.2. Robustness tests

In this subsection, we conduct a battery of robustness tests, including (i) extracting economic expectations from CCIs, (ii) adopting a more balanced dataset, (iii) following an alternative classification for market types, (iv) replacing the average monthly returns with the single-period monthly returns as the dependent variable, (v) controlling for the global financial crisis, (vi) employing an alternative survey-based investor sentiment proxy, (vii) controlling for lagged returns, and (viii) controlling for the US investor sentiment and macroeconomic variables.

Investor sentiment, beyond an irrational component, also carries a business cycle component, i.e. that investor sentiment varies with the business cycle in part for rational reasons. It is, hence, possible that our presented negative sentiment-return relation is not driven by investor sentiment but by the expected business conditions, due to the significantly negative impact of expected business conditions on expected excess returns (Campbell and Diebold 2009). To address the concern, in this robustness test we remove the expected business conditions, as represented by the economic sentiment index (ESI), from investor sentiment, as represented by CCI, and so we will have a clean impact of the latter. The ESI is accessible for 19 markets, which remains a representative international sample including 12 developed and 7 emerging markets.[10] We filter the expected economic conditions by regressing the CCI on the ESI, following,

$$cci_t^i = \upsilon + \varphi^i esi_t^i + cci_t^{i,\perp} \tag{8}$$

where the orthogonalized term $cci_t^{i,\perp}$ is the residual series representing the investor sentiment that cannot be explained by the business or economic expectations, i.e. when investor sentiment is high or low '*for no good reason*' (Baker and Wurgler 2006, 1657). We use $cci_t^{i,\perp}$ to replace cci_t^i in Equation (7). If the CCI contains unique variations beyond the expected economic conditions, and meanwhile this component holds predictive power to stock market returns, $cci_t^{i,\perp}$ would have a significant impact. Panel A of Table 5 shows qualitatively similar results to those in Table 4, confirming the sentiment-return relation overnight and intraday and in all, developed, emerging markets. For all markets, investor sentiment can affect stock market returns overnight and intraday for the following 3 to 36 months and 2 to 36 months, respectively, and the impact is stronger intraday than overnight for the following 3 to 36 months. Still, the impact appears to be more persistent in developed markets (the subsequent 6 to 36 months for both overnight and intraday returns) but more prompt in emerging markets (the subsequent 3 to 12 and 2 to 36 for overnight and intraday returns), and the impact is stronger intraday than overnight.

As shown in Table 1, our sample markets, subject to data availability, have different starting months. To avoid our results are mainly driven by the markets with longer sample periods, we manually cut earlier observations to make more balanced samples. Note that emerging markets tend to have much shorter samples than developed markets, so we apply different starting months for the two types of markets and do not replicate the all-market test. In particular, the new starting months for developed and emerging markets, in this robustness test, are January 2000 and January 2006, respectively. Results in Panel B of Table 5 provide broadly consistent results with those reported in Table 4.

In the remaining six robustness tests, we (i) apply an alternative developed/emerging market classification benchmark following FTSE Annual Country Classification Review to reclassify the sample stock markets, (ii) replace the average monthly market returns $\left(\frac{1}{T}\sum_{\tau=1}^{T} r_{t+\tau}^i\right)$ with the single-period monthly market returns ($r_{t+\tau}^i$) in that the impact of investor sentiment fades away over longer forecast horizons and using the average monthly returns might inflate the persistence of the impact of investor sentiment, (iii) control for the global financial crisis (GFC) spanning from July 2008 to June 2009 (Baur 2012) given the fact that the impact of investor sentiment varies across market regimes (Kadilli 2015; Wang, Su, and Duxbury 2022), (iv) adopt OECD CCIs, where available, as an alternative survey-based investor sentiment proxy to largely ensure the CCI data are from the same source with the consistent compilation approaches,[11] (v) control for lagged overnight or intraday returns to account for differences in the patterns of returns per se, as exhibited in Table 1,[12] and (vi) control for the US investor sentiment and the US macroeconomic factors.[13] Panels C–H of Table 5, again, support our previous conclusions.

4.3. *Individual market evidence*

In this subsection, we examine the sentiment-return relation in individual stock markets. As results are correlated across forecast horizons, we adopt a joint test for predictability (Ang and Bekaert 2007; Schmeling 2009). Particularly, we jointly estimate Equation (7) for T months ($T = 1, 2, 3, 6, 12, 24$, and 36) in a seven-equation system using the generalized method of moments (GMM) to test whether there exists a jointly significant impact of investor sentiment on stock market returns – that is, we test the form of $\beta^{i,(1)} = 0$, $\beta^{i,(2)} = 0$, $\beta^{i,(3)} = 0$, $\beta^{i,(6)} = 0$, $\beta^{i,(12)} = 0$, $\beta^{i,(24)} = 0$, and $\beta^{i,(36)} = 0$. The seven-equation system is jointly estimated for each individual market i following,

Table 5. Robustness tests.

Months	1	2	3	6	12	24	36
Panel A.1. Extraction of the ESI, all markets							
Overnight	−0.060	−0.106	−0.180[c]	−0.163[a]	−0.152[a]	−0.133[a]	−0.052[a]
Intraday	−0.095	−0.166[c]	−0.246[b]	−0.287[a]	−0.295[a]	−0.302[a]	−0.201[a]
Difference (O – I)	0.035	0.060	0.066[c]	0.124[a]	0.143[a]	0.169[a]	0.149[a]
Panel A.2. Extraction of the ESI, developed markets							
Overnight	−0.057	−0.102	−0.177	−0.162[a]	−0.165[a]	−0.175[a]	−0.100[a]
Intraday	−0.021	−0.104	−0.190	−0.245[a]	−0.297[a]	−0.321[a]	−0.213[a]
Difference (O – I)	−0.036	0.002	0.013	0.083[c]	0.132[a]	0.146[a]	0.113[a]
Panel A.3. Extraction of the ESI, emerging markets							
Overnight	−0.070	−0.117	−0.190[c]	−0.169[c]	−0.136[a]	−0.068	0.023
Intraday	−0.215	−0.269[c]	−0.342[b]	−0.362[a]	−0.302[a]	−0.281[a]	−0.191[a]
Difference (O – I)	0.146	0.152[c]	0.152[c]	0.193[b]	0.167[a]	0.213[a]	0.215[a]
Panel B.1. More balanced sample, developed markets (post-January 2000)							
Overnight	−0.030	−0.065	−0.143	−0.137[c]	−0.143[a]	−0.136[a]	−0.066[a]
Intraday	−0.085	−0.139	−0.205	−0.234[a]	−0.293[a]	−0.338[a]	−0.228[a]
Difference (O – I)	0.055	0.075	0.062	0.097[c]	0.150[a]	0.202[a]	0.163[a]
Panel B.2. More balanced sample, emerging markets (post-January 2006)							
Overnight	−0.138	−0.179[b]	−0.251[b]	−0.216[a]	−0.153[a]	−0.035	0.054
Intraday	−0.212	−0.258[b]	−0.335[b]	−0.354[a]	−0.301[a]	−0.266[a]	−0.183[a]
Difference (O – I)	0.075	0.079	0.084	0.139[c]	0.148[b]	0.231[a]	0.237[a]
Panel C.1. Alternative market classification, developed markets							
Overnight	−0.041	−0.082	−0.161	−0.156[b]	−0.158[a]	−0.156[a]	−0.083[a]
Intraday	−0.086	−0.145	−0.214	−0.235[a]	−0.259[a]	−0.295[a]	−0.208[a]
Difference (O – I)	0.044	0.063	0.052	0.079[c]	0.102[a]	0.139[a]	0.125[a]
Panel C.2. Alternative market classification, emerging markets							
Overnight	−0.146	−0.186[b]	−0.250[b]	−0.198[a]	−0.130[a]	−0.031	0.044[c]
Intraday	−0.210[c]	−0.265[b]	−0.347[b]	−0.354[a]	−0.307[a]	−0.282[a]	−0.193[a]
Difference (O – I)	0.064	0.080	0.097[c]	0.155[b]	0.178[a]	0.251[a]	0.238[a]
Panel D.1. Impact on single-period returns, all markets							
Overnight	−0.083	−0.131[a]	−0.225[b]	−0.135[a]	−0.155[a]	−0.067	0.089
Intraday	−0.134	−0.230[b]	−0.311[b]	−0.322[a]	−0.361[a]	−0.300[a]	−0.015
Difference (O – I)	0.052	0.094	0.085	0.187[b]	0.206[b]	0.233[a]	0.104
Panel D.2. Impact on single-period returns, developed markets							
Overnight	−0.054	−0.103	−0.196	−0.102	−0.185[a]	−0.128	0.029
Intraday	−0.076	−0.184	−0.267	−0.300[a]	−0.457[a]	−0.370[a]	0.029
Difference (O – I)	0.022	0.081	0.071	0.197[b]	0.271[a]	0.243[b]	0.000
Panel D.3. Impact on single-period returns, emerging markets							
Overnight	−0.126	−0.185[b]	−0.269[b]	−0.184[a]	−0.112[c]	0.024	0.182[b]
Intraday	−0.219[c]	−0.296[b]	−0.375[b]	−0.356[a]	−0.218[b]	−0.198[c]	−0.099
Difference (O – I)	0.093	0.112	0.106[c]	0.172[a]	0.107[c]	0.222[a]	0.280[a]
Panel E.1. Controlling for the GFC, all markets							
Overnight	−0.112	−0.144[c]	−0.212[a]	−0.210[a]	−0.167[a]	−0.123[a]	−0.060[b]
Intraday	−0.158	−0.215[b]	−0.296[a]	−0.313[a]	−0.308[a]	−0.322[a]	−0.223[a]
Difference (O – I)	0.047	0.070[c]	0.085[b]	0.104[a]	0.141[a]	0.200[a]	0.163[a]
Panel E.2. Controlling for the GFC, developed markets							
Overnight	−0.083	−0.111	−0.190[c]	−0.189[a]	−0.174[a]	−0.185[a]	−0.105[a]
Intraday	−0.088	−0.164	−0.243[b]	−0.255[a]	−0.295[a]	−0.324[a]	−0.237[a]
Difference (O – I)	0.004	0.052	0.053[c]	0.066[c]	0.121[a]	0.138[a]	0.131[a]
Panel E.3. Controlling for the GFC, emerging markets							
Overnight	−0.154[c]	−0.200[a]	−0.270[a]	−0.224[a]	−0.160[a]	−0.068	0.013
Intraday	−0.233[c]	−0.304[a]	−0.359[a]	−0.381[a]	−0.323[a]	−0.303[a]	−0.220[a]
Difference (O – I)	0.080	0.103[c]	0.090[b]	0.157[a]	0.163[a]	0.234[a]	0.234[a]

(*continued*).

