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The effects of public sentiments and feelings on stock market behavior: Evidence from Australia

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ABSTRACT

This paper investigates the empirical evidence of the effects of public sentiments on industry stock returns and volatility dynamics in Australia based on the states of the market that relates to the conditional quantiles of public sentiments and sectoral stocks, using the robust nonparametric causality-in -quantile test. We adopt the monthly overall consumer sentiments index and four of its components including the sentiments for rural Australia and the age groups 18–24, 25–44, and 45 and above. Our nine industry stocks include Health Care, Consumer Discretionary, Consumer Staples, Utilities Financials, Real Estate, Industrials, Basic Materials and Energy, with data spanning from October 1974 to October 2020. The results from the nonlinear causality test show a directional and bidirectional causality between measures of consumer sentiments and returns of industry stocks. Interestingly, we note that the sentiments of individuals aged 45 and above cause the returns of all the nine sectors. Next, we explore the predictive power of sentiments on industry stock returns, using the nonparametric causality-in-quantile test. We find that the predictability between sentiments and industry stock returns is high in the normal market state but drops when the consumers' perceptions enter into the extreme bearish and bullish states. Additionally, the findings show a risk (volatility) transfer from sentiments to the industry stock returns in some cases under different market conditions. We offer some implications based on our findings for the stakeholders and market participants who develop their strategies depending on market conditions and sentiments.

1. Introduction

The global stock market is, to a large extent, one of the world's largest financial markets. For the past decade, factors such as financial, economic, political, environmental, and health crises have urged financial researchers to analyze the effects these factors on stock market returns and volatility (e.g., Balcilar et al., 2016; Tiwari et al., 2020; Le et al., 2021 among

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others). Because of its critical implications for portfolio allocation, asset pricing, and policy development, stock return predictability is of interest to both investors and policymakers (Gil-Alana et al., 2018). As a result, many economic agents place a high value on accurate stock market returns and volatility prediction. Naturally, there is a large body of works on the predictability of stock market returns and volatility, with a general conclusion that a range of macroeconomic and financial variables may predict stock returns in both developed and emerging stock markets. Fama and French (1992) show that financial variables such as book-to-market, cash-flow-yields and size have a strong forecasting ability in predicting the U.S. stock market. Similarly, other studies have highlighted the importance of common risk variables such market risk, book-to-market and size in forecasting stock markets (Fama and French, 1993; Gupta et al., 2014), while other studies have underscored the potential predictive power of a set of macroeconomic factors including inflation, interest rates and output (Cochrane, 1991; Fame and French, 1989; Ferson and Harvey, 1993; Persaran and Timmermann, 2000). Since the seminal study of Cootner (1960), the issue of identifying factors that can predict stock returns which are appropriate to conduct such a study has remained a hotly debated topic in the finance and economic research. One general theme that emerges from this literature is that predicting market returns and volatility fluctuations is a difficult task.

From the aforementioned backdrop, the thrust of our study is to employ the novel nonparametric causality-in-quantile test advanced by Balcilar et al. (2016) to examine the predictability of returns and the volatility of industry stocks in Australia over the monthly period 1974:10–2020:10, based on Australia's consumer sentiments. Theorists in the area of behavioral finance argue that investors have bounded rationality and have psychological and emotional factors that influence their decision-making processes. As a result, rather than the statistical features of stock returns, the state of investors' psychology plays a considerably more important role in the price formation process. As Hirshleifer (2001, p2) suggests, " The central task of asset pricing is to examine how expected returns are related to *risk* and to *investor mis-valuation* ". In his extensive review, he finds that over time, a broader psychological paradigm that includes full rationality as a special case will dominate the purely rational paradigm. The optimistic and pessimistic feelings of investors' general emotions about the markets are considered an additional source of undiversifiable or systematic risk in the behavioral finance theories (Kıyılar and Akkaya, 2016). Concisely put, these feelings are known as sentiments, and it has been suggested that unpredictable changes in sentiments are likely to have an impact on stock prices (Verma et al., 2008).

