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Does Fear has Stronger Impact than Confidence on Stock Returns? The Case of Asia-Pacific Developed Markets

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Abstract

Employing data from Australia, Hong Kong, and Japan over the period between January 2004 to December 2017, this study investigates the relationship between investor sentiment and stock returns. We analyze two reversed sentiment indicators, namely Consumer Confidence Index (CCI) and Volatility Index (VIX), in two conversing situations: low and high sentiment. The empirical evidence suggests 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, we 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.

Keywords: investor sentiment; stock returns; consumer confidence index; volatility index.

JEL classification: G10; G15; G40.

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) view 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

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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 is proved in many studies as the explanation for abnormal stock returns, besides traditional factors. Early empirical research, conducted mainly in U.S. stock markets, presents a vital link between investor sentiment and stock returns. For example, Fisher and Statman (2003) report that low returns generally follow high consumer confidence. In the paper of Brown and Cliff (2005), 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) find that the sentiment index significantly predicts Tokyo Stock Exchange prices of three days in advance. Finter *et al.* (2012) show 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) investigate six major stock markets in the world and document that global and local sentiment is contrarian predictors of the time-series of cross-sectional returns within markets. The study on 18 developed markets of Schmeling (2009) and G7 markets of Bathia and Bredin (2013) also provides the same results.

In respect of emerging markets, Corredor *et al.* (2015) show that sentiment is a critical variable in the prices of stocks traded on 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 detect 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) examine Chinese stock markets only and find that investor sentiment has a tremendous impact on stock returns.

However, compared to U.S. and European countries, there is less research related to 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) indicates that European Americans hold a bullish bias in the prediction of positive and negative events. In contrast, the Japanese hold a pessimistic bias for adverse events. Chen *et al.* (2007) find that Chinese investors suffer from three behavioral biases: (i) they tend to sell stocks that have appreciated at a price; (ii) they seem overconfident; and (iii) they appear to believe that past returns are indicative of future returns. In comparison to prior findings, Chinese investors seem more overconfident than U.S. investors, and their disposition effect appears firmer. Recently, Yiend *et al.* (2019) confirm that Hong Kong residents are more positively biased than people living in the UK, consistent with the lower prevalence of psychological disorders in East Asia. These reasons inspire us to carry out the study about the relationship between investor sentiment and stock returns, focus on Asia-Pacific developed markets.

Our research contributes to financial literacy in several ways. To begin with, we discover whether investor sentiment affects market returns or not, and in what direction. In detail, by employing data from Asia-Pacific markets, this paper 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, we 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. We find out that there is a significantly contemporaneous relationship between sentiment indicators and market returns. In addition to that, as expected, "investor fear gauge" represented by VIX proves a more substantial and opposite impact on concurrent returns than CCI computed by "investor confidence". However, the predictive power of CCI and VIX, though it could be enhanced slightly in extreme situations, seems to be non-existence, except for long-term periods in Hong Kong. Our results will be useful for investors interested in investing in the Asian stock market. 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 study, too.

The paper is organized as follows. In Section 2, we present previous empirical literature and construct testing hypotheses. Section 3 introduces the data used and the methodology applied to investigate the relationship between investor sentiment and market returns. Results are reported in Section 4. Section 5 summarizes our paper.

2. LITERATURE REVIEWS

2.1 The Sentiment – Returns 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 connection between sentiment and stock returns has discovered in lots of research. While the contemporaneous relationship between sentiment and returns is undeniable, the role of sentiment as a contrarian predictor of future returns is still controversial. On the one hand, several studies of Baker and Wurgler (2007); Chen (2011); Ding *et al.* (2019); Huang *et al.* (2015); Schmeling (2009) outline a negative relationship between sentiment and future returns. In contrast, Brown and Cliff (2004); Kim and Park (2015); Lansing and Tubbs (2018) show 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 (Horta and Lobao, 2018; Liston, 2016; Schmeling, 2009), investor mood (Kostopoulos and Meyer, 2018), option implied volatility (Bekaert and Hoerova, 2014; Qadan *et al.*, 2019; Smales, 2017), 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 (Anusakumar *et al.*, 2017; Baker and Stein, 2004; Chen *et al.*, 2001), 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) use the communal component of the different measures as a sentiment proxy and find that sentiment has little predictive power for near-term future stock returns. Nevertheless, the results of Lemmon and Portniaguina (2006) prove that investor sentiment measured using consumer confidence can forecast the returns of small stocks and stocks with low institutional ownership. Corredor *et al.* (2013) employ several sentiment indicators for four European stock markets, namely U.K., Spain, France, and Germany and conclude that the results obtained 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 are also affected by the frequency of data and time horizon. Bathia and Bredin (2013) depict 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) also find that in the short run (until three months), the sentiment is leading returns whereas 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- or undervaluation in the short run is gradually corrected in the long term. In contrast, the evidence of Dash and Maitra (2018) supports the fact of whether investors are short-term or long-term traders, their investments activities cannot be delinked from sentiment. It is because they detect 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 is proved.