Table 5. Continued.

Months	1	2	3	6	12	24	36
Panel F.1. Using OECD CCIs where available, all markets							
Overnight	−0.067	−0.110	−0.189[c]	−0.174[a]	−0.155[a]	−0.129[a]	−0.060[b]
Intraday	−0.100	−0.163[c]	−0.237[a]	−0.262[a]	−0.284[a]	−0.306[a]	−0.212[a]
Difference (O – I)	0.033	0.053	0.048	0.088[a]	0.129[a]	0.178[a]	0.153[a]
Panel F.2. Using OECD CCIs where available, developed markets							
Overnight	−0.017	−0.062	−0.147	−0.148	−0.159[a]	−0.182[a]	−0.112[a]
Intraday	−0.031	−0.103	−0.180	−0.202[a]	−0.254[a]	−0.307[a]	−0.216[a]
Difference (O – I)	0.014	0.041	0.033	0.054	0.095[a]	0.125[a]	0.104[a]
Panel F.3. Using OECD CCIs where available, emerging markets							
Overnight	−0.136	−0.177[b]	−0.247[a]	−0.208[a]	−0.145[a]	−0.043	0.026
Intraday	−0.190[c]	−0.241[b]	−0.311[b]	−0.341[a]	−0.321[a]	−0.305[a]	−0.207[a]
Difference (O – I)	0.054	0.064	0.064	0.133[b]	0.176[a]	0.263[a]	0.233[a]
Panel G.1. Controlling for lagged returns, all markets							
Overnight	−0.082	−0.121[c]	−0.194[b]	−0.172[a]	−0.147[a]	−0.108[a]	−0.032[b]
Intraday	−0.142	−0.196[b]	−0.270[a]	−0.284[a]	−0.281[a]	−0.290[a]	−0.201[a]
Difference (O – I)	0.059	0.075[c]	0.076[c]	0.112[a]	0.134[a]	0.182	0.168[a]
Panel G.2. Controlling for lagged returns, developed markets							
Overnight	−0.051	−0.094	−0.166	−0.153[b]	−0.152[a]	−0.154[a]	−0.078[a]
Intraday	−0.087	−0.148	−0.215	−0.236[a]	−0.266[a]	−0.319[a]	−0.214[a]
Difference (O – I)	0.036	0.054	0.049	0.083[b]	0.114[a]	0.145[a]	0.136[a]
Panel G.3. Controlling for lagged returns, emerging markets							
Overnight	−0.120	−0.183[b]	−0.248[b]	−0.217[a]	−0.151[a]	−0.046	0.033
Intraday	−0.220	−0.287[b]	−0.377[a]	−0.374[a]	−0.314[a]	−0.294[a]	−0.198[a]
Difference (O – I)	0.100	0.105[c]	0.129[b]	0.157[b]	0.166[a]	0.248[a]	0.231[a]
Panel H.1. Controlling for the US investor sentiment and macroeconomic variables, all markets							
Overnight	−0.072	−0.111	−0.182[c]	−0.166[b]	−0.135[a]	−0.101[a]	−0.034[b]
Intraday	−0.177	−0.242[a]	−0.317[a]	−0.340[a]	−0.296[a]	−0.258[a]	−0.142[a]
Difference (O – I)	0.105	0.131[c]	0.134[b]	0.184[a]	0.161[a]	0.157[a]	0.108[a]
Panel H.2. Controlling for the US investor sentiment and macroeconomic variables, developed markets							
Overnight	−0.076	−0.111	−0.181	−0.166[b]	−0.178[a]	−0.188[a]	−0.111[a]
Intraday	−0.101	−0.182	−0.263[c]	−0.316[a]	−0.311[a]	−0.272[a]	−0.125[a]
Difference (O – I)	0.024	0.071	0.082	0.149[b]	0.133[a]	0.084[b]	0.015
Panel H.3. Controlling for the US investor sentiment and macroeconomic variables, emerging markets							
Overnight	−0.095	−0.134[c]	−0.205[c]	−0.165[b]	−0.108[c]	−0.014	0.049
Intraday	−0.265[c]	−0.321[a]	−0.396[a]	−0.398[a]	−0.313[a]	−0.283[a]	−0.210[a]
Difference (O – I)	0.170	0.187[b]	0.191[a]	0.233[a]	0.205[a]	0.269[a]	0.258[a]

Notes: This table presents results of eight robustness tests, including (i) extracting the economic sentiment index (ESI) from the CCI (Panel A), (ii) adopting a more balanced sample (Panel B), (iii) adopting a new developed/emerging market classification (Panel C), (iv) using single-period monthly returns to replace average monthly returns (Panel D), (v) controlling for the GFC (Panel E), (vi) using OECD CCIs where available (Panel F), (vii) controlling for lagged returns (Panel G), (viii) controlling for the US investor sentiment and macroeconomic variables (Panel H). In Panel A, the predictive model includes the orthogonalized CCI that is obtained by restoring the residuals from regressing the CCIs on the ESIs. In Panel F, the OECD CCIs are used for the stock markets where the data are available. In Panel H, both market CCIs and the US CCIs are included.

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

$$r_{t+1}^{i} = \alpha^{i,(1)} + \beta^{i,(1)} cci_t^i + \gamma^{i,(1)} \Psi_t^{i,(1)} + \varepsilon_{t+1}^{i,(1)} \tag{9}$$

$$\frac{1}{2}\sum_{\tau=1}^{2} r_{t+\tau}^{i} = \alpha^{i,(2)} + \beta^{i,(2)} cci_t^i + \gamma^{i,(2)} \Psi_t^{i,(2)} + \varepsilon_{t+2}^{i,(2)}$$

$$\frac{1}{3}\sum_{\tau=1}^{3} r_{t+\tau}^{i} = \alpha^{i,(3)} + \beta^{i,(3)} cci_t^i + \gamma^{i,(3)} \Psi_t^{i,(3)} + \varepsilon_{t+3}^{i,(3)}$$

$$\frac{1}{6}\sum_{\tau=1}^{6} r_{t+\tau}^{i} = \alpha^{i,(6)} + \beta^{i,(6)} cci_t^i + \gamma^{i,(6)} \Psi_t^{i,(6)} + \varepsilon_{t+6}^{i,(6)}$$

$$\frac{1}{12}\sum_{\tau=1}^{12} r_{t+\tau}^{i} = \alpha^{i,(12)} + \beta^{i,(12)} cci_t^i + \gamma^{i,(12)} \Psi_t^{i,(12)} + \varepsilon_{t+12}^{i,(12)}$$

$$\frac{1}{24}\sum_{\tau=1}^{24} r_{t+\tau}^{i} = \alpha^{i,(24)} + \beta^{i,(24)} cci_t^i + \gamma^{i,(24)} \Psi_t^{i,(24)} + \varepsilon_{t+24}^{i,(24)}$$

$$\frac{1}{36}\sum_{\tau=1}^{36} r_{t+\tau}^{i} = \alpha^{i,(36)} + \beta^{i,(36)} cci_t^i + \gamma^{i,(36)} \Psi_t^{i,(36)} + \varepsilon_{t+36}^{i,(36)}$$

Results in Table 6 report the average predictive coefficients of the investor sentiment over the subsequent 1, 2, 3, 6, 12, 24, and 36 months, showing that the impact of investor sentiment on stock market returns overnight and intraday is market-specific, which is expected due to the wide variety of the attributes of sentiment investors across markets, and offers further justification for our adoption of the global sample. A total of 22 stock markets, 11 developed and 11 emerging, show a significant difference in the sentiment-return relation across overnight and intraday, accounting for 73.33% of our sample markets, while 8 stock markets, 4 developed and 4 emerging, does not.

Table 6. Individual market results.

