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Investor Sentiment, Portfolio Returns, and Macroeconomic Variables

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Abstract: Investor sentiment is an important aspect of behavioural finance, which provides explanation of anomalies to the asset's intrinsic values. Sentiments can easily affect individual investors. Historically, Australia is regarded as rich in resources but poor in capital, and this motivates the paper to further study and compare the effects of investor sentiment on performance returns. Aggregate and cross-sectional effects, as well as predictive regression analysis to forecast the relationships, while controlling for the macroeconomic variables, are used by employing Consumer Confidence Index (CCI) and trade volume as sentiment proxies. Contrary to some studies with aggregate stock markets, it is discovered that in the short term, investor sentiment poses a positive impact with strong predictive power on the forecast of portfolio returns but not so much in the long run, which supports the classical theories of rational investors. In both Australian and New Zealand markets, the sentiment proxies also cannot predict the returns portfolios with dividends in the long/short portfolio and book-to-market ratio long/short portfolio.

Keywords: investor sentiment; return; investment; predictive power; portfolio returns; market efficiency; EMH; anomalies; behavioural finance; performance measures; unit root; macroeconomic variables; consumer confidence Index (CCI); trade volume; dividend per share (DPS); price earning ratio (PE)

1. Introduction

In the financial field, factors which could influence companies' asset prices or share returns inspire many research works to be conducted, but results remain inconclusive. For example, macroeconomic variables and financial ratios such as the DPS (dividend per share) ratio, the book-to-market ratio, and the PE (price earning) ratio could be used to forecast share return. However, these components can only predict returns through traditional economic settings. It is even argued lately that behavioural aspects, such as investors sentiment, are imperative towards the success of an organisation. Studies on sentiment constructs are still labelled by Aggarwal (2019) as "ill-defined" and whether it can be a part of a prediction model for stock market returns is still uncertain, which calls for more research to be undertaken.

This paper endeavours to add to this growing body of knowledge by using investor sentiment to explain the portfolio returns or performance of equity and apply a simple stylish investment behavioural approach in a macroeconomic setting within these Australasian countries. It is worthwhile to examine the relationships in this region, which can provide empirical evidence there, especially in the sentiment–return relationship. Economic historians concede to the fact that Australia is regarded as a resource-rich country but capital-poor nation; there are demands for more efforts to improve this image through further internal and external investment strategies.

Furthermore, there are already a number of studies that have examined many countries, mostly developed markets, as panel datasets (e.g., (Chung et al. 2012; Fernandes et al. 2013; Uygur and Taş 2014; Zaremba et al. 2020; Zouaoui et al. 2011)). There are two main reasons why this study focuses on share markets in Australia and New Zealand (NZ). The first is that these two countries have a similar environment and culture. Thus, this could avoid many factors which will affect the test results. The second reason is that the economic connection between Australia and NZ makes it possible to combine market indices together and to further construct the Australasia index, which can be used to conduct tests at an aggregate level. Analysing individual market index can help us to investigate the difference between these two countries. Thus, different angles can be investigated to obtain better results.

Some of the challenges that continue to persist in the sentiment literature are how difficult it is to measure investor sentiments (Baker and Wurgler 2006), despite the fact that the research argues that it is unrelated to systematic risks. As defined by Brown and Cliff (2004), sentiment represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average (p. 2). Hence, the main motivation of this paper is to supplement the available findings of empirical research on investor sentiment impacts on share prices. Most studies suggest that sentiment indices have negative effects on share returns and vice versa (Brown and Cliff 2005; Grigaliūnienė and Cibulskienė 2010; Schmeling 2009; Smales 2017). In addition, Baker et al. (2012) and Kumar and Lee (2006) analyse the sentiment effect cross-sectionally, where firms are distributed based on firm size, firm age, value or growth firms, and dividend or non-dividend firms.

For the aggregate level, firstly, the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) unit root test was conducted in order to test data stationarity, then the correlation between sentiment indices and four macroeconomic variables was tested which included inflation rate, interest rate, industrial production, and GDP in each country's data; for the cross-sectional level, companies were sorted based on the book-to-market ratio and dividend per share. Herewith, a Granger causality test and predictive regression were conducted to find out the relationships between share returns and sentiment proxies.