Based on prior research, our first hypothesis is: *The effect of investor sentiment is positive on contemporaneous returns and negative on future returns.*

2.2 Asymmetric Impact of Sentiment

Besides testing the dependence of returns on investor sentiment, the asymmetry in sentiment influence also becomes 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, so in case both offering 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) investigates the link between the lack of consumer confidence and stock returns during market fluctuations and suggests 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, also finds that the relationship between sentiment and returns is asymmetric. He confirms that during bear markets, high sentiment predicts low future returns for the cross-section of speculative stocks and the market overall. In contrast, the relationship during bull markets is weak and often insignificant. Tsai (2017) explores the optimistic and pessimistic sentiments of three major institutional investors (foreign investors, trust investors, and dealers) in the Taiwan stock market. The results confirm that under favorable market performance when institutional investors are optimistic, the diffusion effect of investor sentiment is nonsignificant. By contrast, the diffusion effect of pessimistic sentiment is significant, indicating that investor sentiment contagion is asymmetric.

In another perspective, comparing five sentiment proxies over the period 1990-2015, Smales (2017) demonstrates a strong relationship between investor sentiment and stock returns. More remarkably, he determines 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.

Our second hypothesis, therefore, is the following: *Investor fear generates a stronger impact on stock returns than investor confidence.*

3. DATA AND METHODOLOGY

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

3.1 Stock Market Data and Sentiment Proxies

3.1.1 Stock Market Data

Stock returns at the aggregate market level are represented by the main indexes of each stock exchange, which indicate the overall market performance. These are:

- S&P/ASX 200 Index based on the 200 largest listed stocks in the Australian Securities Exchange.
- Hang Seng Index, including 50 largest listed stocks in the Stock Exchange of Hong Kong.
- Nikkei 225 Index comprised 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. For each index, we collect the end-of-month return index in local currency to compute the monthly time series of stock market returns. Using local currency allows us to avoid currency and exchange rate effects.

3.1.2 Sentiment Proxies

Among various sentiment proxies, in this study, we apply two direct sentiment 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 Corredor *et al.* (2013), 2015); Finter *et al.* (2012); Oprea and Brad (2014); Schmeling (2009).

The other sentiment proxy is VIX appearing in some recent studies by Bekaert and Hoerova (2014); Qadan *et al.* (2019); Smales (2016), 2017). 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. As a result, although the calculation methods are slightly different[2], these measurements seem to be a consistent way to compare between various countries.

3.2 Macroeconomic Variables

It is almost undeniable that stock returns are related to the state of economics. For example, Hsing (2011) finds 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 make sure our results are driven by the effect of market sentiment, not by the fluctuations in the business cycle, some macroeconomic variables are utilized in our empirical analysis. Based on previous research, these four variables are chosen: industrial production index, consumer price index (inflation rate), money supply (M1), and unemployment rate. We convert these series to the monthly growth rates before employing them in our model.

3.3 Methodology

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

$$RI_t = \alpha + \beta.SENT_t + \gamma.M_t + \varepsilon_t \qquad (1)$$

More importantly, we detect whether investor sentiment can be a valid predictor of future market returns through different horizons:

$$\frac{1}{k}\sum RI_{t+k} = \alpha + \beta.SENT_t + \gamma.M_t + \varepsilon_{t+k} \qquad (2)$$

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 model is also controlled by a set of macroeconomic variables described in section 3.2 and represented by the vector M_t. Especially for k = 1, we apply the VAR technique, which is a useful tool for identifying the short-term relationship between time-series data. VAR is employed in previous sentiment work, such as Brown and Cliff (2004); Corredor *et al.* (2013); Sayim and Rahman (2015); Schmeling (2009).

If there is a significant relationship between sentiment and contemporary returns, we expect β in Equation 1 is positive (negative) for CCI (VIX). This impact of investor behavior is estimated to reverse in the future since stock prices back to their equilibrium. Consequently, the β of Equation 2 should be negative (positive).