Developed	Overnight	Intraday	Difference (O – I)	Emerging	Overnight	Intraday	Difference (O – I)
Australia	0.087[a]	0.141	−0.054	Argentina	−0.352[a]	−0.660[a]	0.308[b]
Austria	−0.023[b]	−0.176[a]	0.153[a]	Brazil	−0.015[b]	−0.888[a]	0.873[a]
Belgium	−0.261[a]	−0.423[a]	0.161[b]	Chile	−0.059[a]	−0.345[a]	0.286[a]
Canada	0.023	0.004	0.019	China	0.024[c]	−0.315[b]	0.338[a]
France	−0.187[a]	−0.022	−0.165[a]	Croatia	0.058[b]	−0.167[a]	0.225[c]
Germany	−0.096[b]	−0.261[a]	0.166[b]	Czech Republic	−0.133[a]	0.255[a]	−0.389[a]
Ireland	−0.292[a]	−0.131[a]	−0.161	Hungary	−0.417[a]	0.639[a]	−1.055[a]
Italy	0.020[a]	−0.486[a]	0.506[a]	India	−0.301[a]	−0.224[a]	−0.077
Japan	−0.141[a]	0.012[c]	−0.153[a]	Indonesia	0.508[a]	−0.765[a]	1.273[a]
Luxembourg	0.298[a]	−0.420[a]	0.718[a]	Mexico	−0.037[b]	0.025[c]	−0.062
Netherlands	−0.096[b]	−0.325[a]	0.229[a]	Philippines	−0.044[a]	−0.012[a]	−0.032
Portugal	−0.188[a]	0.183[c]	−0.371[a]	Poland	−0.123[a]	−0.758[a]	0.635[a]
Spain	0.122[a]	−0.051	0.173[b]	South Korea	−0.047[c]	−0.215[a]	0.168[b]
Switzerland	−0.156[a]	−0.097[a]	−0.059	Taiwan	−0.436[a]	−0.110[a]	−0.327[a]
US	0.067[a]	−0.258[a]	0.324[a]	Thailand	−0.030	0.057[c]	−0.088

Notes: This table presents the regression results in each individual market based on a seven-equation system with different forecast horizons. In particular, we jointly estimate for T months ($T = 1, 2, 3, 6, 12, 24$, and 36) in a seven-equation system using the generalized method of moments (GMM) to test whether there exists a jointly significant impact of investor sentiment on stock market returns – that is, we test the form of $\beta^{i,(1)} = 0$, $\beta^{i,(2)} = 0$, $\beta^{i,(3)} = 0$, $\beta^{i,(6)} = 0$, $\beta^{i,(12)} = 0$, $\beta^{i,(24)} = 0$, and $\beta^{i,(36)}$.

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

Within the 22 stock markets exhibiting the significantly different sentiment-return relations overnight and intraday, there are two main types of the relation: The negative relation is (i) stronger (6 markets, 3 developed and 3 emerging), or (ii) weaker (16 markets, 8 developed and 8 emerging) overnight than intraday. There are 3 patterns for the first type. First, in markets including Japan, Portugal, Czech Republic, and Hungary, investor sentiment would significantly negatively affect overnight returns while positively affect intraday returns. Second, in Taiwan, there is a significantly negative sentiment-return relation both overnight and intraday and the negative impact is stronger overnight. Third, investor sentiment in France tends to negatively affect returns overnight and intraday, but it is not significant for the latter, which can be regarded as a weaker form of the second pattern.

We also note 3 patterns for the second type. First, in markets including Austria, Belgium, Germany, Netherlands, Argentina, Brazil, Chile, Poland, and South Korea, investor sentiment would bring a significantly negative impact on stock market returns both overnight and intraday, while the latter is stronger than the former, in line with our main finding at the panel level (i.e. all, developed, and emerging). Second, in markets including Italy, Luxembourg, the US, China, Croatia, and Indonesia, the sentiment-return relation varies overnight and intraday as is significantly positive overnight while significantly negative intraday, leading to a significant difference. Third, investor sentiment in Spain would affect overnight returns positively and intraday ones negatively, while the latter is insignificant, which can be viewed as a weaker form of the second pattern.

For the remaining 8 markets illustrating no significant difference in the sentiment-return relation across overnight and intraday, investor sentiment may still have an impact. In markets including Ireland, Switzerland, India, Mexico, and Philippines, investors sentiment can significantly affect both overnight and intraday returns, despite that the magnitude tends to be statistically equivalent, while in Australia and Thailand, investor sentiment can only affect overnight or intraday returns. Canada is the only exception in our sample where the sentiment-return relation is insignificant for both overnight and intraday returns.

In addition to the direction, the impact magnitude varies across markets as well. For example, the impact of investor sentiment exerts a strong impact on overnight returns in Ireland (−0.292), Hungary (−0.417), and Taiwan (−0.436), and on intraday returns in Belgium (−0.423), Brazil (−0.888), and Poland (−0.758), while a relatively weaker impact on overnight returns in Austria (−0.023) and Brazil (−0.015), and on intraday returns in Switzerland (−0.097) and Philippines (−0.012).

5. Cross-market investigation

Given the cross-market differences in the sentiment-return relation overnight and intraday as reported in Section 4, we explore possible determinants and explanations from the perspectives of cultural dimensions and market integrity in this section.

5.1. Cultural dimensions

We assess six cultural dimensions, including individualism (IDV), the uncertainty avoidance index (UAI), masculinity (MAS), the power distance index (PDI), long-term orientation (LTO), and indulgence (IDG). Since the sentiment-return relation is determined by investor rationality in trading, we base our discussion below on this focus to explore the possible influence of cultures on the sentiment-return relation, via the route of investor rationality. While the cultural framework has been widely examined in the finance literature, the six cultural dimensions are not evenly examined in the literature (Choi 2020; Wang, Su, and Duxbury 2021). Our discussion below, as a result, is based on both theoretical analyses that have been established in literature, as well as inferences drawn from the extant evidence.

5.1.1. Indicators

Prior studies distinguish between IDV and its opposite, collectivism (CLT), in the following way: Individuals in IDV cultures are more autonomous and independent, while those in CLT cultures are more connected with others (Breuer, Riesener, and Salzmann 2014; Černe, Jaklič, and Škerlavaj 2013; García-Gómez, Demir, and Díez-Esteban 2022; Gelfand et al. 2002; Heine and Lehman 1995; Markus and Kitayama 1991). Investors in IDV cultures tend to exhibit overconfidence and thus to commit cognitive biases in trading (Chui, Titman, and Wei

2010; Heine et al. 1999; Li et al. 2013), while those in CLT cultures are more likely to exhibit herding and thus to trade in concert and induce overreaction (Beckmann, Menkhoff, and Suto 2008; Markus and Kitayama 1991). Cognitive biases led by IDV and overreaction led by CLT, can potentially cause irrational trading behaviors leading to a stronger impact of investor sentiment on stock market returns.

UAI measures the extent to which individuals react to uncertainty (Bova and Vance 2019; Galariotis and Karagiannis 2021; Hofstede 2001). Investors in high UAI cultures are uncomfortable with uncertainty and thus are likely to overreact (Kwok and Tadesse 2006), but it also allows them to make more prudent and careful trading decisions ex-ante to reduce uncertainty ex-post (García-Gómez, Demir, and Díez-Esteban 2022; Nguyen and Truong 2013). Investors in low UAI cultures having a high level of risk tolerance, in contrast, are more willing to accept uncertain situations and tend not to overreact when uncertainty occurs (Chui and Kwok 2008), which may lead to rational reactions in uncertain situations but may also lead to irrational trading behaviors ex-ante.

MAS refers to the pursuit of decisiveness, assertiveness, and competitiveness, more related to males, while its opposite, femininity (FEM), represents modesty, cooperation, and caring for the weak and life quality, more related to females (Bhatta, Marshall, and Thapa 2018; Choi 2020; Hofstede 2001; Kanagaretnam, Lim, and Lobo 2011). Compared with those in high FEM cultures, on the one hand, investors in high MAS cultures are more subject to overconfidence and self-attribution (Barber and Odean 2001; Lundeberg, Fox, and Punćcohaŕ 1994) and thus would trade more irrationally, but on the other hand, overconfidence predicts excessive trading, which, although is thought to be less rational, allows more accurate ability inference that help investors to become more informed (Feng and Seasholes 2005; Nicolosi, Peng, and Zhu 2009; Seru, Shumway, and Stoffman 2010; Shu et al. 2004).

PDI reflects the extent to which subordinates expect and accept power to be unequally distributed (Dang et al. 2022; García-Gómez, Demir, and Díez-Esteban 2022; Hofstede 2001; Levis, Muradoğlu, and Vasileva 2016; Madan, Savani, and Katsikeas 2022). High PDI implies a high level of centralized control by authorities, implying stock markets to be more administered and thus irrational components may be suppressed, and not be as pronounced as in low PDI markets (Wang, Su, and Duxbury 2021). However, subordinates in high PDI markets, surrendering more authority to their superiors, are likely to expect the latter to take care of their welfare and to provide adequate protection (Chui and Kwok 2008), which may cause their excessive reliance on the superiors, and thus, less informed trading.

LTO refers to the focus of people's efforts, whether is on the future, or on the present and past (short-term orientation, STO) (Hofstede and Bond 1988). Investors in LTO cultures prefer family business and real estate, while those in STO cultures prefer stocks and mutual funds (Hofstede, Hofstede, and Minkov 2010), indicating that STO markets would observe a high level of participation of retail investors who are likely, on the one hand, to be uninformed traders (Abreu and Mendes 2020; Chang 2020; Dimpfl and Jank 2016; Grinblatt and Keloharju 2000; Kumar and Lee 2006; Lee and Swaminathan 2002; Wang, Su, and Duxbury 2021), and on the other hand, to learn by trading (Feng and Seasholes 2005; Nicolosi, Peng, and Zhu 2009; Seru, Shumway, and Stoffman 2010; Shu et al. 2004).

