Doctoral Dissertation

Sentiment-return relationship and moderating effect of country-specific factors

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Abstract

Besides the introduction and conclusion, this dissertation, using data of Asian and European markets, encompasses three main chapters that investigate the relationship between investor sentiment and stock returns and determine which and how the local characteristics affect this inference. Below are the individual abstract for each chapter:

Chapter 2: Effect of investors' confidence and fear on stock returns: The case of Asia-Pacific developed markets

Employing data from Australia, Hong Kong, and Japan over the period between January 2004 to December 2017, this chapter focuses on the relationship between investor sentiment and stock returns. I analyze two reversed sentiment indicators: consumer confidence index (*CCI*) and volatility index (*VIX*), in two conversing situations: low and high sentiment. The results imply that sentiment has a significant link with concurrent returns, but its influence seems to wipe out quickly as the little to no return predictability is detected. More importantly, I find that "investor fear gauge" (*VIX*) generates a more significant contemporaneous effect on market returns than investor confidence. The impact on future returns, on the contrary, is inconclusive since low *CCI* and *VIX* dominate the opposite ones most of the time.

Chapter 3: Impact of financial development on sentiment-return relationship: Insight from Asia-Pacific markets

Using investor sentiment created from the first principal component of consumer confidence index, advance/decline ratio, and volatility premium, I examine the potential return predictability of investor sentiment in six Asia-Pacific markets between January 2004 and December 2016. The empirical evidence proves that market sentiment could be a valid forecaster of stock returns in short-term horizons. Additionally, by decomposing total sentiment in each market into regional and local indices, I discover that the market-level outcomes are driven mostly by local sentiment. More importantly, this study detects that financial development differences across markets significantly influence the sentiment-return relationship.

Chapter 4: Moderating effect of market-specific factors in the return predictability of investor sentiment

Chapter 4 explores the relationship between investor sentiment and future returns using data from twelve Asian and European markets from 2004 to 2016. The results suggest that sentiment could be a contrarian predictor of market returns across different horizons. Moreover, this study primarily reveals an essential role of local factors in the sentiment-return diversifications among individual and regional markets. I find that the moderating effect of market-specific characteristics is time-varying and different between Asian and European areas. As a result, sentiment has a more immediate impact in Europe but a more long-lasting one in Asia.

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Chapter 1

Introduction

Behavioral finance is the research area where psychology is applied to financial models to explain market anomalies, according to Shiller (2003). It focuses on investor behaviors and their impact on stock markets under the viewpoint of a psychologist. The foundation of behavioral finance shed light on the birth of lots of new concepts. One of them, i.e., investor sentiment, has become a trendy topic in behavioral studies recently.

Investor sentiment can be defined as investor opinion, usually influenced by emotion, about future cash flows and investment risk (Corredor et al., 2013). Until now, a great number of sentiment research have been carried out with the primary purpose is to analyze how sentiment affects stock markets (Barberis et al., 1998) and other economic activities (Cheong et al., 2017). Among related themes, scientists have enormously tried to verify the role of sentiment to explain abnormal stock returns. However, the findings are inconclusive as some studies claim a significant relationship between investor sentiment and stock returns (Fisher and Statman, 2003; Edmans et al., 2007; Bathia and Bredin, 2013; Huang et al., 2015; Cheema et al., 2020; Gao et al., 2020). Conversely, others prove that sentiment has little to no return predictability, such as Brown and Cliff (2004), Oprea and Brad (2014), Kim and Park (2015), and Lansing and Tubbs (2018).

Such results, which are diverse considerably between countries, inspire researchers to determine the causes behind them. Besides stock characteristics proposed by Lee et al. (1991), Baker and Wurgler (2006), Berger and Turtle (2012), Zhu and Niu (2016), and Ding et al. (2019), institutional quality and cultural factors are suggested as potential determinants of the variation in sentiment-return relation. According to several previous studies, the question about the role of these country-specific factors originates from the fact that market quality might affect the market outcome. Rajan and Zingales (1998) proved that countries with better developed financial systems show superior growth in capital-extensive sectors that rely heavily on external finance. Porta et al. (1998) found the link between the legal system and economic development. The evidence from Chiou et al. (2010) also suggested that the legal environment affects performance and risk premiums. In another view, Chui et al. (2010) stated that cultural differences across countries might be a component of behavioral bias. Following these issues, several sentiment findings relating to the divergences between countries all over the world have been reported, including Schmeling (2009), Chang et al. (2011), and Corredor et al. (2013, 2015). However, compared to the role of stock fundamentals, which is widely testified, few studies are about the impact of country-specific factors. Notably, such studies remain narrow in focus dealing only with countries having an equivalent level of growth (Schmeling, 2009; Corredor et al., 2013), which might rule out the role of financial development. They also choose countries having similar characteristics (Corredor et al., 2015), which makes it difficult to detect "country-only" effects or just study some aspects of governance and cultural dimensions (Schmeling, 2009; Chang et al., 2011).

In addition to that, the choice of sentiment proxy is also a strong justification for various sentiment intensity across markets. Plentiful measurements have been applied in prior studies, from direct indicators, for example, investor survey (Solt and Statman, 1988; Grigaliūnienė and Cibulskienė, 2010; Oprea and Brad, 2014), option implied volatility index (Smales, 2017; Qadan et al., 2019) to indirect ones, including trading volume (Pan and Poteshman, 2006), closed-end fund discount (Gizelis and Chowdhury, 2016), and price-earnings ratio (Cheema et al., 2020). Nonetheless, there is no clear evidence on which is the ideal proxy.

Finally, Kim and Nofsinger (2008) stated that "*Asia is an interesting place to study behavioral finance because of the different levels of capitalism and financial market experience of its participants*." Moreover, since Asian stock markets have become more attractive to investors over past decades, as reported by Organization for Economic Cooperation and Development (OECD) in 2019, knowing how investor behaviors affect these markets' activities is inevitable. Nonetheless, compared to the U.S. and European markets, there is less investigation about sentiment-return inference in Asian ones.

These research limitations above motivate me to implement a comprehensive study on the association between sentiment and stock returns, concentrating on the

Asian region. Overall, my dissertation has several significant contributions to financial literacy. By employing data from Asian stock markets, I provide out-of-sample tests for the findings about sentiment-return nexus in the U.S. and Europe. Additionally, each Asian market's total sentiment is separated into regional and local components to testify whether the sentiment effect is mainly internal or external. I also compare the results for markets in Asia and Europe to verify that sentiment intensity is different across markets and regions that have never been done before. Secondly, my research discloses which proxy is better to capture the impact of market sentiment for my studied countries. This detection arises by employing variant sentiment indicators, from consumer confidence index, volatility index to a composite index combining explicit and implicit proxies. In the end, by expanding to fourteen country-specific factors, the moderating role of local characteristics in the return predictability of sentiment is also investigated and detected comprehensively. Especially, to the best of my knowledge, this dissertation is the first to assess the potential influence of financial development on sentiment-return nexus and differentiate the domestic effects between Asian and European markets to reveal which region is more vulnerable.

The dissertation proceeds as follows. The next three chapters are the core content, where I present my findings from three independent studies. These chapters address different research questions and share the unique purpose of providing a clearer picture of the sentiment role in stock markets. The conclusions for my research are summarized in the last part.

Chapter 2

Effect of investors' confidence and fear on stock returns: The case of Asia-Pacific developed markets

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2.1. Introduction

In recent decades, researchers have questioned the validity of the market efficiency theory base on the observations of so-called "*anomalies*." Tversky and Kahneman (1986) viewed market anomalies as "*deviation from the presently accepted paradigms that is too widespread to be ignored, too systematic to be dismissed as random error, and too fundamental to be accommodated by relaxing the normative system*." The existence of anomalies required the financial market to be considered in a broader perspective. They motivated academics to look to cognitive psychology to make up the irrational and illogical behaviors that modern finance had failed to explain. This inspiration laid the foundation for the birth of behavioral economics.

According to behavioral theory, investor sentiment has been proved in many studies to explain abnormal stock returns, besides traditional factors. Early empirical research, conducted mainly in U.S. stock markets, presented a vital link between investor sentiment and stock returns. For example, Fisher and Statman (2003) reported that low returns generally follow high consumer confidence. In Brown and Cliff's (2005) paper, market pricing errors implied by an independent valuation model are positively related to sentiment. Future returns over multiyear horizons are negatively associated with the sentiment.

Regarding other advanced markets, Ishijima et al. (2015) found that the sentiment index significantly predicts Tokyo Stock Exchange prices three days in advance. Finter et al. (2012) showed that their sentiment indicator explains the return spread between sentiment stocks and stocks that are not sensitive to sentiment fluctuations. Globally, Baker et al. (2012) investigated six major stock markets and documented that global and local sentiment are contrarian predictors of the time-series of cross-sectional returns within markets. The studies on 18 developed markets of Schmeling (2009) and G7 markets of Bathia and Bredin (2013) also provided the same results.

In respect of emerging markets, Corredor et al. (2015) showed that sentiment is a critical variable in the prices of stocks traded in three Central European countries: the Czech Republic, Hungary, and Poland, and has a more substantial impact here than in more developed European ones. Using panel regression with firm fixed effects, Anusakumar et al. (2017) also detected that stock-specific sentiment strongly and positively affects stock returns after controlling for firm characteristics in eight emerging Asian countries. Previously, Chi et al. (2012) examined Chinese stock markets only and found that investor sentiment has a tremendous impact on stock returns.

However, compared to U.S. and European countries, there is less research on behavioral finance in Asia. Though "*Asian financial markets are among the largest in the world, and there is some evidence – anecdotal, theoretical, and empirical – that Asians suffer from cognitive biases on a different level than people of other cultures…*" as stated in Kim and Nofsinger (2008). As an illustration, a cross-cultural research into the optimistic and pessimistic bias of Chang and Asakawa (2003) indicated that European Americans hold a bullish bias in predicting positive and negative events. Conversely, the Japanese hold a pessimistic bias for adverse events. Chen et al. (2007) found that Chinese investors suffer from three behavioral biases: (i) they tend to sell stocks that have been appreciated at a price; (ii) they seem overconfident; and (iii) they appear to believe that past returns are indicative of future returns. Compared to prior findings, Chinese investors seem more overconfident than U.S. investors, and their disposition effect appears firmer. Recently, Yiend et al. (2019) confirmed that Hong Kong residents are more positively biased than people living in the U.K., consistent with the lower prevalence of psychological disorders in East Asia. These reasons inspire me to study the relationship between investor sentiment and stock returns, focusing on Asia-Pacific developed markets.

My research contributes to financial literacy in several ways. First, I discover whether investor sentiment affects market returns or not, and in what direction. In detail, by employing data from Asia-Pacific markets, this research provides an out-of-sample test for previous outcomes in the U.S. and European countries. More fundamentally, the diversion in sentiment intensity is detected based on two steps. Firstly, I utilize two reversed sentiment indicators: the consumer confidence index (*CCI*) and the volatility index (*VIX*). The next stage is applying these measures in two contrary scenarios: extreme low and high sentiment. I find out that there is a significantly contemporaneous relationship between sentiment indicators and market returns. In addition to that, as expected, the "investor fear gauge" represented by *VIX* proves a more substantial and opposite impact on concurrent returns than *CCI* computed by "investor confidence." However, though it could be enhanced slightly in extreme situations, the predictive power of *CCI* and *VIX* seems to be non-existence, except for long-term periods in Hong Kong.

The chapter is organized as follows. In Section 2.2, I present previous empirical literature and construct testing hypotheses. The next section introduces the data used and the methodology applied to investigate the relationship between investor sentiment and market returns. Results are reported in Section 2.4. The last part summarizes this study.

2.2. Literature reviews and hypothesis development

2.2.1. Sentiment – return relationship

According to Edelen et al. (2010), sentiment in an investment context may refer to fluctuations in risk tolerance or overly optimistic or pessimistic cash flow forecasts. Along with the foundation and development of behavioral finance, the sentiment-return connection has been discovered in lots of research. While the contemporaneous relationship between sentiment and returns is undeniable, the role of sentiment as a valid predictor of future returns is still controversial. On the one hand, several studies of Baker and Wurgle (2007), Schmeling (2009), Chen (2011), Huang et al. (2015), and Ding et al. (2019) outlined a negative relationship between sentiment and future returns. In contrast, Brown and Cliff (2004), Kim and

Park (2015), and Lansing and Tubbs (2018) showed that sentiment has little to no predictive power to stock returns.

One of the explanations for this issue is the selection of sentiment proxy. As stated in previous studies, researchers have employed various indicators, such as investor survey (Schmeling, 2009; Liston, 2016; Horta and Lobão, 2018), investor mood (Edmans et al., 2007; Kostopoulos and Meyer, 2018), option implied volatility (Bekaert and Hoerova, 2014; Smales, 2017; Qadan et al., 2019), closed-end fund discount (Doukas and Milonas, 2004; Gizelis and Chowdhury, 2016), mutual fund flows (Chi et al., 2012; Massa and Yadav, 2015), turnover or trading volume (Chen et al., 2001; Baker and Stein, 2004; Anusakumar et al., 2017), and composite sentiment indexes combining these proxies (Baker and Wurgler, 2006; Finter et al., 2012; Khan and Ahmad, 2018). Nevertheless, there are no explicit evidence claims which indicator is the most efficient one. Take the U.S stock market as an example. Brown and Cliff (2004) used the communal component of the different measures as a sentiment proxy and found that sentiment has little predictive power for near-term future stock returns. Nevertheless, the results of Lemmon and Portniaguina (2006) proved that investor sentiment measured by consumer confidence could forecast the returns of small stocks and stocks with low institutional ownership. Corredor et al. (2013) employed several sentiment indicators for four European stock markets, namely the U.K., Spain, France, and Germany, and concluded that the results obtained from using the proxy developed by Baker and Wurgler (2006) are the clearest in reveling the effect of sentiment.

Additionally, the relationship between sentiment and stock returns is also affected by data and time horizon frequency. Bathia and Bredin (2013) depicted a negative correlation between investor sentiment and future returns. Nonetheless, the predictive power of sentiment gradually decreases beyond the one-month forecast horizon. Likewise, based on the monthly S&P500 index and two alternative monthly U.S. sentiment indicators, Marczak and Beissinger (2016) found that the sentiment leads returns in the short run (until three months). In contrast, for periods above three months, the opposite can be observed. Moreover, the initially strong positive relationship becomes less pronounced with increasing time horizon, thereby indicating that the over/undervaluation in the short run is gradually corrected in the long term. In contrast, the evidence of Dash and Maitra (2018) supported whether investors are short-term or long-term traders, their investment activities cannot be delinked from sentiment. They detected a strong effect of sentiment on return both in the short-and long-run by employing decomposed returns and sentiment proxies at different time-scale frequencies.

Based on prior research, my first hypothesis is:

H1: *Investor sentiment affects contemporaneous and future returns.*

2.2.2. Asymmetric impact of sentiment

Besides testing the dependence of returns on investor sentiment, the asymmetry in sentiment influence has also become an appealing topic for many researchers, even though most of the studies concentrate on the U.S. markets. This imbalance in sentiment intensity can be explained partly by Prospect Theory. This theory proposes that losses cause a more significant emotional impact on an individual than an equal quantity of gains do. In case both offer the same result, an individual will pick the option offering perceived benefits. It implies that investors might be more concerned about market downturns than upturns. Therefore, when the market is not doing well, investor sentiment is expected to have a more massive effect. Previous empirical results are consistent with this perspective.

Chen (2011) investigated the link between the lack of consumer confidence and stock returns during market fluctuations and suggested that market pessimism has broader impacts on stock returns during bear markets. Similarly, Lutz (2016), using the returns on lottery-like stocks to construct a novel index for investor sentiment in the stock market, found that the relationship between sentiment and returns is asymmetric. He confirmed that high sentiment predicts low future returns for the cross-section of speculative stocks and the market overall during bear markets. In contrast, the relationship during bull markets is weak and often insignificant. Tsai (2017) explored the optimistic and pessimistic sentiments of three major institutional investors (foreign investors, trust investors, and dealers) in the Taiwan stock market. The results confirmed that under favorable market performance, investor sentiment's diffusion effect is nonsignificant when institutional investors are optimistic. By contrast, pessimistic sentiment's diffusion effect is significant, indicating that investor sentiment contagion is asymmetric.

In another perspective, comparing five sentiment proxies over 1990-2015, Smales (2017) demonstrated a strong relationship between investor sentiment and stock returns. More remarkably, he determined that among those indicators, VIX as the representation for “investor fear gauge” is the preferred measure of sentiment in terms of improving model fit and adding explanatory power.

My second hypothesis, therefore, is the following:

H2: *Investor fear generates a stronger impact on stock returns than investor confidence.*

2.3. Data and methodology

The chapter examines the sentiment impact on stock returns using monthly time series from January 2004 to December 2017. According to the MSCI market classification, five markets are ranked as developed markets in the Asia-Pacific region, including Australia, Hong Kong, Japan, New Zealand, and Singapore. However, my sample was finalized with Australia, Hong Kong, and Japan due to data availability. All data were obtained from Thomson Reuters Datastream. For time series available on a quarterly frequency only, I used a cubic spline interpolation method to create monthly data[1].

2.3.1. Market returns and sentiment proxies

2.3.1.1. Market returns

Stock returns at the aggregate market level are represented by each stock exchange's main index, which indicates the overall market performance. They are:

- S&P/ASX 200 Index, based on the 200 largest listed stocks on the Australian Securities Exchange.

- Hang Seng Index, including the 50 largest listed stocks on the Stock Exchange of Hong Kong.

- Nikkei 225 Index, comprising of 225 stocks in the 1st section of the Tokyo Stock Exchange.

S&P/ASX 200 and Hang Seng are value-weighted indices, while Nikkei 225 is a price-weighted index. I collected the end-of-month return index in local currency for each index to compute the monthly time series of stock market returns. Using local currency allows me to avoid currency and exchange rate effects.

2.3.1.2. Sentiment proxies

Among various sentiment proxies, in this study, I applied two direct ones, namely *CCI* and *VIX*, as the representation for "hope" and "fear" of investors.

CCI implies the optimism/pessimism of households about the future developments of their consumption and saving, based upon answers regarding their expected financial situation, their sentiment about the general economic situation, unemployment, and capability of savings. It is one of the most popular indicators broadly employed in sentiment research, including Schmeling (2009), Finter et al. (2012), Corredor et al. (2013, 2015), and Oprea and Brad (2014).

The other sentiment proxy is *VIX* appearing in some recent studies by Bekaert and Hoerova (2014), Smales (2016, 2017), and Qadan et al. (2019). It represents the expected degree in the fluctuation of the stock market in the future. The higher the index values are, the larger fluctuation investors expect in the market. *VIX* is considered as "fear gauge" (Whaley, 2000) because it is likely to increase dramatically when the market goes down sharply during the financial stress period.

The significant advantage of *CCI* and *VIX* is that they are available in some industrialized countries and can be obtained easily for reasonable periods. Additionally, although the calculation methods are slightly different[2], these measurements seem to be consistent to compare between various countries.

2.3.2. Macroeconomic variables

It is almost undeniable that stock returns are related to the state of economics. For example, Hsing (2011) found that the U.S. stock market index is positively associated with real GDP, stock earnings, the trade-weighted nominal effective exchange rate, and the U.K. stock market index and negatively influenced by the government debt/GDP ratio, the M2/GDP ratio, the real Treasury bill rate, the actual corporate bond yield, the expected inflation rate, and the U.K. Treasury bill rate. Therefore, to ensure my results are driven by market sentiment, not by the fluctuations in the business cycle, some macroeconomic variables were utilized in my empirical analysis. Based on previous research, these four variables were chosen: industrial production index (*IP*), consumer price index (*CPI*), money supply (*MS*), and unemployment rate (*UR*). I converted these series to the monthly growth rates before employing them in my model.

2.3.3. Methodology

As a starter, the concurrent effect of sentiment on stock returns was tested by running the following regression model for the data set of each market in my sample:

$$RI_t = \alpha + \beta SENT_t + \gamma M_t + \varepsilon_t \qquad (2.1)$$

More importantly, I detected whether investor sentiment could be a valid predictor of future market returns through different horizons:

$$\frac{1}{k}\sum RI_{t+k} = \alpha + \beta SENT_t + \gamma M_t + \varepsilon_{t+k} \qquad (2.2)$$

In which: $\frac{1}{k}\sum RI_{t+k}$ is the k-month average return of the stock market with k = 3, 6, 12, and 24. RI_t and $SENT_t$ are the stock returns and investor sentiment measured at time t. The models were also controlled by a set of macroeconomic variables described in Section 2.3.2 and represented by the vector M_t. Especially for k = 1, I applied the VAR technique, which is a useful tool for identifying the short-term relationship between time-series data. VAR was employed in previous sentiment work, such as Brown and Cliff (2004), Schmeling (2009), Corredor et al. (2013), and Sayim and Rahman (2015).

If there is a significant relationship between sentiment and contemporary returns, I expect β in Equation (2.1) is positive (negative) for *CCI* (*VIX*). This impact of investor behavior is estimated to reverse in the future since stock prices return to equilibrium. Consequently, the β of Equation (2.2) should be negative (positive).

I computed the variance inflation factor (VIF) for each independent variable in the model to determine the multicollinearity problem[3]. Besides, the presence of heteroskedasticity and autocorrelation in the residual terms were also analyzed during the estimation of regression using the White test and Breusch-Godfrey test, in turn. If heteroskedasticity is detected only, the White correction is applied, and if errors are autocorrelation, the Newey-West estimator is used.

Additionally, I examined the enhancement in explanation power and model fit in case investor sentiment proxies are added in my model by comparing adjusted R^2 (Adj. R^2) and Akaike Information Criterion (AIC). An increase in Adj. R^2 and a decrease in AIC demonstrate the model's improvement. The residual plots between different models were also evaluated[4]. This information provides more details about the effect of sentiment on stock returns and the various intensity between *CCI* and *VIX*.

Finally, I distinguished the return predictability of extreme low and high sentiment by creating two dummy variables. DUM_{High} (DUM_{Low}) takes the value one if the sentiment is one standard deviation above (below) its mean, and 0 otherwise[5]. Then, the revised version of Equation (2.2) was utilized:

$$\frac{1}{k}\sum RI_{t+k} = \alpha + \beta . DUM_{High/Low} . SENT_t + \delta . M_t + \varepsilon_{t+k} \qquad (2.3)$$

If the second hypothesis is convincing, low *CCI* should have a more powerful effect than high *CCI*, while the contrary will be observed in the case of *VIX*.