Interestingly, many small and medium enterprises (SMEs) yearned to be listed in the share exchange market as to acquire funds in the pursuit for wealth maximation (Pastusiak et al. 2016). Therefore, the findings from this paper also may benefit SMEs to utilise this notion as another aspiration towards their goal.

The remainder of this paper is separated into four sections. The next section reviews existing literature. Section 3 describes the data and variables used in this study. Section 4 outlines the methodology, while Section 5 discusses the results and conclusions.

2. Literature Review

The quantifying of investor sentiment as part of a behavioural finance model study may be complicated and have been extensively discussed by researchers. Classical theories opt that it is not possible for irrational investor behaviours or sentiments to significantly impact asset prices and advocate a market which is supposedly efficient, as coined by Fama (1965). Nevertheless, researchers document various prepositions of irrational behaviours effects in their findings, such as in the paper by De Long et al. (1990). They discovered a model that categorises investors into two, which are rational traders and noise traders. The authors noted that noise traders in the Istanbul stock market favour investing based on affiliations to sectors instead of relying on the fundamental elements of investment (Uygur and Taş 2014).

The unpredictable investing trend of noise traders creates a trend in the market for which they influence the fund prices based on their systematic forecast of the future. For example, when these traders become pessimistic about the future, they will act upon their sentiment and sell their funds, which will then drive down the price of funds below the net asset value (De Long et al. 1990, p. 161). This supports the theory that investors tend to pick shares to trade based on "noise" as opposed to fundamental aspects or act rationally, which was originally theorised by Kyle (1985) and Black (1986).

This newly observed breakthrough sparked more interest in the 1990s, as more researchers recognised that the former econometric model lacks the behavioural and human traits of an investor. This means that there are many investors who act on information rather than value, which ultimately influences the asset prices, and in this case, the share price (Fernandes et al. 2013).

Investor sentiment can be defined as the way investors form their beliefs in investing (Barberis et al. 1998) or the act of positivism or pessimism of an investor about future share market activity (Baker and Wurgler 2006). Several financial market anomalies could be explained by noise trader risk at the aggregate level. Additionally, irrational investors could also be measured cross-sectionally as specific shares at different levels could also be affected.

Several studies use survey data to quantify the sentiment that aims at short run implications (Clarke and Statman 1998; Fisher and Statman 2000; Otoo 1999; Solt and Statman 1988). Brown and Cliff (2005) apply a direct survey measure, where they focus on relating sentiment levels directly to share price deviations from their fundamental value. Monthly data consisting of 456 observations were collected from January 1963 until December 2000 by tracking the market newsletter charts for indication of Investors' Intelligence. Their findings suggest that irrational sentiment does affect asset price levels over the next one to three years and propose that the existing pricing models should incorporate the impact of this behavioural attribute.

Nevertheless, the use of a survey may not be able to capture long term effects, as the results for short run predictability are much disputed among researchers (Muhammad A. Cheema et al. (2020)). Hence, many studies prefer secondary data to quantify investor sentiment, which eliminate bias and reliability challenges that may occur in survey data. A paper by Fernandes et al. (2013) applies CCI and the Economic Sentiment Indicator (ESI)[1] data collected from 1997 to 2009 as proxies for investor sentiment and finds that it negatively affects the Portuguese share market returns. Other studies in the European market propose investor sentiment can also negatively affect share returns at cross-sectional effects and the aggregate level (Grigaliūnienė and Cibulskienė 2010).

Some research contributes to the concept that global investor sentiment affects the market returns. Baker et al. (2012) measure sentiment indices for six developed markets vis à vis Canada, France, Germany, Japan, the United Kingdom, and the United States by collecting pooled data from 1981 to 2006. They find evidence that investor sentiment plays a nontrivial role in international market volatility, where it can help to predict returns and how it also spreads across markets. Chung et al. (2012) report in their paper that the predictive power of sentiment is significant only in an economic expansion state. They utilize the multivariate Markov switching model to capture unobservable dynamic changes in the various economic regions against the returns of portfolios formed on 11 different anomalies such as book-to-market equity ratio, dividend yield, and growth opportunities.