Finally, IDG refers to the restraints on gratification and basic human desires in relation to enjoying life (Hofstede, Hofstede, and Minkov 2010). People in high IDG cultures are more likely to enjoy life while those in low IDG (or high restraints, RES) cultures show restraints (Ortas and Gallego-Álvarez 2020), and compared with those in high IDG cultures, consumers in low IDG cultures would purchase goods only when they need (Minkov 2011), suggesting that high IDG markets, like STO markets, may have a high level of presence of retail investors who are likely to be uninformed traders but meanwhile also to learn by trading (Wang, Su, and Duxbury 2021).

A clear message conveyed by the theoretical analyses and inferences above is that each culture dimension may lead to opposing effects, i.e. that cultures at one end (high or low) can imply either rational or irrational trading behaviors. Put differently, it indicates that the relation between culture and investor rationality is not monotonic, and each cultural dimension carries two components, rational and irrational, with respect to its influence on investor rationality and trading behaviors. For example, high IDV predicts a low level of herd-led overreaction (i.e. a rational element), but meanwhile a high level of overconfidence and cognitive biases (i.e. an irrational element), while high CLT leads to a low level of overconfidence and cognitive biases (i.e. a rational element) but a high level of overreaction (i.e. an irrational element), meaning that both ends of IDV, i.e. high IDV and high CLT, can be related to rational or irrational trading. This is confirmed in prior empirical evidence:

For instance, Schmeling (2009) finds that investors in CLT markets are more irrational and hence the impact of investor sentiment on stock market returns in markets with CLT cultures is more pronounced, while Wang, Su, and Duxbury (2021) report the opposite that investors in IDV markets are more irrational, bringing stronger impact of investor sentiment on stock market returns. Therefore, instead of putting forward formal hypotheses, we shall let the empirical findings show the influence.

5.1.2. Data

We collect culture data from Hofstede's website.[14] Scores for each dimension, ranging from 0 to 100, are assigned to the 30 sample stock markets and compiled in Panel A of Table 7. Scores of our sample markets scatter widely in all the six cultural dimensions: The range (i.e. the difference between the maximum and the minimum) varies from 69 (UAI) to 83 (PDI), with an average as high as 77.167, and the standard deviation ranges from 17.365 (MAS) to 23.719 (IDV), with an average of 19.927. This is an important feature considering the discussion above that for every cultural dimension, both ends, like LTO and STO, or IDG and RES, could be linked to investor irrationality that finally leads to a stronger impact of investor sentiment on stock market returns. If scores center around one end – for example, all markets are in LTO or IDG cultures while no market is in STO or RES cultures – we might fail to reveal the influence of the other end on the sentiment-return relation and thus draw inaccurate conclusions.[15]

We compute pairwise correlations as reported in Panel B of Table 7. Overall, the correlation tends to be low and only 3 out of 15 are significant. IDV and PDI are negatively correlated (−0.621), indicating that people in collectivistic cultures are more likely to expect and accept cultures to be unevenly distributed, partly in line with Hofstede (1983) reporting a global relation that high CLT exhibits high PDI. IDG is negatively correlated with PDI (−0.353) and negatively correlated with LTO (−0.431), indicating that people in low PDI and high STO cultures are more likely to enjoy life. While some studies posit a negative relation between IDV and UAI, in that low IDV and high UAI both suggest overreaction as we explained above (Niszczota 2014; Schmeling 2009; Wang and Duxbury 2021; Zouaoui, Nouyrigat, and Beer 2011), the correlation between the two in our sample is insignificant though being negative (−0.126).

5.1.3. The impact of cultural dimensions

Our empirical model is described by the following equation,

$$\frac{1}{T}\sum_{\tau=1}^{\mathrm{T}} r_{t+\tau}^{i} = \alpha^{(T)} + \beta culture + [\gamma_0^{(T)} + \gamma_1 culture]cci_t^i + \gamma^{(T)}\Psi_t^{i,(T)} + \varepsilon_{t+1\to T}^{i,(T)} \tag{10}$$

where *culture* is a matrix of the six cultural dimensions and is time-invariant; and δ is the impact of culture on the sentiment-return relation: If γ_1 is positive (negative), an increase in cultural dimension values makes a weaker (stronger) impact of investor sentiment on stock market returns; and T is assigned 12, i.e. the subsequent one year, following Schmeling (2009) and Wang, Su, and Duxbury (2021), to check a long-term impact. Results appear in Table 8.

At the first glance, we see that cultural dimensions have a wide influence on the sentiment-return relation. To start, IDV and the sentiment-return relation are negatively related overnight while positively related intraday, meaning that high (low) IDV would make the negative sentiment-return relation stronger (weaker) overnight but weaker (stronger) intraday, and the difference is significant. The results imply that when stock markets are closed, with increases in IDV, the noise trading caused by overconfidence and cognitive biases, i.e. the irrational element of IDV, dominates the non-overreaction, i.e. the rational element of IDV, so that irrational trading would be more prevalent, leading to a stronger sentiment-return relation. By contrast, when stock markets are open, the informed trading caused by non-overreaction dominates the noise trading caused by overconfidence and cognitive biases, so that the impact of investor sentiment would be reduced. The finding concurs with our theoretical discussion that the two poles of IDV, i.e. individualism and collectivism, can be related to irrational trading behaviors, and based on our design, there is a clear cut across non-trading and trading hours. Linking the sentiment-return relation with investor rationality, it seems that in IDV cultures overnight traders are less informed than intraday traders, which implies that the two can be fundamentally different.

Table 7. Cultural dimensions and market integrity.

Market	IDV	UAI	MAS	PDI	LTO	IDG	MKI
Panel A Values							
Argentina	46	86	56	49	20	62	22.498
Australia	90	51	61	36	21	71	36.974
Austria	55	70	79	11	60	63	31.238
Belgium	75	94	54	65	82	57	32.955
Brazil	38	76	49	69	44	59	26.225
Canada	80	48	52	39	36	68	37.298
Chile	23	86	28	63	31	68	26.194
China	20	30	66	80	87	24	–
Croatia	27	80	40	73	58	33	–
Czech Republic	58	74	57	57	70	29	–
France	71	86	43	68	63	48	34.506
Germany	67	65	66	35	83	40	33.129
Hungary	80	82	88	46	58	31	–
India	48	40	56	77	51	26	26.704
Indonesia	14	48	46	78	62	38	–
Ireland	70	35	68	28	24	65	–
Italy	76	75	70	50	61	30	30.648
Japan	46	92	95	54	88	42	34.321
Luxembourg	60	70	50	40	64	56	–
Mexico	30	82	69	81	24	97	26.799
Netherlands	80	53	14	38	67	68	34.694
Philippines	32	44	64	94	27	42	25.145
Poland	60	93	64	68	38	29	–
Portugal	27	99	31	63	28	33	23.533
South Korea	18	85	39	60	100	29	28.640
Spain	51	86	42	57	48	44	31.460
Switzerland	68	58	70	34	74	66	35.986
Taiwan	17	69	45	58	93	49	31.946
Thailand	20	64	34	64	32	45	27.978
US	91	46	62	40	26	68	36.370

	IDV	UAI	MAS	PDI	LTO	IDG
Panel B Pairwise correlations: cultural dimensions						
IDV						
UAI	−0.126					
MAS	0.302	−0.080				
PDI	−0.621[a]	0.095	−0.220			
LTO	−0.126	0.105	0.085	−0.030		
IDG	0.270	−0.087	−0.037	−0.353[c]	−0.431[b]	

	ADR	GVC	ACS	EJS	ROL	ROE	RCR
Panel C Pairwise correlations: market integrity							
ADR							
GVC	−0.054						
ACS	0.113	0.344					
EJS	0.028	0.790[a]	0.422[c]				
ROL	−0.126	0.931[a]	0.311	0.742[a]			
ROE	−0.139	0.863[a]	0.388[c]	0.725[a]	0.905[a]		
RCR	−0.288	0.804[a]	0.384[c]	0.632[a]	0.876[a]	0.951[a]	

Notes: This table presents the values of cultural dimensions and market integrity (Panel A), along with the pairwise correlations (Panel B and C). 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 at https://www.hofstede-insights.com. Market integrity includes anti-director rights (ADR), government corruption (GVC), accounting standards (ACS), efficiency of judicial systems (EJS), the rule of law (ROL), risk of expropriation (ROE), and risk of contract repudiation (RCR), all sourced from La Porta et al. (1998), and as the seven variables capture different aspects of market integrity, instead of examining them separately, we use the principal component analysis (PCA) to form a composite indicator of overall market integrity capturing common information across the variables. We employ the first two PCs (explaining about 80.883% of the total variance) and construct the market integrity indicator (MKI) for each market based on available data.

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

Table 8. Cultural dimensions and market integrity: a linear influence.

	IDV	UAI	MAS	PDI	LTO	IDG	MKI
Overnight	−0.174[b]	−0.528[a]	−0.185[c]	0.154[c]	−0.123[c]	0.029	0.849[a]
Intraday	0.278[c]	0.333[c]	0.349[b]	−0.119	−0.042	−0.390[b]	1.376[c]
Difference (O – I)	−0.451[a]	−0.860[a]	−0.534[a]	0.273	−0.081	0.419[b]	−0.528[b]

Notes: This table presents the results of the influence of cultural dimensions and market integrity on the sentiment-return relation.
[a], [b], and [c] represent statistical significance at the 1%, 5%, and 10% level, respectively.