One of the notable elements of the literature of behavioral finance is the concentration on both the sentiments and the causal relationship existing between sentiments and stock returns. To this end, we contribute to the strand of the literature on the relation between sentiments and stock returns, by using a direct unique survey data on public sentiments in Australia which is published by the Melbourne Institute and Westpac.[1] Specifically, we use the aggregate Australian Consumer Sentiment Index (CSI). Brown and Cliff (2004) suggest that the aggregate measure of consumer sentiments may not provide a sufficient impact on stock returns. Additionally, market players may have different expectations, risk profiles, views, and information set among other things (Mensi et al., 2016). Hence, we examine the influence of disaggregate measures of the overall consumer sentiment index on sectoral stock returns comprising of sentiments for Rural Australia, and sentiments for ages: 18 to 24; 25 to 44, and 45 and above. Baker et al. (2003) suggested that the extent of the effect of consumers' and investors' propensity to speculate on stocks may vary across different industries, according to the subjectivity of their valuations. Hence, for our measure of industry stock returns, we consider all the nine sectors of Australia's stock markets: Financials, Health Care, Consumer Discretionary, Consumer Staples, Industrials, Basic Materials, Real Estate, Energy and Utilities.

Our choice of the Australian stock market is because the majority of earlier studies rely on indirect measures of sentiments such as the close-end-fund discounts, the advance/decline ratio (Swaminathan, 1996; Neal and Wheatley, 1998) and share turnovers (Deuskar, 2004) or the extrapolations constructed on these measurements. However, the Australian consumer sentiment index, which is a direct survey published by the Melbourne Institute and Westpac, has several unique features that should help us better comprehend the influence of sentiments on stock price movement. First, it is a regular survey of public opinion on existing and future economic conditions. It is one of the most widely followed and covered monthly news stories in the media, along with other macroeconomic data. As a result, the survey should provide a thorough picture of public opinion on the economy. Second, the composite index is made up of five survey items, conducted approximately one week before the consumer sentiment is made public. It is therefore a reliable indication of how people feel about the economy, personal finances, and spending (Akhtar et al., 2010). Third, the Australian consumer sentiment index has both an aggregate index for the overall country and disaggregate measures for different age groups and regions, which provides enough opportunity to conduct an in-depth analysis of the subject matter. In addition, the Australian sentiment index is only provided once a month, but other markets such as the U.S. sentiment data is frequently released in stages throughout the month, making the reliability and compatibility of the measurement problematic (Akhtar et al., 2010).

In recent years, several studies in the finance and economic literature have examined the relationship between sentiments and stock behavior across different markets including the European markets (Jansen and Nahuis, 2003), the U.S. markets (Gupta et al., 2014), the Asian markets (Akhtar et al., 2010), and the Shanghai stock exchange (Kling and Gao, 2008), using diverse estimation techniques. In this literature, studies in this area have used linear models, cointegration models, vector autoregressive (VAR) models among other linear models. However, due to the limitations of linear correlation models,

[1] The Australian Consumer Sentiment Index (CSI) is comparable to the CSI produced by the University of Michigan's Survey Research Center in the United States.

the multivariate GARCH models have emerged as the standard method for modeling time-varying correlations between sentiments and stock returns. As a result, Patton (2006) and Garcia and Tsafack (2011) documented one important constraint of the multivariate GARCH approach which is the assumption that returns innovations are characterized by a symmetric multivariate normal or Student-*t* distribution. Therefore, this assumption is inconsistent with the empirical evidence because financial return distributions differ from normal distributions in that they have heavier tails (Embrechts et al., 2002). In view of this literature, researchers in modern times have resorted to the use of new robust estimation techniques such as copulas, among others, to examine dependence among finance and economic variables since these new methods overcome the drawbacks of earlier models (e.g., Abakah et al., 2021a; Abakah et al., 2021b; Mensah and Alagidede, 2017; Aviral et al., 2021).

To differentiate our paper from prior empirical studies in terms of methodology (e.g., Lee et al., 2002; ; Schmeling, 2009), we employ Balcilar et al. (2016) novel nonparametric causality-in-quantile test to assess the sensitivity of sentiments of consumers in Australia to the cross sections of its industry stock returns. This causality-in-quantile test, which we use in this paper, combines the frameworks of Nishiyama et al. (2011)'s k-th order causality and Jeong et al. (2012)'s quantile causality, and can thus be considered a more general version of the former. The following are some of the innovative features of the causality-in-quantile approach. Firstly, it is robust to misspecification errors due to its ability to detect the underlying dependence structure between the time series under investigation. This could be particularly crucial, given that stock prices are well known to have nonlinear dynamics (Abakah et al., 2018).

