Does Investor Sentiment Matter in New Zealand and Australian Stock Markets?

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Abstract

Investor sentiment is an important aspect of behavioral finance, which provides explanations to anomalies such as January effect, Momentum effect, and Monday effect. More and more evidences suggest that sentiment of investors can effectively affect returns, but most of empirical researches investigate American and European stock markets rather than New Zealand and Australian stock markets. Thus, this paper focus on this gap, intending to study and compare effects of investor sentiment on stock returns in these countries. This paper uses Consumer Confidence Index (CCI) and trade volume as sentiment proxies from 2004 to 2017. It also employs macro-economic variables such as IPI, GDP, inflation rate and interest rate to investigate the aggregate effects of sentiments. Based on book-to-market ratio and DPS, this paper divides whole sample into subsamples to study the cross-sectional effects of sentiment on different portfolios. This paper finds that in the short term, investors' sentiment can positively predict stock returns but not in the long term. This finding partly support existing empirical researches. In addition, the results also suggest that with the increase of forecast horizon, the predictive power of sentiment will decrease.

JEL Classification: G11, and G15

Keywords: Investor sentiment, return, investment, predictive power

1.0 Introduction

In financial field, the factors which could affect stock returns have been drew more attention in recent years. For example, macro-economic variables and financial ratios such as DPS ratio, the book-to-market ratio and the PE ratio could be used to forecast the stock return. However, these components only can predict return through traditional economic settings. Thus, this paper wants to focus on this gap and uses investor sentiment to predict the stock return by behavioral approach.

Based on empirical researches, most of their results suggest that sentiment indices have a negative effect on stock returns and vice versa (Schemeling, 2007; Charoenrook, 2003; Grigaliuniene & Cibulskiene, 2010; Brown & Cliff, 2005). In addition, Baker, Wurgler & Yuan (2012) and Kumar & Lee (2006) analyzes the sentiment effect on cross-sectional effects which are distributed firms based on firm size, firm age, value or growth firms, and dividend or non-dividend firms.

On the other hand, empirical researches mainly focus on discussing the U.S. or European countries' stock markets and ignore other stock markets. Thus, our paper mainly focuses on discussing sentiment indices which could be used to predict stock returns in Australia and New Zealand stock markets at aggregate level and cross-sectional level. This paper uses consumer confidence index (CCI) and the log of trade volume as proxy for investor sentiment. For the aggregate level, it firstly conducts the KPSS test of unit root test in order to test stationary of the data, and it also tests the correlation between sentiment indices and four macro-economic variables, including inflation rate, interest rate, industrial production, GDP in each country's data.

For the cross-sectional level, it sorts firms based on book-to-market ratio and dividend per share. And then this paper conducts granger causality test and predictive regression to find out the relationship between stock returns and sentiment proxies. The main motivation of this paper is to complete and supplement findings of empirical researches at a global level, comparing results with empirical researches and explaining why these differences exist.

There are two main reasons why this study compares New Zealand and Australia stock markets. The first is that these two countries have similar environment and culture. Thus, it could avoid many factors which will affect test results. The second reason is that the economic connection between New Zealand and Australia makes it possible to combine market indices together and further to construct the Australasia index which can be used to conduct tests at an aggregate level. Analyzing individual market index can help us to investigate difference between these two countries. Thus, we can analyze from different angles and obtain better results.

The paper is organized as follow: it reviews empirical researches at aggregate level and cross-sectional level in the second part. In the third part, the paper provides brief introduction of data and methodology. The fourth part conducts tests and discusses findings of these tests. The last part provides the conclusion of this paper.

2.0 Literature Review

DeLong, Shilefer, Summers & Waldmann (1990) present the noise trader model. They find that noise traders' beliefs could affect the stock return. After that, there are many papers test whether the investor sentiment will affect the stock price by two perspectives. One is aggregate effects. Their results argue that a number of financial market anomalies could be explained by noise trader risk at the aggregate level. Another is cross-section effects. This means that irrational investors could affect some specific stocks at different level. Thus, this paper will discuss not only aggregate effects but also cross-sectional effects.

Brown & Cliff (2005) tests the link between asset valuation and investor sentiment. They use survey data which is an investor's intelligence as a measure of investor sentiment. In addition, this paper's data start in the January 1963 and end in December 2000. Their sample includes 456 observations in the long term. In order to complete their findings, they also test whether sentiment affect stock return in the short term. Thus, the sample for the short-term test includes in 235 observations from January 1979 to July 1999. In terms of the results, they find that sentiments have no relationship with predictive stock return in the short term, but sentiments have a negative effect on an asset valuation and future return in the long term.

Charoenrook (2003) tests the long-term impact of investors' sentiment on stock returns. The paper uses the University of Michigan Consumer Sentiment Index as a proxy of sentiment indices. For the data, the paper uses excess market returns which are calculated by the Center for Research in Security Prices market index minus the one-month return of Treasury bills. In addition, the sample firms included in Amex, NYSE, and the NASDAQ. Moreover, the paper uses quarterly CSI survey data from November 1952 to January 1978 as a measure of sentiment index. As a result, the paper suggests that consumer sentiment is unrelated to time-varying expected returns.