A similar, opposing influence of cultural dimensions on the sentiment-return relation is also observed for UAI and MAS. Increased UAI and MAS cultures tend to bring a negative influence on the sentiment-return relation overnight but a positive influence on the relation intraday. When stock markets are closed, the sentiment-return relation is more negative (or, stronger) in markets with high UAI and high MAS, while by contrast, when stock markets are opened, the relation becomes more negative (or, stronger) in markets with low UAI and low MAS. In markets with high UAI where people are more uncomfortable with uncertainty, as an example, overnight traders tend to overreact to market shocks, leading to uninformed trading that finally causes a stronger impact of investor sentiment, while the intraday traders are likely to make careful and rational trading decisions ex-ante to reduce potential uncertainty ex-post, resulting in an alleviated impact of investor sentiment.

While the remaining three dimensions, PDI, LTO, and IDG, do not exhibit the opposing influence overnight and intraday, they still have an impact on the sentiment-return relation, and such impact can vary across non-trading and trading hours. High PDI markets would see a weaker impact of investor sentiment overnight while on the contrary, high LTO would lead to a stronger impact overnight. The two dimensions do not hold predictability to the impact intraday and the difference between overnight and intraday is insignificant. However, the sentiment-return relation intraday would be stronger in high IDG markets and the difference is significant.

While there are a wide range of potential factors influencing the sentiment-return relation overnight and intraday, based on the results in Table 8 from the perspective of the cultural dimensions, we can understand the cultural driving forces of the presented sentiment-return relation as shown in Table 6. For instance, in the US stock market we observe a positive sentiment-return relation overnight while a negative one intraday. Checking Table 8, we note that the positive relation overnight is mainly due to low UAI and low LTO, while the negative relation intraday is mainly due to low UAI and high IDG. By contrast, there is a negative sentiment-return relation overnight but a positive on intraday in Japan, and as per Table 8, the negative relation overnight is mainly due to high UAI, high MAS, low PDI, high LTO, and the positive relation intraday is mainly due to high UAI, high MAS, low PDI, high IDG. Clearly, although there is a significant difference in the sentiment-return relation overnight and intraday in Japan, the cultural dimensions driving the relation exhibit a high level of consistency because of their opposing effects. While we find a negative sentiment-return relation both overnight and intraday in Poland, the cultural dimensions driving the negative relation are not the same: The negative relation overnight is mainly due to high IDV, high UAI, and high MAS, whereas the negative relation intraday is mainly due to high PDI.

In the analysis above, we assume a linear impact of cultural dimensions on the sentiment-return relation as in Shao, Kwok, and Guedhami (2010), Zheng et al. (2013), and An et al. (2018). In an alternative test, we adopt a median approach as in Ji et al. (2021), Wang and Duxbury (2021), and Machokoto, Gyimah, and Ibrahim (2022), which can reveal the actual sentiment-return relations for different cultures. To elucidate, we rank the 30 markets based on each of the scores of the 6 dimensions in a descending order and split them into upper (above-median) and lower (below-median) groups. The overall weak pairwise correlation, as reported in Table 7, reassures our separation based on each dimension to be unique. Regressions are run for upper and lower groups jointly, following,

$$\frac{1}{T}\sum_{\tau=1}^{\mathrm{T}} r^{i}_{t+\tau} = \alpha^{u,(T)} + \alpha^{l,(T)} + \beta^{u,(T)} cci^{u,i}_{t} + \beta^{l,(T)} cci^{l,i}_{t} + \gamma^{u,(T)} \Psi^{u,i,(T)}_{t} + \gamma^{l,(T)} \Psi^{l,i,(T)}_{t} + \varepsilon^{i,(T)}_{t+1\to T} \tag{11}$$

where $\beta^{u,(T)}$ and $\beta^{l,(T)}$ denote the impact of investor sentiment on upper and lower stock market returns, respectively; and T is also assigned 12 as above to examine the persistent impact. Note, however, that due to

Table 9. Cultural dimensions and market integrity: the actual sentiment-return relation.

	Upper layer (U)			Lower layer (L)			U – L	
	Overnight	Intraday	Difference (O – I)	Overnight	Intraday	Difference (O – I)	Difference (O)	Difference (I)
IDV	−0.176[a]	−0.239[a]	0.063	−0.114[a]	−0.320[a]	0.207[a]	−0.062[b]	0.082[c]
UAI	−0.227[a]	−0.208[a]	−0.020	−0.054	−0.357[a]	0.303[a]	−0.173[a]	0.150[a]
MAS	−0.174[a]	−0.227[a]	0.053	−0.116[b]	−0.333[a]	0.217[a]	−0.059[c]	0.106[c]
PDI	−0.130[b]	−0.348[a]	0.218[a]	−0.161[a]	−0.219[a]	0.059	0.030	−0.129[c]
LTO	−0.144[a]	−0.344[a]	0.200[a]	−0.151[a]	−0.208[a]	0.057	0.007	−0.136[b]
IDG	−0.167[a]	−0.374[a]	0.207[a]	−0.125[b]	−0.168[b]	0.043	−0.042	−0.206[a]
MKI	−0.178[a]	−0.229[a]	0.051	−0.167[a]	−0.344[a]	0.178[a]	−0.012	0.115[c]

Notes: This table presents the sentiment-return relation in upper and lower groups based on cultural dimensions and market integrity.
[a], [b], and [c] represent statistical significance at the 1%, 5%, and 10% level, respectively.

the differences in the empirical designs of the two specifications of Equations (10) and (11), we do not require the conclusions drawn from the two approaches to be identical.

The results in Table 9 are largely consistent with our discussion above. For IDV, for instance, a one-standard-deviation increase (decrease) in investor sentiment would be followed by 0.176% and 0.239% decrease (increase) in average monthly returns in high IDV markets for the following 12 months, while by 0.114% and 0.320% decrease (increase) in average monthly returns in low IDV, or high CLT, markets for the following 12 months, overnight and intraday, respectively. The difference in the impact overnight and intraday is insignificant in high IDV market (0.063) but significant in high CLT markets (0.207[a]), implying that the impact of investor sentiment on stock market returns appears to stand at a similar level across non-trading and trading hours for high IDV markets, but such impact is stronger intraday than overnight for high CLT markets. Looking across upper and lower layers, we note a significant difference in the influence of IDV on the sentiment-return relation overnight and intraday: The negative influence is significantly stronger for high IDV markets overnight (−0.062[b]), while for low IDV markets intraday (0.082[c]), which is in line with our conclusions drawn from the first linear approach above. The consistent findings are also presented for UAI and MAS – the negative influence of UAI and MAS on the impact of investor sentiment on stock market returns is stronger for high UAI and MAS markets overnight (−0.173[a] and −0.059[c], respectively), while for low UAI and MAS markets intraday (0.150[a] and 0.106[c]), along with IDG – there is no significant difference overnight, but the negative influence is stronger for high IDG markets intraday (−0.206[a]). For PDI and LTO, we reveal an insignificantly positive influence on the relation overnight but a significantly negative influence intraday, which is similar, though not exactly the same, to the findings from the first approach.

Overall, our results document that culture is an important driver for the differential patterns of sentiment-return relation worldwide, and more importantly, for the first time, we reveal that the influence of cultural dimensions is not monotonic or constant in different times of a day but varies overnight and intraday. While such different or opposing influences of cultural dimensions on the sentiment-return relation overnight and intraday appear to be counter-intuitive, we find support from prior studies. By analyzing managers' behaviors, An et al. (2018) confirm stock crash risk to be more (less) likely to happen in markets with IDV (CLT) cultures, while from the perspective of retail investor sentiment, Zouaoui, Nouyrigat, and Beer (2011) find that the probability of occurrence of stock market crises is higher (lower) in markets with CLT (IDV) cultures, suggesting that cultural dimensions, and in particular IDV/CLT, may influence individuals within a given market in different, or even opposite, ways. Likewise, Wang, Su, and Duxbury (2021), looking into retail investors, report a stronger (weaker) sentiment-return in IDV (CLT) markets, meaning that retail investors in IDV (CLT) markets tend to be less (more) rational, while Wang and Duxbury (2021) show a stronger (weaker) impact of institutional investor sentiment on the mean-variance relation in CLT (IDV) markets, drawing an opposite conclusion to Wang, Su, and Duxbury (2021) that institutional investors in IDV (CLT) markets tend to be more (less) rational. The two comparisons above seem to highlight a potentially critical role of the interaction between cultural dimensions and clienteles in the determination of financial relations, i.e. investors or managers, and retail investors or institutional investors, and the conclusions can be different or opposite when the research focuses are different. Our findings, therefore, may also be ascribed to different clienteles, i.e. overnight traders and intraday traders.

Considering the data availability and the scope of our paper, we leave detailed investigations into this to future studies.

5.2. Market integrity

A high level of market integrity improves information flow and dissemination, making markets more efficient (La Porta et al. 1998; Schmeling 2009; Wang, Su, and Duxbury 2021; Zouaoui, Nouyrigat, and Beer 2011), so the impact of investor sentiment, as a factor driving markets to be inefficient, is likely to be limited in markets with high market integrity. We consider seven market integrity variables in total, including anti-director rights (ADR), government corruption (GVC), accounting standards (ACS), efficiency of judicial systems (EJS), the rule of law (ROL), risk of expropriation (ROE), and risk of contract repudiation (RCR), all sourced from La Porta et al. (1998).[16] Scores are assigned to each factor with high (low) scores indicating high-level (low-level) market integrity. As the seven variables capture different aspects of market integrity, instead of examining them separately, we use the principal component analysis (PCA) to form a composite indicator of overall market integrity capturing common information across the variables. We employ the first two PCs (explaining about 80.883% of the total variance) and construct the market integrity indicator (MKI) for each market based on available data (see, Table 7).