The benefit of these types of long run analyses is that both short and long run results can be determined. Few long run studies predict that there is a contrarian predictor of share markets (Baker et al. 2012; Brown and Cliff 2005), while short run returns remain uncertain (Brown and Cliff 2004). Cheema et al. (2020) sum the notion that the impact of sentiment on market returns of the following period is harder when the investment equity is positively related to the sentiment variable.

By exploring 25 years of time series data, Lemmon and Portniaguina (2006) apply consumer confidence as their measurement of investor optimism. They have divided their data into small and large companies and suggest from their findings that investors appear to overvalue small shares as opposed

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1 The ESI is a composite indicator produced by the European Commission. The calculation is scaled to a long-term mean of 100 and a standard deviation of 10. Values above 100 assume above-average economic sentiment and vice versa (European Commission 2020).

to larger shares during periods when consumer confidence is high and vice versa. This may indicate that shares held mostly by individual investors tend to be exposed to mispricing due to sentiment.

In fact, it is also conjectured that the relationship between sentiment and returns can be measured by Granger causality to demonstrate the existence of co-movements. Both papers by Brown and Cliff (2004) and Schmeling (2009) find either two-way causality as such that CCI (proxy as sentiment) and returns depend on previous sentiment movements. Meanwhile, other studies report a one-way causality, suggesting returns Granger cause significant changes in sentiment (Grigaliūnienė and Cibulskienė 2010).

Studies in Asian markets also produce interesting but mixed results for sentiment as a momentum predictor for assets performance. On average, investors' trade appears to be significantly different during boom versus bust economic periods. By studying monthly market returns in China over a period of 2006 to 2008, Cheema et al. (2018) state that there is a positive association between the sentiment during the bubble period, for which it becomes insignificant when the bubble is removed from the equation. Hung (2016) notes from his study on 4 years of intraday data from the Taiwan Share Exchange Corporation, that people on average, place larger orders with less aggressive prices in the optimistic periods, but put smaller ones with more aggressive prices during the pessimistic period (p. 139).

Chen et al. (2013) employ a panel dataset of 11 selected Asian markets by comparing industries, which may be affected by the local market and global sentiments.

3. Data and Methodology

3.1. Data

This paper uses quarterly data from ASX100 and NZX50 index portfolio returns common for Australia and NZ for the period between 2004 and 2019 (a total of 56 observations). These portfolio data, which are the trading volume, price, dividend per share, and book-to-market ratio of companies in the Australian and NZ market were collected from Datastream. Meanwhile, to measure the evidence that sentiment is related to overall economic activity, the main macroeconomic variables available in Yahoo Finance were employed.

To proxy for investor sentiment, the Consumer Confidence Index (CCI) is used; it is widely cited in the other studies mentioned earlier. CCI indicates the future development of households' consumption and saving, based upon answers in surveys undertaken by the Economic Co-operation and Development (OECD 2020)[2]. The variable is supported by Qiu and Welch (2004), as CCI relies less on the sentiment theory but directly quantifying investors' irrational behaviour from direct survey questions.

3.2. Methodology

Aggregate and cross-section analyses are utilised to answer the research objectives. For the aggregate analysis, investor sentiments are analysed using Jarque–Bera, unit root, and correlation tests (Grigaliūnienė and Cibulskienė 2010; Schmeling 2009; Vuchelen 2004). For the cross-sectional analysis, this paper includes the Granger causality test and predictive regression (Schmeling 2009; Smales 2017).

3.3. Aggregate Level

The following Jarque–Bera model tests the normality of the sentiment raw data. Accordingly, under the null hypothesis of a normal distribution, the Jarque–Bera statistic is distributed as 2 χ with 2 degrees of freedom. The null hypothesis of the Jarque–Bera test is that skewness and kurtosis of the

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[2] An indicator above 100 signals a boost in the consumer's confidence towards the future economic situation; therefore, they will save less and more inclined to spend money on major purchases in the next 12 months.

sample data are zero, and the sample data do not deviate from normality. Following the method by Grigaliūnienė and Cibulskienė (2010), with the existence of the unit root problem within the raw data; then, the KPSS test can be conducted to eliminate the issues in the macroeconomic variables, which are inflation rate, interest rate, industrial production, and GDP. Subsequently, the autocorrelation problem was then verified with a correlation test. Schmeling (2009) suggests positive correlation in an irrational environment as prices are driven away from fundamental levels, whereas negative correlation shows rational behaviours supporting classical theory (p. 10).