2.4. Results

2.4.1. Descriptive statistics

Table 2.1: Descriptive statistics for main variables

	Mean	Min.	Max.	SD	Skewness	Kurtosis	Partial autocorrelation at lag				Unit root test
							1	*2*	*3*	*4*	
Panel A: Australia											
S&P/ASX200	0.802	-12.605	7.983	3.744	-0.824	3.684	0.124	0.039	0.129	0.041	-11.349***
CCI	115.787	90.4	133.2	8.389	-0.721	3.750	0.875	-0.030	0.122	-0.201	-5.086***
VIX	19.511	10.139	54.126	8.252	1.622	5.838	0.849	0.054	0.122	-0.032	-3.844**
Panel B: Hong Kong											
Hang Seng	1.121	-22.423	18.352	5.842	-0.473	4.818	0.114	0.065	0.027	-0.049	-11.679***
CCI	89.069	64.946	115.700	15.246	0.348	1.600	0.990	-0.850	0.721	-0.732	-2.231
VIX	18.909	11.680	42.770	5.321	1.721	7.227	0.694	0.162	-0.018	-0.015	-3.038**
Panel C: Japan											
Nikkei 225	0.755	-23.828	12.973	5.447	-0.691	4.733	0.143	-0.013	0.098	0.023	-11.226***
CCI	41.577	27.500	50.100	4.767	-0.753	3.906	0.957	0.042	-0.006	-0.398	-2.584*
VIX	24.047	12.520	92.030	9.287	3.357	21.342	0.754	-0.012	0.179	0.058	-3.521***

The table shows the descriptive statistics for stock market returns and investor sentiment represented by *CCI* and *VIX* in three markets, namely Australia (Panel A), Hong Kong (Panel B), and Japan (Panel C). The unit root test provided is the t-statistics of the augmented Dickey-Fuller test, in which the number of lags is selected to minimize AIC. The data period is from January 2004 to December 2017.

*, **, ***: significance at 10%, 5%, and 1% confidence level, respectively

Table 2.1 reports the summary statistics for market returns, *CCI,* and *VIX* of Australia (Panel A), Hong Kong (Panel B), and Japan (Panel C). As can be seen from the table, on average, Hong Kong's stock market earned the highest return with a mean of 1.121% per month over the period from January 2004 to December 2017, followed by Australia and Japan at 0.802% and 0.755%, respectively. However, with a standard deviation of 5.842, trading in Hong Kong is also the riskiest. The negative skewness and positive excess kurtosis indicated that all return series are skewed left and leptokurtic. Autocorrelation in returns seems relatively small and wipe out quickly.

Regarding sentiment measures, since *CCI* as 100 in Australia and Hong Kong and 50 in Japan indicate neutrality, the average of 116 implies Australian investors' optimistic outlook on the economic situation. On the contrary, investors in Hong Kong and Japan seem to lack confidence. Besides that, the expected fluctuation in all stock markets during the sample period was relatively high, with an average *VIX* of around 20. Noticeably, the lowest mean of *CCI* and the highest mean of *VIX* belonged to Japan, implying investors' awareness of the Japanese market's unstable situation.

Finally, the augmented Dickey-Fuller test was executed, proving that all time series in my sample are stationary, except for Hong Kong's *CCI*. To solve this problem, I created a time variable and regressed *CCI* against it. The residuals series from this regression does not have a unit root and is used as a replacement for *CCI* in Hong Kong. Since the series are evaluated to be stationary, I can apply the ordinary least square (OLS) regression model for my empirical framework.

2.4.2. Correlation

Table 2.2: Correlation matrix

	RI	CCI	VIX	UR	IP	CPI	MS
Panel A: Australia							
RI	1.000						
CCI	0.251***	1.000					
VIX	-0.478***	-0.446***	1.000				
UR	0.144*	0.050	-0.570***	1.000			
IP	0.005	0.121	-0.197**	0.013	1.000		
CPI	0.019	0.118	-0.073	-0.310***	0.240***	1.000	
MS	-0.068	0.043	-0.065	0.041	-0.058	0.029	1.000
Panel B: Hong Kong							
RI	1.000						
CCI	0.153**	1.000					
VIX	-0.416***	-0.190*	1.000				
UR	0.168**	0.608***	0.085	1.000			
IP	0.121	-0.025	0.101	0.035	1.000		
CPI	0.156**	-0.012	0.028	-0.104	-0.092	1.000	
MS	0.047	0.038	-0.091	0.055	0.026	0.019	1.000
Panel C: Japan							
RI	1.000						
CCI	0.177**	1.000					
VIX	-0.445***	-0.639***	1.000				
UR	0.021	-0.095	0.136*	1.000			
IP	0.209***	0.243***	-0.306***	0.057	1.000		
CPI	0.061	0.028	-0.154**	-0.157**	0.070	1.000	
MS	0.232***	0.008	-0.126	-0.105	-0.024	0.197***	1.000

The table presents the correlation coefficients between stock returns, sentiment proxies (*CCI* and *VIX*), as well as macroeconomic variables (*UR*, *IP*, *CPI*, and *MS*) in Australia (Panel A), Hong Kong (Panel B), and Japan (Panel C). p-values are unreported. The data period is from January 2004 to December 2017.

*, **, ***: significance at 10%, 5%, and 1% confidence level, respectively

Table 2.2 shows the correlation coefficients between market returns and two sentiment proxies, including *CCI* and *VIX*, as well as four macroeconomic control variables. The results were identical for all markets. More particularly, positive coefficients were revealed for returns and *CCI*, whereas the negative ones for the former and *VIX* with the highest belonging to Australia of 0.251 and -0.478, in turn. Remarkably, *VIX*'s coefficients were much higher than *CCI*, indicating the more substantial impact of *VIX* on stock returns. Besides that, *CCI* and *VIX* also exhibited a significantly negative relationship, especially in Japan and Australia. The contrary effect of *CCI* and *VIX* could be explained as *CCI* is the measure of "confidence," while *VIX* represents "fear." The correlation matrix outcomes give me general ideas about the concurrent connection between two sentiment proxies and market returns, which were investigated more extensively in the next section.

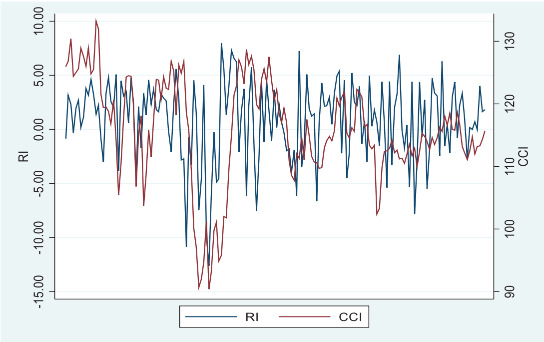
2.4.3. Investor sentiment and contemporaneous returns

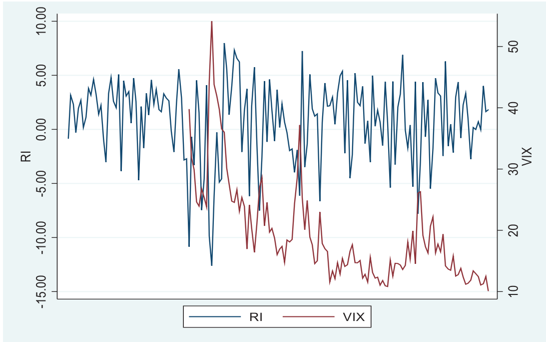
Figure 2.1 depicts the relationship between monthly market returns and two sentiment proxies, namely *CCI* and *VIX*, in Australia, Hong Kong, and Japan. In tandem with the correlation matrix, the positively (negatively) immediate influence of sentiment on stock returns could be witnessed clearly in all sample markets. The outcomes from correlation analysis and graphical illustration motivate me to investigate these relationships more precisely by applying Equation (2.1) for the contemporaneous specification.

The results for OLS regression between investor sentiment and contemporaneous returns are presented in Table 2.3, including coefficient estimation for sentiment measure as well as Adj. R^2 and AIC to compare the suitability of *CCI* and *VIX* when being added to my model. As is shown in the table, the synchronous return-sentiment relationship is convinced and can be stand out from the impact of economic cycles on stock returns. In detail, an increase in *CCI* would be accompanied by a rise in market returns and vice versa. On the contrary, returns are predicted to drop simultaneously by growth in *VIX*. As reflected in the table, Hong Kong's stock market seems to be influenced most by *VIX*, with the highest coefficient of -0.400. Interestingly, with the coefficients were estimated at approximately 0.100 (Australia 0.110, Hong Kong 0.099, and Japan 0.156), the impact of *CCI* on returns is quite similar in the three markets. All of the sentiment coefficients were statistically significant, except for the *CCI* of Japan.

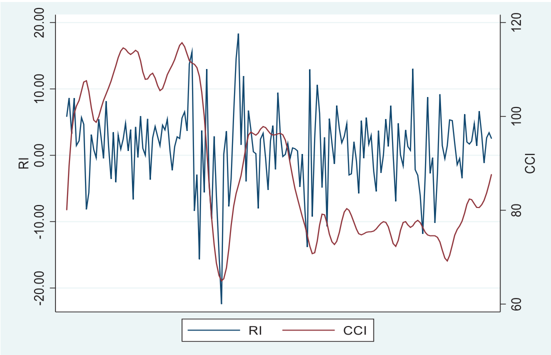
Figure 2.1: Investor sentiment and contemporaneous returns

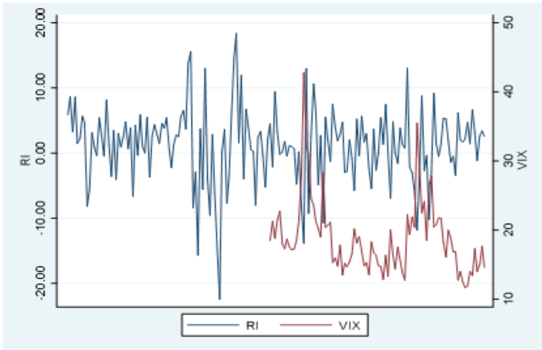
Panel A: Australia



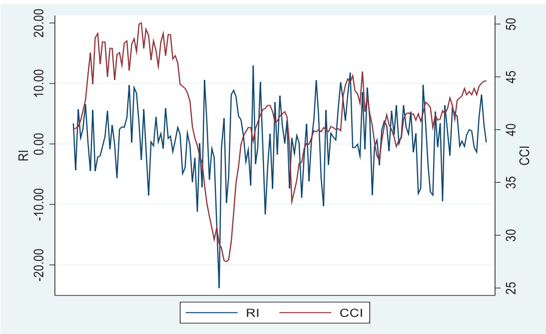


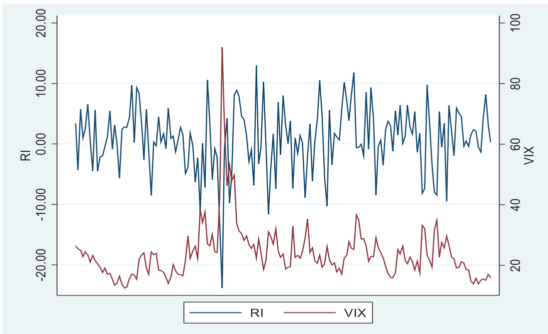
Panel B: Hong Kong





Panel C: Japan





The figure illustrates the contemporaneous relationship between stock returns and investor sentiment measured by *CCI* and *VIX* in Australia (Panel A), Hong Kong (Panel B), and Japan (Panel C). The data period is from January 2004 to December 2017.

Comparing *CCI* and *VIX*, the latter exposed a higher coefficient than the former in all research markets, with the most substantial gap in Hong Kong (0.099 and -0.400, respectively). Besides, when being included in my model, *VIX* also enhances the model better as Adj. R^2 rose and AIC reduced a higher quantity than those of *CCI*, especially in Hong Kong and Japan. Take Japan as an example. Compare to the model having macroeconomic variables only, the presence of *VIX* increased Adj. R^2 by 0.165 and dropped AIC by 28.161 while those of *CCI* were 0.013 and 1.310, in turn. Based on these outcomes, I might conclude that *VIX*, which measures investors' “fear,” seems to have a stronger concurrent impact on stock returns than *CCI*. A similar result for the U.S. market was reported by Smales (2017), who determined that *VIX* is the preferred measure of sentiment in improving model fit and adding explanation power.

Table 2.3: Investor sentiment and contemporaneous returns

	Australia		Hong Kong		Japan	
	CCI	*VIX*	*CCI*	*VIX*	*CCI*	*VIX*
Sentiment	0.110^{W***}	-0.218^{W***}	0.099**	-0.400^{W***}	0.156^{W}	-0.241^{W***}
	[0.005]	[0.001]	[0.023]	[0.002]	[0.140]	[~0]
Adj. R^2	0.062	0.229	0.078	0.164	0.092	0.224
△Adj. R^2	0.054	0.111	0.023	0.169	0.013	0.165
AIC	915.406	653.184	1099.729	537.280	1054.442	1027.591
△AIC	-14.907	-15.207	-3.402	-15.640	-1.310	-28.161
Wald F-stat	8.060***	10.733***	5.297**	10.617***	2.196	16.856***

The table reports the regression results obtained from Equation (2.1). The dependent variable is market returns calculated from S&P/ASX200 Index (Australia), Hang Seng Index (Hong Kong), and Nikkei 225 Index (Japan). The independent variable is concurrent sentiment. Four macroeconomic variables, including *UR*, *IP*, *CPI*, and *MS*, control the equation. The presence of heteroskedasticity and autocorrelation in the residual terms are analyzed during the estimation of regression using the White test and Breusch-Godfrey test, in turn. If heteroskedasticity is detected only, the White correction is applied, and if errors are autocorrelation, the Newey-West estimator is used. ^{W} indicates the results are received from White correction. Only the estimation for sentiment is reported. p-values are presented in brackets. △Adj. R^2 and △AIC imply the model change fit when sentiment proxy is added to the equation. The data period from January 2004 to December 2017.

*, **, ***: significance at 10%, 5%, and 1% confidence level, respectively

2.4.4. Investor sentiment and future returns

2.4.4.1. Short-term effect of sentiment on stock returns

To test the impact of investor sentiment on near future returns, I employed the VAR technique. As stated in previous studies, for example, Schmeling (2009) and Corredor et al. (2013), VAR could be a simple and helpful tool for analyzing short-term time-series dependence. These authors applied VAR using one-month lagged returns and then used regressions for detecting long-term relationships. However, their findings are somehow different. While Schmeling (2009) stated a two-way causality between sentiment and returns for a pool of 18 developed markets, Corredor et al. (2013), who also examined this relationship in four industrialized countries in Europe, found that for each market in most cases, there is one-way feedback only.

Table 2.4: Granger causality test

	CCI ⇆ RI		VIX ⇆ RI	
	CCI → RI	*RI → CCI*	*VIX → RI*	*RI → VIX*
Australia	0.044**	0.206	0.897	0.702
Hong Kong	0.028**	0.362	0.117	0.145
Japan	0.638	0.208	0.080*	0.000***

The table presents the pairwise Granger causality test results between contemporaneous sentiment and next month returns in Australia, Hong Kong, and Japan's stock markets. The number of lags is selected to minimize AIC. The data period from January 2004 to December 2017.

*, **, ***: significance at 10%, 5%, and 1% confidence level, respectively

My results for Asia-Pacific developed markets exhibited in Table 2.4 support Corredor et al.'s (2013) research. Unlike the apparent relationships, the outcomes were not homogeneous across Australia, Hong Kong, and Japan. There was substantial evidence in two former markets that the causality runs from sentiment represented by *CCI* to returns and not vice versa. In contrast, Japan's stock market witnessed a two-way effect between *VIX* and returns, indicating that past returns drive current *VIX,* and past *VIX* drives current market returns. This finding assists Qiu and Welch (2004), who pointed out that sentiment "*should not fall like manna from heaven*," but should be related to some variables, such as returns, macro variables. In general, my outcomes suggest that *CCI* could be applied for predicting next month's returns in Australia and Hong Kong. At the same time, for the Japanese market, *VIX* might be a better-estimated indicator.

2.4.4.2. Long-term effect of sentiment on stock returns

In this part, I investigate the ability of sentiment to predict future returns by running Equation (2.2) for near to mid-term periods (k = 3, 6, 12, and 24 months, respectively). Table 2.5 presents coefficient estimators for two sentiment proxies and some relevant results derived from OLS regressions. The findings were slightly disparate between the three research markets.

Firstly, look at Table 2.5, in Australia and Hong Kong's stock markets, *CCI* continues to impact short-term future returns positively. Australia can serve as an example with its sentiment's coefficients to the next 3-month and 6-month returns being 0.052 and 0.038, in turn. After that, this effect started reversing with a negative coefficient for *CCI* in one and two-year lagged return specification models. The positive relationship between *CCI* and stock returns even remained longer in Japan as the negative coefficient was exposed in the last horizontal model, implying returns tend to be lower (higher) following an increase (decrease) in *CCI* only after two years. These results are divergent to Fisher and Statman (2003), Schmeling (2009), and Corredor et al. (2015). They discovered that investor sentiment measured by *CCI* has a significantly negative impact on future stock returns at very near forecast horizons (1 to 6 months).

Table 2.5: Investor sentiment and future returns

	Australia		Hong Kong		Japan	
	CCI	*VIX*	*CCI*	*VIX*	*CCI*	*VIX*
R_{t+3}						
Sentiment	0.052	0.035	0.062	-0.001	0.136	-0.032
	[0.268]	[0.531]	[0.352]	[0.986]	[0.304]	[0.438]
Adj. R^2	0.120	0.156	0.054	-0.051	0.006	-0.022
△Adj. R^2	0.029	~0	0.022	-0.013	0.028	~0
AIC	740.335	527.493	928.819	435.644	899.577	904.148
△AIC	-4.341	0.847	-2.865	2.000	-3.623	0.948
Wald F-stat	1.238	0.396	0.873	0.001	1.066	0.604
R_{t+6}						
Sentiment	0.038	0.063	0.018	0.015	0.098	-0.015
	[0.372]	[0.117]	[0.730]	[0.764]	[0.319]	[0.632]
Adj. R^2	0.160	0.325	0.041	-0.040	0.034	0.005
△Adj. R^2	0.024	0.036	-0.002	-0.011	0.025	-0.004
AIC	641.909	437.732	810.495	349.638	786.772	791.646
△AIC	-3.614	-4.912	1.218	1.835	-3.298	1.576
Wald F-stat	0.803	2.496	0.120	0.091	1.000	0.230
R_{t+12}						
Sentiment	-0.008	0.022	-0.045	0.055**	0.034	-0.020
	[0.726]	[0.293]	[0.127]	[0.012]	[0.500]	[0.452]
Adj. R^2	0.140	0.339	0.111	0.140	0.144	0.011
△Adj. R^2	-0.003	0.007	0.054	0.051	0.136	0.003
AIC	529.124	307.807	632.320	242.911	653.176	652.885
△AIC	1.536	-0.269	-8.722	-3.510	0.755	0.464
Wald F-stat	0.123	1.119	2.350	6.611**	0.456	0.567
R_{t+24}						
Sentiment	-0.006	0.005	-0.030**	0.052***	-0.033	0.003
	[0.635]	[0.621]	[0.033]	[~0]	[0.416]	[0.867]
Adj. R^2	0.152	0.242	0.253	0.311	0.055	0.041
△Adj. R^2	-0.002	-0.005	0.090	0.310	0.007	-0.007
AIC	368.384	143.029	371.032	80.478	507.678	509.856
△AIC	1.343	1.501	-16.333	-23.601	-0.221	1.957
Wald F-stat	0.227	0.246	4.643**	28.912***	0.666	0.028

The table reports the regression results obtained from Equation (2.2). The dependent variable is average market returns for the next 3, 6, 12, and 24 months calculated from S&P/ASX200 Index (Australia), Hang Seng Index (Hong Kong), and Nikkei 225 Index (Japan). The independent variable is concurrent sentiment. Four macroeconomic variables include *UR*, *IP*, *CPI*, and *MS,* control the equation. The presence of heteroskedasticity and autocorrelation in the residual terms are analyzed during the estimation of regression using the White test and Breusch-Godfrey test, in turn. If heteroskedasticity is detected only, the White correction is applied, and if errors are autocorrelation, the Newey-West estimator is used. Since both heteroskedasticity and autocorrelation are detected, Newey-West correction is employed here. Only the estimation for sentiment is reported. p-values are presented in brackets. △Adj. R^2 and △AIC imply the model change fit when sentiment proxy is added to the equation. The data period from January 2004 to December 2017.

*, **, ***: significance at 10%, 5%, and 1% confidence level, respectively

On the other hand, the response of returns after being affected by *VIX* seems faster as the coefficient correlations between *VIX* and future returns converted from negative to positive over the following three months in Australia and six months in Hong Kong at 0.035 and 0.015, respectively. Once again, Japan's stock market is distinctive from other markets when the reversal was delayed until two years later, being in harmony with its *CCI*.

However, in conclusion, *CCI* and *VIX*'s effect on future returns seems non-existent as most of the coefficients were not statistically significant, except mid-term horizons in Hong Kong. It might be because, during my sample period, the sentiment is comparatively modest, especially in Australia and Japan. According to Li et al. (2017), investor sentiment could provide incremental predictability for the stock returns under the extreme market situation. Consequently, I checked out the results for the intense low and high sentiment situation exhibited in Table 2.6.

As shown from the table, Australia and Japan share the same pattern in both *CCI* and *VIX*, whereas Hong Kong is slightly different. For the two former markets, low *CCI* and low *VIX*, with higher coefficients most of the time, had a more powerful influence on future returns than the opposite situations. On the other hand, the effect of high *CCI* and high *VIX* in Hong Kong dominated in two short-term horizons, from three to six months, before being overcome by the low ones in the more extended periods. In addition to that, the gaps between low and high *VIX* coefficients were more remarkable than the ones belong to *CCI*. For example, for the one-year horizon, the difference between low and high *VIX* in Hong Hong's market was 0.030, while those for *CCI* was only 0.001. Lastly, extreme *VIX* had a much more statistically significant impact on subsequent returns compared to extreme *CCI*.

Generally, my results imply that an exceptional situation could relatively increase *VIX*'s predictive power on stock returns but might not be accurate in the case of *CCI*. Besides that, low *CCI* and *VIX* seem to have a more intense relationship with future returns in Australia, Hong Kong, and Japan than the opposite ones.

2.5. Conclusion

Employing two direct sentiment measures, including *CCI* and *VIX*, the chapter investigated stock returns' dependence on investor sentiment in three Asia-Pacific developed markets from January 2004 to December 2017. Overall, I observed a significantly contemporaneous link between sentiment indicators and market returns. Remarkably, *VIX*, as a representative for "investor fear gauge," proved a more powerful impact on concurrent returns than *CCI* computed by "investor confidence." Moreover, in respect of enhancing explanation power and model fit, *VIX* also demonstrated better performance. My finding is in line with the behavioral conception that fear is a more powerful force than confidence.

Nevertheless, the influence of sentiment on stock returns seems to die out quickly since the return predictability appeared non-existent for both *CCI* and *VIX* over near and mid-term forecast horizons. The only exception belonged to *VIX* of Hong Kong in the long-term periods, from one to two years. Additionally, by separately analyzing the impact of investor sentiment on two opposite sides: positive and negative, I discovered that extremely low and high sentiment could increase the estimation capacity, though not too remarkable. Besides that, my results were also not homogeneous across markets. It is consistent with previous studies, such as Lemmon and Portniaguina (2006), Schmeling (2009), and Corredor et al. (2013), which revealed that the divergence in the intensity of the market sentiment depends not only on stock characteristics but also on market-specific factors. Generally, the findings suggest that *CCI* and *VIX* might not be suitable proxies to capture sentiment effect in these stock markets, calling for future research to find more ideal ones.