Uygur and Tas (2012) tests the effect of noise traders' demand. Their finding suggests that there is a correlation between stock earning and conditional volatility by using conditional volatility model. They use GARCH, TARCH and EGARCH models to test whether earning shocks would be affected by conditional volatility in the high sentiment period. Their data are weekly and daily returns of Nasdaq, Dow, S&P500, Nikkei225, HangSeng, FTSE100, CAC40, DAX and ISE index. Besides that, they use percentage change of weekly and daily trade volume as a measure of investor sentiment. As a result, they find that high sentiment lead earning shocks to be more affected by conditional volatility.

Baker, Wurgler & Yuan (2012) study the sentiment effects of global market. They focus on six developed stock markets which are Canada, France, Germany, Japan, the United Kingdom, and the United States. For the methodology, they decompose six major markets' indices into one global and six local indices to do research respectively. The time period of the paper is from 1981 to 2006. Moreover, they also use monthly market return which is obtained from DataStream. As a result, they found the global and local sentiment indices could help to predict the time-series of cross-section returns, and the result also proves that future returns have a negative correlation with sentiment.

Grigaliuniene & Cibulskiene (2010) study whether the investor sentiment can be affected by stock returns at cross-sectional effects and aggregate level. They use consumer confidence index (CCI) and economic sentiment indicator (ESI) test the sentiment effect. For aggregate effect, they use KPSS of unit-root test to do the "stationary" hypothesis test, and they also test the correlation between macro-economic variables and sentiment index. For the cross sectional effect, they divide the whole sample based on book-to-market ratio and dividend per share. Their result suggests that sentiment proxies have negative effect on forecast stock returns.

Qiu & Welch (2005) use consumer confidence survey and the closed-end fund discount as measurements of investor sentiment in this paper. They compare these two groups of data, and they find these two groups of data are not correlated with another one. They use small firm excess returns and sentiment proxies in the UK stock market to run the regression. As a result, they find consumer confidence only can predict small stock returns.

Lemmon & Golubeva (2006) study the time series relationship between sentiment indices and small stock premium. They find the sentiment proxies could be used to predict the returns of small stocks and stocks with low institutional ownership. However, the sentiment proxies could not forecast time-series of valuation and momentum premiums. They also explore the cross-sectional effects. They find that sentiment proxies have a significant effect on the stock returns of value stocks, but the sentiment only have week effects on stock return of growth stocks.

Glushkov (2006) use sentiment beta which measure the investor sentiment by a novel stock-by-stock to do research. The paper also tests whether sentiment change can affect stock returns. The paper's sample period is from March 1975 to Dec 2003. The paper finds that stocks with small, younger, greater short-sales constrain, higher idiosyncratic volatility and low dividend yields are more affected by the sentiment. On the other hand, the paper also finds higher sentiment indices' stocks are normally holding by individually.

Zhu & Niu (2016) conducted a study on Shanghai stock market and found that investor sentiment can change both the expected earnings growth and the required rate of return, thus affecting the stock price. However, the sentiment effect during pessimistic period is evidently different from that when sentiment is relatively high, especially for the required rate of return. Li, Rhee, & Wang (2017) found that institutional investors react asymmetrically to up- and down-market movements, whereas individual investors do not. The findings of another study by Rizvi, Arshad, & Alam (2015) support the popular belief, that the majority of the global shocks since 1996 were transmitted via excessive linkages from US to Asia Pacific, while the recent subprime crisis reveals a fundamental based contagion. Hung (2016) did a study on Taiwan Stock Exchange and concludes that people's order submission behavior is quite different in optimistic versus pessimistic periods while the sensitivity of order submission decisions on investor sentiment is significantly different across different trader classes. Yang, Jhang, & Chang (2016) found that investor sentiment, as measured by the option volatility index (VIX) and put-call open interest ratio (PCO), and the catastrophic factors of earthquakes (EQ) can help explain realized volatility and that the PCO has the best predictive ability.

The empirical results of a study by Smales & Kininmonth (2016) indicate a negative relationship between daily returns on high-interest rate (investing) currencies and changes in the implied volatility index, while the association is positive for low-interest rate (funding) currencies. They suggest that investing (funding) currencies tends to depreciate (appreciate) when investor fear increases. Furthermore, they also found that during crisis period, currency returns are much more sensitive to changes in investor fear, and this is particularly so for funding currencies that are perceived to present a safe-haven.

Li, Guo & Park (2017) found that the causal relationship between investor sentiment and stock returns strengthens when a tail quantile interval is considered. They further suggest that the findings can be explained by investors' loss aversion and herding behavior. Cheema, Man, & Szulczyk (2018) found a strong positive association between investor sentiment and subsequent market returns during the bubble period in China. However, investor sentiment has a negligible impact on subsequent monthly market returns once the bubble period is excluded.

3.0 Data and methodology

3.1 Data

This paper aims to find out aggregate effects and cross-sectional effects of investor sentiment. For aggregate effects, this paper employs macro-economic variables such as GDP, IPI, the inflation rate and interest rate in New Zealand and Australia to show the descriptive statistics and find out the relationship with sentiment proxies. The returns of market index are also used, such as NZX 50 and ASX 100. In terms of the sentiment proxies; this paper firstly uses Consumer Confidence Indices (CCI) which is most widely used in the papers to discuss the investor sentiment. In detail, CCIs was a survey data, and it was surveyed by whether consumers have positive confidence on future economic environment. Based on the definition of the CCI, the market with higher CCI means consumers prefer to use their income instead of save their income in the bank, such as investing some stocks, bonds or real estate.