Secondly, through this methodology we render the ability to test not just for causality-in-the mean (the 1st moment), but also for causality in the tails of the variables' joint distribution, which is especially crucial if the dependent variable bears fat tails. Finally, we are able to look into the causality-in-variance, and hence the volatility spillovers, because there are times when the causality in the conditional-mean does not occur, but higher order interdependencies may emerge.

This study further uses a nonlinear causality test to examine the consumer sentiment-stock return relationship. The inclusion of nonlinear causality tests seeks to overcome the bottlenecks that characterize the linear causality tests. The inability of linear causality to detect nonlinear relationships present in the economic and financial variables is catered for by nonlinear causalities employed in this study. The presence of nonlinearity could result in a multiplicative and disproportionate impacts on financial variables (Abakah et al., 2018; Kyrtsou and Labys, 2006), which for this study is stock returns, due to minute changes in other variables such as consumer sentiments.

A critical question that we have yet to address is: What are the intuitive and theoretical reasons that can lead one to think that consumer sentiments predict sectoral stock returns and volatility? According to the rational asset pricing theory, there is a positive relationship between expected returns and risk following the assertion of Merton (1980). However, behavioral theorists in finance added the concept of noise trader sentiment predictive power and its effects prevalent in financial markets for strategic and prudent allocation of financial assets (De Long et al., 1990a; Fisher and Statman, 2000). The theoretical idea provides a pragmatic proof that the consumer sentiments can impact the prices of financial assets under two assumptions: (i) the predominant role of sentiment (noise) traders in the movement of assets is crucial, and (ii) the limitation of arbitrage in terms of transaction costs is prevailing. Some empirical findings[2] argue from the conventional wisdom, and thus makes a contribution to the subject by providing strong evidence that investor sentiments affect stock returns.

At the most basic level, one could consider sentiments to be either optimistic or pessimistic regarding the economy. Positive expectations are seen to boost stock prices, while negative expectations are thought to depress them. When sentiments are strong and persistent, they can lead to irrational exuberance, as seen in the late-90 s high-tech financial bubble known as the Dot com, or the panic scenario that occurred during the October 1987 crisis. Such occurrences do not indicate any abrupt changes in the fundamentals, but rather significant adjustments in consumer or investor sentiments (Siegel, 1992). At this extreme level, investor sentiments may be linked to the propensity to speculate. Furthermore, given that financial asset returns are a function of the state of the economy, which is susceptible to fluctuations caused by sentiments, uncertainties, and other factors, would suggest an indirect channel via which sentiments can affect stock returns and volatility. Benigno and Ricci (2011) and Martín and Urrea (2007) formalize these channels using new Keynesian general equilibrium frameworks.

Our contribution to the literature on the relationship between the public sentiment and the returns of stocks is fivefold. First, to the best of our knowledge, this work premieres the use of the causality-in-quantile approach to investigate the predictability of industry stock returns and volatility simultaneously using public sentiment in Australia. Thus, we give new empirical evidence on the impact of public sentiment on stock returns based on the states that pertain to the market. This corresponds to the conditional quantiles of the sentiments and stock markets, based on Bacilar et al. (2016)'s novel nonparametric test. The causality-in-quantile methodology is unique because it is unaffected by outlier observations. It can also typify Granger causality throughout the entire distribution. Because financial time series are characterized by fat tails due to the occurrence of either individual or simultaneous co-jumps in financial and commodity markets, which constitute the basis for our stock sectors, this method takes care of regime changes and jumps in the data (Dungey and Hvozdyk, 2012;Chevallier and Lelpo, 2014).

[2] (Baker and Wurgler, 2006; Kumar and Lee, 2006; Tetlock, 2007; Edmans et al., 2007; Da et al., 2011; Stambaugh et al., 2012; Siganos et al., 2014; Da et al., 2015; Huang et al., 2015).