Table 2.6: Return predictability of low and high sentiment

	Australia				Hong Kong				Japan			
	CCI		VIX		CCI		VIX		CCI		VIX	
	CCI_L	CCI_H	VIX_L	VIX_H	CCI_L	CCI_H	VIX_L	VIX_H	CCI_L	CCI_H	VIX_L	VIX_H
R_{t+3}												
Sentiment	-0.009	-0.001	-0.104	0.020	0.059	0.118	0.028	0.048*	-0.085	0.013	0.094	0.004
	[0.599]	[0.972]	[0.211]	[0.502]	[0.605]	[0.242]	[0.685]	[0.071]	[0.195]	[0.428]	[0.209]	[0.905]
Adj. R^2	0.097	0.086	0.157	0.155	0.038	0.050	-0.049	-0.021	0.033	-0.024	-0.022	-0.028
△Adj. R^2	0.006	-0.005	0.066	0.064	0.006	0.018	-0.081	-0.053	0.055	-0.002	-0.001	-0.006
AIC	744.482	746.673	527.396	527.689	931.671	929.518	435.501	433.079	894.846	904.476	904.156	905.165
△AIC	-0.194	1.997	-217.280	-216.987	-0.013	-2.166	-496.183	-498.605	-8.354	1.276	0.956	1.965
Wald F-stat	2.069*	1.861	1.775	1.773	1.602	2.267*	0.249	1.066	0.519	0.208	0.412	0.071
R_{t+6}												
Sentiment	-0.004	0.002	-0.108**	0.047**	-0.014	0.076	0.017	0.030	-0.080	0.012	0.199***	0.019
	[0.770]	[0.590]	[0.010]	[0.033]	[0.875]	[0.358]	[0.755]	[0.141]	[0.111]	[0.364]	[0.004]	[0.276]
Adj. R^2	0.134	0.134	0.295	0.346	0.038	0.054	-0.041	-0.014	0.099	0.010	0.047	0.012
△Adj. R^2	-0.002	-0.002	0.159	0.210	-0.005	0.011	-0.084	-0.057	0.090	0.001	0.038	0.003
AIC	646.833	646.870	442.618	434.163	811.080	808.212	349.694	347.455	775.239	790.881	784.582	790.552
△AIC	1.310	1.347	-202.905	-211.360	1.803	-1.065	-459.582	-461.822	-14.831	0.811	-5.488	0.482
Wald F-stat	1.092	1.050	3.565***	3.909***	1.215	1.494	0.273	0.660	1.044	0.990	2.639	1.207
R_{t+12}												
Sentiment	0.007	0.001	-0.054*	0.011	-0.070**	-0.071	-0.068***	0.030***	-0.024	0.006	0.113**	-0.004
	[0.194]	[0.763]	[0.071]	[0.507]	[0.025]	[0.358]	[0.003]	[0.003]	[0.231]	[0.652]	[0.037]	[0.803]
Adj. R^2	0.161	0.139	0.332	0.335	0.123	0.085	0.111	0.147	0.019	0.004	0.026	0.002
△Adj. R^2	0.018	-0.004	0.189	0.192	0.067	0.029	0.054	0.090	0.011	-0.004	0.018	-0.006
AIC	525.394	529.300	309.032	308.553	630.174	637.129	245.483	242.228	651.486	653.912	650.377	654.284
△AIC	-0.194	1.712	-218.556	-219.035	-10.868	-3.913	-395.560	-398.814	-0.935	1.491	-2.044	1.863
Wald F-stat	2.199*	1.742	13.329***	12.852***	2.015*	1.652	3.572***	5.842***	1.661	1.939*	2.672**	1.683
R_{t+24}												
Sentiment	0.003	0.002	-0.030**	0.004	-0.043***	-0.018	-0.029**	0.025***	-0.006	-0.018	0.033	0.004
	[0.250]	[0.395]	[0.015]	[0.524]	[0.006]	[0.598]	[0.026]	[~0]	[0.638]	[0.113]	[0.555]	[0.561]
Adj. R^2	0.160	0.160	0.249	0.246	0.261	0.165	0.024	0.252	0.043	0.105	0.045	0.043
△Adj. R^2	0.006	0.006	0.095	0.092	0.098	0.002	-0.139	0.089	-0.005	0.057	-0.003	-0.005
AIC	367.012	366.975	142.213	142.622	369.523	387.886	103.437	85.894	509.549	499.824	509.251	509.661
△AIC	-0.029	-0.066	-224.828	-224.419	-17.842	0.521	-283.928	-301.471	1.650	-8.075	1.352	1.762
Wald F-stat	4.148***	4.479***	8.854***	5.252***	4.448***	5.030***	1.960*	14.012***	2.156*	2.611**	2.240*	2.291**

The table reports the regression results obtained from Equation (2.3) when a dummy variable for extremely high and low sentiment is presented. The DUM_{High} (DUM_{Low}) takes the value one if the sentiment is one standard deviation above (below) its mean, and 0 otherwise. The dependent variable is average market returns for the next 3, 6, 12, and 24 months calculated from S&P/ASX200 Index (Australia), Hang Seng Index (Hong Kong), and Nikkei 225 Index (Japan). The independent variables are the interactive variable between sentiment and two dummy variables. Four macroeconomic variables, including *UR*, *IP*, *CPI*, and *MS*, control the equation. The presence of heteroskedasticity and autocorrelation in the residual terms are analyzed during the estimation of regression using the White test and Breusch-Godfrey test, in turn. If heteroskedasticity is detected only, the White correction is applied, and if errors are autocorrelation, the Newey-West estimator is used. Since both heteroskedasticity and autocorrelation are detected, Newey-West correction is employed here. Only the estimation for sentiment is reported. p-values are presented in brackets. △Adj. R^2 and △AIC imply the model change fit when sentiment proxy is added to the equation. The data period from January 2004 to December 2017.

*, **, ***: significance at 10%, 5%, and 1% confidence level, respectively

Chapter 3

Impact of financial development on sentiment-return relationship: Insight from Asia-Pacific markets

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3.1. Introduction

Along with behavioral finance development, the relationship between investor sentiment and stock returns, specifically the return predictability of sentiment, has been mentioned and explored in numerous studies. However, the results are controversial. Take developed markets as an example. Baker and Wurgler (2007) used six sentiment proxies to create an inclusive index and found a negative correlation between sentiment and U.S. subsequent returns. Conversely, the paper of Finter et al. (2012) for Germany suggested that sentiment does not generally predict future returns. The mixed conclusions are also detected in the studies that focus on emerging markets or studies that use global data from countries worldwide (Yoshinaga and Castro Junior, 2012; Sayim and Rahman, 2015; Gao et al., 2020).

Due to the inconsistent findings across markets, many researchers have been attracted to exploring such divergence causes. Alongside stock characteristics suggested by Baker and Wurgler (2006), Lemmon and Portniaguina (2006), Mian and Sankaraguruswamy (2012), and Zhu and Niu (2016), Schmeling (2009) and Zouaoui et al. (2011) provided evidence that country-specific factors, including institutional quality and culture, are strong determinants of the sentiment-return relation. The moderating effect of these local characteristics can be explained for the reason that their differences partly lead to the variation in investors' misperceptions, which influences significantly stock pricing, as claimed by De Long et al. (1990), Barber (1994), Hirshleifer (2001), and Ding et al. (2019).

Asia-Pacific markets and their investors have unique characteristics of culture, institutional governance, and others, making them distinctive to each other and other markets in the world. Thus, I expect to discover some dissimilar findings of the link between sentiment and stock returns from existent literature for the U.S. and European markets. Moreover, compared to these countries, there is less work about this topic in the Asian ones. These reasons motivate me to research the return predictability of investor sentiment, focusing on the Asia-Pacific region. In my study, by using a sample of six Asia-Pacific markets, I can contribute to current views about sentiment-return relation, not only in terms of the individual markets but also in the regional aspect.

As the interconnectedness among markets has become more significant due to globalization, some studies have raised questions about the role of sentiment in a broader context, such as Chang et al. (2011) and Baker and Wurgler (2012). Chang et al. (2011) used the first principal component of the U.S., the U.K., German, and French consumer confidence indices as the proxy for global sentiment and found a powerful and pervasive global effect on 23 developed and emerging markets all over the world. Inspired by the idea of the contagion effect of sentiment across markets, with data from Asia-Pacific countries only, I create a regional sentiment index, not a global one like previous research. My purpose is to examine the existence of the regional effect, i.e., the extent to which a regional sentiment indicator influences local stock returns, and check whether its impact is the same as global sentiment or not. Second, I investigate whether the overall sentiment effect is truly domestic or derived from regional sentiment.

Finally, until now, among market-specific factors, no study pays attention to the potential impact of development level on sentiment-return inference, even though market quality might affect the market outcome, according to Rajan and Zingales (1998). By employing a variant set of samples, including developed and emerging markets, my research aims to address this limitation.

In general, this study makes several contributions to contemporary literature. Firstly, by investigating the relationship between investor sentiment and subsequent stock returns, I provide more empirical evidence for prior results about the return predictability of sentiment. Secondly, by focusing on the Asia-Pacific region only, I split market-specific sentiment into regional and local components and detect whether sentiment effect is a twofold phenomenon. This matter was brought up and examined in a few studies before, but from a global perspective, not concentrating on a specific region as I do. Thirdly, to the best of my knowledge, this research is the first to testify financial development's role in the variation in sentiment-return relation across markets.

The chapter proceeds as follows. Section 3.2 reviews prior related research and initiates my testing hypotheses. The next section describes the types of data used in my analysis. The method to construct a comprehensive sentiment index and how I test my research problems are also mentioned. The empirical results are presented and analyzed in Section 3.4. The last part summarizes my findings.

3.2. Literature reviews and hypothesis development

3.2.1. Return predictability of investor sentiment

Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand (Baker and Wurgler, 2007). According to behavioral theory, investor sentiment could explain abnormal returns, besides traditional factors in stock markets. To test this hypothesis, researchers have carried out many studies about the effect of sentiment on future stock returns until now.

Regarding the U.S. market, Edelen et al. (2010) detected that high levels of relative retail sentiment are associated with significantly lower future excess equity returns. Similar outcomes were presented in Chen's (2011) and Huang et al.'s (2015) research. Yoshinaga and Castro Junior (2012) also indicated a significant and negative relationship between the Brazilian market sentiment index and future return rates. Eventually, in Japan, Ishijima et al. (2015) proved that the daily sentiment index constructed by the text mining technique significantly predicts Tokyo Stock Exchange prices three days in advance.

On the contrary, Brown and Cliff (2004) and Lansing and Tubbs (2018) showed that sentiment has little predictive power for near-term future stock returns in the U.S. Kim and Park's (2015) evidence for the South Korea stock market indicated the same closure. Concerning emerging markets, Oprea and Brad (2014) argued that investor sentiment's impact appears to be mitigated and removed by the rational investors in less than a month in Romania.

Especially, few studies reported a positive relationship between sentiment and subsequent returns. Cheema et al. (2020) found a robust positive association between investor sentiment and future market returns during China's bubble period. Nevertheless, investor sentiment negligibly impact on subsequent monthly market returns once the bubble period is excluded.

From a global perspective, Schmeling (2009) investigated the relationship between investor sentiment and stock returns for 18 industrialized markets and found that sentiment is a significant predictor of expected returns on average across markets. However, in individual country regressions, the outcomes were not universal since sentiment does not contain predictive power for several countries. The research using Google search behavior to construct a weekly sentiment measure for 38 countries of Gao et al. (2020) revealed similar outcomes.

Since the findings of previous studies are inconclusive, I propose my first hypothesis:

H1: *Investor sentiment has an impact on future stock returns*

Moreover, recently, some scholars have begun to examine the sentiment-return inference from a more expansive aspect. Baker and Wurgler (2012) decomposed total sentiment indices of Canada, France, Germany, Japan, the U.K., and the U.S. into a single "global" index and six "local" indices. They detected that the global component of the total index could be a contrarian predictor of country-level market returns. Corredor et al. (2015) used a set of the American and European consumer confidence indicators as global sentiment proxies and revealed the same conclusion for Poland and the Czech Republic. In the most recent paper for 38 markets globally, Gao et al. (2020) proved that global sentiment, rather than local sentiment, plays a significant role in predicting future returns for both developed and emerging countries. However, the return prediction of global sentiment is more pronounced in developed countries, while local sentiment has similar predictive power in emerging and developed countries.

Based on the research mentioned above, my first hypothesis is expanded as follow:

H1a: *Regional sentiment has an impact on future stock returns*

H1b: *Local sentiment has an impact on future stock returns*

3.2.2. Impact of financial development

Since the findings on sentiment-return nexus are considerably diverse across markets, researchers have raised the question about the moderating effect of country-specific factors on this relationship. Schmeling (2009) and Zouaoui et al. (2011) suggested that the impact of sentiment on returns is higher for markets that are culturally more prone to herd-like investment behavior as hypothesized by Chui et al. (2010) and for markets that have less efficient regulatory institutions or less market integrity. In line with the studies mentioned above, Corredor et al. (2013) focused only on four European markets and documented that the variation in sentiment intensity across markets appears to involve both stock characteristics and cross-country cultural or institutional differences. Recently, the work of Wang et al. (2019) on 50 markets globally showed heterogeneity in the sentiment-return relationship at the individual market level and found that different cultural dimensions and market institutions, along with intelligence and education, can justify such divergence.

In another domain, Rajan and Zingales (1998) proved that countries with better developed financial systems show superior growth in capital-extensive sectors that rely heavily on external finance. Evidence of Chordia et al. (2011) indicated that secular decreases in trading costs influence the U.S. market's turnover trend. Overall, these studies reveal the influence of the market development level on market outcome. Like other local features, I suppose that this factor could affect the link between investor sentiment and future returns. Hence, my second hypothesis is:

H2: *Financial development has a moderating impact on return predictability of investor sentiment*

3.3. Data and methodology

My study was carried out based on monthly data from six Asia-Pacific markets, including Australia, Hong Kong, Indonesia, Japan, South Korea, and Thailand, between January 2004 to December 2016. Most data were obtained from Thomson Reuters Datastream. Following Ajao et al. (2012) and Bathia and Bredin

(2013), for time series available on a quarterly frequency only, I used a cubic spline interpolation method to create monthly data.

3.3.1. Market returns and sentiment proxies

3.3.1.1. Market returns

Stock returns at the aggregate market level are represented by each stock exchange's main index, which indicates the overall market performance. They are:

- S&P/ASX 200 Index tracking the performance of 200 largest listed stocks on the Australian Securities Exchange.

- Hang Seng Index comprising the 50 largest listed stocks on the Stock Exchange of Hong Kong.

- The Jakarta Stock Price Index tracks the performance of all companies listed on the Indonesia Stock Exchange.

- Nikkei 225 Index constructed based on 225 stocks in the 1st section of the Tokyo Stock Exchange.

- The Korea Stock Exchange Composite KOSPI including all common shares listed on the Korean Stock Exchange.

- The Bangkok SET50 Index tracking the performance of the top 50 common stocks listed on the Stock Exchange of Thailand.

All series are capitalization-weighted index, except the price-weighted Nikkei 225 index. I collected the end-of-month price index in local currency for each market to compute the monthly time series of stock returns: $R_t = 100*\ln(P_t/P_{t-1})$. Using local currency allows me to avoid currency and exchange rate effects.

3.3.1.2. Sentiment proxies

The literature has employed abundant measures of investor sentiment. Most of these indicators can be sorted into two main approaches: explicit sentiment proxies based on surveys and implicit sentiment proxies based on market variables. Besides that, according to Burghardt (2011), there is a third type that is based on neither pure market data nor investor surveys called meta-measure. In this study, I combined both direct and indirect approaches by using three sentiment proxies, namely consumer confidence index (*CCI*), advance/decline ratio (*ADR*), and volatility premium (*VP*), to construct a comprehensive sentiment index.

CCI implies the optimism/pessimism of households about the future developments of their consumption and saving, based upon answers regarding their expected financial situation, their sentiment about the general economic situation, unemployment, and capability of savings. It was utilized widely in sentiment research, including Fisher and Statman (2003), Qiu and Welch (2004), Schmeling (2009), and Oprea and Brad (2014). Consistent with previous findings, high *CCI* is a sign of positive sentiment. *CCI*'s significant advantage is that it is available in many markets and can be obtained easily for reasonable periods. Additionally, *CCI* is not collected from trading data, but respondents' replies via surveys. Hence it is independent of market trading.

The second proxy is *ADR,* which is a popular market breadth indicator applied in the sentiment studies of Brown and Cliff (2004), Gunathilaka et al. (2017), and Dash and Maitra (2018). *ADR* compares the number of stocks that closed higher against the number of stocks that closed lower than their previous session's closing prices. This ratio indicates the direction of the market on a net basis. If the ratio is higher (lower) than one, it will imply a bullish (bearish) market sentiment, whereas a value of one means that, on average, the market is neither bullish nor bearish. In my study, *ADR* was calculated by dividing the number of advancing stocks by declining stocks during a month.

Finally, to obtain *VP*, at the beginning of year *t*, I sorted all stocks in each market into low volatility (the bottom 30%) and high volatility (the top 30%) stocks based on their standard deviations of the prior year. *VP* was the log of the average market-to-book ratio of high volatility stocks over the average market-to-book ratio of low volatility stocks. The usage of this proxy originates from the theoretical prediction that sentiment has the most definite impact on hard to value and hard to arbitrage stocks proved by the results of Bathia and Bredin (2013), Raissi and Missaoui (2015), and Ding et al. (2019). Like the other two indicators, I suppose a positive relationship between *VP* and composite sentiment index.

Table 3.1 summarizes the main statistics for stock returns and three sentiment proxies in Australia (Panel A), Hong Kong (Panel B), Indonesia (Panel C), Japan (Panel D), South Korea (Panel E), and Thailand (Panel F). As shown in the table, during the period between January 2004 to December 2016, Indonesia’s stock market witnessed the highest average return at 1.305% per month, more than double other markets where investors earned the monthly returns from 0.347% (Australia) to 0.587% (South Korea). The same pattern could be seen for the standard deviation of stock returns since Australia is the safest market with the lowest standard deviation of 3.913. At the same time, the highest one belonged to Indonesia at 6.196. However, these figures were not too much different across markets. Furthermore, the negative skewness and positive excess kurtosis indicated that all return series are skewed left and leptokurtic, which are consistent with the findings of return distributions of Lux (1998) and Chen et al. (2001).

Table 3.1: Summary statistics for main variables

	Mean	Min.	Max.	SD	Skewness	Ex. Kurtosis
Panel A: Australia						
Market returns	0.347	-13.538	7.055	3.913	-0.887	0.715
CCI	115.93	90.400	133.20	8.673	-0.749	0.585
ADR	1.031	0.662	1.553	0.174	-0.011	-3.467
VP	0.207	-0.898	1.541	0.402	0.364	2.280
Panel B: Hong Kong						
Market returns	0.359	-25.445	15.763	6.143	-0.695	2.007
CCI	89.278	64.946	115.70	15.719	0.305	-1.479
ADR	0.997	0.524	1.476	0.202	0.057	-3.426
VP	-0.003	-0.588	0.327	0.164	-0.969	1.189
Panel C: Indonesia						
Market returns	1.305	-37.719	18.341	6.196	-1.716	9.297
CCI	104.47	76.900	120.60	10.952	-0.424	-0.781
ADR	1.001	0.525	1.797	0.199	0.387	-2.169
VP	-1.095	-7.250	1.342	2.715	-1.230	-0.123
Panel D: Japan						
Market returns	0.373	-27.216	12.089	5.716	-0.966	2.644
CCI	41.436	27.500	50.100	4.947	-0.661	0.612
ADR	1.004	0.627	1.473	0.191	0.307	-3.261
VP	0.261	0.007	0.501	0.114	0.324	-0.971
Panel E: South Korea						
Market returns	0.587	-26.311	12.682	5.315	-0.840	3.759
CCI	100.66	69.400	120.60	8.352	-0.999	2.469
ADR	0.996	0.650	1.459	0.167	0.396	-3.112
VP	0.283	-0.795	0.529	0.176	0.624	-2.898
Panel F: Thailand						
Market returns	0.444	-35.919	13.082	5.916	-1.722	8.127
CCI	71.978	57.700	107.50	9.456	1.596	2.801
ADR	0.999	0.502	1.592	0.216	0.093	-3.286
VP	-0.132	-0.843	0.521	0.328	-0.796	-0.568

The table shows the descriptive statistics for stock market returns and three investor sentiment components used to construct each market sentiment index. The first proxy, *CCI*, is the public index based on direct surveys. The second proxy, *ADR*, is measured by dividing the number of advancing stocks by the number of declining stocks during a month. The third proxy, *VP*, is the log of the average market-to-book ratios between high and low volatility stocks. The market returns are calculated from the price index. The data period is from January 2004 to December 2016.

Concerning sentiment proxies, while Australia, Indonesia, and South Korea expose positive expectation about economic conditions represented by the average of their *CCIs* were over 100, people in remaining markets seem to be pessimistic about the future (average *CCI* was under 100 for Hong Kong and Thailand and 50 for Japan). Likewise, *VPs* were equally divergent among six markets, with Australia, Japan, and South Korea having the positive averages, approximately 0.2 per month. In contrast, the negative ones were held by Hong Kong, Indonesia, and Thailand at -0.003, -1.095, and -0.132, in turn. Conflicting with other proxies, *ADRs* were almost similar to the average ratio of approximately 1 per month in all six markets.

3.3.2. Macroeconomic variables

According to previous studies, such as Baker and Wurgler (2007), Schmeling (2009), and Smales (2017), macroeconomic conditions might affect the variation in sentiment proxies as well as stock returns. Therefore, to isolate the impact of market sentiment and prevent my results from being pushed by the business cycle's fluctuation, five macroeconomic variables were employed in my empirical analyses. These are the industrial production index (*IP*), consumer price index (inflation rate) (*CPI*), unemployment rate (*UR*), dividend yield (*DY*), and short-term interest rate (*SR*). All series were converted into monthly growth rate before use.

3.3.3. Financial development index

To investigate the impact of financial development on the correlation between investor sentiment and stock returns, I utilized the Financial Development Index series (*FD*) created by the International Monetary Fund (IMF). According to *FD*, markets are ranked based on their financial institutions and financial markets' depth, access, and efficiency. It is an aggregate index of the financial institutions (*FI*) and the financial markets (*FM*). I downloaded *FI*, *FM,* and *FD* series from the IMF's website. These yearly series are available from 1980 to 2016.

3.3.4. Methodology

Before employing in my empirical analyses, I executed augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for all data series to ensure that they do not have a unit root. For non-stationary series, their first differencing was used instead. Besides that, to apply principal component analysis (PCA) later, I standardized sentiment indicators described in Section 3.3.1.2 to get a mean of zero and a standard deviation of one.

3.3.4.1. Construction of composite sentiment index

Complying with Baker and Wurgler (2012), Finter et al. (2012), and Corredor et al. (2013), I created a comprehensive sentiment index for each market from standardized sentiment proxies. The construction is as follows:

Firstly, to remove unrelated-sentiment information about expected returns from my sentiment proxies, I orthogonalized these indicators on five macroeconomic variables by running the following regression:

$$Sent_{i,t} = \alpha_i + \beta_{1,i}UR_t + \beta_{2,i}IP_t + \beta_{3,i}CPI_t + \beta_{4,i}DY_t + \beta_{5,i}SR_t + \varepsilon_{i,t} \qquad (3.1)$$

In which $Sent_{i,t}$ is one of three sentiment indicators. The explanatory variables are the growth rate of *UR*, *IP*, *CPI*, *DY*, and *SR*. The residuals, $\varepsilon_{i,t}$, from these regressions were considered as orthogonalized sentiment indicators, $Sent_{i,t}^{T}$, with $Sent_{i,t}^{T} = \varepsilon_{i,t}$ and employed in the next steps.