As a result, investor sentiment in this market is higher as well. Secondly, log of quarterly trading volume indices also used as a proxy for investor sentiment in this paper. However, different countries have significant different trading volume. Such as New Zealand and Australia, the New Zealand’s stock market significant smaller than Australia’s stock market, so New Zealand’s stock trading volumes are significant less than Australia. Therefore, this paper uses the log of trade volume in order to decrease the standard deviation and let the data easy to be compared. Therefore, the Consumer Confidence Indices and log of trade volume indices are used as proxy for sentiment in this paper.

All above data are quarterly data which obtained from Datastream and Yahoo finance. Since New Zealand trade volume only available in Yahoo finance from 2004 till now and identical frequency of data should be used to compare results from different tests, the sample period is fourteen years from 2004 to 2017.

In terms of the cross-sectional effects of investor sentiment, this paper uses trading data, including price, dividend per share and book to market ratio of companies in New Zealand market and Australian market. Companies are selected based on the following criteria:

1. Selected companies should have the trading data this paper needed. If the missing data of stocks are existed, these companies should be eliminated;
2. Selected companies should be listed for more than 10 years. If the history of this company is shorter than 10 years, this company should be excluded; and
3. Selected companies should have uninterrupted trading records during the study period from 2004 to 2017, eliminating stocks which are suspended for more than 10 days.

As a result, in New Zealand stock market, only 66 companies are available for the test. In order to conduct tests for both New Zealand and Australia and further to compare the results, this paper also choose 66 companies of Australia to construct the growth portfolio, value portfolio, high dividend portfolio and low dividend portfolio.

3.2 Methodology

For the methodology, this paper discusses the whether the investor sentiments affect the stock return through aggregate analysis and cross-section analysis. For the aggregate analysis, this paper analyzes the investors' sentiment by three tests which are Jarque-Bera test, unit root test and correlation test. For the cross-sectional analysis, this paper includes Granger causality test and predictive regression.

3.2.1 Aggregate level

From the aggregate analysis, this paper summarizes the descriptive statistics which are the mean, the standard deviation, minimum, maximum and Jarque-Bera. The Jarque-Bera model test the whether the sentiment indices have skewness and kurtosis matching a normal distribution as follow:

$$\mathrm{JB} = \frac{n}{6}\left(s^2 + \frac{1}{4}(k-3)^2\right)$$

The raw consumer confidence index and log of trading volume may raise some statistical problem, so in this paper, the unit-root test is used to test whether a time series variables is non-stationary using an autoregressive model. However, there are three varieties of tests belongs to the unit root test which are Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test and the KPSS test. This paper follows the Grigaliunie & Cibulskiene (2010)'s paper which is selected the KPSS test in their paper. Thus, KPSS test is used to test the sample data is stationary around a deterministic trend.

For the correlation test, this paper describes macro variables which are inflation rate, interest rate, industrial production and GDP. Based on asset pricing theory, these macro-economic variables could well predict the stock return. In addition, some empirical research also prove that these macro variables are motivated by asset pricing theory, such as Schmeling (2009) proves industrial production could affect the stock return. Thus, if the macro variables have strong correlation with sentiment indices, the result can prove the sentiment indices could be used to predict stock returns.

3.2.1 Cross-sectional level

For cross-sectional analysis, this paper includes two tests, and the first test is granger causality test. This test is used to find out whether investor sentiment can predict stock returns or whether stock returns can forecast investors' sentiment. This test is proposed by Granger (1969), which is widely used in financial field. In order to conduct granger causality test, it should firstly decide the lag length of variables. Different lag lengths may lead to different results of this test. In result part, this paper will introduce more about how to select lag length. However, in this paper, the granger causality test only includes one lag length, which makes the results to be biased. Thus, this paper wants to do further study on stock returns and investor sentiment.

Then, this paper uses lagged stock returns of different categories and sentiment proxies to run predictive regression. The equation is shown as following:

$$R_{it} - R_{rfr} = \alpha_0 + \alpha_1 * T_{t-k} + \varepsilon_{it}$$

This test is utilized to check the impact of investor sentiment on forecast stock returns. In this test, this paper not only focuses on a single lag length, it pays attention to more lag lengths. Because of the longer lagged period, this paper not only can investigate the short-term impact of investor sentiment, but also can study the long-term influence of sentiment.

Lastly, this paper also uses long-short portfolio to study the conditional characteristics effects of investors' sentiment. Long-short portfolios are constructed by the method that long on stocks with high value and short on stocks with low value. The selecting criteria are dividend per share and price-to-book ratio. This paper uses these two ratios to classify growth stocks, value stocks, high dividend stocks and low dividend stocks. The equation of this test is presented below:

$$R_{high\ value} - R_{low\ value} = c + d * sentiment_{t-1} + \varepsilon_{it}$$

This test also includes macro variables such as GDP, IPI and T-Bill rate. This paper aims to compare the results without controlling for macro variables and controlling macro variables.

4.0 Results and discussions

4.1 Aggregate level

Table 1 indicates the mean, the standard deviation, the maximum and minimum value and Jarque-Bera statistic for two Australasian countries. Jarque-Bera is used to test whether skewness and kurtosis of the sample data match a normal distribution (Grigaliunie & Cibulskiene, 2010). In addition, the null hypothesis of the Jarque-Bera test is that Skewness and Kurtosis of the sample data are being zero, and the sample data not similar to a normal distribution. In addition, if p-value less than 0.1, it means the result rejects the null hypothesis. Overall, the table 1 shows that the New Zealand logs of trade volume and Australia CCI to be normally distributed at 0% and 8% significance level respectively. However, New Zealand CCI and Australia trade volume cannot reject the null hypothesis, due to their p-value larger than the 0.1.