Schmeling (2009) also suggests utilising Granger causality test as a method to check for time series dependency between cross-sectional sentiment and share returns data. Effects of sentiment can be indicated in two-way or even one-way causalities in the Granger tests (Brown and Cliff 2004; Grigaliūnienė and Cibulskienė 2010; Qiu and Welch 2004). Lagged share returns of different categories and sentiment proxies were run as a predictive regression.

4. Results and Discussion

4.1. Aggregate Level

Table 1 shows descriptive statistics for the two markets. The mean values for the sentiment proxies of both countries show almost identical results in the indexes, indicating similar economic performances in terms of CCI and trade volume.

Table 1. Descriptive statistics on investor sentiment in Australasian countries.

	Panel A: NZ			
	Mean	Standard Deviation	min	max
Consumer confidence index (CCI)	110.1083	9.4922	81.7000	130.2000
Trade volume (log VOLUME)	17.3379	0.2191	16.5870	18.0184
	Panel B: Australia			
	Mean	Standard Deviation	min	max
Consumer confidence index (CCI)	115.8611	9.1782	94.4300	128.9000
Trade volume (log VOLUME)	20.6876	0.2903	20.1995	21.2658

Table 2 summarises the empirical results of unit root analysis from the Augmented Dickey Fuller (ADF) and KPSS test results. As mentioned earlier, the KPSS test is preferred as it is consistent under the null "stationary" hypothesis as opposed to a wide range of non-stationary reasons (Grigaliūnienė and Cibulskienė 2010). The ADF and KPSS test results show that the raw sentiment data are all consistent except for trade volume in NZ. Nevertheless, all sentiment measures are used in the first difference to ascertain that the proxies are consistent of non-unit root and stationary time series.

Table 2. Unit root and "stationary" hypothesis test.

Sentiment Proxy	**Country**	**p(ADF) with Intercept**	**KPSS with Intercept**				**Conclusion for ADF**	**Conclusion for KPSS**
			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)

Meanwhile, the ADF result shows that only the Australian log of the trade volume's p-value is 0.4198, and this means only this factor is non-stationary in the ADF test. Therefore, the results of the ADF and the KPSS tests are similar, except for the log of trading volume. However, this paper desires to support the KPSS application due to the fact that ADF has weak explanatory power (Kling and Gao 2008, p. 379). As the first differences in sentiment indices are all stationary, it is acceptable that these sentiment measures are used as regressors for further analysis.

The first two columns (the main discussion for this paper) and rows of Panels A and B in Table 3 show the correlation between sentiment indices and macroeconomic variables, while the last four columns present the correlation within macroeconomic variables. It is found that the correlation between most of the macroeconomic variables is weak, suggesting that investors may not be influenced by economic behaviours. The only relatively high and positive correlation is between GDP and trade volume for both countries. This suggests that investors may assume that increasing GDP could be a positive outlook to invest in equity.

Table 3. Sentiment proxies correlation with macro variables.

Panel A: NZ						
	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-Sectional Level*

Cross-sectional effects are investigated by shares 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 a growth share. Otherwise, it should be regarded as value share. Then, all the growth shares and value shares 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 share is higher than the median of the whole sample, it can be regarded as a high dividend share. Otherwise, it can be considered as a low dividend share. Thereafter, high dividend shares and low dividend shares are used to construct a 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 NZ.

It was discussed earlier that noise traders who trade on sentiment will affect the price of the funds, which will further influence the future return of investments (De Long et al. 1990). 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 a higher rate of returns. While on the contrary, when noise traders are pessimistic, investments will be undervalued, and the trading prices will decrease, which will cause a discount on the investments.

In this situation, the research supports the notion that sentiment has a bidirectional relationship between the sentiment and market returns (Cagli et al. 2020). By employing the Granger (1969) causality test and predictive regressions, the paper can analyse whether sentiment variables have an impact on returns or vice versa (Shi et al. 2018).