We compute 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 are 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, we also examine the enhancement in explanation power and model fit in case investor sentiment proxies are adding in our model by comparing adjusted R^2 (Adj. R^2) and Akaike Information Criterion (AIC) to the model with macroeconomic variables only. An increase in Adj. R^2 and a decrease in AIC demonstrate the model's improvement. The residual plots between different models are also evaluated[4]. This information provides more details about the effect of sentiment on stock returns as well as to differentiate the intensity between CCI and VIX.

Finally, we distinguish 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 1 is utilized:

$$\frac{1}{k}\sum RI_{t+k} = \alpha + \beta.DUM_{High/Low}.SENT_t + \delta.M_t + \varepsilon_{t+k} \quad (3)$$

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

4. RESULTS

4.1 Descriptive Statistics

Table no. 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 earns 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 the standard deviation of 5.842, trading in Hong Kong is also riskiest. The negative skewness and positive excess kurtosis indicate that all return series are skewed left and leptokurtic. Autocorrelation in returns seems quite small and wipe out quickly.

Regarding sentiment measures, since CCI as 100 in Australia and Hong Kong, and 50 in Japan indicates the neutrality, the average of 116 implies the positive outlook of Australian investors 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 is relatively high, with average VIX of around 20. Noticeably, the lowest mean of CCI and the highest mean of VIX belong to Japan, implying the awareness of investors about the unstable situation of the Japanese market.

Table no. 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 Consumer Confidence Index (CCI) and Volatility Index (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

Finally, the results of the augmented Dickey-Fuller test are represented, proving that all time series in our sample are stationary, except for Hong Kong's CCI. To solve this problem, we create a time variable and regress CCI against it. The residuals series from this regression does not have a unit root and will be used as a replacement for CCI in Hong Kong. Since the series are evaluated to be stationary, we can apply the ordinary least square (OLS) regression model for our empirical framework.

4.2 Correlation

Table no. 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 are identical for all markets. More particularly, for returns and CCI, positive coefficients are revealed when the negative ones for the former and VIX with the highest belong to Australia of 0.251 and -0.478, in turn. Remarkably, the coefficients of VIX are much higher than CCI might indicate the stronger impact of VIX on stock returns. Besides that, CCI and VIX also exhibit 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". These outcomes of the correlation matrix give us general ideas about the concurrent connection between two sentiment proxies and market returns, which is investigated more in detail in the next section.

Table no. 2 – Correlation matrix

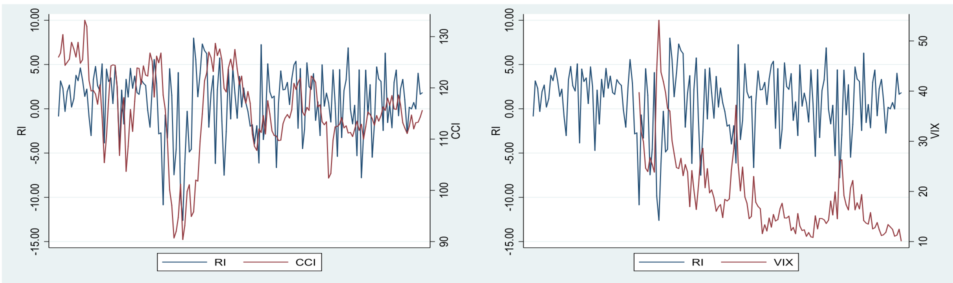
Panel A: Australia							
	RI	*CCI*	*VIX*	*UNRATE*	*INSPROD*	*CPI*	*MOSUP*
RI	1.000						
CCI	0.251***	1.000					
VIX	-0.478***	-0.446***	1.000				
UNRATE	0.144*	0.050	-0.570***	1.000			
INSPROD	0.005	0.121	-0.197**	0.013	1.000		
CPI	0.019	0.118	-0.073	-0.310***	0.240***	1.000	
MOSUP	-0.068	0.043	-0.065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