Table 1: Descriptive Statistics on Investor Sentiment in Australasian countries, from 2004 to 2017

Panel A: New Zealand						
	mean	standard deviation	min	max	Jarque-Bera	p-value
consumer confidence index (CCI)	110.1083	9.4922	81.7000	130.2000	2.7181	0.2569
trade volume (VOLUME)	17.3379	0.2191	16.5870	18.0184	26.5855	0.0000
Panel B: Australia						
	mean	standard deviation	min	max	Jarque-Bera	p-value
consumer confidence index (CCI)	115.8611	9.1782	94.4300	128.9000	4.9159	0.0856
trade volume (VOLUME)	20.6876	0.2903	20.1995	21.2658	1.2467	0.5362

Mean of the New Zealand CCI is closing to the maximum of the CCI not closing the minimum CCI in New Zealand. This means, a large percentage of the New Zealand CCI's data are larger than 110. Thus, the non-normal distribution will lead to p-value of Jarque-Bera not at significant level.

In addition, the significantly level of the data groups which are New Zealand's trade volume and Australia's CCI are similar with a normal distribution. On the other hand, standard deviation and mean of New Zealand's CCI are similar to that of Australia's CCI. Similarity, standard deviation of the volume in New Zealand is also similar to that of Australia's.

Table 2: Unit-root and "stationary" hypothesis test

			KPSS with intercept				conclusion for ADF	conclusion for KPSS
sentiment proxy	country	p(ADF) with intercept	test	1% critical value	5% critical value	10% critical value	H0: I(1); H1: I(0)	H0: I(1); H1: I(0)
CCI	NZ	0.0241	0.2327	0.739	0.463	0.347	I(0)	I(0)
	AU	0.0288	0.086	0.739	0.463	0.347	I(0)	I(0)
trade volume	NZ	0.0012	0.7369	0.739	0.463	0.347	I(0)	I(1)
	AU	0.4198	0.4186	0.739	0.463	0.347	I(I)	I(0)
D(CCI) first difference in CCI	NZ	0	0.1814	0.739	0.463	0.347	I(0)	I(0)
	AU	0.0004	0.0677	0.739	0.463	0.347	I(0)	I(0)
D(trade volume) first difference in trade volume	NZ	0	0.4564	0.739	0.463	0.347	I(0)	I(0)
	AU	0	0.3003	0.739	0.463	0.347	I(0)	I(0)

**the conclusions are derived at 5% significant level*

The table 2 summarizes the results of unit root test. According to the definition of the unit boot test, there is three kinds of test could belong to the unit root tests which are Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test and KPSS test. In addition, this paper selects the KPSS test and ADF test to prove the sentiment indices are stationary. For the ADF test, this paper is derived at 5% significant level. Thus, if the ADF's p-value to intercepts are larger than 0.05, the null hypothesis would be rejected. The result shows that only Australian log of trade volume's p-value is 0.4198, and it means only this factor is non-stationary in the ADF test.

For the KPSS test, this paper just consider 5% critical value which means if the test value larger than 0.463, the null hypothesis which is the sample data is stationary would be rejected. After checking the result, this paper finds New Zealand's log of trade volume is not stationary. However, this paper also uses the first difference in sentiment proxies to test stationary of the sentiment indices. The result shows all the indices are stationary. Based on the table 2, the result of the ADF and the KPSS test are similar except the log of trading volume. However, this paper desires to support the KPSS application. In particular, this paper finds that sentiment indices are stationary for both countries expect for New Zealand's log of trade volume. However, the first difference in sentiment indices is all stationary, so this paper could use the lagged sentiment indices to do the regression in future analysis.

The table 3 shows the correlations between sentiment indices and macro-economic variables. In addition, macro-economic variables could be regarded as a positive prediction of stock return. Thus, the strong correlation between sentiment proxies and macro-economic variables also supports the results that sentiment indices could affect stock returns. From table 3, first two columns and two rows show the correlation between sentiment indices and macro-economic variables, and last four columns present the correlation within macro-economic variables, so this paper mainly discusses first two columns.

Firstly, the correlation between log trade volume and CCI are negative and not strong for all panels. The reason is that a large percentage of investors belong to irrational investors. Thus, they do not have enough knowledge to make rational decisions. Based on table 3, GDP have a strong and positive correlation with the log of trade volume in two countries, because countries with higher GDP means the countries develop well in this period and people do not worried poverty, so they prefer to use more money to invest. Therefore, trade volume would increase because of the higher GDP.

Comparing the log of trade volume and inflation rate and interest rate, these two macro-economic variables only have weakly and negatively coefficient to the log of trade volume in these two countries. This would be because if the bank with higher interest rate, investors prefer to deposit their money in the bank instead of buying stocks. Therefore, the log of trade volume would be decreased since the interest rate is high. On the other hand, the higher inflation rate would lead to nationals should use more money to buy food, so they will leave less money to do investment. Thus, the relationship would be negative. For the industrial production, the result shows the log of trade volume have negatively and weakly correlation with industrial production in the New Zealand market, but have a strong and positive relationship with industrial production in Australia market. However, all the macro-economic variables only have a weakly relationship with CCI.