In this paper, the lag length, which can be used to minimise SIC[3], is 2. Since the data used are quarterly data, the lag length is 2 quarters. Thus, lagged portfolio returns and lagged sentiment proxies are employed. The non-hypothesis of this test is that X may not provide significant useful information for future values of Y. This means that sentiment variables have no significant impact on future returns or returns have no significant impact on forecast sentiment proxies. If the *p*-value is smaller than its significance level, it means that the results will denote no causality direction. The results are shown in Table 4.

Table 4. Granger causality test.

Ho Pairwise	Index	Value Portfolio	Growth Portfolio	High Dividend	Low Dividend
Panel A: NZ					
CCI ≠> R	2.02577	1.87173	4.08249 **	2.31328	1.7635
R ≠> CCI	2.58861 *	0.99998	2.75776 *	1.38886	5.4446 ***
VOL ≠> R	0.69458	0.25606	1.38178	1.03545	0.42979
R ≠> VOL	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
VOL ≠> R	0.37438	0.55315	0.63055	0.4872	0.96023
R ≠> VOL	3.97461 **	4.54513 **	3.37532 **	4.88032 **	1.27337

Note: ≠> denotes no causality direction, for instance, CCI ≠> R denotes no causality running from Sentiment to return. *** significance at 0.01 ** significance at 0.05 * significance at 0.1.

Only the growth portfolio in NZ has two-way causality relationships with both sentiment variables (sentiment proxies can forecast portfolio returns and vice versa), which is also suggested by Schmeling (2009). Nonetheless, only a unidirectional relationship is detected between returns proxied by index, value portfolio, and low dividend with CCI, which means that optimistic or pessimistic news on share returns in the current period will effectively influence the sentiment of investors in the following period. No significant relationships are detected when sentiment is proxied by trade volume, which suggests inconsistency for investor sentiment to predict portfolio returns.

As for the Australian market, data for return variables, especially value portfolio and growth dividend equities, are consistent in indicating that there are significant probabilities of a one-way causal relationship between returns and sentiment, using both the CCI and volume. However, there are no two-way relationships that can be detected here. This may indicate that the traders are behaving rationally toward the performance as opposed to trading based on sentiment alone.

The one-way causality between returns and sentiment proxies may also suggest that we can use historical data of share returns to infer investors' sentiment in the next period. However, it can be argued that the existence of one-way causality may be 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. Therefore, more lag lengths are included to further investigate this notion in the predictive regression between share returns and investor sentiment.

In the financial field, when academics investigate the relationship between share returns and investor sentiment, they may assume that investors are over-optimistic or over-pessimistic. This belief may drive the share 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 share price will be back to its intrinsic value (Stambaugh et al. 2012). Short-term high sentiment of investors will drive the share price to move up and cause a positive impact on share returns. However, in the long term, the enthusiasm of share return will be corrected where eventually, the sentiment will have a negative influence on share returns.

[3] 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 minimise SIC, this lag length can be used for the Granger causality test.

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

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

$$R_{it} = \alpha_0 + \alpha_1 \times T_{t-k} + \varepsilon_{it} \quad (1)$$

where R_{it} is the share 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; k is the lagged period.

In this paper, the lagged periods are one quarter, three quarters, six quarters, and nine quarters. This paper aims to employ two sentiment proxies, including trade volume and CCI. In order to obtain more exact results, it is better to exclude the impact of risk-free return. Thus, the equation can be added with the variables, as shown below:

$$R_{i,t+k} - R_{rfr,t+k} = \alpha_0 + \alpha_1 T_t + \alpha_2 M_t + \varepsilon_{i,t+k} \quad (2)$$

where $R_{i,t+k}$ is the share return of portfolio i in period $t + k$; $R_{rfr,t+k}$ is the risk free return in the period $t + k$; α_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 Tables 5–7. Table 5 presents the forecast results for one, three, six, and nine quarters' Australasia index, value, growth, high yield, and low yield portfolios. The returns can be obtained by averaging the relative information of the Australian market and NZ market (Australasian).

Table 5. Predictive regression.