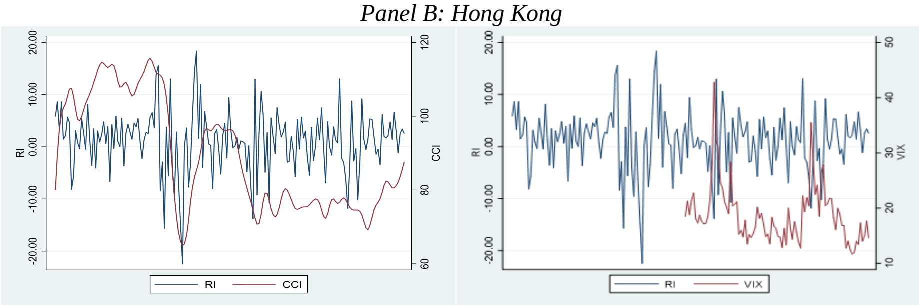
4.3 Investor Sentiment and Contemporaneous Returns

Figure no. 1 depicts the relationship between monthly market returns and two sentiment proxies, namely CCI and VIX, in Australia, Hong Kong, and Japan. In the tandem of the correlation matrix, the positively (negatively) immediate influence of sentiment on stock returns can be witnessed clearly in all sample markets. The outcomes from correlation analysis and graphical illustration motivate us to investigate more specifically about these relationships by applying Equation 1 for the contemporaneous specification.

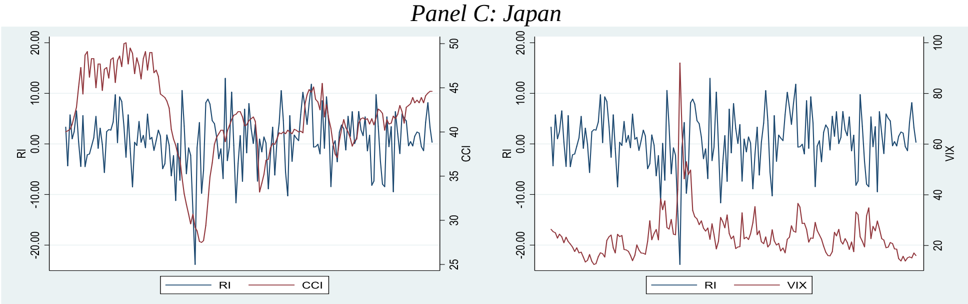
Panel A: Australia



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.

Figure no. 1 – The concurrent relationship between investor sentiment and market returns

Table no. 3 – The relationship between investor sentiment and contemporaneous returns

	Australia		Hong Kong		Japan	
Sentiment Measures	*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
$\triangle$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
$\triangle$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 (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. The equation is controlled by four macroeconomic variables, include Unemployment Rate, Industrial Production Index, Consumer Price Index, and Money Supply 1. 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 parentheses. $\triangle$Adj. R^2 and $\triangle$AIC imply the change in model 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

Table no. 3 presents the results for OLS regression between investor sentiment and contemporaneous returns, 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 into our model.

As is shown in the table, the synchronous return-sentiment relationship is convinced and could 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. Hong Kong's stock market seems most influenced by VIX with the highest coefficient of -0.400, as reflected in the table. Interestingly, with the coefficients are estimated at approximately 0.100 (Australia 0.110, Hong Kong 0.099, and Japan 0.156), the impact of CCI on returns are quite similar in three markets. All of the sentiment coefficients are statistically significant, except for the CCI of Japan.

Comparing CCI and VIX, the latter exposes the higher coefficient than the former in all research markets, with the most substantial gap belonging to Hong Kong (0.099 and -0.400, respectively). In addition to this, when being included in our model, VIX also enhances the model better as Adj. R^2 rises, and AIC reduces 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 increases Adj. R^2 by 0.165 and drops AIC by 28.161 while those of CCI are 0.013 and 1.310, in turn. Based on these outcomes, we might conclude that VIX, which measures the "fear" of investors, seems to have a stronger concurrent impact on stock returns than CCI. A similar result for the U.S. market is reported by Smales (2017), who determines that VIX is the preferred measure of sentiment in terms of improving model fit and adding explanation power.

4.4 Investor Sentiment and Future Returns

4.4.1 Short-term effect of sentiment on stock returns

To test the impact of investor sentiment on near future returns, we employ 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 use regressions for detecting long-term relationships. However, their findings are somehow non-identical. While Schmeling (2009) states a two-way causality between sentiment and returns for a pool of 18 developed markets, Corredor *et al.* (2013), who also examine this relationship in four industrialized countries in Europe, find that for each market in most cases, there is one-way feedback only.