Table 3: Sentiment Proxies Correlation with Macro Variables

Panel A: New Zealand

	NZ ln trade volume	*CCI*	*inflation rate*	*interest rate*	*industrial production*	*GDP*
NZ ln trade volume	1.0000					
CCI	-0.3198	1.0000				
inflation rate	-0.2716	-0.2004	1.0000			
interest rate	-0.5069	0.0332	0.4226	1.0000		
industrial production	-0.3390	0.2329	0.0936	0.5282	1.0000	
GDP	0.7146	-0.4328	-0.3376	-0.4909	-0.1330	1.0000

Panel B:Australia

	AU-ln trade volume	*CCI*	*inflation rate*	*interest rate*	*industrial production*	*GDP*
AU-ln trade volume	1.0000					
CCI	-0.1214	1.0000				
inflation rate	-0.1251	-0.3796	1.0000			
interest rate	-0.4065	0.1169	0.5441	1.0000		
industrial production	0.5917	-0.0751	-0.1874	-0.5832	1.0000	
GDP	0.6476	-0.1434	-0.2314	-0.6025	0.9287	1.0000

4.2 Cross-section level

Lee, Shleifer and Thaler (1991) firstly propose the investor sentiment theory. They believe that among all the holders of closed-end fund, there are many noise traders. Because of numerous risk factors which are existed in real market, these noise traders will have biases of investments and the biased toward investments will further to influence the future return of investments. Specifically, when noise traders are optimistic, investments will be overvalued and their trading prices will be higher than their intrinsic values. Thus, investors can earn higher rate of returns. However, when noise traders are pessimistic, investments will be undervalued and the trading prices will decrease. Thus, there are discounts on the investments. Stock returns will be lower.

In order to find out the relationship between stock returns and investors' sentiment, in this part, further studies such as Granger causality test and predictive regressions are employed to find out both cross-sectional effects and aggregate effects of investors' sentiment. Cross-sectional effects are investigated by stocks that are sorted by book-to-market ratio and dividend per share. Specifically, if the book-to-market ratio of one investment is higher than the median, it can be regarded as growth stock. Otherwise, it should be regarded as value stock. Then, all the growth stocks and value stocks are used to construct the growth portfolio and value portfolio.

This method is also applied to dividend per share. If the dividend per share of a stock is higher than the median of whole sample, it can be regarded as high dividend stock. Otherwise, it can be considered to be low dividend stock. Then, high dividend stocks and low dividend portfolios are used to construct high dividend portfolio and low dividend portfolio. The aggregate effects are studied by constructing the Australasia index. This index is the average index of ASX100 and NZX50. The growth portfolio, value portfolio, high dividend portfolio and low dividend portfolio of Australasia are also the average of these portfolios in both Australia and in New Zealand.

Granger (1969) proposes Granger causality test which is used to find out whether sentiment variables have impact on returns or whether returns have impact on sentiment variables. The lagged sentiment variables and lagged returns are used to construct this test. The lag length is decided by the SIC (Schwartz information criterion). If one lag length can minimize SIC, this lag length can be used to do the Granger-causality test. In this paper, the lag length which can be used to minimize SIC is 2. Since the data we used are quarterly data, the lag length is 2 quarters. Thus, lagged portfolio return and lagged sentiment proxies are employed to conduct this test. The non-hypothesis of this test is that X cannot predict Y. This means that sentiment variables have no impact on future returns or returns have on impact on forecast sentiment proxies. If the p-value is smaller than its significance level, it means that the results will reject the non-hypothesis and one variable will influence another variable. The results are shown in the table 4.

Table 4:Granger Causality test

Ho Pairwise	**Index**	**Value portfolio**	**Growth portfolio**	**High dividend**	**Low dividend**
Panel A: New Zealand					
CCI-R	2.02577	1.87173	4.08249**	2.31328	1.7635
R-CCI	2.58861*	0.99998	2.75776*	1.38886	5.4446***
VOLUME-R	0.69458	0.25606	1.38178	1.03545	0.42979
R-VOLUME	0.2316	0.44136	0.55553	0.94379	0.35138
Panel B: Australia					
CCI-R	0.00195	0.17482	0.06381	0.02589	0.09562
R-CCI	3.2993	3.32859**	1.44424	2.83046*	0.42265
VOLUME-R	0.37438	0.55315	0.63055	0.4872	0.96023
R-VOLUME	3.97461**	4.54513**	3.37532**	4.88032**	1.27337

****significance at 0.01** significance at 0.05 *significance at 0.1*

In table 4, for the lag length equals 2, only growth portfolio of New Zealand is consistent with the result of two way causality (sentiment proxies can forecast portfolio returns and portfolio returns can in return to cause sentiment proxies) which is suggested by Schmeling (2009). Most of the results in both New Zealand and Australia are one-way causality (only returns can cause sentiment variables). It means that the performance of portfolio will effectively influences the sentiment of investors. Hence, good or bad news on stock returns in this period will effectively influence the sentiment of investors in next period.

However, the situations are different in New Zealand and in Australia. For New Zealand, only returns of market index, Growth and Low dividend portfolios have deep impact on forecast consumer confidence index (CCI). Portfolio returns cannot predict the trade volume. In Australia, the returns of Value and High dividend portfolios can predict sentiment of investors, but returns of market index, growth portfolio and low dividend portfolio cannot forecast investors' sentiment. Additionally, in Australia, forecast stock trade volume will also be influenced by returns.