Second, because the rejection of causality-in-mean does not rule out the possibility of causation in higher moments, the paper looks into causality-in-variance between sentiments and Australian sectoral stocks. Third, determining the intensity and direction of causation under varied market circumstances would be beneficial to stakeholders who develop their strategies depending on conditions of the market. Fourth, since consumers may differ in terms of expectations, beliefs, and risk profiles, we use a component of the overall aggregate measure of consumer sentiments, including sentiments for rural Australia and different age groups. We are the first to examine the impact of sentiments of various age groups and rural Australia on industry stock returns and volatility dynamics in different market conditions. This is a noble contribution to the literature. Fifth, we examine the cross-sectional effect of sentiments on sectoral stock returns. Evidently, while several studies have assessed the effect of sentiments or the emotional states of asset traders on stock prices (see Akhtar et al., 2011; Baker and Wurgler, 2006; Breaban and Noussair, 2018; Chu et al., 2016; Hu et al., 2015), the decomposition of the aggregate stocks in relation to sentiments is largely unexplored. In particular, the paper examines the distributional predictability between changes in consumer sentiments and nine stock sectors, mindful that sectors with less predictable cash flows are more likely to face swings in sentiment than the traditional and matured sectors (Baker and Wurgler, 2006).

Our findings from the nonlinear causality test reveal a directional causality between Overall CSI and Health Care, and Financial sectors. We further note that CSI Rural Australia granger causes stock returns of Energy, Utilities and Basic Materials sectors. Additionally, sentiments of consumers aged between 18 and 24 cause Health Care, Financial, Real Estate, Industrials, Energy and Utilities sectors. The findings show a bidirectional relationship between sentiments of the individuals aged between 25 and 44 and Real Estate, Industrials Basic Materials and Utilities sectors. Finally, we document directional causality between CSI for the age group 45 and above and the nine sectors. The result from the nonparametric causality-in-quantile reveals the causality-in-return is asymmetric and unidirectional running from consumer sentiments to sectoral stock returns in some cases, implying that the predictability of the sectoral stock returns is high in the normal market but drops when the consumers' perceptions shift to the extreme bearish and bullish states. Under certain market situations, the causality-in-variance shows a directional and bidirectional causality between sentiments and industry returns.

The remainder of the paper is structured as follows. The second section briefly reviews the existing literature. The third section presents the methodological framework adopted in the study. We then analyze the findings and conclude the paper in the fourth and fifth sections, respectively.

2. Literature review

Asymmetric information in the financial markets influences investor behaviors (Shleifer and Vishny, 1990). The imperfection of the hypothesis for efficient markets, which states that prices of stocks do not reflect all available information in the market could be attributed to (irrational) investor behaviors that are seldom quantifiable (Hsu et al., 2005). Shleifer and Summers (1990) also allude to the existence of rational and irrational traders that are very likely to influence equity prices. Thus, an investor sensitivity nexus to stock returns has attracted research concerns.

Several studies in the finance and economic literature have examined the relationship between sentiments and stock behavior. For example, Jansen and Nahuis (2003) find evidence of a positive correlation between investor sentiments and stock returns of 11 European stock markets. Similar results were obtained by Gupta et al. (2014) in the U.S. stock market returns.. However, Brown and Cliff (2004) find no predictability power of stock returns emanating from both investor and institutional sentiments. Other subsequent studies indicate that consumer sentiments contrarily predict future stock returns (Bathia and Bredin, 2013; Schmeling, 2009), whereas by using the Shanghai stock exchange movement, Kling and Gao (2008) detect a reverse causality from stock returns to institutional investor sentiments in the short run. However, this relation did not exist for the long-run, and further negative returns were more sensitive and impactful than positive returns. Li (2019) finds an existence of a contagious effect from investor sentiments to stock returns and volatilities, thereby affirming the sentiment-stock price relationship. Otoo (1999) also demonstrates for the U.S. stock market that changes in equity values and changes in consumer sentiments are concurrently correlated. Moreover, rises in equity prices enhance consumer confidence with a (short) lag, but that the reverse does not hold. Measuring sentiments based on the COVID-19 pandemic, several studies show that investor sentiments impact stock market returns (Haroon and Rizvi, 2020; Lyócsa et al., 2020; Salisu and Vo, 2020).