As shown in prior studies, the three proxies, as mentioned earlier, might capture some aspects of investor sentiment. However, even after macro-adjusting, there is a possibility that they still comprise idiosyncratic components that do not relate to investor behavior. Consequently, PCA was employed to extract the sentiment component from these proxies. Besides that, Huang et al. (2015) argued that some sentiment proxies might take more time to reveal the same sentiment than others leading to lead-lag relationships. As a result, through PCA, I estimated the first principal component of CCI_t, ADR_t, VP_t, and their one-year lags, denoted as CCI_{t-1}, ADR_{t-1}, and VP_{t-1}. This step gave the first-stage index with six loadings. After that, the correlations between the first-stage index and each pair of sentiment proxies, i.e., sentiment indicator and its lag, were calculated. PCA was repeated for three components having a stronger relationship with the first-stage index in each pair. The first principal component estimated from this process was stored and viewed as the total sentiment index. Six total sentiment indices were standardized and plotted in Figure 3.1. The index loadings for each market are as follows:

$$Sent_{AU,t}^{Total} = 0.627CCI_{t-1} + 0.622ADR_t + 0.018VP_t \qquad (3.2a)$$

$$Sent_{HK,t}^{Total} = 0.337CCI_{t-1} + 0.485ADR_{t-1} + 0.507VP_t \qquad (3.2b)$$

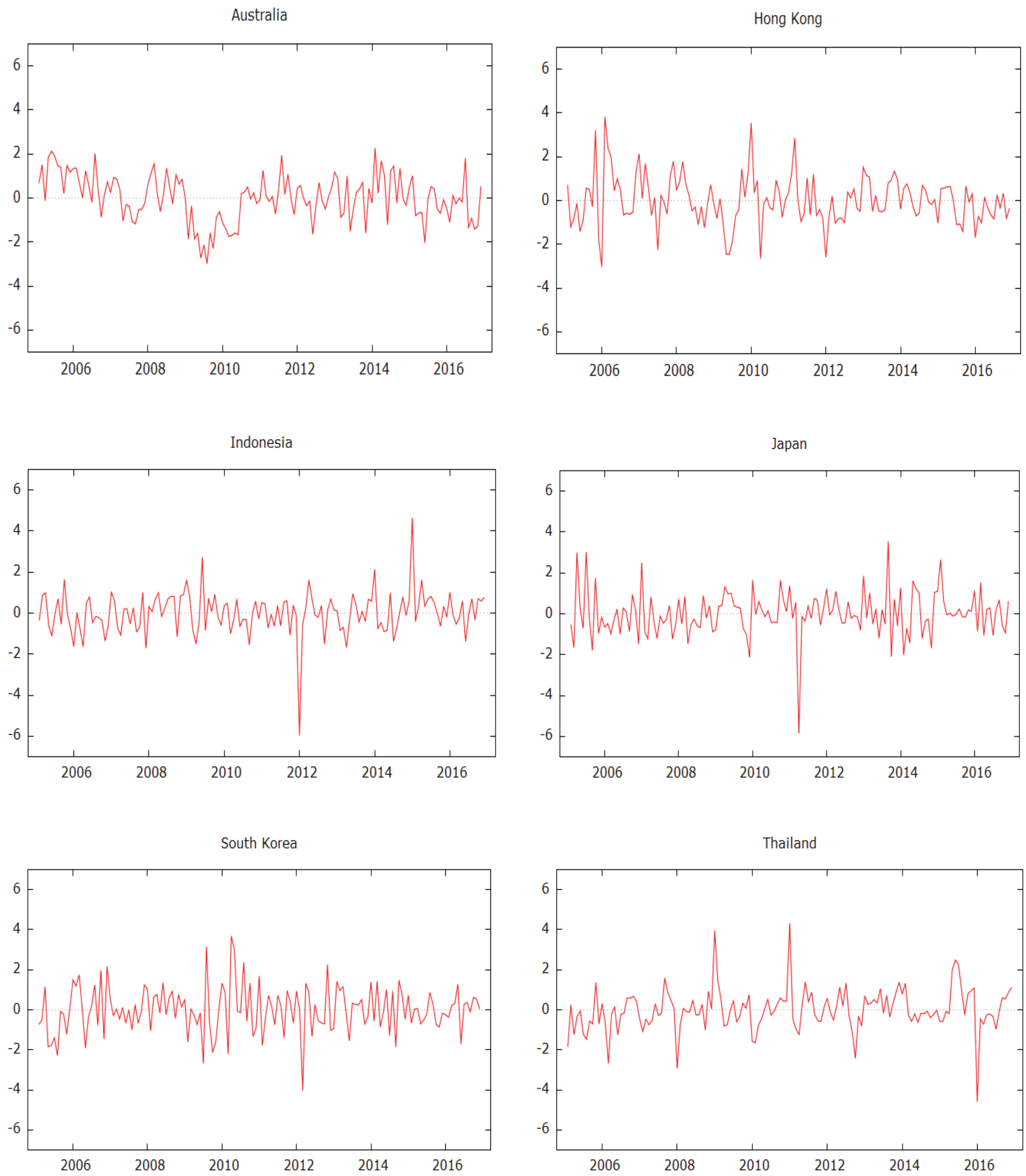
$$Sent_{ID,t}^{Total} = 0.197CCI_{t-1} - 0.689ADR_t + 0.624VP_t \quad (3.2c)$$

$$Sent_{JP,t}^{Total} = 0.564CCI_t - 0.068ADR_{t-1} + 0.569VP_t \quad (3.2d)$$

$$Sent_{KO,t}^{Total} = 0.538CCI_{t-1} - 0.535ADR_{t-1} + 0.148VP_{t-1} \quad (3.2e)$$

$$Sent_{TH,t}^{Total} = 0.645CCI_{t-1} - 0.274ADR_t + 0.554VP_{t-1} \quad (3.2f)$$

Figure 3.1: Total sentiment index



The figure illustrates the standardized total sentiment index of six markets, including Australia, Hong Kong, Indonesia, Japan, South Korea, and Thailand. The total sentiment index is formed from the first principal component of the *CCI*, *ADR*, and *VP* of a given market. The data period is from January 2004 to December 2016.

AU, HK, ID, JP, KO, and TH represent Australia, Hong Kong, Indonesia, Japan, South Korea, and Thailand. In order of listed markets, the first principal component explains 37.74%, 42.82%, 35.07%, 41.46%, 43.11%, and 37.32% of total variance. The correlations between the total index and three sentiment proxies are presented in detail in Table 3.2. As presumably, *CCI* and *VP* exposed a positive impact on all six markets' underlying sentiment index. The only unevenly distributed indicator is *ADR,* which had a positive relationship with the total sentiment of Australia and Hong Kong and a negative one to other markets' index.

Table 3.2: Correlation of total sentiment index

	Correlation with total sentiment		Loading	Correlation between sentiment components			p-values		
	Coef.	*p-value*		*CCI*	*ADR*	*VP*	*CCI*	*ADR*	*VP*
Panel A: Australia									
CCI_{t-1}	0.755***	0.000	0.627	1.000			(.)		
ADR_t	0.750***	0.000	0.622	0.132	1.000		0.114	(.)	
VP_t	0.022	0.791	0.018	0.033	-0.014	1.000	0.694	0.867	(.)
Panel B: Hong Kong									
CCI_{t-1}	0.491***	0.000	0.337	1.000			(.)		
ADR_{t-1}	0.706***	0.000	0.485	0.077	1.000		0.343	(.)	
VP_t	0.738***	0.000	0.507	0.113	0.219***	1.000	0.179	0.009	(.)
Panel C: Indonesia									
CCI_{t-1}	0.212**	0.011	0.197	1.000			(.)		
ADR_t	-0.744***	0.000	-0.689	-0.024	1.000		0.779	(.)	
VP_t	0.674***	0.000	0.624	-0.010	-0.041	1.000	0.908	0.617	(.)
Panel D: Japan									
CCI_t	0.782***	0.000	0.564	1.000			(.)		
ADR_{t-1}	-0.094	0.265	-0.068	0.005	1.000		0.957	(.)	
VP_t	0.790***	0.000	0.569	0.172**	-0.034	1.000	0.033	0.691	(.)
Panel E: South Korea									
CCI_{t-1}	0.792***	0.000	0.538	1.000			(.)		
ADR_{t-1}	-0.787***	0.000	-0.535	-0.282***	1.000		0.000	(.)	
VP_{t-1}	0.218***	0.007	0.148	0.047	-0.034	1.000	0.563	0.674	(.)
Panel F: Thailand									
CCI_{t-1}	0.765***	0.000	0.645	1.000			(.)		
ADR_t	-0.324***	0.000	-0.274	-0.063	1.000		0.457	(.)	
VP_{t-1}	0.656***	0.000	0.554	0.088	0.014	1.000	0.277	0.870	(.)

The table presents the correlation coefficients and p-values of the total sentiment index and three sentiment proxies, including *CCI*, *ADR*, and *VP*, as well as the relationship between these proxies in each market. The total sentiment index is the first principal component of sentiment indicators of a given market. The loadings of each component in the total index are also reported. The data period is from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

In addition to that, I divided total sentiment indices into one regional and six local components. The same PCA process was applied to form an aggregate index for all six markets, denoted as $Sent_t^{Regional}$. Since the aggregate index is established based on markets in the Asia-Pacific region only, I considered it as regional sentiment instead of global sentiment as in previous studies.

$$Sent_t^{Regional} = -0.465 Sent_{AU,t}^{Total} - 0.316 Sent_{HK,t}^{Total} + 0.310 Sent_{ID,t}^{Total} + 0.275 Sent_{JP,t}^{Total} + 0.171 Sent_{KO,t}^{Total} + 0.203 Sent_{TH,t}^{Total} \quad (3.3)$$

Finally, the total sentiment index in each market was orthogonalized on the regional index. The residuals extracted from this regression were considered as local sentiment index in subsequent analyses. Figure 3.2 illustrates the regional and local indices. The connections between total, regional, and local sentiment are revealed in Table 3.3. It is clear from the table that most markets' total sentiment positively correlates with the regional index, except Australia and Hong Kong. Aside from that, pure local sentiment across markets seems to link more firmly than total sentiment.

3.3.4.2. Return predictability of investor sentiment

The relationship between investor sentiment and future market returns was investigated by manipulating the following regression models. The regressions were run separately for each market in my sample and the Asia-Pacific region, i.e., all six markets together.

$$\frac{1}{k}\sum R_{t+k} = \alpha + \beta Sent_t^{Total} + \varepsilon_{t+k} \quad (3.4)$$

$$\frac{1}{k}\sum R_{t+k} = \alpha + \beta_1 Sent_t^{Regional} + \beta_2 Sent_t^{Local} + \varepsilon_{t+k} \quad (3.5)$$

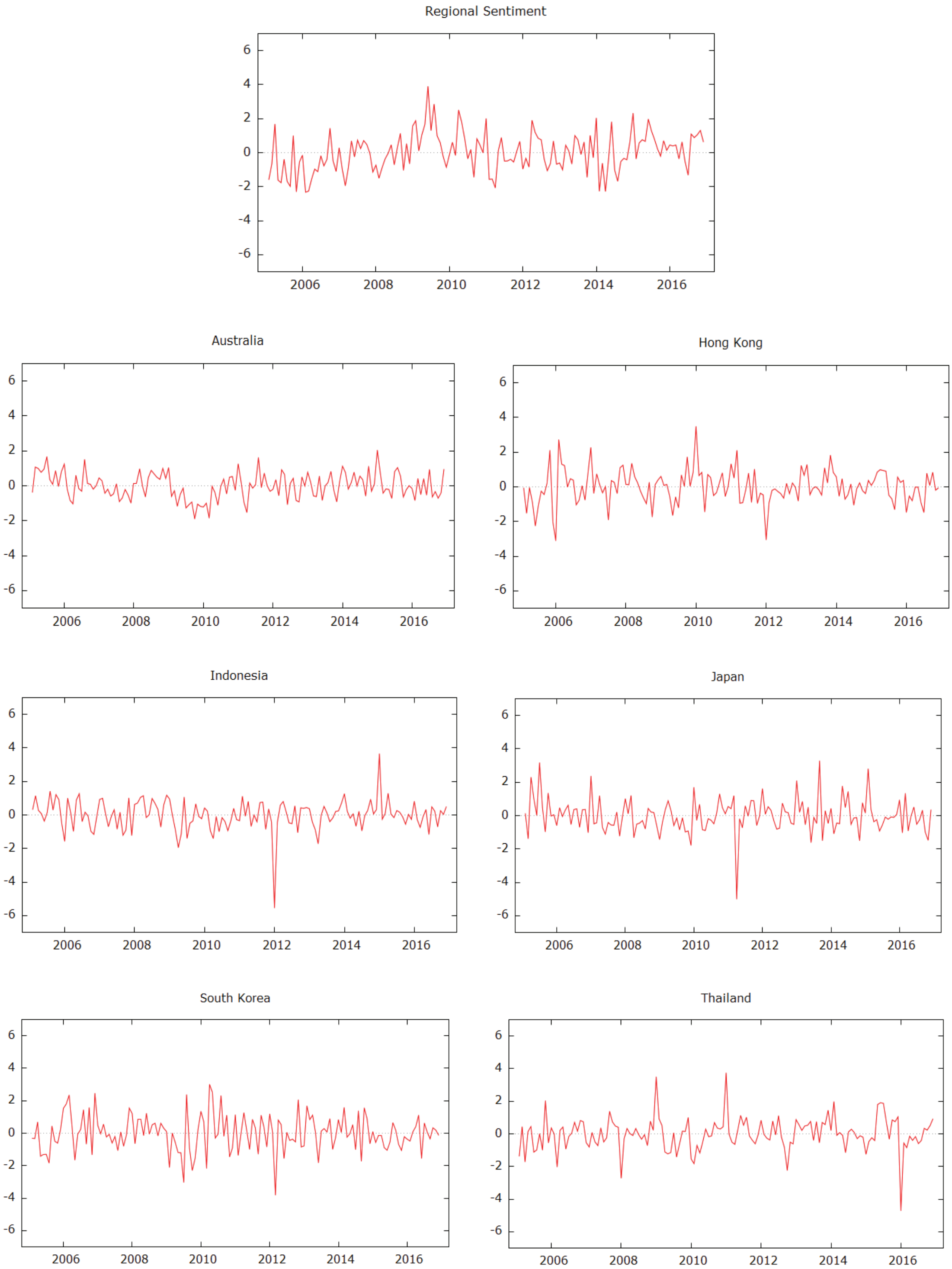
In which: $\frac{1}{k}\sum R_{t+k}$ is the k-month average return of the stock market with $k =$ 1, 3, 6, 12, and 24. $Sent_t$ is the investor sentiment at time t. I ran regional and local sentiment together in one model to discover whether the domestic effect endures or fades when the regional effect is also considered.

To get individual market coefficients, I applied the Newey-West standard errors for OLS estimations. The estimation procedure for all markets was pooled OLS regressions with cross-section fixed effects and month-clustered standard errors.

3.3.4.3. Impact of financial development

To examine the potential influence of financial development on the sentiment-return relationship, I divided my sample into two groups: above and below the median, based on three financial development series described in Section 3.3.3, then applied Equations (3.4) and (3.5) for each group and compared the results.

Figure 3.2: Regional and local sentiment indices



The figure illustrates the standardized Asia-Pacific regional sentiment index, established from the first principal component of total sentiment indices of Australia, Hong Kong, Indonesia, Japan, South Korea, and Thailand. The local sentiment indices of these given markets, which are the residuals from orthogonalizing the total indices on the regional one, are also presented. The data period is from January 2004 to December 2016.

Table 3.3: Correlation between total, regional and local sentiment indices

Panel A: Total and regional sentiment

	Correlation with regional sentiment		Loading	Correlation between total sentiment indices						p-values					
	Coef.	*p-value*		*AU*	*HK*	*ID*	*JP*	*KO*	*TH*	*AU*	*HK*	*ID*	*JP*	*KO*	*TH*
AU	-0.720***	0.000	-0.465	1.000						(.)					
HK	-0.490***	0.000	-0.316	0.156*	1.000					0.064	(.)				
ID	0.479***	0.000	0.310	-0.154*	0.033	1.000				0.066	0.700	(.)			
JP	0.426***	0.000	0.275	-0.100	-0.096	0.091	1.000			0.236	0.256	0.282	(.)		
KO	0.265***	0.001	0.171	-0.045	-0.049	0.058	0.011	1.000		0.596	0.563	0.490	0.901	(.)	
TH	0.315***	0.000	0.203	-0.124	-0.050	0.042	-0.066	0.004	1.000	0.140	0.557	0.620	0.433	0.963	(.)

Panel B: Local sentiment

	Correlation between local sentiment indices						p-values					
	AU	*HK*	*ID*	*JP*	*KO*	*TH*	*AU*	*HK*	*ID*	*JP*	*KO*	*TH*
AU	1.000						(.)					
HK	-0.325***	1.000					0.000	(.)				
ID	0.313***	0.349***	1.000				0.000	0.000	(.)			
JP	0.329***	0.143*	-0.143*	1.000			0.000	0.088	0.089	(.)		
KO	0.218***	0.096	-0.081	-0.117	1.000		0.009	0.252	0.335	0.163	(.)	
TH	0.156*	0.127	-0.131	-0.233***	-0.087	1.000	0.063	0.132	0.119	0.005	0.302	(.)

The table reveals the relationship between total sentiment indices and the Asia-Pacific regional sentiment index. The regional index is the first principal component of total sentiment indices of Australia (AU), Hong Kong (HK), Indonesia (ID), Japan (JP), South Korea (KO), and Thailand (TH). The correlation among total and local indices of given markets is presented too. The local index for each market is the residuals from orthogonalizing the total index on the regional one. The data period is from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

Subsequently, I also ran panel regressions on the full set of markets. I included (a) an interaction term between sentiment and financial development component, and (b) a dummy variable indicating markets having higher financial development.

$$\frac{1}{k}\sum R_{t+k} = \alpha + \beta_1 Sent_t^{Total} + \beta_2 Sent_t^{Total} FD + \varepsilon_{t+k} \quad (3.4a)$$

$$\frac{1}{k}\sum R_{t+k} = \alpha + \beta_1 Sent_t^{Regional} + \beta_2 Sent_t^{Regional} FD + \beta_3 Sent_t^{Local} + \beta_4 Sent_t^{Local} FD + \varepsilon_{t+k} \quad (3.5a)$$

$$\frac{1}{k}\sum R_{t+k} = \alpha + \beta_1 Sent_t^{Total} + \beta_2 Sent_t^{Total} DM + \varepsilon_{t+k} \quad (3.4b)$$

$$\frac{1}{k}\sum R_{t+k} = \alpha + \beta_1 Sent_t^{Regional} + \beta_2 Sent_t^{Regional} DM + \beta_3 Sent_t^{Local} + \beta_4 Sent_t^{Local} DM + \varepsilon_{t+k} \quad (3.5b)$$

3.4. Results

3.4.1. Investor sentiment and future returns

Table 3.4 reveals the results by regressing Equations (3.4) and (3.5), which indicate the relationship between investor sentiment and subsequent stock returns. Regarding the total sentiment index in each market, the outcomes were almost homogenous during the first six months. Despite the differences in magnitude, most of the markets witnessed negative return predictability of sentiment. The most considerable influence belonged to Indonesia with a coefficient of -0.884 for the three months, followed by -0.749 and -0.630 in South Korea and Thailand for the first horizon, respectively.

However, the results became diverse as the effect of total sentiment in Australia and Thailand reversed and turned positive over the next 6 to 18 months. Japan is the only market where the positive correlation between the return spread and investor sentiment was exposed all the time.

Nevertheless, these figures were statistically significant, mostly in Japan, South Korea, and Thailand for short-term horizons only. My results reflect those of Gao et al. (2020). They also observed in their study using Google Search Volume Index for 38 countries around the world that all countries, except Israel and Mexico, present a negative relationship between sentiment and next week's returns, and 20 of the 38 countries display a pattern that is significant at the 5% level.

Table 3.4: Return predictability of investor sentiment in different horizons

	Total			Regional		Local		
	Coef.	*p-value*	R^2	*Coef.*	*p-value*	*Coef.*	*p-value*	R^2
R_{t+1}								
Australia	-0.627*	0.061	2.74%	0.390	0.238	-0.676	0.186	2.79%
Hong Kong	-0.419	0.275	0.57%	0.344	0.449	-0.326	0.394	0.66%
Indonesia	-0.357	0.428	0.34%	-0.037	0.944	-0.437	0.358	0.40%
Japan	0.522	0.107	0.98%	-0.282	0.499	0.789**	0.022	2.14%
South Korea	-0.749**	0.044	2.70%	0.160	0.675	-0.883**	0.020	3.59%
Thailand	-0.630**	0.038	1.24%	0.172	0.659	-0.766**	0.036	1.75%
All markets	-0.382**	0.013	0.81%	0.125	0.730	-0.379**	0.02	0.75%
R_{t+3}								
Australia	-0.049	0.873	0.04%	0.020	0.938	-0.071	0.849	0.05%
Hong Kong	-0.432	0.194	1.53%	0.029	0.921	-0.550*	0.082	1.90%
Indonesia	-0.884**	0.010	4.76%	-0.016	0.966	-1.137**	0.012	6.06%
Japan	0.395*	0.057	1.37%	-0.362	0.220	0.678***	0.005	4.53%
South Korea	-0.414*	0.051	2.36%	-0.054	0.827	-0.443*	0.056	2.56%
Thailand	-0.465**	0.022	1.68%	0.130	0.638	-0.565**	0.020	2.39%
All markets	-0.299***	0.004	1.48%	-0.042	0.839	-0.344***	0.008	1.53%
R_{t+6}								
Australia	-0.050	0.822	0.07%	0.050	0.782	-0.027	0.924	0.09%
Hong Kong	-0.278	0.243	1.17%	0.120	0.601	-0.287	0.207	1.17%
Indonesia	-0.394	0.134	1.58%	0.035	0.891	-0.535	0.134	2.27%
Japan	0.280*	0.053	1.18%	-0.300	0.130	0.503***	0.007	4.60%
South Korea	-0.285*	0.097	1.90%	-0.001	0.996	-0.296*	0.098	1.93%
Thailand	-0.188	0.446	0.45%	0.284	0.190	-0.317	0.189	2.36%
All markets	-0.148*	0.068	1.47%	0.031	0.829	-0.162	0.105	1.46%
R_{t+12}								
Australia	0.052	0.717	0.15%	0.027	0.839	0.147	0.389	0.61%
Hong Kong	-0.300	0.131	3.03%	0.019	0.911	-0.382**	0.040	3.75%
Indonesia	-0.205	0.228	0.90%	0.122	0.574	-0.352	0.153	2.44%
Japan	0.155	0.149	0.74%	-0.091	0.577	0.238*	0.097	1.73%
South Korea	-0.078	0.448	0.34%	0.087	0.497	-0.108	0.349	1.02%
Thailand	0.090	0.643	0.22%	0.357**	0.038	-0.037	0.839	4.15%
All markets	-0.050	0.388	2.65%	0.087	0.389	-0.090	0.222	3.05%
R_{t+24}								
Australia	0.123	0.279	2.04%	0.004	0.965	0.258**	0.038	4.46%
Hong Kong	-0.173*	0.093	3.72%	-0.029	0.802	-0.249***	0.003	5.84%
Indonesia	-0.002	0.985	0.01%	0.036	0.817	-0.028	0.842	0.15%
Japan	0.134	0.130	1.11%	0.018	0.868	0.156	0.186	1.23%
South Korea	-0.113	0.106	2.36%	0.058	0.562	-0.137*	0.060	3.84%
Thailand	0.088	0.514	0.55%	0.267**	0.023	-0.021	0.879	6.88%
All markets	0.001	0.990	7.59%	0.060	0.393	-0.029	0.575	8.00%

The table reports the regression results obtained from Equations (3.4) (first column) and (3.5) (second and third column). The dependent variable is the average market return for the next 1, 3, 6, 12, and 24 months. The independent variable is the total sentiment for Equation (3.4) and regional and local sentiment for Equation (3.5). Individual market coefficients are estimated by applying Newey-West correction for OLS estimations. The estimation procedure for all markets is pooled OLS regressions with cross-section fixed effects and month-clustered standard errors. Estimated coefficients, corresponding p-values, and R^2 are presented. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

The less significant forecast ability of total sentiment in some markets could be because this index cannot capture the impact of investor sentiment fully, which is inclined to a more global phenomenon. This viewpoint argued and proved in the studies of Chang et al. (2011), Baker and Wurgler (2012), and Corredor et al. (2015) inspired me to decompose my total sentiment into regional and local indices and discover their influence on stock returns. As can be seen from Table 3.4, the local sentiment shared the same sign and trend with those of total ones with slightly higher intensity. On the other hand, the regional impact was more dissimilar across markets and reversed to local impact in most cases. In addition to that, in contrast to the strong effect of local sentiment, most regional coefficients were statistically insignificant. Therefore, in general, I conclude that the market-level results are driven mostly by local sentiment. This outcome is in line with Corredor et al. (2013). They also created a composite index from the sentiment proxies of France, Germany, Spain, and the U.K. and found that this proxy captures investor sentiment limitedly. Besides that, the reverse influences of regional and local sentiment might partly explain the total sentiment's frail significance in my sample markets. Lastly, in tandem with the prior work, I observed the weakening effect of investor sentiment over the period when the magnitude and significance of all estimated coefficients declined through short-term to long-term horizons.