While the sample is reduced to 22 markets due to data limitations,[17] it remains a representative global sample since it covers four continents and includes both developed and emerging markets. Again, we apply the two approaches as discussed above and specified in Equations (10) and (11). Results are presented in Tables 8 and 9. High MKI would reduce the negative impact of investor sentiment on stock market returns, in both non-trading and trading hours, confirming the positive role that an advanced market integrity plays in reducing market frictions and improving market efficiency, in line with the unconditional empirical evidence in Schmeling (2009) and Wang, Su, and Duxbury (2021). Despite this, the difference in the influence overnight and intraday is significant (−0.528[b]), with the latter stronger than the former. While the actual sentiment-return relation is statistically similar in non-trading hours across upper- and lower-layer markets, that in trading hours show a significant difference.

Revealing the difference in the influence of cultural dimensions and market integrity on the sentiment-return relation overnight and intraday, our results suggest that first, different types of traders in stock markets tend to trade at different times during the day (Hendershott, Livdan, and Rösch 2020; Lou, Polk, and Skouras 2019), and such difference in trader types can be surprisingly considerable in that the influence of culture and market integrity, which is deep-rooted, on their trading behaviors can be different; and second, looking into the aggregate influence of cultural dimensions and market integrity on financial markets without distinguishing different times or clienteles might be misleading, and based on this, we suggest that future studies applying the two perspectives to explain financial markets or relations need to distinguish different time periods and clienteles.

6. Some further tests

In this section, we provide some further tests on the sentiment-return relation. Those tests are suggested by anonymous referees, and we thank them for these helpful suggestions.

6.1. Different types of investor sentiment proxies

In our main analysis, we use the survey-based CCI as the proxy for investor sentiment due to its wide availability in the global stock markets. In this subsection, we examine a trade-based investor sentiment proxy, following Mai, Pukthuanthong, and Zhou (2022).[18] To begin with, we construct six individual technical indicators for each market i, including trading volume ratio (TV), price-based William's %R (WR), nearness to a recent high (NH), momentum (MOM), moving average (MA), and on-balance volume (OBV). We compute the first indicator, TV, following,

$$TV_t^i(L) = \log\left(\frac{TV_t^i}{TV_{t-(L-1)}^i}\right) \tag{12}$$

where TV_t^i is the trading volume in month t; and L refers to the lag in months. A high (low) level of $TV_t^i(L)$ suggests a high (low) level of investor sentiment. The second indicator, WR, refers to Williams' %R, following,

$$WR_t^i(L) = \frac{P^i_{max,t}(L) - P_t^i}{P^i_{max,t}(L) - P^i_{min,t}(L)} \tag{13}$$

where $P^i_{max,t}(L)$ and $P^i_{min,t}(L)$ denote the highest and the lowest stock market indices in stock market i during the months from (t–(L–1)) to t, respectively. By definition, $WRS_t^i(L)$ varies between 0 and 1 when P_t^i is equivalent to $P^i_{max,t}(L)$ and $P^i_{min,t}(L)$, respectively. A high (low) level of $WRS_t^i(L)$ indicates a low (high) level of investor sentiment, and for consistency, therefore, we adopt the negative $WRS_t^i(L)$ in our analyses. The third indicator, NH, is similar to WR, following,

$$NH_t^i(L) = \frac{P_t^i}{P^i_{max,t}(L)} \tag{14}$$

A high (low) level of $NH_t^i(L)$ suggests a high (low) level of investor sentiment. The fourth indicator, MOM, is a momentum-based indicator, following,

$$MOM_t^i(L) = \begin{cases} 1 \text{ } if \text{ } P_t^i \geq P^i_{t-(L-1)} \\ 0 \text{ } if \text{ } P_t^i < P^i_{t-(L-1)} \end{cases} \tag{15}$$

One (zero) is assigned to $MOM_t^i(L)$ if the market index in month t is above (below) that in month (L–1), denoting a high (low) level of investor sentiment. The above four indicators all have a lag parameter L, and like Mai, Pukthuanthong, and Zhou (2022), we assign several values to L, including 5, 10, 20, 50, and 100, and therefore, each of the four indicators has five sub-indicators. The fifth indicator is MA based on the moving average rule, following,

$$MA_t^i(s, l) = \begin{cases} 1 \text{ } if \text{ } MA^i_{s,t} \geq MA^i_{l,t} \\ 0 \text{ } if \text{ } MA^i_{s,t} < MA^i_{l,t} \end{cases} \tag{16}$$

where $MA^i_{s,t}$ and $MA^i_{l,t}$ denote the moving average of the market index from month (s–1) and (l–1) to month t, respectively. We choose 10 and 20 for s to represent the short-period trend, while 50 and 100 for l to represent the long-period trend, and there are four sub-indicators for MA as a result. One (zero) is assigned to $MAS_t^i(s, l)$ if the short-period moving average is above (below) the long-period moving average, indicating a high (low) level of investor sentiment. And the sixth indictor, OBV, considers both market indices and trading volume, and we first define,

$$V_t^i = \sum_{k=1}^{t} TV_k^i D_k^i \tag{17}$$

where TV_k^i is the trading volume in month k, and D_k^i is one (minus one) if $P_k^i \geq P^i_{k-1}$ ($P_k^i < P^i_{k-1}$). We then compute the short-term moving average and the long-term moving average following $MA^{V,i}_{s,t} = \frac{1}{s}\sum_{k=0}^{s-1} V^i_{t-k}$ and $MA^{V,i}_{l,\,t} = \frac{1}{l}\sum_{k=0}^{l-1} V^i_{t-k}$, respectively. And we finally have,

$$OBV_t^i(s, l) = \begin{cases} 1 \text{ } if \text{ } MA^{V,i}_{s,t} \geq MA^{V,i}_{l,t} \\ 0 \text{ } if \text{ } MA^{V,i}_{s,t} < MA^{V,i}_{l,t} \end{cases} \tag{18}$$

We also adopt 10 and 20 for s while 50 and 100 for l, and hence we have four sub-indicators for OBV. Accordingly, one (zero) is assigned to $OBV_t^i(s, l)$ if the short-period moving average is above (below) the long-period moving

Table 10. Trade-based investor sentiment.

Months	1	2	3	6	12	24	36
Panel A. All markets							
Overnight	−0.022	−0.058	−0.126[a]	−0.091[a]	−0.046[b]	−0.033	0.017
$\Delta adj.\ R^2$	0.00	0.00	0.01	0.02	0.03	0.01	0.00
Intraday	−0.040	−0.093	−0.166[a]	−0.174[a]	−0.164[a]	−0.226[a]	−0.194[a]
$\Delta adj.\ R^2$	0.00	0.00	0.02	0.04	0.04	0.04	0.03
Difference (O – I)	0.018	0.034	0.039	0.082	0.118[a]	0.193[a]	0.211[a]
Panel B. Developed markets							
Overnight	−0.025	−0.055	−0.112[b]	−0.095[b]	−0.055[c]	−0.048[c]	0.022
$\Delta adj.\ R^2$	0.00	0.00	0.02	0.02	0.02	0.01	0.00
Intraday	−0.038	−0.088	−0.148[a]	−0.189[a]	−0.236[a]	−0.305[a]	−0.265[a]
$\Delta adj.\ R^2$	0.00	0.00	0.02	0.03	0.05	0.06	0.06
Difference (O – I)	0.014	0.034	0.037	0.094[b]	0.180[a]	0.257[a]	0.287[a]
Panel C. Emerging markets							
Overnight	−0.013	−0.062	−0.147[a]	−0.085[a]	−0.033	−0.005	−0.002
$\Delta adj.\ R^2$	0.00	0.00	0.02	0.02	0.01	0.00	0.00
Intraday	−0.055	−0.105[b]	−0.209[a]	−0.152[c]	−0.109[b]	−0.113[a]	−0.082[b]
$\Delta adj.\ R^2$	0.00	0.01	0.02	0.02	0.02	0.03	0.03
Difference (O – I)	0.041	0.043	0.062[c]	0.068[c]	0.075[c]	0.107[b]	0.080[c]

Notes: This table presents the panel regression results of using the composite trade-based investor sentiment proxy. The composite proxy extracts the common information from 28 sub-indicators from six individual technical indicators, including trading volume ratio (TV), price-based William's %*R* (WR), nearness to a recent high (NH), momentum (MOM), moving average (MA), and on-balance volume (OBV), via the principal component analysis (PCA).

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

average, suggesting a high (low) level of investor sentiment. We in total have 28 sub-indicators from the six individual investor sentiment indicators, and then, we employ the PCA to extract the common variation from the 28 sub-indicators and use the composite index as the trade-based proxy for investor sentiment. Results appear in Table 10.