The one-way causality between returns and sentiment proxies suggests that we can use historical data of stock returns to infer investors' sentiment next period. The existence of one-way causality may due to the selection of lag length. Although this paper uses strict criteria to decide the lag length, the limited lag length may show us biased results. However, it is more important to use investors' sentiment to predict returns. That is to say, it makes us to assume whether we can use sentiment variables to predict time series returns. Thus, in the predictive regression, it will include more lag lengths to find out more exact relationship between stock returns and investors' sentiment.

In financial field, when academic investigate the relationship between stock returns and investor sentiment, they may assume that investors are over-optimistic or over-pessimistic. This belief may drive the stock price far from its fundamental value in the short term. However, in the long term, the over-optimism or over-pessimism will be corrected and the stock price will be back to its intrinsic value. That is to say, short-term high sentiment of investors will drive the stock price to move up and further to have a positive impact on stock returns. However, in the long term, the enthusiasm of stock return will be corrected. So the sentiment will have a negative influence on stock returns.

Therefore, this paper proposes an assumption that in the short term, the stock return will be positively influenced by sentiment and in the long term, the stock return will be negatively influenced by sentiment. In next section, this paper uses lagged portfolio returns and investors' sentiment to run regression and further to identify the relationship between returns and sentiment proxies.

In order to run predictive regression, this paper employs an equation as following:

$$R_{it} = \alpha_0 + \alpha_1 * T_{t-k} + \varepsilon_{it}$$

Where R_{it} is the stock return of portfolio i in period t; α_0 is the intercept of this equation; ε_{it} is the disturbance term of this equation; T is sentiment proxies; and k is the lagged period.

In this paper, the lagged periods are 1 quarter, 3quarters, 6quarters and 9quarters. This paper aims to employ two sentiment proxies, including trade volume and CCI. In order to get more exact results, it is better to exclude the impact of risk free return. Thus, the equation can be changed into:

$$R_{i,t+k} - R_{rfr,t+k} = \alpha_0 + \alpha_1 T_t + \alpha_2 M_t + \varepsilon_{i,t+k}$$

Where $R_{i,t+k}$ is the stock return of portfolio i in period t+k; $R_{rfr,t+k}$ is the risk free return in the period t+k, $\alpha_0$is the intercept of the equation; $\varepsilon_{i,t+k}$ is disturbance term of this equation in period; α_1 and α_2 are the correlation coefficient of CCI(T_t) and Volume(M_t).

The null hypothesis of this regression is that sentiment proxies have no relationship with forecast portfolio returns. If the p-value is less than significance level, the result

rejects the null hypothesis and claims that sentiment proxies can be used to predict portfolio returns. Otherwise, the result will accept the null hypothesis that forecast portfolio returns have no relationship with sentiment proxies. The results are shown in table 5, 6, 7. Table 5 presents the forecast results for 1,3,6,9 quarters' Australasia index, value, growth, high yield and low yield portfolios. The returns can be obtained by averaging the relative information of Australian market and New Zealand market.
From table 5, it can be found that, in 1 quarter and 3 quarters, the coefficient correlations of CCI in all categories are positive but in 6 quarters and 9 quarters, the coefficient

Table 5: Predictive regression

Australasia Forecast Horizon								
	1quaters		3quarters		6quarters		9quarters	
INDEX								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.006831	0.09473	0.003596	-0.06744	-0.00299	-0.1664	-0.00189	-0.11192
P-VALUE	0***	0.095*	0.0487**	0.3968	0.100*	0.0858*	0.3523	0.3961
GROWTH PORTFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.005655	0.079115	0.002419	-0.07141	-0.00281	-0.1476	-0.00116	-0.06949
P-VALUE	0***	0.1215	0.135	0.3198	0.0805*	0.0827*	0.5231	0.5571
VALUE PORFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.00628	-0.01562	0.002613	-0.1622	-0.00194	-0.29021	-0.00034	-0.28271
P-VALUE	0.0008***	0.8288	0.204	0.0822*	0.3183	0.0079***	0.8767	0.0542*
HIGH DIVIDEND PORTFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.006632	0.031724	0.002419	-0.14994	-0.00247	-0.25455	0.00019	-0.20478
P-VALUE	0.0001***	0.6125	0.2051	0.0834*	0.179	0.0124**	0.9293	0.1497
LOW DIVIDEND PORTFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.00617	0.056995	0.002019	-0.10238	-0.00348	-0.16189	-0.00157	-0.08703
P-VALUE	0***	0.296	0.2461	0.1909	0.0436**	0.0741*	-0.08703	0.4987

****significance at 0.01. ** significance at 0.05. *significance at 0.1*

correlations of CCI in all categories are negative. In terms of trade volume, within 1quarter, the change of trade volume in most categories will positively influence the portfolio returns. But in 3, 6, 9 quarters, the trade volume of different portfolios will negatively influence the stock returns. It confirms the assumption that the sentiment proxies have positive impact on short-term stock returns and negative influence on long-term stock returns.

In terms of the P-value, in short period, most of them are statistically significant. It means that, results reject the null hypothesis that sentiment proxies have no relationship with forecast stock returns. But in 9 quarters, all P-values in different categories are not statistically significant. It accepts the null hypothesis and suggests the sentiment proxies cannot predict stock returns. From the test, it can be found that the predictable power of sentiment variables will decrease with the increase of the forecast period.