The outcomes for the panel regressions of all markets shared the same picture with those of individual markets. In conclusion, for these six Asia-Pacific markets, investor sentiment can be a valid predictor of stock returns over the next six months. Remarkably, I noticed that the sentiment effect seems to be shorter but sharper in developing markets than a more prolonged but weaker impact in developed ones. These findings support the work of Wang et al. (2019), which outlined that sentiment exerts a more immediate impact in emerging markets but a more enduring impact in developed markets. They also questioned the role of market-specific factors, especially financial development, in sentiment-return relation, which was investigated closer in the next section.

3.4.2. Impact of financial development

To explore the potential effect of financial development on the relationship between investor sentiment and stock returns, I separated my sample markets into two groups: above and below-median, based on three criteria, namely financial institutions, financial markets, and financial development. Then, I ran Equations (3.4) and (3.5) for each group and compared their estimated coefficients. During most of the research period, the above-median group comprises Australia, Japan, and South Korea. Simultaneously, the remaining markets are affiliated to the below-median group, excluding two exceptions: Hong Kong replaces Japan in 2008 and 2011 in terms of financial markets and South Korea in 2008 in terms of financial development. Firstly, I look at the outcomes for the total sentiment index summarized in Table 3.5.

Table 3.5: Return predictability of total sentiment index in high and low financial development groups

	Below median			Above median			Difference	p-value
	Coef.	*p-value*	*R^2*	*Coef.*	*p-value*	*R^2*		
R_{t+1}								
Financial Institutions	-0.469**	0.020	0.94%	-0.303	0.140	0.49%	-0.166	0.542
Financial Markets	-0.507**	0.029	1.11%	-0.257	0.204	0.34%	-0.250	0.420
Financial Development	-0.564**	0.016	1.19%	-0.217	0.279	0.23%	-0.347	0.265
R_{t+3}								
Financial Institutions	-0.580***	0.001	2.43%	-0.039	0.754	0.17%	-0.541***	0.010
Financial Markets	-0.603***	0.000	3.44%	0.007	0.955	0.16%	-0.596***	0.005
Financial Development	-0.705***	0.000	4.27%	0.074	0.559	0.12%	-0.631***	0.001
R_{t+6}								
Financial Institutions	-0.284**	0.031	2.13%	-0.023	0.796	0.31%	-0.261*	0.096
Financial Markets	-0.245*	0.067	1.82%	-0.049	0.590	0.37%	-0.196	0.219
Financial Development	-0.358**	0.012	2.61%	0.044	0.619	0.16%	-0.314**	0.018
R_{t+12}								
Financial Institutions	-0.145	0.149	2.89%	0.038	0.571	0.69%	-0.183	0.143
Financial Markets	-0.086	0.348	2.88%	-0.014	0.856	0.60%	-0.072	0.559
Financial Development	-0.126	0.195	2.61%	0.020	0.787	0.41%	-0.146	0.252
R_{t+24}								
Financial Institutions	-0.042	0.561	7.44%	0.038	0.399	1.55%	-0.080	0.336
Financial Markets	-0.034	0.616	6.84%	0.037	0.415	1.68%	-0.071	0.374
Financial Development	-0.039	0.590	6.89%	0.035	0.444	0.39%	-0.074	0.379

The table shows pooled OLS regression results with cross-section fixed effects and month-clustered standard errors for Equation (3.4). Each market is classified into either above or below-median group, based on three criteria in the first column. Estimated coefficients, corresponding p-values, and R^2 for each group are presented. The differences between coefficients of the two groups are examined by the Seemingly Unrelated Estimation and Chow test. p-values of the Chow test are also reported. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

As shown in the table, with larger and more significant estimated coefficients of the below-median group all the time, I detected that markets having the more inferior financial environment expose the more substantial effect of sentiment on subsequent returns. In another way, sentiment impact tends to be opposed to the financial development of a market. To validate my results, I applied the Chow test for the differences between the two groups' sentiment coefficients. I found that financial development has a statistically significant effect on the relation between market sentiment and the next 3 to 6-month returns with p-values of 0.001 and 0.018.

Take a closer glance at two aspects of financial development, the growth of financial institutions and financial markets revealed the same influence as total financial development on the sentiment-return relationship. Nevertheless, financial markets' impact seems weaker than those of financial institutions since its effect was statistically significant over the first three months only.

Additionally, some impressive results are reported in Table 3.6 through regional and local indices' regressions. In harmonization with the total sentiment, regional and local sentiment outcomes were homogenous for all three criteria. Specifically, I proved that an improvement in market development could reduce regional and local sentiment's predictive power. This effect is apparent both in statistical and economic significance. My findings for the Asia-Pacific markets further support the idea of a more powerful sentiment effect in a weaker trading environment, as stated in Chang et al. (2011) for the locally sourced sentiment. They are also in line with Corredor et al. (2015), who argued that global sentiment has a more substantial impact on Central European emerging markets than developed ones.

Compared with the total sentiment, the moderating impact of financial development on local sentiment seems to be sharper, with more enormous gaps between the two groups' coefficients and long-lasting, over one year. Surprisingly, although there was no statistical evidence that regional sentiment and return spread are related in both below and above-median groups, the moderating role of market development on regional sentiment is undeniable, especially in mid-term horizons from 6 to 12 months.

In the end, I also ran the regressions for all markets when (a) interaction terms of sentiment and financial development indicators and (b) dummy variables for more developed markets were added into my models. Table 3.7 represents the results for the model having the appearance of interaction variables. It is apparent from this table that the outcomes provided the same picture, as shown in Tables 3.5 and 3.6. The findings remained unchanged when I substituted interaction terms with dummy variables[6].

Table 3.6: Return predictability of regional and local sentiment index in high and low financial development groups

	Below median			Above median			Differences	
	Regional	*Local*	*R^2*	*Regional*	*Local*	*R^2*	*Regional*	*Local*
R_{t+1}								
Financial Institutions	0.159	-0.517**	1.02%	0.090	-0.243	0.31%	0.069	-0.274
	[0.691]	[0.026]		[0.797]	[0.325]		[0.745]	[0.413]
Financial Markets	0.197	-0.579**	1.29%	0.057	-0.166	0.16%	0.140	-0.413
	[0.624]	[0.013]		[0.872]	[0.506]		[0.521]	[0.213]
Financial Development	0.140	-0.589**	1.14%	0.109	-0.176	0.18%	0.031	-0.413
	[0.725]	[0.014]		[0.757]	[0.481]		[0.887]	[0.233]
R_{t+3}								
Financial Institutions	0.048	-0.726***	3.78%	-0.132	0.031	0.39%	0.180	-0.757***
	[0.837]	[0.000]		[0.521]	[0.838]		[0.192]	[0.002]
Financial Markets	0.057	-0.763***	4.30%	-0.133	0.103	0.48%	0.190	-0.866***
	[0.801]	[0.000]		[0.523]	[0.520]		[0.162]	[0.000]
Financial Development	0.045	-0.865***	5.09%	-0.128	0.164	0.50%	0.173	-1.029***
	[0.841]	[0.000]		[0.541]	[0.294]		[0.201]	[0.000]
R_{t+6}								
Financial Institutions	0.146	-0.370**	2.80%	-0.084	0.043	0.49%	0.230**	-0.413**
	[0.390]	[0.019]		[0.543]	[0.701]		[0.045]	[0.029]
Financial Markets	0.138	-0.343**	2.55%	-0.072	0.030	0.44%	0.210*	-0.373**
	[0.410]	[0.022]		[[0.609]	[0.795]		[0.066]	[0.034]
Financial Development	0.149	-0.463***	3.53%	-0.086	0.132	0.54%	0.235**	-0.595***
	[0.369]	[0.005]		0.542]	[0.221]		[0.039]	[0.002]
R_{t+12}								
Financial Institutions	0.166	-0.249**	4.49%	0.008	0.065	0.77%	0.158**	-0.184**
	[0.159]	[0.042]		[0.937]	[0.456]		[0.037]	[0.040]
Financial Markets	0.165	-0.213*	4.52%	0.011	0.038	0.65%	0.154**	-0.175*
	[0.158]	[0.055]		[0.910]	[0.674]		[0.042]	[0.074]
Financial Development	0.159	-0.253**	4.41%	0.014	0.069	0.55%	0.145**	-0.184**
	[0.163]	[0.030]		[0.885]	[0.437]		[0.050]	[0.026]
R_{t+24}								
Financial Institutions	0.092	-0.105	8.76%	0.028	0.041	1.62%	0.064	-0.064
	[0.275]	[0.235]		[0.673]	[0.479]		[0.252]	[0.157]
Financial Markets	0.091	-0.101	8.09%	0.031	0.045	1.81%	0.060	-0.056
	[0.283]	[0.228]		[0.643]	[0.438]		[0.284]	[0.138]
Financial Development	0.091	-0.105	8.22%	0.029	0.041	1.26%	0.062	-0.064
	[0.280]	[0.223]		[0.660]	[0.484]		[0.279]	[0.157]

The table shows pooled OLS regression results with cross-section fixed effects and month-clustered standard errors for Equation (3.5). Each market is classified into either above or below-median group, based on three criteria in the first column. Estimated coefficients, corresponding p-values, and R^2 for each group are presented. The differences between coefficients of the two groups are examined by the Seemingly Unrelated Estimation and Chow test. p-values of the Chow test are also reported. p-values are in brackets. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

3.5. Conclusion

The chapter investigated the relationship between investor sentiment and future stock returns using empirical data from six Asia-Pacific markets from January 2004 to December 2016. Through principal component analysis, a composite index was formed for each market based on three sentiment proxies, including *CCI*, *ADR*, and *VP*. My regression results suggest that investor sentiment can be a valid predictor for market returns in short-term horizons, from 1 to 6 months, despite not matching across markets.

Table 3.7: Impact of financial development on sentiment-return relationship

	Financial Institution			Financial Markets			Financial Development		
	Coef.	*p-value*	R^2	*Coef.*	*p-value*	R^2	*Coef.*	*p-value*	R^2
R_{t+1}									
Total	-0.741	0.375	0.84%	-0.345	0.599	0.81%	-0.537	0.482	0.81%
Total*Index	0.489	0.653		-0.054	0.952		0.216	0.832	
Regional	0.178	0.814	0.85%	-0.094	0.866	0.76%	0.051	0.939	0.78%
Regional*Index	-0.077	0.911		0.323	0.520		0.105	0.858	
Local	-1.135	0.140		-0.497	0.444		-0.827	0.257	
Local*Index	1.044	0.305		0.172	0.850		0.629	0.524	
R_{t+3}									
Total	-1.659***	0.009	2.50%	-1.205**	0.017	2.02%	-1.469**	0.013	2.27%
Total*Index	1.857**	0.020		1.312**	0.050		1.632**	0.030	
Regional	0.318	0.465	3.26%	0.061	0.861	2.30%	0.206	0.604	2.78%
Regional*Index	-0.510	0.221		-0.150	0.665		-0.355	0.354	
Local	-2.248***	0.001		-1.570***	0.006		-1.970***	0.002	
Local*Index	2.630***	0.001		1.780**	0.015		2.285***	0.005	
R_{t+6}									
Total	-0.728	0.110	1.78%	-0.499	0.167	1.61%	-0.627	0.135	1.69%
Total*Index	0.791	0.164		0.507	0.282		0.667	0.209	
Regional	0.413	0.190	2.39%	0.135	0.592	1.77%	0.288	0.316	2.06%
Regional*Index	-0.537*	0.088		-0.153	0.565		-0.367	0.208	
Local	-1.128**	0.029		-0.748*	0.080		-0.970**	0.047	
Local*Index	1.335**	0.036		0.850	0.119		1.136*	0.063	
R_{t+12}									
Total	-0.311	0.358	2.79%	-0.223	0.392	2.72%	-0.274	0.372	2.76%
Total*Index	0.357	0.403		0.251	0.469		0.312	0.428	
Regional	0.427*	0.054	3.91%	0.226	0.197	3.37%	0.337*	0.093	3.63%
Regional*Index	-0.478**	0.029		-0.205	0.241		-0.358*	0.071	
Local	-0.646*	0.089		-0.471	0.116		-0.580*	0.097	
Local*Index	0.768	0.103		0.552	0.150		0.688	0.117	
R_{t+24}									
Total	-0.061	0.773	7.61%	0.008	0.964	7.59%	-0.026	0.896	7.60%
Total*Index	0.083	0.750		-0.010	0.963		0.037	0.883	
Regional	0.187	0.265	8.23%	0.085	0.551	8.02%	0.141	0.371	8.09%
Regional*Index	-0.178	0.281		-0.036	0.797		-0.115	0.458	
Local	-0.172	0.460		-0.066	0.736		-0.123	0.577	
Local*Index	0.199	0.488		0.053	0.828		0.132	0.628	

The table shows the regression results for Equations (3.4) and (3.5) when the interaction terms between sentiment and financial development indices are added to the models. Estimated coefficients, corresponding p-values, and R^2 are obtained from pooled OLS regressions with cross-section fixed effects and month-clustered standard errors. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

In addition to that, the weak significance of total sentiment in some markets motivated me to pay attention to a broader aspect of this matter, which was also mentioned in the research of Chang et al. (2011), Baker and Wurgler (2012), and Corredor et al. (2015). By splitting total sentiment into regional and local indices, I demonstrated the strong effect of so-called pure local sentiment on stock returns, either from the statistical or economic perspective. Regional impact, on the contrary, seems not to exist in these markets. However, this outcome must not be overlooked since my research included only six markets that might not be suitable to represent regional sentiment. The results, nevertheless, inspire further studies to achieve better understandings.

Finally, the variation in estimated coefficients of sentiment indices among markets raised doubts about the role of market-specific factors on sentiment-return relation. Unlike other studies that focus on the level of governance or cultural features, in this study, I decided to concentrate on the impact of financial development since my sample comprises both advanced and developing markets. I found out that the degree of financial development could considerably affect the sentiment-return relationship. Comparing two aspects of financial development, the dispersion in financial institutions' growth level across markets might lead to a more decisive influence on the correlation between market sentiment and future returns than those of financial markets.

Chapter 4

Moderating effect of market-specific factors on the return predictability of investor sentiment

The original paper is submitted in the International Economics

4.1. Introduction

According to Brown and Cliff (2004), sentiment represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever "average" maybe. Since the 1990s, accompanied by the foundation of behavioral finance, the explanation role of sentiment for abnormal returns has been questioned and investigated in various research. However, the findings are mixed. While some studies claim that investor sentiment has a significant impact, positively or negatively, on stock returns (Grigaliūnienė and Cibulskienė, 2010; Bathia and Bredin, 2013; Oprea and Brad, 2014; Dash and Maitra, 2018; Gao et al., 2020), the others detect that the sentiment-return inference is negligible (Sol and Statman, 1988; Kim and Kim, 2014; Gizelis and Chowdhury, 2016).

The heterogeneous findings in the sentiment-return studies across markets questioned researchers to discover the causes behind. Among research implemented to address this issue, some authors, such as Schmeling (2009), Zouaoui et al. (2011), and Corredor et al. (2013), declared that market-specific characteristics play a vital role in the sentiment-return variation worldwide. Nonetheless, the verification of the local effect on sentiment-return inference is still insufficient with few studies. Moreover, these works also have some limitations. The papers of Schmeling (2009) and Zouaoui et al. (2011) only testify a few aspects of culture and institutional governance. Schmeling (2009) and Corredor et al. (2013) eliminate the potential role of development differences by investigating industrialized countries comparable in growth level. Incredibly, none of these studies pay attention to the local effect's possible changes across time horizons, which might also influence sentiment-return inference in different predictive periods.

To address these disadvantages, I examine the return predictability of sentiment in a broader scope by using a varied sample that comprises twelve markets in Asia and Europe. I combine both direct and indirect sentiment proxies by applying consumer confidence index (*CCI*), advance/decline ratio (*ADR*), and volatility premium (*VP*) to create a composite index for each market. My first motivation is to detect whether sentiment intensity is alike or variant across different groups of markets. Some prior studies, such as Corredor et al. (2015), Jacobs (2016), and Gao et al. (2020), questioned the difference in sentiment impact between developed and emerging markets. However, none investigated cross-market variation in geography, carried out in my research by comparing Asian and European markets. Secondly, I discover the driving forces of such differences, focusing on three local features: financial development, institutional qualities, and culture.

Overall, my study contributes to financial literature in some perspectives. First, I provide more evidence about the relationship between investor sentiment and subsequent stock returns for multiple markets, at the aggregate, regional, and individual levels. More importantly, by comparing Asian and European markets, I reveal the considerably diversified sentiment power for the return predictability across markets. Such differences vary with the length of the time horizons, from 1 to 24 months. Also, the role of market-specific factors as one of the underlying causes for the heterogeneity in sentiment-return correlation is examined extensively by employing a diverse set of fourteen local characteristics. With the advantage of my various samples, I can validate the moderating impact of these market features and demonstrate that such impact is time-varying and different between Asia and Europe.

The remainder of this chapter is organized as follows. Section 4.2 outlines significant research about the sentiment-return nexus and presents my hypotheses. Section 4.3 introduces the data set and the methods used to address my research problems. Preliminary tests and empirical results are described and discussed in Section 4.4. The final part concludes my main findings.

4.2. Literature reviews and hypothesis development

4.2.1. Sentiment-return relationship

Up to now, despite being investigated extensively, the sentiment impact on stock returns is still inconclusive as the results from both direct and indirect approaches classified by sentiment proxy used are considerably diverse.

The most popular direct sentiment proxies are indices derived from investor surveys used by Solt and Statman (1988), Lee et al. (2002), Grigaliūnienė and Cibulskienė (2010), Bathia and Bredin (2013), and Oprea and Brad (2014). Sol and Statman (1988) documented that the Bearish Sentiment Index constructed from Investors' Intelligence's survey is unsuitable as an indicator of forthcoming U.S. stock price change. On the other hand, the studies of Grigaliūnienė and Cibulskienė (2010) for Scandinavian stock markets and Bathia and Bredin (2013) for G7 markets found evidence of a negative relationship between consumer confidence index and aggregate market returns. Oprea and Brad (2014) proved a positive correlation between changes in consumer confidence and stock market returns in Romania. However, they observed that the influence of individual investor sentiment seems to be quickly removed by the force of arbitrage in less than a month.

In parallel, the results obtained from other explicit indicators, including investor mood (Yuan et al. 2006; Kim 2017), option implied volatility (Bekaert and Hoerova 2014; Qadan et al. 2019), and text-based index (Kim and Kim 2014; Ishijima et al. 2015; Gao et al. 2020), are also divergent. The text-based index can serve as an example of divergent results. Kim and Kim (2014) used a dataset of more than 32 million messages on 91 firms posted on the Yahoo! Finance message board. They found no evidence that investor sentiment forecasts future stock returns either at the aggregate or individual firm levels. In contrast, Ishijima et al. (2015) claimed that the daily sentiment index from the text mining technique could significantly predict Tokyo Stock Exchange prices three days in advance. More recently, Gao et al. (2020) employed households' Google search behavior to construct weekly sentiment indices for thirty-eight markets and showed that their sentiment measure is a contrarian predictor of country-level market returns.

The research that employed indirect sentiment proxies shares the same vein with heterogeneous outcomes. Pan and Poteshman (2006) presented strong evidence that option trading volume contains information about future U.S. stock prices. Likewise, using a broad set of implicit sentiment proxies and value-weighted market indices, Dash and Maitra (2018) examined the relationship between investor sentiment and stock returns in the Indian stock market. They detected a strong sentiment effect on return both in the short-and long-run. Conversely, Gizelis and Chowdhury (2016) showed that investor sentiment, measured by closed-end fund discount/premium, weakly explains returns in Athens stock markets. Especially, Cheema et al. (2020) constructed sentiment index from price-earnings ratio, turnover ratio, and the number of newly opened individual investor accounts and revealed a strong positive association between investor sentiment and subsequent market returns during the bubble period of China. Nevertheless, once the bubble period is excluded, they found out that the sentiment impact on future returns becomes negligible.

Since the previous findings are mixed, I propose my first hypothesis as follow:

H1: *Investor sentiment has an impact on future stock returns*

4.2.2. Impact of market-specific factors

Besides examining the sentiment-return relationship, researchers also pay attention to explaining the diversification in sentiment impact on stock returns across markets.

De Long et al. (1990), Hirshleifer (2001), Jacobs (2016), and Ding et al. (2019) declared that the heterogeneity in investors' misperceptions could significantly affect stock pricing. Since investors in different markets may have different misperceptions due to the divergences in culture, market integrity, and development level, the impact of investor sentiment on stock returns realized by investors' behaviors is also expected to be different.

Besides, Aggarwal et al. (2005) observed that institutional investors, who are more likely to be arbitrageurs, invest more in open emerging markets with stronger accounting standards, shareholder rights, and legal frameworks. Fernandes et al. (2010) demonstrated that non-U.S firms' shareholders tend to place significant value on U.S. securities regulations, especially when the investor protections in their home countries are weak. These two papers imply that a weak trading environment might demoralize activities from both arbitrageurs and behavioral investors, thus influencing market sentiment.