Our principal findings from the main tests are largely supported here. Investor sentiment significantly affects stock market returns in the subsequent 3 to 12 months overnight and 3 to 36 months intraday for global markets, 3 to 24 months overnight and 3 to 36 months intraday for developed markets, and 3 to 6 months overnight and 2 to 36 months intraday for emerging markets. The impact is stronger intraday than overnight, from the subsequent 12 to 36 months, 6 to 36 months, and 3 to 36 months for all, developed, and emerging markets, respectively. Comparing the relations between developed and emerging markets, we still find that the impact is more persistent in the former, mainly for overnight (up to 24 months in the former compared with 6 months in the latter), while more prompt in the latter, mainly for intraday (from 2 months in the latter compared with 3 months in the former). This, therefore, provides us with confidence to confirm that the presented impact of investor sentiment on stock market returns is not due to the selected proxy, but investor sentiment per se.

For global and emerging markets, the CCI can affect stock market returns in a wider range of forecast horizons than the trade-based composite measure, while for developed markets, the return predictability of the composite measure appears to be stronger in the short term but not so in the long term. This is also confirmed by the incremental change in adjusted R^2s due to the addition of the two investor sentiment types. It is, therefore, less clear in terms of which investor sentiment proxy, the survey-based CCI or the trade-based composite measure, unconditionally performs better in return predictability, and at least from our results, it seems that the market development may play a role. Despite this, it does not necessarily mean that the trade-based composite proxy is inferior to the survey-based proxy in return predictability in the context of all and emerging markets, as return predictability, as exhibited in our results, is subject to the sample markets. For the future research, as the trade-based proxy proposed by Mai, Pukthuanthong, and Zhou (2022) is constructed by using only the market index and trading volume, it can be widely employed for global stock markets especially in those where the survey-based proxies, like the CCI, are unavailable. Also, the trade-based composite proxy provides great flexibility as it can be used for both markets and firms,[19] as well as for different intervals.

In addition to the trade-based investor sentiment proxies, some studies also adopt text-based proxies. Based on the US stock market, for example, Mai, Pukthuanthong, and Zhou (2022) compare the return predictability of the trade-based and the text-based investor sentiment measures, documenting that the former outperforms the latter. Due to data availability and subscription, we, however, are unable to obtain such a proxy for our global study with a total of 30 stock markets.[20] Another crucial consideration is the global applicability and suitability of the established text-based proxies. Here, we give three specific examples.

First, Mai, Pukthuanthong, and Zhou (2022) adopt the Refinitiv MarketPsych Indices (RMI) that were constructed only based on English-language texts before February 2020. In other words, in our sample periods up to December 2018, only English texts were included for RMI construction, suggesting that RMI might not be a suitable measure for our global study with most of the sample markets not using English as the first or official language. While 'the most critical' news are also often published in English and 'informed traders' likely post news in English (Mai, Pukthuanthong, and Zhou 2022, 7), it might still cause selection biases in non-English speaking sample markets, especially in the emerging ones where investors are more likely to be *uninformed* and hence, to react to *less critical* news or even noise (Morck, Yeung, and Yu 2000), calling the representativeness of the selected sample used for RMI construction into question.

Second, Financial and Economic Attitudes Revealed by Search (FEARS) using Google Search Volume Index (SVI) data has been confirmed to be an excellent investor sentiment proxy in the US stock market (Da, Engelberg, and Gao 2015); however, Google's share of search traffic is in excess of 80% in the US but is also below 10% in China,[21] a key emerging stock market in a global study (see, also, Wang, Su, and Duxbury 2022). In addition, the words reflecting investor sentiment, i.e. optimism and pessimism, may vary across markets, and a valid cross-market, or global, benchmark appears to be missing at the moment. For example, the commonly used dictionary in the text analytics literature in finance is Harvard IV-4 Dictionary but it is primarily used in the US market (Da, Engelberg, and Gao 2015; Price et al. 2012; Tetlock 2007; Tetlock, Saar-Tsechansky, and Macskassy 2008), rather than other markets, especially the emerging ones. In addition, Loughran and McDonald (2011) cast doubt on the use of the Harvard Dictionary, since 73.8%, nearly three-fourths, of the negative words as per the Harvard list are attributable to words that are normally not negative in a financial context.

Third, Renault (2017) constructs investor sentiment proxies based on messages published on the social media platform StockTwits (see, also, Karampatsas et al. 2023). Traffic to stocktwits.com by country shows the US leads the way with 69.18% of traffic, with Canada (7.12%) and Germany (2.98%) a distant second and third, respectively,[22] implying that StockTwits might not be a well representative investor sentiment indicator in the non-US stock markets.

6.2. Out-of-sample predictability

In this subsection, we extend our tests to the out-of-sample predictability. Since we show from the main analyses that the impact of investor sentiment on stock market returns is stronger intraday than overnight, here we check if investor sentiment also holds stronger out-of-sample predictability to intraday returns than overnight returns.[23]

As reported in Table 1, developed stock markets usually have longer sample periods than emerging counterparts, so to avoid the results of the initial estimation period to be dominantly driven by the former, we separately investigate the two types of markets. The issue may also appear within developed or emerging stock markets, so we apply the same dataset as we do in Panel B of Table 5, i.e. January 2000 for developed stock markets and January 2006 for emerging ones, given that a more balanced dataset as employed in Panel B of Table 5 generates similar results with the full dataset. Finally, to ensure our forecast evaluation period to have a relatively large proportion of the entire available sample (Hansen and Timmermann 2012; Rossi and Inoue 2012), we use data from January 2000 to December 2007 and from January 2006 to December 2010 for developed and emerging stock markets, respectively. Accordingly, the forecast evaluation period spans from January 2008 to December 2018 and from January 2011 to December 2018 for developed and emerging stock markets, respectively. Results in Table 11 present the mean absolute percentage errors (MAPEs), and we observe that the MAPEs are lower in intraday than overnight, suggesting a stronger out-of-sample predictability of investor sentiment to stock market returns intraday than overnight, confirming our previous in-sample results.

Table 11. Out-of-sample tests.

Months	1	2	3	6	12	24	36
Panel A. Developed markets							
Overnight	7.412	8.789	9.620	7.700	6.161	5.945	4.504
Intraday	3.241	3.538	3.326	4.084	3.965	3.694	3.332
Panel B. Emerging markets							
Overnight	8.113	7.329	4.651	9.971	10.085	9.410	9.135
Intraday	2.097	2.090	2.146	2.059	2.529	3.294	2.158

Notes: This table presents the mean absolute percentage errors (MAPEs) from the out-of-sample tests. For developed and emerging stock markets, the starting months are January 2000 and January 2006, respectively. To ensure our forecast evaluation period to have a relatively large proportion of the entire available sample (Hansen and Timmermann 2012; Rossi and Inoue 2012), we use data from January 2000 to December 2007 and from January 2006 to December 2010 for developed and emerging stock markets, respectively. Accordingly, the forecast evaluation period spans from January 2008 to December 2018 and from January 2011 to December 2018 for developed and emerging stock markets, respectively.

Table 12. Daily data.

Months	1	2	3	4	5
Panel A. All markets					
Overnight	0.001	0.001	0.001	0.006	0.006
Intraday	−0.018[a]	−0.014[a]	−0.013[a]	−0.009[a]	−0.008[a]
Difference (O – I)	0.019[a]	0.014	0.013	0.015[a]	0.014[a]
Panel B. Developed markets					
Overnight	0.013	0.005	0.003	0.007	0.006
Intraday	−0.017[a]	−0.013[a]	−0.013[a]	−0.009[b]	−0.008[b]
Difference (O – I)	0.030[a]	0.017[b]	0.016[b]	0.016[a]	0.013[b]
Panel C. Emerging markets					
Overnight	−0.017[a]	−0.006	−0.003	0.005	0.006
Intraday	−0.021[a]	−0.016[a]	−0.012[a]	−0.007[a]	−0.007[a]
Difference (O – I)	0.004	0.009	0.009	0.012[c]	0.014[b]

Notes: This table presents the panel regression results at the daily interval. Investor sentiment is proxied by the composite trade-based investor sentiment measure. We control for lagged market returns (up to five lags), the detrended short-term interest rate, and dividend yield, and following Da, Engelberg, and Gao (2015), we test the impact of investor sentiment on stock market returns from day $(t + 1)$ to $(t + 5)$.

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

6.3. Daily data

In our main analyses, we emphasize the impact of investor sentiment on stock market returns in the long run from the subsequent 1 to 36 months. Some studies also use daily data and examine the sentiment-return relation in the short run (e.g. Da, Engelberg, and Gao 2015; Mai, Pukthuanthong, and Zhou 2022; Obaid and Pukthuanthong 2022). Here, we test the short-run impact of investor sentiment by employing daily data, and we adopt the composite trade-based investor sentiment proxy, as explained in Subsection 6.1, but construct it at the daily interval as Mai, Pukthuanthong, and Zhou (2022).

Slightly different from Equation (7) that is designed for the monthly interval as we run in the main analyses, for the daily interval regression we control for lagged market returns (up to five lags), the detrended short-term interest rate, and dividend yield, and following Da, Engelberg, and Gao (2015), we test the impact of investor sentiment on stock market returns from day $(t + 1)$ to $(t + 5)$.

Results reported in Table 12 reveal that at the global level, there is a negative sentiment-return relation intraday, from the subsequent first to the fifth days, but not overnight. The difference in the impact between overnight and intraday is significant on the first, the fourth, and the fifth days, supporting our conclusions drawn from the monthly tests that overnight traders tend to be more rational than the intraday counterparts and hence, one would observe a stronger impact of investor sentiment intraday than overnight. The sentiment-return relation in developed and emerging markets is similar to that at the global level. In developed markets, there is a negative impact from the first to the fifth days, but no impact overnight, while in emerging markets, the negative impact is present from the first to the fifth days intraday, and on the first day overnight. The difference in the impact overnight and intraday is significant from the first to the fifth days and from the fourth to the fifth days in developed and emerging markets, respectively.