Table no. 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 results of the pairwise Granger causality test 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

Our results for Asia-Pacific developed markets exhibited in Table no. 4 are in support of Corredor *et al.* (2013)'s research. Different from the apparent relationships, the outcomes are not homogeneous across Australia, Hong Kong, and Japan. In two former markets, there is strong evidence that the causality runs from sentiment represented by CCI to returns and not vice versa. In contrast, Japan's stock market witnesses a two-way effect between VIX and returns. It implies that past VIX and current VIX driving current market returns are also driven by past returns. This finding assists Qiu and Welch (2004), who point out that sentiment "*should not fall like manna from heaven*", but should be related to some variables, such as returns, macro variables. In general, our 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.

4.4.2 The long-term effect of sentiment on stock returns

In this part, we investigate the ability of sentiment to predict future returns by applying Equation 2 in near to mid-term period (k = 3, 6, 12, and 24 months, respectively). Table no. 5 presents coefficient estimators for two sentiment proxies and some relevant results derived from OLS regressions. The findings are somewhat disparate between three research markets.

Table no. 5 – Return predictability of investor sentiment in different horizons

	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). The dependent variable is average market returns for 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. The equation is controlled by four macroeconomic variables, include Unemployment Rate, Industrial Production Index, Consumer Price Index, and Money Supply 1. 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 parentheses. △Adj. R^2 and △AIC imply the change in model 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

Firstly, look at Table no. 5, in Australia and Hong Kong's stock markets, CCI continues to have a positive impact on short-term future returns. Take Australia as an example. The coefficients of this sentiment to the next 3-month and 6-month returns are 0.052 and 0.038, in turn. After that, this effect starts 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 remains longer in Japan as the negative coefficient is 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 discover that investor sentiment measured by CCI has a significantly negative impact on future stock returns at very near forecast horizons (1 to 6 months).

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

However, in conclusion, the effect of CCI and VIX as sentiment proxies on future returns seems to be non-existent as most of the coefficients are not significant statistically, except mid-term horizons in Hong Kong. It might be because, in our 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, we will check out the results for the intense low and high sentiment situation exhibited in Table no. 6.

As can be seen 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, have 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 dominate 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 seem to be 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 is 0.030, while the one for CCI is only 0.001. Lastly, compared to extreme CCI, extreme VIX is also the sentiment proxy, which has a much more statistically significant impact on subsequent returns.

Table no. 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
$\triangle$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
$\triangle$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
$\triangle$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
$\triangle$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
$\triangle$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
$\triangle$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
$\triangle$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
$\triangle$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 (3) when a dummy variable for extremely high and low sentiment is presented. The Dummy High (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 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. The equation is controlled by four macroeconomic variables, include Unemployment Rate, Industrial Production Index, Consumer Price Index, and Money Supply 1. 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 parentheses. □Adj. R2 and □AIC imply the change in model 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

Generally, our results imply that an exceptional situation could relatively increase the predictive power of VIX on stock returns but might not 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.

5. CONCLUSION

Employing two direct sentiment measures, including CCI and VIX, the paper investigates the dependent of stock returns on investor sentiment in three Asia-Pacific developed markets during the period from January 2004 to December 2017. Overall, we observe a significantly contemporaneous link between sentiment indicators and market returns. Remarkably, VIX, as a representative for "investor fear gauge", proves 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 demonstrates better performance. Our 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 appears to be non-existent for both CCI and VIX over near and mid-term forecast horizons. The only exception belongs 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, we also discover that extremely low and high sentiment could increase the estimation capacity, though not too remarkable. Besides that, our results are 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 reveal 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 out more ideally ones. The studies that broaden sample and add developing markets to testify the impact of market-specific factors on the sentiment-return relationship are also compelling.

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ANNEX

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 both 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 take part in the survey. They are asked to answer questions about their financial situation, their perception towards the business environment, the economic outlook, employment as well as 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 the implied volatility of these options. 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 as the basis of ATM, the volatility of near-term option and next-term option are calculated with OTM option prices of each delivery month. Then, the index value is calculated by linear interpolation or linear extrapolation between the volatilities of each delivery month to take the time to expiration as 30 days.	12th June 1989	Daily

Notes

1. Based on the empirical evidence, Ajao *et al.* (2012) find that cubic spline interpolation is a powerful data analysis tool since splines correlate data efficiently and 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. Bathia and Bredin (2013) also use this method in their sentiment research about G7 markets, including Japan.
2. The methodology to compute CCI and VIX in Australia, Hong Kong, and Japan are provided in Appendix
3. VIF values of explanatory variables are below 3 in all empirical regressions implying that multicollinearity does not happen in our 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 the insufficiency of values, we choose one standard deviation as the threshold for extreme sentiment.

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