Generally, these authors suggest the market-specific factors could partly explain the differences in sentiment-return nexus, which was proved through the research of Schmeling (2009), Zouaoui et al. (2011), Corredor et al. (2013), and Wang et al. (2019). Zouaoui et al. (2011) investigated the U.S. and fifteen European countries and claimed that collectivistic, high uncertainty avoidance, and low-quality institutional countries suffer from the sentiment impact more than individualistic, low uncertainty avoidance, and high-quality institutional ones, as stated similarly in Schmeling (2009). Corredor et al. (2013) discovered that the variation in sentiment-return correlation across markets appears to involve both stock characteristics and cross-country cultural or institutional differences. The recent study of Wang et al. (2019) supported that the heterogeneity in sentiment impact can be explained by cross-market differences in culture and institutions, along with intelligence and education, to varying degrees. They suggest a more complete system of market institutions to alleviate the impact of investor sentiment globally, given that culture is rather difficult to change and the influence of intelligence and education is mixed.

Based on these studies, my second hypothesis is:

H2: *Market-specific factors have a moderating effect on sentiment-return relationship*

4.2.3. Asia versus Europe

As stated in Kim and Nofsinger (2008), Asians suffer from cognitive biases more than people of Western cultures do. They explained that Western societies are individualistic, prioritizing the self over the group, whereas East Asian societies are collectivistic, prioritizing the group (Hofstede, 1980). These divergences manifest in patterns of cognition and behavior concerning the self and others. For example, some studies argued that collective-oriented societies could cause individuals to be overconfident, which is a behavioral bias (Markus and Kitayama, 1991; Schmeling, 2009).

Empirically, some evidence exists that prove the differences in Easterners and Westerners' biases. Chang et al. (2001) showed that European Americans, compared with Japanese, are more likely to predict positive events to occur to themselves than to others. In contrast, the opposite pattern emerged in the prediction of negative events. Similarly, Hamamura et al. (2009) discovered that East Asians attend more to avoidance-oriented information, whereas Westerners attend more to approach-oriented information. On the contrary, Yiend et al. (2019) found that Hong Kong residents are more positively biased than people living in the U.K. on several measures, consistent with the lower prevalence of psychological disorders in East Asia. They also observed that migrants to the U.K. reduce positive biases on some tasks, while migrants to Hong Kong are more optimistic, compared to their respective home counterparts, consistent with acculturation in attention and interpretation biases.

The outcomes revealed from these studies lead to the expansion of my two above hypotheses:

H3: *Sentiment impact on future returns is different between Asian and European markets*

H4: *Moderating effect of market-specific factors on sentiment-return relationship is different between Asian and European markets*

4.3. Data and methodology

To carry out this study, I employed a set of monthly data from twelve markets (six in Asia: China, Hong Kong, Indonesia, Japan, South Korea, Thailand and six in Europe: Czech Republic, Hungary, Italy, Netherlands, Sweden, the United Kingdom) over the period between 2004 and 2016. According to the MSCI market classification, half of my sample, comprising Hong Kong, Japan, Italy, Netherlands, Sweden, and the United Kingdom, represents developed markets. The other half is emerging ones. The markets were selected based on their data availability, location, and development level. This selection process aimed to form an economically and geographically diversified sample that allows me to testify the impact of market-specific factors in subsequent analyses. Stock data, sentiment indicators, and macroeconomic series were acquired from Thomson Reuters Datastream. Following Ajao et al. (2012) and Bathia and Bredin (2013), I applied a cubic spline interpolation method to convert quarterly series to monthly ones.

4.3.1. Data

4.3.1.1. Market returns and sentiment proxies

First, I chose the main stock index for each market, representing the overall market performance[7]. Then, I created a monthly return series from the end-of-month price index: $R_{i,t} = 100*\ln(PI_{i,t}/PI_{i,t-1})$. The price indices were collected in local currency to prevent currency and exchange rate effects.

Regarding sentiment measurement, I applied *CCI*, *ADR*, and *VP* to construct a composite index among numerous implicit and explicit proxies employed in previous research. The most common composite index is Baker and Wurgler's sentiment index built for the U.S. market from six indicators: dividend premium, first-day returns on IPOs, IPO volume, equity shares in new issues, and market turnover (Baker and Wurgler, 2007). However, due to the availability of sentiment proxies, Baker et al. (2012) elected to use only four proxies: volatility premium, turnover, IPO volume, and first-day returns on IPOs, to construct a sentiment index for their study of six international stock markets. The authors have recently removed market turnover from their composite index since they argued that turnover does not mean what it once did, given the explosion of high-frequency institutional trading and the migration of trading to various venues. Consequently, I kept the volatility premium from Baker and Wurgler's index, replaced turnover by advance/decline ratio, and used the consumer confidence index to compensate for the lack of IPO data, according to Corredor et al. (2013).

The first indicator, *CCI*, is an economic indicator based on direct surveys about residents/households' opinions regarding their expected consumptions and savings. *CCI* was used as a sentiment measure in the paper of Grigaliūnienė and Cibulskienė (2010), Bathia and Bredin (2013), and Corredor et al. (2015). The second proxy, *ADR*, is the market indicator comparing the number of stocks that increased in value to the number of stocks that decreased in value. In my study, *ADR* was calculated by dividing the number of rising stocks by the number of falling stocks during a month. Since it might signify the market direction, *ADR* was implemented by Brown and Cliff (2004) and Dash and Maitra (2018) for their studies about the sentiment-return relationship. Lastly, I utilized *VP* as the third sentiment indicator for my analyses as difficult-to-value stocks are likely more affected by the sentiment effect, as stated by Baker et al. (2012) and Rashid et al. (2019). *VP* was the log of the average market-to-book ratios between high (the top 30%) and low (the bottom 30%) volatility stocks after stocks had been sorted every year depend on theirs standard deviation of the prior year. Along with other research, I suppose a positive relationship between these proxies and the comprehensive index.

Table 4.1: Descriptive statistics for main variables

	Returns		CCI		ADR		VP	
	μ	σ	μ	σ	μ	σ	μ	σ
Panel A. Asian markets								
China	0.467	8.676	106.087	4.166	1.001	0.250	0.018	0.250
Hong Kong	0.359	6.143	89.278	15.719	0.997	0.202	-0.003	0.164
Indonesia	1.305	6.196	104.465	10.952	1.001	0.199	0.020	0.440
Japan	0.373	5.716	41.436	4.947	1.004	0.191	0.261	0.114
South Korea	0.587	5.315	100.662	8.352	0.996	0.167	0.283	0.176
Thailand	0.444	5.916	71.978	9.456	0.999	0.216	-0.132	0.328
Panel B. European markets								
Czech Republic	0.214	6.317	93.040	10.792	1.091	0.242	0.014	0.281
Hungary	0.787	6.795	-36.320	15.039	0.964	0.153	0.102	0.281
Italy	-0.215	5.967	98.653	7.598	0.992	0.191	0.061	0.191
Netherlands	0.230	5.090	-9.045	17.354	1.010	0.163	0.030	0.279
Sweden	0.557	4.648	100.120	9.484	1.082	0.238	0.246	0.182
United Kingdom	0.299	3.760	-10.883	8.435	1.051	0.175	0.213	0.405

The table shows the mean (μ) and standard deviation (σ) for market returns and three sentiment proxies, namely consumer confidence index (*CCI*), advance/decline ratio (*ADR*), and volatility premium (*VP*). The data period is from January 2004 to December 2016.

Table 4.1 presents the main statistics for stock returns and three sentiment proxies in twelve sample markets from 2004 to 2016. As can be seen from the table, all markets, except Italy, experienced a positive average monthly return, ranging from 0.214% in the Czech Republic to 1.305% in Indonesia. Italian markets' outcome is predictable as this country has been one of the slowest gainers since the Great Recession. Asian emerging markets outperformed the developed ones with higher expected returns and similar standard deviations. In contrast, European region results were inconclusive since the Czech Republic market earned the lowest positive estimate point of returns, followed by the Netherlands. Generally, compared to other markets in the same area, South Korea and Sweden could be considered as potential ones for investment with the second-largest monthly average returns at 0.587% and 0.557% and one of the lowest standard deviations at 5.315 and 4.648, respectively.

Regarding sentiment proxies, while Hong Kong, Japan, and Thailand revealed the pessimistic perception towards the economic outlook, proving by under-neutral average *CCIs*, the people in remaining Asian markets seem to be optimistic about the business condition in the future. In Europe, the residents' expectations about economic prospects are worse since five out of six markets witnessed a negative average *CCI*. Concerning *ADR*, the Asia region results were almost homogeneous as the average *ADRs* were approximately 1 per month for all markets. In contrast, European markets were more heterogeneous, with *ADRs* being fluctuated from 0.964 in Hungary to 1.091 in the Czech Republic. Lastly, all European and two-thirds of Asian markets possessed a positive monthly average of *VPs.* The exception was held by Hong Kong and Thailand, with their average *VPs* being -0.003 and -0.132, respectively. Compared to the *CCI* series, the standard deviations of *ADR* and *VP* were much smaller.

4.3.1.2. Macroeconomic variables

Prior studies, for example, Subeniotis et al. (2011), Smales (2017), and Rashid et al. (2019), suggested that economic conditions might play a significant role in the movement of stock returns and affect findings about the sentiment-return relationship. As a result, I decided to add five macroeconomic series into my regression models as control variables. They are the industrial production index (*IP*), consumer price index (*CPI*), unemployment rate (*UR*), dividend yield (*DY*), and short-term interest rate (*SR*). All series were converted into monthly growth rates.

4.3.1.3. Market-specific factors

My study examines the impact of local characteristics on the relationship between sentiment and subsequent returns in perspectives of financial development, institutional governance, and culture[8]. To perform these examinations, I first employed the Financial Development Index provided by the International Monetary Fund. The Financial Development series assess the differences in financial growth level across countries based on two aspects: financial institutions (*FI*) and financial markets (*FM*). Financial institutions comprise banks, insurance companies, mutual funds, and pension funds, whereas financial markets include stock and bond markets. Countries are then ranked by the depth, access, and efficiency of their financial markets and institutions. These series are available until 2016, leading to the end of my sample this year.

Furthermore, to measure the divergences in institutional qualities among my sample markets, I selected the Worldwide Governance Indicators reported annually by the World Bank. As claimed by the World Bank, Worldwide Governance Indicators include six aggregate indices constructed from individual indicators of over 30 underlying data sources. These indicators are termed as Voice and Accountability (*VA*), Political Stability and Absence of Violence (*PA*), Government Effectiveness (*GE*), Regulatory Quality (*RQ*), Rule of Law (*RL*), and Control of Corruption (*CC*). In detail, *VA* measures the degree of freedom of a country's citizens, *PA* captures the level of political instability, *GE* reflects the quality of public services and their independence from politics, *RQ* explores the quality in polices and regulations of government toward the private sector, *RL* demonstrates the extent to which rules of society are implemented, and *CC* expresses how the public power is executed for private benefits.

Finally, I chose Hofstede's six cultural dimensions to represent a nation's cultural characteristics. These dimensions comprise: (i) Power Distance Index (*PDI*) captures the acceptance degree of unequally distributed power; (ii) Individualism vs. Collectivism (*IDV*) explores the independent/dependent level of people in a society; (iii) Uncertainty Avoidance Index (*UAI*) measures how people react to uncertain situations; (iv) Masculinity vs. Femininity (*MAS*) expresses the degree of competitiveness in a society; (v) Long-term vs. Short-term Orientation (*LTO*) demonstrates whether the focus of individuals' actions is on the past and present, or in the future; (vi) Indulgence vs. Restraint (*IVR*) reflects the extent to which individuals receive freedom from the society to fulfill their desires.

4.3.2. Methodology

4.3.2.1. The construction of sentiment index

Based on the three sentiment proxies introduced in Section 4.3.1.1, I constructed an inclusive sentiment index for individual markets in my sample. Since *CCI*, *ADR*, and *VP* were calculated on different scales, I first standardized each proxy to get a series with a mean of zero and a standard deviation of one. Although these indicators were validated in the previous research to embody some market sentiment features, they might also capture other idiosyncratic, non-related sentiment components. Therefore, I applied the principal component analysis (PCA) to extract the proxies' sentiment component.

By way of PCA, the first principal component of CCI_t, ADR_t, $VP_{t,}$, and their one-year lags, symbolized as CCI_{t-1}, $ADR_{t-1,}$ and VP_{t-1}, was estimated. I viewed it as the first-stage index with six loadings. The appearance of lag variables in my procedure is because some sentiment indicators might take more time to release the same effect than others, according to Corredor et al. (2013) and Huang et al. (2015). I then compared the correlation between the first-stage index and each pair of sentiment proxies, i.e., the proxy and its lag. Finally, PCA was replicated for three loadings, either *t* or *t-1*, depending on which was the most highly correlated with the first-stage index. I stored the first principle component from this step and used it as the sentiment index in subsequent analyses. The outcomes for the sentiment index of each market are summarized in Table 4.2.

Table 4.2: Market-specific sentiment index

	Sentiment proxies	Correlation with sentiment index		Loading	Correlation between sentiment proxies			p-values		
		Coef.	*p-value*		*CCI*	*ADR*	*VP*	*CCI*	*ADR*	*VP*
Panel A. Asian markets										
China	CCI$_{t-1}$	0.640***	0.000	0.436	1.000			(.)		
(43.02%)	ADR$_{t-1}$	0.563***	0.000	0.384	0.065	1.000		0.437	(.)	
	VP$_t$	-0.751***	0.000	-0.512	-0.199**	-0.162*	1.000	0.017	0.052	(.)
Hong Kong	CCI$_t$	0.876***	0.000	0.399	1.000			(.)		
(56.35%)	ADR$_{t-1}$	0.360***	0.000	0.164	0.114	1.000		0.173	(.)	
	VP$_{t-1}$	-0.891***	0.000	-0.405	-0.633***	-0.161**	1.000	0.000	0.045	(.)
Indonesia	CCI$_t$	0.724***	0.000	0.459	1.000			(.)		
(45.16%)	ADR$_{t-1}$	-0.615***	0.000	-0.390	-0.180**	1.000		0.031	(.)	
	VP$_t$	0.672***	0.000	0.426	0.095	-0.131	1.000	0.240	0.117	(.)
Japan	CCI$_t$	0.791***	0.000	0.418	1.000			(.)		
(50.95%)	ADR$_{t-1}$	0.484***	0.000	0.256	0.132	1.000		0.115	(.)	
	VP$_{t-1}$	0.818***	0.000	0.433	0.433***	0.175**	1.000	0.000	0.029	(.)
South Korea	CCI$_{t-1}$	0.663***	0.000	0.417	1.000			(.)		
(45.38%)	ADR$_t$	-0.653***	0.000	-0.411	-0.154*	1.000		0.065	(.)	
	VP$_{t-1}$	0.704***	0.000	0.443	0.182**	-0.190**	1.000	0.023	0.023	(.)
Thailand	CCI$_{t-1}$	0.776***	0.000	0.469	1.000					
(46.66%)	ADR$_{t-1}$	-0.515***	0.000	-0.311	-0.168**	1.000		0.037	(.)	
	VP$_{t-1}$	0.730***	0.000	0.441	0.307***	-0.104	1.000	0.000	0.197	(.)
Panel B. European markets										
Czech Republic	CCI$_t$	0.818***	0.000	0.488	1.000			(.)		
(46.99%)	ADR$_{t-1}$	0.594***	0.000	0.355	0.267***	1.000		0.001	(.)	
	VP$_{t-1}$	-0.623***	0.000	-0.372	-0.283***	-0.042	1.000	0.001	0.603	(.)
Hungary	CCI$_t$	0.820***	0.000	0.418	1.000			(.)		
(52.20%)	ADR$_t$	0.391***	0.000	0.199	0.082	1.000		0.307	(.)	
	VP$_{t-1}$	-0.861***	0.000	-0.439	-0.506***	-0.186**	1.000	0.000	0.026	(.)
Italy	CCI$_t$	0.868***	0.000	0.461	1.000			(.)		
(50.78%)	ADR$_{t-1}$	0.283***	0.000	0.150	0.151*	1.000		0.071	(.)	
	VP$_{t-1}$	0.831***	0.000	0.442	0.495***	0.024	1.000	0.000	0.763	(.)
Netherlands	CCI$_t$	0.641***	0.000	0.421	1.000			(.)		
(44.14%)	ADR$_{t-1}$	0.721***	0.000	0.473	0.188**	1.000		0.024	(.)	
	VP$_{t-1}$	0.627***	0.000	0.412	0.115	0.160**	1.000	0.172	0.046	(.)
Sweden	CCI$_t$	0.766***	0.000	0.495	1.000			(.)		
(44.56%)	ADR$_{t-1}$	0.653***	0.000	0.422	0.232***	1.000		0.005	(.)	
	VP$_t$	0.569***	0.000	0.368	0.177**	0.074	1.000	0.027	0.376	(.)
United Kingdom	CCI$_t$	0.660***	0.000	0.430	1.000			(.)		
(44.33%)	ADR$_{t-1}$	0.645***	0.000	0.421	0.145*	1.000		0.084	(.)	
	VP$_t$	0.692***	0.000	0.451	0.130	0.170**	1.000	0.105	0.042	(.)

The table displays the correlation between the market-specific sentiment index and its components, including *CCI*, *ADR*, and *VP*. The last six columns show the correlation coefficients and p-values between the sentiment components of each market. The data period is from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

Table 4.2 displays the explanation power of sentiment index for each market, i.e., the percentage of total variance explained by the first principal component, varying from 43.02% of China to 56.35% of Hong Kong. The details about the loading of each component in the total index are also reported. I observed that two-thirds of the markets have nearly equal loadings for all components, except Hong Kong, Japan, Hungary, and Italy, where *ADR* loading is much lower than others.

The relationship of each sentiment component with its corresponding index is also shown in Table 4.2. As presented in the table, all estimated coefficients were statistically significant. Specifically, *CCI* positively correlates with the sentiment index in all markets. The results for *ADR* and *VP*, on the contrary, were diverse. Concerning *ADR*, three out of twelve markets, namely Indonesia, South Korea, and Thailand, displayed a negative relationship between this proxy and sentiment index. The proportion of *VP* was slightly higher, with one-third of my sample showing a negative coefficient. Lastly, the sentiment components themselves also revealed a strong connection with each other since at least two out of three pairs in every market had significant coefficients, excluding Indonesia.

4.3.2.2. The return predictability of investor sentiment

Before employing my empirical analyses, I performed panel unit root tests to investigate whether the sentiment index and five macroeconomic variables across markets are stationary. The results for Levin-Lin-Chu, Im-Pesaran, and augmented Dickey-Fuller-Fisher (ADF) tests confirmed that there is no unit root in these series[9].

I first assessed the relationship between sentiment and future returns by running the following regression:

$$\frac{1}{k}\sum R_{i,t+k} = \alpha_i + \beta_i Sent_{i,t} + \gamma_i \psi_{i,t} + \varepsilon_{i,t} \qquad (4.1)$$

Where $\frac{1}{k}\sum R_{i,t+k}$ is the *k*-month average return of market *i* at month *t*. *k* = 1, 3, 6, 12, and 24.

$Sent_{i,t}$ is the investor sentiment of market *i* at month *t*.

$\psi_{i,t}$ is the matrix of five macroeconomic variables, including the *IP*, *CPI*, *UR*, *DY*, and *SR*, of market *i* at month *t*.

According to Ang and Bekaert (2007) and Schmeling (2009), the estimated results are correlated across various forecast horizons. Therefore, a joint test for predictability is more reasonable than tests for each horizon separately. Following these authors, for the individual market, I jointly estimated Equation (4.1) for multiple periods of 1, 3, 6, 12, and 24 months in a regression equation system using the generalized method of moment. These estimations aimed to examine whether there is a significantly combined impact of sentiment on subsequent 1, 3, 6, 12, and 24-month returns. Meanwhile, all markets' estimation procedure was pooled OLS regressions with cross-market fixed effect and time dummies.

Additionally, I investigated whether there is any heterogeneity in sentiment intensity between Asian and European markets by generating a dummy variable, denoted as *AS*. *AS* gets the value 1 for Asian markets and 0 for otherwise. Then, I ran the models having the interaction term between sentiment and this dummy variable to clear this matter:

$$\frac{1}{k}\sum R_{i,t+k} = \alpha_i + \beta_i\, Sent_{i,t} + \gamma_i Sent_{i,t} * AS + \delta_i \psi_{i,t} + \varepsilon_{i,t} \qquad (4.2)$$

In the end, I compared the estimated coefficients of Asian and European markets across horizons by executing Seemingly Unrelated Estimation and Chow tests.

4.3.2.3. The impact of market-specific factors

To investigate the moderating role of market-specific factors in sentiment's return predictability, I first classified my sample into two groups: below and above-median, based on fourteen local characteristics mentioned in Section 4.3.1.3. Equation (4.1) was then run for both groups to explore the effect of sentiment in markets with different features in development level, governance, and culture. Eventually, the estimated results were differentiated to find out any discrepancies between these groups.

Further, I also created interaction terms between sentiment and market-specific factors, then ran the following regression model to verify my results:

$$\frac{1}{k}\sum R_{i,t+k} = \alpha_i + \beta_i\, Sent_{i,t} + \gamma_i Sent_{i,t} * MF_{i,j} + \delta_i \psi_{i,t} + \varepsilon_{i,t} \qquad (4.3)$$

In which $MF_{i,j}$ is the specific factor *j* of market *i*.

Finally, I tested whether the effect of local qualities is the same for markets in Asia and Europe by both comparing the coefficients of sentiment-factor interaction variables after Equation (4.3) was run for the groups of Asian and European market and executing the below equation:

$$\frac{1}{k}\sum R_{i,t+k} = \alpha_i + \beta_i\, Sent_{i,t} + \gamma_i Sent_{i,t} * MF_{i,j} + \delta_i Sent_{i,t} * MF_{i,j} * AS + \theta_i \psi_{i,t} + \varepsilon_{i,t} \quad (4.4)$$

4.4. Results

4.4.1. The return predictability of investor sentiment

4.4.1.1. Aggregate markets

Table 4.3: Return predictability of sentiment across markets

	R_{t+1}		R_{t+3}		R_{t+6}		R_{t+12}		R_{t+24}	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Sent	-0.065	-0.064	-0.138**	-0.122**	-0.151***	-0.147***	-0.137***	-0.137***	-0.150***	-0.150***
	[0.511]	[0.515]	[0.015]	[0.024]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
UR		0.020*		-0.001		0.002		-0.001		-0.001
		[0.097]		[0.937]		[0.647]		[0.803]		[0.753]
IP		0.025		0.029		0.009		-0.001		-0.002
		[0.543]		[0.209]		[0.641]		[0.937]		[0.803]
CPI		-0.085		0.078		-0.093		-0.060		-0.056
		[0.673]		[0.458]		[0.265]		[0.300]		[0.167]
DY		0.004		-0.083***		-0.046***		-0.026***		-0.014***
		[0.786]		[0.000]		[0.000]		[0.000]		[0.004]
SR		-0.003		-0.001		-0.000		-0.001		-0.001
		[0.548]		[0.583]		[0.755]		[0.199]		[0.257]
Const.	6.133***	6.004***	1.853**	1.724**	1.642***	1.553**	2.288***	2.280***	2.385***	2.392***
	[0.000]	[0.000]	[0.012]	[0.015]	[0.007]	[0.011]	[0.000]	[0.000]	[0.000]	[0.000]
Obs	1716	1716	1692	1692	1656	1656	1584	1584	1440	1440
R^2	0.5997	0.6007	0.6640	0.6850	0.7045	0.7153	0.7132	0.7198	0.6819	0.6870
F-stat.	14.90***	14.51***	18.00***	19.39***	22.28***	22.68***	27.59***	27.39***	29.51***	28.45***

The table reveals the pooled OLS regressions with cross-market fixed effect and time dummies for Equations (4.1). p-values are in brackets. The data period from January 2004 to December 2016.