	Australasian Forecast Horizon							
	1 quarter		3 quarters		6 quarters		9 quarters	
	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
	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
	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 *
	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
	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

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

From Table 5, it can be found that in one quarter and three quarters, the coefficient correlations of CCI in all categories are positive but in six quarters and nine quarters, the coefficient correlations of CCI in all categories are mostly negative. In terms of trade volume, within one quarter, the change in trade volume in most categories positively influences the portfolio returns. Nevertheless in three, six, and nine quarters, the trade volume of different portfolios is found to be negatively influencing the share returns. It confirms the assumption that the sentiment proxies have a positive impact on short-term share returns and a negative influence on long-term share returns.

In terms of the *p*-value, in the short period, most of them are statistically significant. This means that the results reject the null hypothesis that sentiment proxies have no relationship with forecast share returns. However, in nine quarters, all *p*-values in different categories are not statistically significant. This accepts the null hypothesis and suggests that sentiment proxies cannot predict share returns. From the test, it can be found that the predictive power of sentiment variables will decrease with the increased value of the forecast period.

Table 6. Predictive regression.

	Australia Forecast Horizon							
	1 quarter		3 quarters		6 quarters		9 quarters	
	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
	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
	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
	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

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

Table 7. Predictive regression.

	NZ Forecast Horizon							
	1 quarter		3 quarters		6 quarters		9 quarters	
	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
	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
	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
	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
	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

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

Tables 6 and 7 present the results of predictive regression for the Australian and NZ markets. They have the same trend that in the short-term period, the sentiment proxies will have positive coefficients on portfolio returns. However, as the period exceeds the first quarter, the sentiment proxies show a negative influence towards returns. In terms of *p*-value, all portfolios in both two countries tend to have statistically significant results in the short-term period, but results are not significant in the long term. This means that in the short term, the ability of sentiment proxies to forecast portfolio returns is stronger than that in the long term. In both Australia and NZ, the *p*-value of CCI is much smaller than that of trade volume, where this could suggest that the predictive power of CCI in both countries is higher than that of trade volume.

There are still many differences of results that exist in the Australian share market and in the NZ share market. For example, in terms of the different types of portfolios in the 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 NZ. This means that the predictive power of sentiment is much lower in the value portfolios and high dividend portfolios than in the growth and low dividend portfolios in NZ. However, the situation is adverse in Australia. The predictive power of sentiment proxies is higher in the value portfolios and high dividend portfolios than in the growth and low dividend portfolios.

Overall, the results can be interpreted in two ways. Firstly, in the short term, the sentiment poses a positive impact on forecast portfolio returns, while in the long term, sentiment will negatively influence the predicted portfolio returns, albeit insignificant in most cases. Secondly, the predictive power of sentiment is stronger in the short term than in the long term.

For the results of this paper, it is partly consistent with empirical research. Specifically, for the short term, this paper's results agree the finding of some empirical research works such as in Brown and Cliff (2004, 2005), where they claim that even though sentiment is correlative with share returns, it cannot be used to predict short-term share returns.

Following Chung et al. (2012), this paper also uses sentiment proxies, macroeconomic variables, as well as forecast returns of long/short portfolios to run in the regression analysis and to further study the conditional characteristic effects of portfolios. Long/short portfolios are shares which are expected to rise or be high in value, and short positions on equities are expected to decline or be low in value (Stambaugh et al. 2012). 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. Hence, to find out the predictive power of sentiment proxies under different economic conditions, this paper also uses macro variables such as GDP (Gross Domestic Product), IPI (Industrial Production Index) and T-Bill (Treasury Bill) rate in the equations which are shown below.

Without controlling for macro variables:

$$R_{growth} - R_{value} = c + d \times sentiment_{t-1} + \varepsilon_{it} \tag{3}$$

$$R_{high\ dividend} - R_{low\ dividend} = c + d \times sentiment_{t-1} + \varepsilon_{it} \tag{4}$$

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:

$$R_{growth} - R_{value} = c + d \times sentiment^{*}_{t-1} + a \times GDP_{t-1} + b \times IPI_{t-1} + q \times Tbill_{t-1} + \varepsilon_{it} \tag{5}$$

$$R_{highdiv} - R_{low\ div} = c + d \times sentiment^{*}_{t-1} + a \times GDP_{t-1} + b \times IPI_{t-1} + q \times Tbill_{t-1} + \varepsilon_{it} \tag{6}$$

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, and q are the correlation coefficient of GDP, IPI, and T-Bill rate.