Our results are in line with a number of prior studies. Da, Engelberg, and Gao (2015) document a positive relation between FEARS and stock market returns. As FEARS is an inverse measure of investor sentiment, a positive FEARS-return relation signifies a negative sentiment-return relation, supporting our results. Likewise, Obaid and Pukthuanthong (2022) report a positive pessimism-return relation by adopting photo pessimism sourced from the Wall Street Journal and Getty Images, also in line with our results. More recently, Mai, Pukthuanthong, and Zhou (2022) employ both trade-based and text-based investor sentiment measures, evidencing a negative sentiment-return relation, as shown in our results. In addition to the consistency, for the first time, we reveal that the negative sentiment-return relation is mainly driven by intraday, which appears to be different from our main results derived from the monthly data that the negative sentiment-return relation is jointly driven by intraday and overnight. Moreover, the forecast horizon in developed markets shown in Table 12 is comparable with that in the US stock market as presented in Da, Engelberg, and Gao (2015), Obaid and Pukthuanthong (2022), and Mai, Pukthuanthong, and Zhou (2022): In the US stock market, the negative sentiment-return relation is significant on the first and the second days in Da, Engelberg, and Gao (2015), on the first, the second, and the fifth days in Obaid and Pukthuanthong (2022), and at least the first five days in Mai, Pukthuanthong, and Zhou (2022), while in the developed markets as examined in our paper, the relation is significant for at least the first five days as well.

7. Conclusion

In this paper, we examine the sentiment-return relation overnight and intraday based on 30 global stock markets. Empirical evidence reveals a negative sentiment-return for the subsequent 2 to 36 months at the global level both overnight and intraday, and more importantly, we note that the impact is significantly stronger intraday than overnight for the subsequent 2 to 36 months, suggesting that the widely documented negative sentiment-return relation is mainly driven by intraday traders. A similar pattern is also shown for developed and emerging markets when the two market types are assessed separately, but meanwhile we report that the impact tends to be more immediate in emerging markets (the subsequent 2 to 12 months for overnight returns and the subsequent 1 to 36 months for intraday returns), while more persistent in developed markets (the subsequent 6 to 36 months for overnight and intraday returns). These findings are robust to a series of alternative empirical designs and specifications. The confirmation of the negative sentiment-return relation in non-trading and trading hours reaffirms investor sentiment as a contrarian factor in predicting stock market returns. Then we investigate individual stock markets and reveal that the sentiment-return relation varies across markets in terms of both influence direction and magnitude, again, across overnight and intraday, indicating that the impact of investor sentiment on stock market returns is market-specific.

To the extent that differences are revealed, we conduct cross-market analyses to explore the driving forces of divergences in the impact of investor sentiment from the perspectives of cultural dimensions and market integrity. Evidence reveals that both two perspectives induce heterogeneity in the sentiment-return relation, and more importantly, we, for the first time, report that the influence can vary across non-trading and trading hours. The implications of our results are twofold. First, different types of traders in stock markets tend to trade at different times during the day (Hendershott, Livdan, and Rösch 2020; Lou, Polk, and Skouras 2019), and such difference in trader types can be surprisingly considerable in that the influence of culture and market integrity, which is deep-rooted, on their trading behaviors can be different, or even opposite. Second, the impact of cultural dimensions and market integrity on financial relations could be more complex than we used to theorize, and consequently, looking into the aggregate influence of the two aspects on financial markets without distinguishing different times or clienteles might be misleading, and based on this, we call for that future studies applying the two perspectives to explain financial markets or relations need to distinguish different time periods within each trading day and clienteles.

In the end, we conduct three further analyses, evidencing that (i) the sentiment-return relation largely holds when investor sentiment is measured by a trade-based composite proxy, and its return predictability is comparable with the survey-based CCI; (ii) our finding that investor sentiment affects the intraday stock market returns more than the overnight ones is supported by the out-of-sample tests; and (iii) the negative sentiment-return relation is also present when regressions are run at the daily interval.

Notes

1. See, Lou, Polk, and Skouras (2019), for details about the rationale behind the decomposition.
2. Measuring the persistence of intraday and overnight returns, Lou, Polk, and Skouras (2019, 195) further highlight that the decomposition seems to be '*natural*'.
3. Aboody et al. (2018) accumulate weekly overnight returns as the average daily overnight returns for that week multiplied by 5, i.e. an average approach. Wang (2021) accumulates monthly overnight returns as the average daily overnight multiplied by the actual number of trading days of that month, i.e. a sum approach. Using the two approaches generates qualitatively consistent results with our main multiplication approach as specified in Equations (3) and (4).
4. Some surveys, such as Directorate General for Economic and Financial Affairs in many European markets, apply '0' as the neutral value, i.e. that a positive (negative) value suggests investors' optimism (pessimism). Some surveys, such as National Bureau of Statistics in China, apply '100' as the neutral value, while in trivial cases, such as Refinitiv/Ipsos in Canada, '50' is used as the neutral value.
5. See, Schmeling (2009), for details about employing the moving-block bootstrap to address the issue associated with the highly persistent time series.
6. See, Appendix C of Schmeling (2009) for detailed discussion on the bias adjustments.
7. Using other block lengths, including 6, 10, and 12, does not affect our results.
8. For the tests of individual markets, we also employ the Newey and West (1987) standard errors with different truncation parameters, such as T–1, $1.3T^{1/2}$, and $T^{1/3}$ (see, e.g. Kostakis, Magdalinos, and Stamatogiannis 2015; Lazarus et al. 2018), does not affect our results. This approach is also widely seen in this literature, such as Brown and Cliff (2004) and more recently Kaivanto and Zhang (2023). We thank one anonymous referee for this suggestion.
9. In addition to investor sentiment, some other factors can explain the different patterns of overnight and intraday returns, like the institutional factors in Bogousslavsky (2021). Unfortunately, we are unable to extend the investigation to the global sample due to data availability, and hence, we acknowledge this as a potential caveat in our paper.
10. The reduced sample includes Australia, Austria, Belgium, China, Croatia, Czech Republic, France, Germany, Hungary, Italy, Japan, Luxembourg, Netherlands, Poland, Portugal, South Korea, Spain, Thailand, and the US. Examples of the ESI include the Economic Sentiment Indicator reported by the DG ECFIN for all European markets and the Purchasing Manager Index reported by Institute for Supply Management for the US (Bathia and Bredin 2013; Koutmos et al. 2018; Keiber and Samyschew 2019; Ibhagui 2021; McMillan 2021; Wang, Su, and Duxbury 2021; Clerides et al. 2022; Kaivanto and Zhang 2023).
11. OECD CCIs are sourced from Refinitiv and available for 24 stock markets in our sample, including Australia, Austria, Belgium, Brazil, Canada, Chile, China, Czech Republic, France, Germany, Hungary, Indonesia, Ireland, Italy, Japan, Luxembourg, Mexico, Netherlands, Poland, Portugal, South Korea, Spain, Switzerland, and the US. The following two points worth noting here. First, Canada OECD CCI data are available until December 2017, so we treat the period from January 2018 to December 2018 as missing. Second, Indonesia OECD CCI data are available from December 2010, so we treat the period from June 2005 to November 2010 as missing.
12. We adopt different return lags from 1 to 3, as well as the combination of lags 1 and 2, and lags 1, 2, and 3. Panel G of Table 5 reports results from lags 1, 2, and 3. Different specifications generate qualitatively similar results.
13. Accordingly, we remove the US from our test, making the number of all and developed markets of 29 and 14, respectively.
14. We are grateful to Prof. Geert Hofstede for making the data available at https://www.hofstede-insights.com.
15. As discussed above, Schmeling (2009) reveals that irrational trading is more related to CLT cultures due to overreaction while Wang, Su, and Duxbury (2021) report the opposite that irrational trading is more linked to IDV cultures due to overconfidence. Noting the contradictory conclusions, Wang, Su, and Duxbury (2021) conjecture that it could be due to their enlarged sample including both developed and emerging stock markets, compared with Schmeling's (2009) developed markets, significantly extending the IDV scale. This confirms the importance of having extended cultural dimension scales, as embodied in our sample.
16. For the recent adoption of the data in La Porta et al. (1998), see, Bilinski, Lyssimachou, and Walker (2013), Ahern, Daminelli, and Fracassi (2015), Scharfstein (2018), and Wang and Duxbury (2021).
17. Some markets do not have all the seven indicators, so we remove them due to the PCA process.
18. We convert all daily frequency computations in Mai, Pukthuanthong, and Zhou (2022) to monthly.
19. While earlier studies of investor sentiment mainly examine the market-level, or market-wide, investor sentiment, the role of firm-level, or firm-specific, investor sentiment grabs attention in more recent studies (see, e.g. Karampatsas et al. 2023; Guo, Yin, and Zeng 2023).
20. We acknowledge this as a limitation of our paper and leave it to future studies.
21. https://www.statista.com/statistics/220534/googles-share-of-search-market-in-selected-countries, accessed on 9 May 2023.
22. https://www.similarweb.com/website/stocktwits.com/#overview, accessed on 9 April 2023.
23. See, Clark and West (2007), Campbell and Thompson (2008), Welch and Goyal (2008), and Huang et al. (2015) for the benefits of out-of-sample tests.

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No potential conflict of interest was reported by the author(s).

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