*, **, ***: significance at 10%, 5%, and 1% confidence level, respectively.

Table 4.3 displays the panel regression results of Equation (4.1) for sentiment index across markets in various forecast horizons. As is shown in the table, sentiment could be a valid contrarian predictor of future returns as its estimated coefficients were significantly negative over the next 3 to 24 months. My findings are in tandem with Baker and Wurgler (2007), Huang et al. (2015), and Khan and Ahmad (2018), who also used sentiment index combined from many explicit and implicit proxies.

4.4.1.2. Asia versus Europe

Apart from all markets' results, I wonder whether the return predictability of sentiment is the same or varied between Asian and European regions. Therefore, I created and added a dummy variable for Asian markets into Equation (4.1). The interaction term outcomes between sentiment and the dummy variable, i.e., *Sent*AS* of Equation (4.2), reported in Table 4.4, partly address the heterogeneity in sentiment intensity among different groups of markets. Consequently, I classified my sample based on their geography and executed Equation (4.1) for each group to achieve a more precise conclusion. The regression results for these groups are presented in Table 4.5.

Table 4.4: Sentiment-return relationship – Effect of market location

	R_{t+1}		R_{t+3}		R_{t+6}		R_{t+12}		R_{t+24}	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Sent	-0.154	-0.149	-0.160**	-0.158**	-0.225***	-0.227***	-0.232***	-0.236***	-0.160***	-0.162***
	[0.255]	[0.267]	[0.034]	[0.028]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Sent*AS	0.158	0.149	0.038	0.062	0.128	0.139*	0.159***	0.167***	0.016	0.019
	[0.384]	[0.408]	[0.707]	[0.522]	[0.112]	[0.077]	[0.009]	[0.006]	[0.707]	[0.647]
UR		0.019		-0.001		0.002		-0.001		-0.001
		[0.105]		[0.926]		[0.680]		[0.766]		[0.748]
IP		0.026		0.030		0.010		0.001		-0.002
		[0.520]		[0.201]		[0.594]		[0.967]		[0.823]
CPI		-0.084		0.079		-0.092		-0.059		-0.056
		[0.677]		[0.455]		[0.275]		[0.320]		[0.169]
DY		0.004		-0.083***		-0.047***		-0.026***		-0.014***
		[0.797]		[0.000]		[0.000]		[0.000]		[0.004]
SR		-0.002		-0.001		-0.000		-0.001		-0.001
		[0.566]		[0.599]		[0.815]		[0.235]		[0.262]
Const.	6.148***	6.019***	1.857**	1.730**	1.655***	1.567**	2.308***	2.302***	2.387***	2.394***
	[0.000]	[0.000]	[0.013]	[0.015]	[0.008]	[0.013]	[0.000]	[0.000]	[0.000]	[0.000]
Obs	1716	1716	1692	1692	1656	1656	1584	1584	1440	1440
R^2	0.5999	0.6009	0.6640	0.6851	0.7050	0.7159	0.7148	0.7214	0.6819	0.6871
F-stat.	14.87***	14.47***	17.90***	19.32***	22.54***	23.04***	27.12***	26.95***	29.50***	28.47***

The table reveals the pooled OLS regressions with cross-market fixed effect and time dummies for Equations (4.2). p-values are in brackets. The data period from January 2004 to December 2016.

*, **, ***: significance at 10%, 5%, and 1% confidence level, respectively.

As can be seen from Table 4.5, there is solid evidence that the correlation of investor sentiment with future market returns is divergent between Asian and European markets. I found that sentiment has a more immediate impact in Europe but a more long-lasting impact in Asia. In detail, the estimated coefficient of sentiment index for the next month stock returns in Asian markets was insignificant (coefficient = -0.072, p-value = 0.609). At the same time, it was significant in European markets at the 10% level (coefficient = -0.242, p-value = 0.077), indicating that the impact of investor sentiment is more instantaneous in European markets. Over the next 3 to 12 months, the predictability power of sentiment in the European region continued to be greater than in the Asian one, with the largest gap between two areas belonging to the 6-month horizon of 0.195. Nevertheless, this trend reversed in the last horizons since the sentiment coefficient in Asian markets was -0.166 with p-value = 0.000. In contrast, the figure for European markets was only -0.033 and not significant anymore. Moreover, these outcomes imply that the discrepancies in sentiment impact fluctuate with the length of forecast horizons since the two groups' discrepancies were only statistically significant after six months.

Table 4.5: Return predictability of sentiment: Asia versus Europe

	R_{t+1}		R_{t+3}		R_{t+6}		R_{t+12}		R_{t+24}	
	AS	*EU*	*AS*	*EU*	*AS*	*EU*	*AS*	*EU*	*AS*	*EU*
Sent	-0.072	-0.242*	-0.115	-0.218***	-0.100	-0.295***	-0.088*	-0.234***	-0.166***	-0.033
	[0.609]	[0.077]	[0.158]	[0.003]	[0.112]	[0.000]	[0.068]	[0.000]	[0.000]	[0.240]
Diff.	0.170		0.103		0.195***		0.146***		-0.133***	
	[0.356]		[0.292]		[0.010]		[0.007]		[0.001]	
UR	0.011	0.032	0.001	-0.005	0.003	0.001	-0.002	0.003	-0.002	0.005
	[0.440]	[0.203]	[0.951]	[0.711]	[0.622]	[0.926]	[0.721]	[0.658]	[0.506]	[0.237]
IP	0.024	-0.005	0.043	0.000	0.019	-0.005	0.001	-0.006	0.002	-0.011
	[0.695]	[0.935]	[0.223]	[0.989]	[0.477]	[0.832]	[0.959]	[0.710]	[0.887]	[0.330]
CPI	0.115	-0.306	0.115	0.155	-0.085	0.146	-0.072	0.028	-0.065	-0.031
	[0.667]	[0.325]	[0.451]	[0.352]	[0.468]	[0.209]	[0.415]	[0.732]	[0.303]	[0.585]
DY	0.015	-0.004	-0.100***	-0.052***	-0.056***	-0.032***	-0.036***	-0.014***	-0.021***	-0.006*
	[0.554]	[0.824]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.054]
SR	0.006	-0.000	-0.001	0.001	0.002	0.001	-0.007	0.001	-0.005*	0.000
	[0.615]	[0.911]	[0.852]	[0.678]	[0.737]	[0.681]	[0.300]	[0.335]	[0.088]	[0.662]
Const.	4.935**	6.748***	0.294	2.572***	0.180	2.341***	1.582**	2.450***	2.190***	1.785***
	[0.011]	[0.000]	[0.792]	[0.000]	[0.833]	[0.000]	[0.014]	[0.000]	[0.000]	[0.000]
Obs	858	858	846	846	828	828	792	792	720	720
R^2	0.6052	0.7482	0.6872	0.8144	0.7036	0.8537	0.6887	0.8602	0.6074	0.8542
F-stat.	7.05***	13.67***	10.10***	20.17***	10.89***	26.78***	10.11***	28.12***	7.01***	26.54***

The table reveals the pooled OLS regressions with cross-market fixed effect and time dummies for Equation (4.1) when each market is classified into either Asian or European groups. p-values are in brackets. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

4.4.1.3. Individual markets

Up to now, I have run panel regressions and revealed the impact of cross-market sentiment on stock returns. Nonetheless, the relationship between sentiment and future returns in individual markets has not been discovered. As a result, I performed joint estimations for multiple periods of 1, 3, 6, 12, and 24 months of Equation (4.1) using the generalized method of moments to determine the predictability power of sentiment in each market. The results for twelve markets in my sample are reported in Table 4.6, showing the noticeable dissimilarities of sentiment effect between individual markets.

Firstly, I observed a significantly positive or negative sentiment impact over the next 24-month returns in most markets, at least at a 10% confidence level, excluding Japan and Sweden. Among the significant markets, half of the sample showed a negative coefficient. The other half got a positive one. The mixed sign in the sentiment coefficients seems unrelated to the market location or its development degree as the negative or positive coefficients were witnessed in both Asian and European markets and advanced and emerging ones.

Table 4.6: Return predictability of investor sentiment in individual markets

Asian markets				European markets			
Markets	*Coef.*	*p-value*	*HS test*	*Markets*	*Coef.*	*p-value*	*HS test*
China	-0.743**	0.012	0.456	Czech Republic	-1.418***	0.000	0.154
Hong Kong	0.605***	0.000	0.564	Hungary	-0.295**	0.015	0.732
Indonesia	0.349***	0.000	0.151	Italy	1.225***	0.000	0.154
Japan	0.021	0.817	0.276	Netherlands	1.632***	0.003	0.284
South Korea	-0.351***	0.006	0.429	Sweden	0.180	0.294	0.438
Thailand	0.333*	0.091	0.368	United Kingdom	-1.556***	0.000	0.602

This table reveals the results for estimated coefficients and p-values for each market's investor sentiment across various forecast horizons. p-values of Hansen (HS) test for over-identifying restrictions are also reported. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

Besides the mixed coefficients, I found that except for Hungary, sentiment impact seems stronger in European markets than Asian ones. For example, the largest estimated coefficients of sentiment in Europe belonged to the Netherlands at 1.632 (p-value = 0.003) and the United Kingdom at -1.556 (p-value = 0.000), whereas in Asia, they belonged to China and Hong Kong at -0.743 (p-value = 0.012) and 0.605 (p = 0.000), respectively. These individual results can partly prove my previous findings when I pool markets into different groups.

4.4.2. Impact of market-specific factors

4.4.2.1. Aggregate markets

Table 4.7 displays the panel regression results for 3, 12, and 24-month periods when dividing my sample into two groups: below and above-median, based on fourteen market-specific factors in the first column[10]. The first observable finding from the table is that the local characteristics have a moderating effect on the relationship between sentiment and future returns. Nevertheless, this effect varies depending on the length of forecast horizons. In particular, over the following three months, the differences between the two groups' estimated coefficients were significant only in one market factor, namely *PA.* After 12 months, such differences increased to fifty percent. In the last period, eleven local qualities exposed a significant impact on the sentiment-return relationship. Additionally, over various horizons, three cultural dimensions, including *MAS, UAI,* and *IVR*, showed no statistically significant influence at all.

Table 4.7: Return predictability of sentiment: Below versus above-median group

	R_{t+3}			R_{t+12}			R_{t+24}		
	Below	*Above*	*Diff.*	*Below*	*Above*	*Diff.*	*Below*	*Above*	*Diff.*
Panel A. Financial development indices									
FI	-0.085	-0.179***	0.094	-0.159***	-0.166***	0.007	-0.223***	-0.155***	-0.068*
	[0.331]	[0.003]	[0.331]	[0.001]	[0.000]	[0.898]	[0.000]	[0.000]	[0.086]
FM	-0.096	-0.104*	0.008	-0.173***	-0.076**	-0.097*	-0.242***	-0.072***	-0.170***
	[0.278]	[0.086]	[0.936]	[0.001]	[0.027]	[0.075]	[0.000]	[0.007]	[0.000]
Panel B. Institutional factors									
CC	-0.179**	-0.095	-0.084	-0.282***	-0.019	-0.263***	-0.298***	-0.053**	-0.245***
	[0.048]	[0.122]	[0.408]	[0.000]	[0.579]	[0.000]	[0.000]	[0.040]	[0.000]
GE	-0.179**	-0.095	-0.084	-0.282***	-0.019	-0.263***	-0.298***	-0.053**	-0.245***
	[0.048]	[0.122]	[0.408]	[0.000]	[0.579]	[0.000]	[0.000]	[0.040]	[0.000]
PA	-0.214***	0.006	-0.220**	-0.194***	0.073	-0.267***	-0.246***	0.175***	-0.421***
	[0.009]	[0.939]	[0.037]	[0.000]	[0.107]	[0.000]	[0.000]	[0.000]	[0.000]
RQ	-0.195**	-0.047	-0.148	-0.238***	0.060	-0.298***	-0.256***	0.106***	-0.362***
	[0.023]	[0.542]	[0.164]	[0.000]	[0.136]	[0.000]	[0.000]	[0.001]	[0.000]
RL	-0.179**	-0.095	-0.084	-0.282***	-0.019	-0.263***	-0.298***	-0.053**	-0.245***
	[0.048]	[0.122]	[0.408]	[0.000]	[0.579]	[0.000]	[0.000]	[0.040]	[0.000]
VA	-0.107	-0.163**	0.056	-0.122***	-0.139***	0.017	-0.172***	-0.040	-0.132***
	[0.189]	[0.020]	[0.568]	[0.010]	[0.000]	[0.730]	[0.000]	[0.142]	[0.000]
Panel C. Cultural dimensions									
PDI	-0.148*	-0.147*	-0.001	-0.194***	-0.127***	-0.067	-0.040	-0.198***	0.158***
	[0.059]	[0.067]	[0.996]	[0.000]	[0.004]	[0.192]	[0.195]	[0.000]	[0.000]
IDV	-0.115	-0.218***	0.103	-0.088*	-0.234***	0.146***	-0.166***	-0.033	-0.133***
	[0.158]	[0.003]	[0.292]	[0.068]	[0.000]	[0.007]	[0.000]	[0.240]	[0.001]
MAS	-0.215***	-0.122	-0.093	-0.194***	-0.218***	0.024	-0.220***	-0.234***	0.014
	[0.001]	[0.286]	[0.460]	[0.000]	[0.002]	[0.722]	[0.000]	[0.000]	[0.784]
UAI	-0.179**	-0.154**	-0.025	-0.113**	-0.195***	0.085	-0.164***	-0.132***	-0.032
	[0.038]	[0.033]	[0.809]	[0.023]	[0.000]	[0.152]	[0.000]	[0.000]	[0.426]
LTO	-0.116	-0.090	-0.026	-0.105**	-0.111**	0.006	-0.017	-0.161***	0.144***
	[0.106]	[0.290]	[0.792]	[0.015]	[0.020]	[0.922]	[0.594]	[0.000]	[0.002]
IVR	-0.144*	-0.077	-0.067	-0.157***	-0.127***	-0.030	-0.142***	-0.140***	-0.002
	[0.094]	[0.243]	[0.487]	[0.002]	[0.001]	[0.599]	[0.000]	[0.000]	[0.968]

The table reveals the results for pooled OLS regressions with cross-market fixed effect and time dummies for Equation (4.1) when each market is classified into either below or above-median group, based on market-specific factors in the first column. For each group, the estimated coefficients and corresponding p-values for the sentiment variable over the next 3, 12, and 24-month returns are reported. p-values are in brackets. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

Secondly, I found out that financial development indices and institutional factors negatively affect the return predictability of sentiment. In other words, the sentiment impact is weaker in markets that are more matured in terms of financial and administrative qualities and vice versa. Since Chui et al. (2010) stated that a better flow of information characterizes a higher level of institutional sophistication and makes the market more efficient, my empirical results are expected. Besides that, comparing two aspects of financial development, the moderating effect of *FM* seems to be more assertive with higher and more significant gaps between low and high-quality *FM* groups than the ones of *FI*. Concerning institutional dimensions, *PA* and *RQ* are the two features that have the most substantial influence on the sentiment-return relationship.

In contrast, cultural characteristics demonstrated more diverse outcomes among dimensions and the different time horizons of each dimension. This issue can be illustrated briefly by the case of *IDV*. From 3 to 12-month periods, individualistic markets suffer from sentiment impact more extremely than collectivistic ones. For instance, the estimated sentiment coefficients for subsequent twelve-month returns were -0.234 (p-value = 0.000) and -0.088 (p-value = 0.068) for individualistic and collectivistic markets, respectively. Nonetheless, in the longest horizon, the coefficients changed to -0.033 (p-value = 0.234) for high *IDV* group and -0.166 (p-value = 0.000) for low *IDV* group, indicating that the sentiment effect becomes weaker in individualistic cultures. My results support both streams of literature about the *IDV* dimension. The first opinion is that individuals in individualistic cultures tend to be overconfident and thus commit cognitive biases, as suggested by Baker and Nofsinger (2002) and Breuer et al. (2014). On the contrary, Markus and Kitayama (1991) and Schmeling (2009) argued that people in collectivistic countries tend to connect in strong groups and overweigh consensus opinion, which results in a herd-like overreaction among investors. Hence, collectivism escalates overreaction.

PDI's case is even more unclear as the sentiment effect is nearly equal in the short-term period, more dominant in low *PDI* markets in the mid-term, but less in the long-term. Conversely, the moderating role of *LTO* is more vital for short-term oriented markets in a 3-month horizon but weaker in a 24-month one, while it is approximately the same for both groups in the next 12 months. However, the gaps between low and high *PDI* and short-term and long-term oriented markets were significant only in the 24-month horizon. I also noticed that cultural dimensions' impact is more fragile compared to development and governance factors.

Finally, I ran Equation (4.3), having interaction variables between sentiment and local features, to validate my prior findings.

The outcomes exhibited in Table 4.8 confirmed my observation about the moderating effect of market characteristics on sentiment-return inference. The exception relates to *VA*, *MAS*, *UAI*, and *IVR*. While the variation between low and high *VA* groups was significant in the 24 months, there was no significant interaction variable between sentiment and *VA* for all forecast horizons. Conversely, the interaction coefficients demonstrated the significant influence of *MAS*, *UAI*, and *IVR* on the correlation between sentiment and subsequent returns. Nevertheless, the differences between low and high *MAS*, *UAI*, and *IVR* markets were not statistically significant, as mentioned before.

Table 4.8: Impact of market-specific factors on sentiment-return relationship

	Coef.					p-value				
	R_{t+1}	R_{t+3}	R_{t+6}	R_{t+12}	R_{t+24}	R_{t+1}	R_{t+3}	R_{t+6}	R_{t+12}	R_{t+24}
Panel A. Financial development indices										
Sent	0.251	0.239	0.086	-0.027	-0.209**	0.504	0.254	0.625	0.840	0.014
Sent*FI	-0.476	-0.546*	-0.352	-0.168	0.090	0.365	0.060	0.147	0.363	0.443
Sent	0.216	0.175	0.056	-0.070	-0.118*	0.450	0.247	0.631	0.387	0.054
Sent*FM	-0.452	-0.479**	-0.327*	-0.109	-0.052	0.299	0.034	0.058	0.355	0.546
Panel B. Institutional factors										
Sent	-0.024	-0.102	-0.148**	-0.156***	-0.196***	0.849	0.152	0.012	0.001	0.000
Sent*CC	-0.066	-0.034	0.002	0.030	0.071***	0.514	0.548	0.970	0.420	0.002
Sent	0.000	-0.076	-0.153*	-0.181***	-0.246***	0.999	0.439	0.067	0.006	0.000
Sent*GE	-0.072	-0.051	0.007	0.048	0.106***	0.606	0.515	0.913	0.368	0.001
Sent	-0.064	-0.127**	-0.154***	-0.148***	-0.179***	0.561	0.037	0.002	0.000	0.000
Sent*PA	-0.002	0.019	0.025	0.040	0.122***	0.988	0.790	0.672	0.384	0.000
Sent	-0.005	-0.080	-0.138	-0.156**	-0.243***	0.977	0.433	0.120	0.025	0.000
Sent*RQ	-0.068	-0.048	-0.011	0.022	0.109***	0.641	0.568	0.883	0.715	0.000
Sent	-0.011	-0.083	-0.134*	-0.145**	-0.208***	0.941	0.333	0.068	0.012	0.000
Sent*RL	-0.073	-0.054	-0.018	0.010	0.079***	0.568	0.462	0.775	0.847	0.010
Sent	-0.019	-0.079	-0.101	-0.086	-0.163***	0.894	0.333	0.154	0.106	0.000
Sent*VA	-0.092	-0.086	-0.089	-0.098	0.024	0.545	0.327	0.252	0.111	0.483
Panel C. Cultural dimensions										
Sent	-0.534	-0.433**	-0.486***	-0.472***	-0.200**	0.177	0.047	0.007	0.001	0.014
Sent*PDI	0.008	0.005	0.006*	0.006**	0.001	0.248	0.169	0.076	0.024	0.552
Sent	0.092	-0.067	-0.032	-0.004	-0.146***	0.636	0.533	0.717	0.947	0.001
Sent*IDV	-0.003	-0.001	-0.003*	-0.003***	-0.000	0.313	0.516	0.097	0.010	0.910
Sent	-0.195	-0.277***	-0.246***	-0.211***	-0.253***	0.270	0.002	0.000	0.000	0.000
Sent*MAS	0.002	0.003*	0.002	0.001	0.002***	0.423	0.066	0.139	0.157	0.006
Sent	-0.128	-0.056	-0.035	0.051	-0.069	0.626	0.702	0.775	0.578	0.221
Sent*UAI	0.001	-0.001	-0.002	-0.003**	-0.001	0.781	0.592	0.277	0.020	0.114
Sent	-0.502	-0.399**	-0.518***	-0.594***	-0.380***	0.127	0.029	0.001	0.000	0.000
Sent*LTO	0.007	0.004	0.006**	0.007***	0.003***	0.193	0.136	0.016	0.000	0.004
Sent	0.197	0.042	0.012	0.035	-0.010	0.360	0.722	0.895	0.619	0.825
Sent*IVR	-0.007	-0.004*	-0.004**	-0.004***	-0.003***	0.132	0.080	0.035	0.002	0.000

The table reveals the pooled OLS regressions with cross-market fixed effect and time dummies for Equations (4.3). The estimated coefficients and corresponding p-values for sentiment and interaction variables are reported. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

4.4.2.2. Asia versus Europe

In this part, I discover whether the local impact on the sentiment-return correlation differs between Asia and Europe by pooling my sample into two groups and executing Equation (4.3) for each of them. The estimated coefficients of the sentiment-factor interaction variable and their dissimilarities for the next 3, 12, and 24 months are presented in Table 4.9.

What can be seen in the table is the inconclusive outcomes when I compare Asian and European markets. Regarding development factors, while *FI* and *FM* negatively affect the return predictability of sentiment in Europe, the moderating influence of these two factors turns positive in Asia after one year. A similar tendency can be seen for institutional characteristics, especially in the last horizon.

At the 24 months, five out of six governance factors exposed a vigorously positive impact in Asian markets, but a slightly negative impact for European ones, except *VA,* whose effect is more substantial in Europe. *PA* is the only element that demonstrated a positive effect in both groups.