Table6:Predictive regression

Australia Forecast Horizon								
	1quaters		3quarters		6quarters		9quarters	
INDEX								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.006165	0.007085	0.003521	-0.09452	-0.0015	-0.13907	-0.00222	-0.113
P-VALUE	0.0003***	0.8817	0.0648*	0.1407	0.4595	0.1034	0.3239	0.359
GROWTH PORTFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.00608	-0.00791	0.00183	-0.12041	-0.00231	-0.12321	-0.00059	-0.07581
P-VALUE	0.0006***	0.8765	0.3573	0.0817*	0.271	0.157	0.8039	0.5592
VALUE PORFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.006075	-0.01651	0.00534	-0.12041	-0.00011	-0.19034	-0.00265	-0.18705
P-VALUE	0.004***	0.7915	0.0168**	0.1025	0.9645	0.0638*	0.3074	0.193
HIGH DIVIDEND PORFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.006863	0.001636	0.003709	-0.12557	-0.00137	-0.16445	-0.00157	-0.12416
P-VALUE	0.0006***	0.9772	0.0948*	0.0967*	0.5639	0.0997*	0.5525	0.3942
LOW DIVIDEND PORFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.003569	-0.02359	0.000797	-0.08061	-0.00239	-0.05815	-0.00048	-0.05999
P-VALUE	0.0019***	0.485	0.5325	0.0714	0.0736*	0.2775	0.7472	0.4604

Table 6 and Table 7 present the results of predictive regression for New Zealand portfolios and Australian portfolios. They have the same trend that in the short-term period, the sentiment proxies will have positive impact on portfolio returns and in the long-term period, the sentiment proxies will have negative influence on predicted stock returns. In terms of the p-value, all portfolios in both two countries tend to have statistically significant results in short-term period, but results are not statistically significant in long term. It means that in the short term, the ability of sentiment proxies to forecast portfolio returns is stronger than that in long term. In both Australia and New Zealand, the P-value of CCI is much smaller than that of trade volume. It means that the predictable power of CCI in both countries is higher than that of trade volume.

There are still many differences of results existed in Australian stock market and in New Zealand stock market. For example, in terms of different types of portfolios in two countries, there are more significant P-values of sentiment proxies in growth and low dividend portfolios than in value and high dividend portfolios in New Zealand. It means that the predictable power of sentiment is much lower in the value portfolios and high dividend portfolios than in the growth and low dividend portfolios in New Zealand. However, the situation is adverse in Australia. The predictable power of sentiment proxies is higher in in the value portfolios and high dividend portfolios than in the growth and low dividend portfolios.

Table 7: Predictive regression

New Zealand Forecast Horizon								
	1quaters		3quarters		6quarters		9quarters	
INDEX								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.004751	0.136827	0.002517	0.060093	-0.00338	0.004435	-0.00127	0.084289
P-VALUE	0.0006***	0.0353**	0.1255	0.4514	0.043**	0.9557	0.487	0.3522
GROWTH PORTFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.003603	0.116783	0.001915	0.070853	-0.00278	0.004975	-0.00151	0.078288
P-VALUE	0.0012***	0.0271**	0.1524	0.2793	0.0448**	0.9403	0.3208	0.2958
VALUE PORFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.003397	0.090989	0.000805	0.134419	-0.00237	0.025698	0.002648	-0.07989
P-VALUE	0.0908*	0.3561	0.7178	0.2262	0.2963	0.818	0.2711	0.4974
HIGH DIVIDEND PORFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.004138	0.114305	0.001366	0.10321	-0.00227	0.036105	0.001861	-0.01678
P-VALUE	0.0129**	0.1544	0.4756	0.2773	0.2491	0.7101	0.3846	0.8727
LOW DIVIDEND PORFOLIO								
	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME	CCI	VOLUME
SENTIMENT	0.004533	0.112612	0.000922	0.049028	-0.0041	0.028691	-0.00158	0.039286
P-VALUE	0.0009***	0.0765	0.5785	0.5494	0.0142**	0.7152	0.4085	0.6745

Overall, this test suggests two results. Firstly, in the short term, the sentiment pose a positive impact on forecast portfolio returns, while in the long term, sentiment will negatively influence the predicted portfolio returns. Secondly, the predictable power of sentiment is stronger in short term than in the long term. For the results of this paper, they are partly consistent with empirical researches. Specifically, for the short term, this paper's results oppose the finding of some empirical researches. Brown and Cliff (2004, 2005) investigate stock returns and sentiment proxies, claiming that sentiment is correlative with stock returns, but sentiment cannot be used to predict short-term stock returns.

However, in the long term, sentiment is negatively related with the forecast stock returns, which is consistent with our results. Schmeling (2009) use panel data of 18 industrial countries to study whether individual investors' sentiment can influence sentiment. He finds that sentiment of investors can negatively influence the forecast stock return. Baker, Wurgler and Yuan (2009) discuss the global impact of investors' sentiment. Their results support the finding of Schmeling (2009). For other results of this paper are consistent with empirical researches.

The differences between our results and empirical researches may due to the selection of sentiment proxies. Based on the investigation of Schmeling (2007), institutional investors can be treated as smart and rational investors, but individual investors can be regarded as irrational investors or noise traders. Thus, the sentiment impact of institutional investor and individual investor is different. Institutional investors can correctly forecast returns of stocks, while individual investors backward predict returns of stocks. That is to say, the sentiment of individual investors will negatively forecast stock returns and the sentiment of institutional investors will positively predict stock returns. Thus, the selection of sentiment proxies will influence the results of tests.