Table 8 reveals results whereby before controlling for macro variables, all the p-values of both countries are not statistically significant. This means that in both Australia and NZ, for both dividend in the long/short portfolio and book-to-market ratio long/short portfolio, the sentiment proxies cannot predict returns of long-short portfolio.

Table 8. Predictive regression of long/short portfolio.

Sentiment Proxy	CCI		CCI (macro)		Volume		Volume (macro)	
	d	p(d)	d	p(d)	d	p(d)	d	p(d)
NZ								
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

** significance at 0.05.

After controlling for macro variables, only the p-values of the high–low dividend portfolio in Australia are statistically significant and the correlation coefficient of this portfolio is positive. This may suggest that when investor 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 forecast returns of high dividend payout portfolios will be lower than that of low dividend payout portfolios. Nevertheless, the results remain inconsistent as the significance is only shown for the CCI variable. The results are consistent with the findings from Grigaliūnienė and Cibulskienė (2010) who did a study on investor sentiment effect on stock returns at the aggregate level and cross-sectionally in the Scandinavian stock market. They suggest that in most cases, the relations between sentiment and stock returns are negative but are not always statistically significant across countries.

5. Conclusions

Investor sentiment is one of the main components of behavioural finance, where it provides explanation to anomalies which exist in the share market. This paper mainly aims at investigating the relationship between investor sentiment and share returns in the Australian and NZ share market. This paper focuses on some of this gap and employs sentiment proxies, which are Consumer Confidence Index and trade volume, to conduct various tests.

One of the contribution points in this paper is that it does not only focus on the aggregate effects, but also pays attention to the cross-sectional effects, focusing only on the Australian region. After ADF and KPSS tests were conducted, correlation analysis was examined between sentiment proxies as well as the macro variables. From these tests, several findings can be found. Firstly, all the sentiment indicators were stationary. Secondly, it is found that the correlations between most of the macroeconomic variables were relatively weak, suggesting that investors may not be influenced by the economic indicator. The only relatively high and positive correlation is between GDP and trade volume for both countries.

In terms of the cross-sectional analysis, the Granger causality test and predictive regression were employed. It was discovered that sentiment influences portfolio returns positively in the short term but in the long term, the reverse occurs, where sentiment negatively influences the predicted portfolio returns, despite being statistically insignificant. The predictive power of sentiment is also found to be stronger in the short term.

Meanwhile, the Granger causality tests suggest that the returns behave only in a one-way causal relationship and affect the investors' reaction. This is an important indicator of the investors' behaviour within the Australasian market. Finally, a robust analysis on the predictive regression does not support that investor sentiment may impact the forecast returns of long/short portfolios, despite controlling for the macroeconomic variables. This is only to show that forecast returns may not be an accurate indicator for sentiment behaviour studies. A limitation of the study must be acknowledged, where data are constrained to limited lag periods that may produce biased results.

In conclusion, it can be deduced that in the short term, portfolio returns, or performance of equity, do impact the sentiment of investors in Australasian share markets. High or low portfolio returns in the current period will influence the sentiment of investors in the following period, which supports the classical theories of rational investors and efficient market (Black 1986; Fama 1965; Kyle 1985). This outcome seems to be different with the findings of a study by Schmeling (2009) for individual countries, as opposed to the aggregate returns of 18 industrialised countries. Jackson (2003) also touts a different opinion, for which they claim that there is little to no evidence of any effects in Australia and NZ.

However, long run impact as well as investor sentiment affecting the returns away from its intrinsic values cannot be proven by this paper. This then supports the above findings of there being no effects due to sentiment reasons. Future studies should also look at the sectoral sentiment–return relationship in Australia and New Zealand, as well as other alternatives to sentiment measurement such as meteorological data, sports results, and even the ongoing pandemic's impact that would affect stocks' performance. Certainly, this paper may create alternative ways for further testing to be conducted in other different markets, which would be interesting to further understand the behaviour of investors and their role in the investment strategy of its country.

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