The sensitivity of stock returns to the sentiments of investors remains fundamentally a central issue in finance and economic research since the existing literature could be recounted as not exhaustive. The inconclusive findings and the divergence in the results continue to attract research in this area. Prior studies, spew mixed findings which could be attributed to the proxies used for investor sentiments (Kothari and Shanken, 1997; Baker and Stein 2004; Baker and Wurgler, 2006; Kurov, 2010; Krokida et al., 2020), the empirical methods adopted and the dynamics of stock markets to asset, institutional and economic heterogeneities in jurisdictions of the concentration of the studies.

Rahman and Shamsuddin (2019) studied the role of investor sentiments in explaining the price-earnings ratios of stocks of the G7 countries. Their findings indicate that the price-to-earnings ratio increased with the improvements in the sentiments of investors in the region. In an earlier study, Baker and Stein (2004) had underscored that irrational investors traded more in a bullish market when these investors felt cheerful, and also traded more in the bearish market when a gloomy feeling was dominant. Again, Chen et al. (2019) contended that investor sentiments have an important effect on the degree of market efficiency and equity mispricing. The literature from Yu and Yuan (2011) also supported earlier assertions that show that market participation increases when there is an increase in sentiment-driven market participants. Those authors' study shows evidence of a strong and positive equity return-volatility trade-off when investor sentiments are low and vice versa.

Akhtar et al. (2011) also analyzed the effect of consumer sentiment announcements on equity markets. Their study indicated that the announcements of consumer sentiments had a significant negative effect on the Australian stock markets. The Akhtar et al. (2011) study endorses previous and later literature that finds an inverse relationship between investor sentiments and stock returns, thus implying that high investor sentiments were related to low future equity returns and vice versa (see Brown and Cliff, 2005; Baker and Wurgler, 2007; Baker et al., 2012; Bathia and Bredin, 2013; Siganos et al., 2014). According to Ritter (2003) and Ljungqvist (2006), the underpricing of IPOs was associated with investor sentiments which were described as enthusiastic. Schmeling (2009) also looked at how consumer confidence (used as a proxy for the sentiment of individual investors) impacted expected stock returns in 18 developed countries. The findings of Schmeling revealed a negative forecast of aggregate stock market returns on average by investor sentiments across the countries studied. Higher levels of investor sentiments (consumer confidence) led to lower future stock returns and vice versa. This relationship, according to Schmeling, held true for the returns of value stocks, growth stocks, small stocks, and different forecasting timeframes.

Gupta and Banerjee (2019) examined the impact of sentiments from foreign news on the financial performance of domestic firms in the energy sector of the Organization of Petroleum Exporting Countries (OPEC). Their study finds a dominance of the negative effect of news on the performances. However, that study reports that in eras of low consumer confidence, positive OPEC news negatively influenced the U.S. energy stock returns. Kim and Kim (2014), using internet messages to measure investor sentiment, find no significant relation between investor sentiments and stock returns. Using Facebook's Gross National Happiness Index, Siganos et al. (2014) investigate the relationship between daily sentiments and trading behavior in 20 international stock markets. They discover a positive contemporaneous relationship between emotions and stock returns. Huynh et al. (2021) used the 17 largest economies' six behavioral indicators (media coverage, false news, fear, sentiment, media hype, and infodemic) during the COVID-19 pandemic to construct connectedness among these indicators and the stock markets. Their study shows that total and net connectedness indicate that China, Germany, the UK and the U.S. were the epicenters of the sentiment shocks that were transferred to other countries.

Using a Granger causality test developed by Shi et al. (2018), Çağlı et al. (2018) analyzed the causal relationship between stock returns and investor sentiments in Borsa Istanbul and found no causality but alluded to the possibility of not using the non-linearity causality. On the other hand, Wang et al. (2006) found that most of measures of investor sentiments were caused by stock returns and volatility rather than by sentiments, therefore causing stock return and volatile behavior. Their study again concludes that all sentiment variables have an extremely limited forecasting power once the returns were included as a forecasting variable.