In this part, this paper uses sentiment proxies, macro-economic variables as well as forecast returns of long-short portfolio to run regression and further to study the conditional characteristics effects of portfolios. Long-short portfolios are constructed by the method that long on stocks with high value and short on stocks with low value. This test is used to find out the relationship between sentiment proxies and the excess returns of different portfolios. More exactly, in a long-short portfolio of P/E ratio, if investor sentiment can positively predict the forecast returns, when investors are optimistic, growth portfolios have higher predicted returns than value portfolios.

While investor sentiment can negatively influence the forecast long-short portfolio returns when investors are optimistic, value portfolios will have higher returns than growth portfolios. In order to find out the predictable power of sentiment proxies under different economic conditions, this paper also takes macro variables, such as GDP IPI and T-Bill rate into consideration. The equations of predictive regression for long-short portfolios are shown below.

Without controlling for macro variable:

$$R_{growth} - R_{value} = c + d * sentiment_{t-1} + \varepsilon_{it}$$

$$R_{high\ \ dividend} - R_{low\ \ dividend} = c + d * sentiment_{t-1} + \varepsilon_{it}$$

Where R is the return for growth, value, high dividend and low dividend portfolios; c is the intercept of this equation; d is the correlation coefficient of sentiment proxies; ε_{it} is the disturbance.

When controlling for macro variables:

$$R_{growth} - R_{value} = c + d * sentiment^{*}_{t-1} + a * GDP_{t-1} + b * IPI_{t-1} + q * Tbill_{t-1} + \varepsilon_{it}$$

$$R_{highdiv} - R_{low\ \ div} = c + d * sentiment^{*}_{t-1} + a * GDP_{t-1} + b * IPI_{t-1} + q * Tbill_{t-1} + \varepsilon_{it}$$

Where R is the return for growth, value, high dividend and low dividend portfolios; c is the intercept of this equation; d is the correlation coefficient of sentiment *; ε_{it} is the disturbance; a, b, q are the correlation coefficient of GDP, IPI and T-Bill rate.

Table 8: Predictive Regression of Long-Short portfolio

Sentiment proxy	CCI		CCI*		Volume		Volume*	
	d	p(d)	d	p(d)	d	p(d)	d	p(d)
New Zealand								
Growth-Value	0.001513	0.4377	0.001423	0.5791	0.032715	0.7242	-0.00487	0.9719
High-low dividend	-0.00029	0.8355	-0.000675	0.7091	0.002768	0.9663	0.049549	0.6131
Australia								
Growth-Value	-0.00011	0.9405	-0.00009	0.9499	0.009297	0.8476	0.059843	0.2976
High-low dividend	0.003275	0.0068	0.003356	0.0068**	0.023717	0.5163	0.041752	0.3713

In table 8, it can be found that before controlling for macro variables, all the P-value of both countries are not statistically significant. It means that, in both New Zealand and Australia, no matter dividend long-short portfolio or book-to-market ratio long-short portfolio, the sentiment proxies cannot predict returns of long-short portfolio. After controlling for macro variables, the P value of High-Low dividend portfolio in Australia is statistically significant and the correlation coefficient of this portfolio is positive. It means that when investors' sentiment is high, the return of high dividend payout portfolios will be higher than that of low dividend payout portfolios. If investors are pessimistic, the return of high dividend payout portfolios will be lower than that of low dividend payout portfolios.

5.0 Conclusion

Sentiment of investors is one of the main components of behavior finance. It provides explanations to anomalies which are existed in the real stock market. Thus, it is meaningful to study the impact of investor sentiment. Thus, this paper mainly focuses on investigating the relationship between investor sentiment and stock returns in New Zealand stock market and Australian stock market, which is seldom studied by academics. This paper focuses on this gap and employs sentiment proxies such as Consumer Confidence Index and trade volume to conduct various tests.

One of the shining points in this paper is that it not only focuses on the aggregate effects but also pays attention to the cross-sectional effects. In order to study the aggregate effects, this paper uses Augmented Dickey-Fuller (ADF) test and KPSS test and it also explores the correlation between sentiment proxies and macro variables. From these tests, several findings can be found. Firstly, all the sentiment indices are stationary. Secondly, industrial production, GDP have significant and positive relationship with the sentiment indices, but inflation rate and interest rate only have negatively and weakly relation with sentiment indices.

In terms of the cross-sectional analysis, this paper conducts granger causality test and predictive regression. In these tests, it can be found that investors' sentiment and stock returns can affect each other. However, the results of this paper are partly consistent with empirical researches. This paper also provides explanations for this situation. For example, this paper concludes one-way causality may due to the limited lag lengths. And the positive relationship between sentiment proxies and forecast returns in the short term which opposes the finding of Schmeling (2009) and Baker, Wugler and Yuan

(2009) may be due to the selection of sentiment proxies. Sentiment of individual investors and sentiment of institutional investors may have adverse impact of predictive stock returns.

From this paper, it can be concluded that in New Zealand and Australian stock markets, the irrational decisions are still existed. It means that investors' investment decisions are often drove by their sentiment. As a result of the existence of irrational investors, stocks prices are far away from their intrinsic values. Thus, it is important to understand the impact of investors' sentiment, which help them make sound investment decisions and further to gain substantial excess returns.

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