Table 4.9: Moderating effect of market-specific factors: Asia versus Europe

	R_{t+3}			R_{t+12}			R_{t+24}		
	AS	*EU*	*Diff.*	*AS*	*EU*	*Diff.*	*AS*	*EU*	*Diff.*
Panel A. Financial development indices									
Sent*FI	-0.214	-0.907***	0.693	0.007	-0.523***	0.530	0.302*	-0.672***	0.974***
	[0.613]	[0.005]	[0.179]	[0.978]	[0.002]	[0.109]	[0.085]	[0.000]	[0.000]
Sent*FM	-0.265	-0.600**	0.335	0.092	-0.425***	0.517*	0.219	-0.545***	0.764***
	[0.591]	[0.011]	[0.457]	[0.748]	[0.000]	[0.067]	[0.279]	[0.000]	[0.000]
Panel B. Institutional factors									
Sent*CC	-0.005	-0.029	0.024	0.059	0.065**	-0.006	0.123***	-0.054**	0.177***
	[0.956]	[0.631]	[0.806]	[0.243]	[0.043]	[0.932]	[0.001]	[0.017]	[0.000]
Sent*GE	-0.035	-0.059	0.024	0.036	0.125**	-0.089	0.129***	-0.054	0.183***
	[0.747]	[0.516]	[0.857]	[0.580]	[0.011]	[0.313]	[0.006]	[0.117]	[0.002]
Sent*PA	0.057	0.123	-0.066	0.082	0.230***	-0.148	0.142***	0.086	0.056
	[0.520]	[0.451]	[0.718]	[0.118]	[0.006]	[0.170]	[0.000]	[0.146]	[0.388]
Sent*RQ	-0.017	-0.092	0.075	0.047	0.226***	-0.179*	0.121***	-0.102*	0.223***
	[0.862]	[0.474]	[0.625]	[0.429]	[0.003]	[0.080]	[0.006]	[0.068]	[0.003]
Sent*RL	-0.043	-0.007	-0.036	0.023	0.154***	-0.131	0.112***	-0.066*	0.178***
	[0.635]	[0.939]	[0.770]	[0.677]	[0.001]	[0.115]	[0.005]	[0.061]	[0.002]
Sent*VA	-0.033	-0.275	0.242	-0.031	0.080	-0.111	0.107***	-0.339***	0.446***
	[0.715]	[0.101]	[0.210]	[0.571]	[0.415]	[0.375]	[0.008]	[0.000]	[0.000]
Panel C. Cultural dimensions									
Sent*PDI	0.007	0.005	0.002	0.006	-0.000	0.006	0.001	0.006***	-0.005
	[0.410]	[0.385]	[0.843]	[0.215]	[0.969]	[0.374]	[0.726]	[0.006]	[0.289]
Sent*IDV	0.006	-0.004	0.010	0.001	-0.006**	0.005	0.000	-0.004**	0.004
	[0.482]	[0.495]	[0.270]	[0.822]	[0.019]	[0.235]	[0.980]	[0.037]	[0.304]
Sent*MAS	0.006	0.001	0.005	0.004	-0.002*	0.006**	0.002	0.002***	0.000
	[0.119]	[0.621]	[0.140]	[0.121]	[0.070]	[0.041]	[0.321]	[0.006]	[0.961]
Sent*UAI	-0.002	0.003	-0.005	-0.003*	-0.002	-0.001	-0.002	0.002**	-0.004**
	[0.518]	[0.187]	[0.170]	[0.089]	[0.244]	[0.500]	[0.217]	[0.014]	[0.011]
Sent*LTO	0.004	0.010	-0.006	0.006***	0.006*	0.000	0.005***	0.004	0.001
	[0.276]	[0.176]	[0.409]	[0.007]	[0.096]	[0.912]	[0.001]	[0.171]	[0.563]
Sent*IVR	-0.005	-0.002	-0.003	-0.018***	0.002	-0.020***	-0.017***	-0.002***	-0.015***
	[0.500]	[0.410]	[0.603]	[0.000]	[0.193]	[0.000]	[0.000]	[0.008]	[0.000]

The table reveals the pooled OLS regressions with cross-market fixed effect and time dummies for Equation (4.3) when each market is classified into either Asian or European groups. The estimated coefficients and the corresponding p-values for interaction variables between sentiment and market-specific factors over 3, 12, and 24 months are reported for each group. p-values are in brackets. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

Concerning cultural aspects, since their impact on sentiment-return correlation is relatively frail, as stated in the last part, I did not observe great variations in the cultural effect between Asian and European markets. The biggest gaps belonged to *IVR* with -0.020 (p-value = 0.000) and -0.015 (p-value = 0.000) for 12 and 24-month horizon, respectively.

Overall, my results indicate that financial development likely has a more substantial moderating effect in Europe, whereas Asia seems to suffer more by the institutional qualities. The cultural impact, in contrast, is mixed. More importantly, along with the time, the local influences in these two regions also tend to change in sign and magnitude, explaining the variations mentioned above in sentiment intensity between Asian and European markets. I verified my inferences by the outcomes of Equation (4.4) exhibited in Table 4.10.

Table 4.10: Impact of local factors on sentiment-return relationship: Asia versus Europe

	Coef.					p-value				
	R_{t+1}	R_{t+3}	R_{t+6}	R_{t+12}	R_{t+24}	R_{t+1}	R_{t+3}	R_{t+6}	R_{t+12}	R_{t+24}
Panel A. Financial development indices										
Sent	0.221	0.227	0.058	-0.063	-0.220***	0.554	0.274	0.741	0.629	0.010
Sent*FI	-0.559	-0.576*	-0.419*	-0.252	0.056	0.304	0.055	0.096	0.188	0.641
Sent*FI*AS	0.237	0.088	0.202**	0.249***	0.088	0.311	0.480	0.043	0.001	0.106
Sent	0.198	0.166	0.038	-0.091	-0.124**	0.488	0.271	0.631	0.257	0.043
Sent*FM	-0.603	-0.550**	-0.451**	-0.253*	-0.101	0.192	0.023	0.018	0.055	0.276
Sent*FM*AS	0.315	0.148	0.266**	0.300***	0.097*	0.222	0.282	0.017	0.000	0.096
Panel B. Institutional factors										
Sent	-0.014	-0.097	-0.139**	-0.144***	-0.182***	0.915	0.169	0.017	0.001	0.000
Sent*CC	-0.116	-0.056	-0.037	-0.017	0.018	0.290	0.340	0.437	0.637	0.416
Sent*CC*AS	0.116	0.050	0.090*	0.111***	0.125***	0.329	0.442	0.079	0.004	0.000
Sent	0.003	-0.075	-0.151*	-0.180***	-0.246***	0.985	0.447	0.071	0.006	0.000
Sent*GE	-0.134	-0.074	-0.039	-0.005	0.066*	0.385	0.381	0.582	0.924	0.053
Sent*GE*AS	0.130	0.049	0.098**	0.120***	0.089***	0.278	0.448	0.047	0.001	0.000
Sent	-0.019	-0.104	-0.111**	-0.095**	-0.141***	0.878	0.124	0.046	0.019	0.000
Sent*PA	-0.133	-0.048	-0.098	-0.111*	0.006	0.497	0.648	0.235	0.074	0.885
Sent*PA*AS	0.184	0.094	0.172**	0.213***	0.161***	0.354	0.368	0.030	0.000	0.000
Sent	0.010	-0.074	-0.126	-0.144**	-0.237***	0.955	0.470	0.155	0.039	0.000
Sent*RQ	-0.134	-0.075	-0.064	-0.038	0.066*	0.401	0.405	0.403	0.530	0.073
Sent*RQ*AS	0.130	0.052	0.107**	0.127***	0.093***	0.291	0.436	0.037	0.001	0.000
Sent	0.000	-0.081	-0.126*	-0.133**	-0.198***	1.000	0.341	0.082	0.019	0.000
Sent*RL	-0.120	-0.062	-0.050	-0.034	0.033	0.372	0.405	0.426	0.485	0.274
Sent*RL*AS	0.103	0.019	0.070	0.098**	0.101***	0.414	0.781	0.197	0.017	0.000
Sent	0.014	-0.076	-0.086	-0.074	-0.141***	0.913	0.302	0.171	0.121	0.000
Sent*VA	-0.159	-0.092	-0.121*	-0.124**	-0.029	0.272	0.245	0.063	0.013	0.382
Sent*VA*AS	0.130	0.011	0.062	0.051	0.107**	0.496	0.913	0.485	0.461	0.015
Panel C. Cultural dimensions										
Sent	-0.682	-0.592**	-0.446*	-0.337***	-0.212**	0.216	0.041	0.058	0.001	0.039
Sent*PDI	0.012	0.010	0.005	0.002	0.001	0.329	0.132	0.348	0.580	0.605
Sent*PDI*AS	-0.002	-0.002	0.001	0.002	-0.000	0.682	0.379	0.769	0.165	0.869
Sent	0.121	-0.102	-0.102	-0.082	-0.209***	0.677	0.519	0.448	0.454	0.004
Sent*IDV	-0.004	-0.001	-0.002	-0.002	0.001	0.383	0.744	0.398	0.202	0.538
Sent*IDV*AS	-0.001	0.001	0.002	0.003	0.002	0.883	0.739	0.446	0.344	0.275
Sent	-0.205	-0.283***	-0.259***	-0.224***	-0.254***	0.244	0.001	0.000	0.000	0.000
Sent*MAS	0.002	0.002	0.001	-0.000	0.002**	0.627	0.176	0.644	0.750	0.013
Sent*MAS*AS	0.002	0.001	0.003*	0.003***	0.000	0.571	0.517	0.063	0.003	0.765
Sent	-0.124	-0.056	-0.030	0.062	-0.069	0.638	0.702	0.809	0.503	0.221
Sent*UAI	0.000	-0.001	-0.003	-0.005***	-0.001	0.936	0.666	0.157	0.002	0.190
Sent*UAI*AS	0.001	-0.000	0.001	0.002**	-0.000	0.669	0.934	0.206	0.016	0.886
Sent	-0.448	-0.391**	-0.448***	-0.504***	-0.390***	0.212	0.047	0.004	0.000	0.000
Sent*LTO	0.005	0.004	0.004	0.004**	0.004**	0.418	0.249	0.147	0.013	0.014
Sent*LTO*AS	0.001	0.000	0.001	0.002*	-0.000	0.738	0.918	0.286	0.064	0.770
Sent	0.191	0.080	0.014	0.058	0.127**	0.453	0.559	0.897	0.493	0.030
Sent*IVR	-0.007	-0.004*	-0.004**	-0.004***	-0.005***	0.146	0.068	0.038	0.002	0.000
Sent*IVR*AS	0.000	-0.001	-0.000	-0.001	-0.004***	0.966	0.586	0.979	0.656	0.001

The table reveals the pooled OLS regressions with cross-market fixed effect and time dummies for Equations (4.4). The estimated coefficients and corresponding p-values for sentiment and interaction variables are reported. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

4.5. Conclusion

The chapter investigated the return predictability of investor sentiment in twelve Asian and European markets from January 2004 to December 2016 using a composite sentiment index constructed from three indicators: *CCI*, *ADR,* and *VP*. My empirical results confirmed the negative relationship between sentiment and subsequent returns over various forecast horizons reported in the previous research of Baker and Wurgler (2007), Schmeling (2009), Bathia and Bredin (2013), and Khan and Ahmad (2018). More substantially, by separating my sample into different groups, this study, to the best of my knowledge, was the first to detect that sentiment has a more immediate impact in Europe but a more long-lasting impact in Asia.

I further demonstrated the remarkable heterogeneity in the power predictability of sentiment at the individual market level. The divergences between individual and regional markets raised a question about the moderating role of market-specific factors in driving sentiment-return relationships. By employing a comprehensive set of fourteen local elements, I discovered that the different levels in financial development and governance environment, along with cultural dimensions, could explain the sentiment-return variations across markets, though with mixed success. My results suggest that a better financial and institutional system might diminish the sentiment effect on stock returns and vice versa. The cultural impact, however, is inconclusive and weaker than the others.

Lastly, I revealed that European markets tend to suffer more from the driving force of financial qualities. Meanwhile, Asian markets are more vulnerable to institutional factors. Notably, the local impact among Asia and Europe is distinguishable between each factor and each predicted horizon, which might play a critical role in the sentiment-return diversifications between these two areas.

Chapter 5

Conclusion

During the past decades, the role of Asian stock markets globally has become more and more crucial. According to the Equity Market Review of OECD (2019), the share of capital raised in these markets has grown steadily over the past 20 years, from representing 19% of the global volume of public equity raised between 2000 and 2002 to 42% the last three years. Additionally, 11 of the top 20 markets globally in terms of non-financial IPOs during the past ten years are in Asia. These figures proved the rising attractiveness of Asian markets to investors, both local and international ones. Investors' extensive participation in Asian markets led to the fact that it is remarkably vital to understand how investor behaviors affect Asia's stock market activities. This dissertation, thus, was carried out to tackle one of those matters, i.e., the impact of investor sentiment on market returns.

First, Chapter 2 examined the nexus between investor sentiment and stock returns in three developed Asian markets, including Australia, Hong Kong, and Japan, from 2004 to 2017. By applying the consumer confidence index (*CCI*) and the volatility index (*VIX*) as the proxies for sentiment, I detected a significant effect of sentiment on concurrent returns with a more powerful one belonging to *VIX*. The sentiment impact on future returns, in contrast, was not strongly verified since the estimated coefficients of *CCI* were statistically significant in Australia and Hong Kong for next month's returns. Simultaneously, those of *VIX* were held by Hong Kong in 12 and 24-month periods only.

I wonder whether *CCI* and *VIX*'s weak influence might originate from these indicators' decent level during my research period. Consequently, I reapplied my empirical models restricting by extremely low and high sentiment situations. The results indicate that an exceptional situation could relatively increase the predictive power of *VIX* on stock returns but not be accurate in the case of *CCI*. Generally, Chapter 2 suggests that *CCI* and *VIX* are not ideal measurements to capture investor moods in Australia, Hong Kong, and Japan's stock markets and calls for a more suitable index in upcoming studies. Moreover, as the results were diverse across markets, the research to determine the causes of various sentiment intensity is also essential.

Grounded on the previous chapter's findings, in the next study, presented in Chapter 3, I established a new sentiment index from the first principal component of consumer confidence index, advance/decline ratio, and volatility premium. The sample was also expanded by adding three emerging markets: Indonesia, South Korea, and Thailand. First, the empirical evidence claimed that sentiment could be a valid predictor of market returns, though its effect only lasts until the next six months. Remarkably, by decomposing each market's total sentiment index into regional and local components, I discovered that sentiment impact is home-grown, i.e., be driven predominantly by domestic one.

Besides that, in the same vein of Chapter 2, I observed the variant power of investor sentiment between studied markets. Since my sample consists of both advanced and emerging ones, I examined the potential impact of financial development on sentiment-return inference, which has never been done before. My results revealed that markets have a more inferior financial environment suffer a more substantial sentiment effect on future returns. In other words, sentiment impact tends to oppose to the level of financial development of a market.

Eventually, Chapter 4 verified Asian markets' results demonstrated in Chapter 3 and compared those with chosen markets in Europe. Using the same composite sentiment index as Chapter 3, I confirmed the negative influence of sentiment on subsequent returns. I also was the first to detect that sentiment has a more immediate impact in Europe but a more long-lasting one in Asia.

Apart from that, the moderating role of country-specific factors on sentiment-return nexus was analyzed comprehensively by appending twelve institutional and cultural qualities along with two aspects of financial development. The evidence from my regression models showed that a higher degree of financial growth and a better governance system could mitigate the sentiment effect on stock markets and vice versa. The impact of cultural dimensions, on the contrary, is assorted and indecisive. More crucially, I found that Asian markets suffer more from the modified force of institutional factors. In contrast, financial development tends to affect European markets more firmly. Finally, the moderating effect of local characteristics is disparate between Asia and Europe and time-variant across forecasted periods. Such disclosures could be a vital explanation for the time and magnitude diversifications in sentiment intensity between these two regions reported in the first part of this chapter.

To sum up, this dissertation provided a more transparent and detailed picture of sentiment-return inference and the moderating impact of local factors on this relationship. The findings from my studies are useful for investors interested in investing in the Asian stock markets. It is also crucial to intra-day traders and practitioners that use technical skills to measure and earn profit from the short-term price changes often inspired by investors' prevailing sentiment toward security. Contrarian investors who like to trade in the opposite direction of this sentiment might get essential information from this dissertation, too.

My research, undeniably, is imperfect. Using data of six Asian markets only, the regional index formed in the second study might not ideally capture the sentiment impact of the Asian area. One of the reasons is that Asia does not have a general index for all markets like what was utilized in Corredor et al. (2015). Their paper applied the consumer confidence index of 27 European Union members and 13 Euro Area members as two indicators for the European regional sentiment index. Therefore, future research to find out or construct a unique index for the Asia region's sentiment intensity is compelling.

Notes

1. Based on the empirical evidence, Ajao et al. (2012) found that cubic spline interpolation is a powerful data analysis tool since splines correlate data effectively, no matter how random the data may seem. They recommend that policymakers, researchers, and users of economic data should exploit this method when splitting low-frequency to higher-frequency data.

2. The methodology to compute *CCI* and *VIX* in Australia, Hong Kong, and Japan are provided in Appendix A.

3. VIF values of explanatory variables were below 3 in all empirical regressions implying that multicollinearity does not happen in my model. For the sake of brevity, the results of VIF are not reported but available upon request.

4. The residual plots depict the same conclusion as Adj. R^2 and AIC. Therefore, to conserve space, they are not documented but available upon request.

5. Since setting two standard deviations above/below mean results in values' insufficiency, I choose one standard deviation as the threshold for extreme sentiment.

6. In favor of brevity, the results are not presented but available upon request.

7. These market indices comprise Shanghai Composite Index-SHCOMP (China), Hang Seng Index-HSI (Hong Kong), Jakarta Stock Price Index-JCI (Indonesia), Nikkei 225 Index-NKY (Japan), Korea Stock Exchange Composite Index-KOSPI (South Korea), Bangkok SET50 Index-SET50 (Thailand), Prague Stock Exchange Index-PX (Czech Republic), Budapest Stock Exchange Index-BUX (Hungary), Milano Italia Borsa Index-FTSE MIB (Italy), Amsterdam Exchange Index-AEX (Netherlands), OMX Stockholm 30 Index-OMX 30 (Sweden), and UK FTSE 100 Stock Market Index-FTSE 100 (United Kingdom).

8. The scores of local factors for each market are reported in Appendix B

9. For the sake of brevity, the results for panel unit root tests are not reported but available upon request.

10. *CC*, *GE*, and *RL* have the same results because the countries belong to below and above-median groups based on these three factors are the same.

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Appendices

Appendix A. Details about CCI and VIX utilized in empirical research

	Methodology	Starting point	Frequency
Panel A: CCI			
Australia	Data is collected based on approximately 1,000 face-to-face interviews each week (about 50,000 per year) in city and country areas, with people aged 14+. The Consumer Confidence Rating is 100.0 plus the simple unweighted average of the difference between the percentage of respondents who give a favorable and those who provide unfavorable answers to five key questions. The index scores above 100 indicate that optimists outweigh pessimists.	March 1973	Weekly (Monthly until August 2008)
Hong Kong	Roughly 500 Hong Kong residents aged 18 or above would be randomly selected to participate in the survey. They are asked to answer questions about their financial situation, their perception towards the business environment, the economic outlook, employment, and their sentiment about consumption. The index levels above 100 indicate optimism, and below 100 indicate pessimism.	Q1 2000	Quarterly
Japan	Collected by direct-visit or mail and covers about 8.400 (6.720 before March 2013) households. The questionnaire covers four subjects: consumer perceptions of overall livelihood, income growth, employment, and willingness to buy durable goods. For each item, an index based on the respondents' evaluation of what they consider the prospects to be over the next six months is created. The CCI is the simple average of the four consumer perception indexes. A score above 50 indicates optimism, while below 50 shows pessimism, and 50 means neutrality.	June 1982	Monthly (Quarterly until March 2004)
Panel B: VIX			
Australia	The S&P/ASX 200 VIX (A-VIX) leverages mid-prices for put and call options on the S&P/ASX 200 index to calculate a weighted average of these options' implied volatility. The index interpolates volatility of the options closest to maturity, relative to those of the options farthest from maturity, to derive a 30-day indication of expected volatility in the equity benchmark.	2nd January 2008	Daily
Hong Kong	The HSI Volatility Index ("VHSI") aims to measure the 30-calendar-day expected volatility of the Hang Seng Index ("HSI"). The expected volatility calculated is derived from HSI put options and HSI call options in the two nearest-term expiration months to bracket a 30-calendar-day period.	16th July 2010	Daily
Japan	The Nikkei Stock Average Volatility Index is calculated by using the prices of Nikkei 225 futures and Nikkei 225 options on the Osaka Exchange (OSE). In the calculation, taking near-term future price based on ATM, the volatility of near-term options and next-term options are calculated with each delivery month's OTM option prices. The index value is then calculated by linear interpolation or linear extrapolation between each delivery month's volatilities to take the time to expiration as 30 days.	12th June 1989	Daily

Appendix B. Scores of market-specific factors

	Financial development		Institutional factors						Cultural dimensions					
	FI	*FM*	*CC*	*GE*	*PA*	*RQ*	*RL*	*VA*	*PDI*	*IDV*	*MAS*	*UAI*	*LTO*	*IVR*
Panel A. Asian markets														
China	0.493	0.584	-0.465	0.124	-0.522	-0.233	-0.479	-1.635	80*	20	66*	30	87*	24
Hong Kong	0.749	0.723*	1.789*	1.789*	1.049*	1.952*	1.610*	0.537	68*	25	57	29	61	17
Indonesia	0.344	0.305	-0.679	-0.251	-0.922	-0.343	-0.592	0.005	78*	14	46	48	62*	38*
Japan	0.888*	0.761*	1.455*	1.543*	0.996*	1.167*	1.369*	1.021*	54	46	95*	92*	88*	42*
South Korea	0.804*	0.840*	0.500*	1.104*	0.342	0.923	0.980*	0.699	60*	18	39	85*	100*	29
Thailand	0.620	0.607	-0.353	0.301	-1.117	0.238	-0.109	-0.522	64*	20	34	64*	32	45*
Panel B. European markets														
Czech Republic	0.522	0.234	0.372	0.958	0.984*	1.117*	0.978	0.998*	57*	58*	57	74*	70*	29
Hungary	0.485	0.486	0.414	0.670	0.756*	0.998	0.733	0.845	46	80*	88*	82*	58	31
Italy	0.806*	0.753*	0.198	0.425	0.448	0.860	0.425	1.022*	50	76*	70*	75*	61	30
Netherlands	0.798*	0.744*	2.051*	1.814*	0.982*	1.769*	1.833*	1.552*	38	80*	14	53	67*	68*
Sweden	0.772*	0.711	2.213*	1.929*	1.161*	1.720*	1.942*	1.587*	31	71*	5	29	53	78*
United Kingdom	0.902*	0.805*	1.753*	1.636*	0.390	1.743*	1.723*	1.346*	35	89*	66*	35	51	69*
Median	0.761	0.717	0.457	1.031	0.602	1.057	0.979	0.921	55.5	52	57	58.5	61.5	34.5

The appendix summarizes the national score of two financial development series: Financial Institutions (*FI*) and Financial Markets (*FM*), six governance dimensions: Control of Corruption (*CC*), Government Effectiveness (*GE*), Political Stability and Absence of Violence (*PA*), Regulatory Quality (*RQ*), Rule of Law (*RL*), and Voice and Accountability (*VA*), and six aspects of culture: Power Distance Index (*PDI*), Individualism vs. Collectivism (*IDV*), Masculinity vs. Femininity (*MAS*), Uncertainty Avoidance Index (*UAI*), Long-term Orientation vs. Short-term Orientation (*LTO*), and Indulgence vs. Restraint (*IVR*) for twelve Asian and European markets during the period from 2004 to 2016. The median score of each local feature is also presented. Data are obtained from the website of the International Monetary Fund, World Bank, and Hofstede Insights.

* indicates markets in the above-median group