The long-term and short-term variation effects of investor sentiments were accounted for by Ni et al. (2015) as their study documents a mean reverting behavior of stock returns, assuming predictability with a large and positive effect in the short-run and a contrary (small and negative) effect in the long-run. Alouiet al., (2021) examine the relevance of investor sentiments to the Islamic stock-bond interplay in the time-frequency domain, using a multiple and partial wavelet coherence as well as bivariate and multivariate nonlinear causality tests. They conclude that connectedness exists in both the long-run and short-run horizons. Using Consumer Confidence Index and Investor Intelligence survey in the United States, Lemmon and Portniaguina (2006) and Qiu and Welch (2004) indicate that investor sentiments were useful in predicting the equity returns of stocks with less than large capitalizations and successive equity returns. Chen et al. (2019) document an investigation of the impact of investor sentiments on the probability of offering seasoned stocks and stock price performance of these stocks. Their study finds a positive impact on the probability of offering seasoned equities and shows the short-run price falls during periods of high investor sentiments.

Extending the arguments beyond stock returns, French and Li (2017) examined the impact of investor sentiments on Thailand's equity market returns and foreign equity flows. They find a strong negative effect of global risk aversion on foreign investment flows in Thailand, whereas sentiments positively impact foreign equity flows and is a significant variable for forecasting returns in the markets in Thailand. Using investor sentiments created from the first principal component of the consumer confidence index, advance/decline ratio, and volatility premium, Vuong and Suzuki (2020) suggested that the market sentiments can be a valid predictor of stock returns in the short-term horizons. Additionally, by decomposing the total sentiment in each market into regional and local indices, Vuong and Suzuki (2020) find that the market-level results are driven mostly by the local sentiments. Some studies (Berger and Turtle, 2012; Hirshleifer et al., 2006) consider the sensitivity of stock returns to the market sentiments. Yang and Hu (2021) show that sensitivity of stock returns in China which changes with respect to individual stock sentiments. By supporting previous studies, their research shows that the effect of the beta of individual stock sentiment on stock returns is positive and significant in different stock markets.

The abovementioned literature can be recounted as non-exhaustive in the investor sentiment- stock returns controversy. The current study further investigates the impacts of sentiments considering sectoral stocks in Australia. Interestingly, it aims to fill this gap in the literature by examining the predictability of the sentiments on the sectoral stocks by making use of the nonlinear causality-in-quantile method proposed by Balcilar et al. (2016). This paper differs from the existing literature, as it examines the age-varying effect of the consumer sentiments on returns, using the causality-in-quantile and nonlinear causality tests, which predicts a near accurate relationship of series.

3. Empirical methodology: Causality- in- quantiles test

We investigate the causality-in-quantiles between the components of consumer sentiments ((y_t) and aggregate sectoral stock returns (x_t) in Australia, using the unique nonlinear causality-in-quantile approach proposed by Balcilar et al. (2016). Following Jeong et al. (2012) ,[3] we test that x_t does not cause y_t in the θ-quantile with regards to the lag-vector of $\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\}$ if

$$Q_\theta(y_t|y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}) = Q_\theta(y_t|y_{t-1}, \ldots, y_{t-p}) \tag{1}$$

However, x_t presumably causes y_t in the θ-th quantile with regards to $\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\}$ if

$$Q_\theta(y_t|y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}) \neq Q_\theta(y_t|y_{t-1}, \ldots, y_{t-p}) \tag{2}$$

where $Q_\theta(y_t|\cdot)$ is the θ-th quantile of y_t. The conditional quantiles of y_t, $Q_\theta(y_t|\cdot)$ depend on t, and the quantiles are limited to a range of zero to one, i.e., $0 < \theta < 1$.

Let us express the vectors $Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \ldots, x_{t-p})$, and $Z_t = (X_t, Y_t)$. The functions $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ are the conditional distribution functions of y_t conditioned on vectors Z_{t-1} and Y_{t-1}, respectively. The conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is presumed to be completely continuous in y_t for nearly all Z_{t-1}. By defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we can see that

$$F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta,$$

which is true with a probability of one. As a result, based on Eqs. (1) and (2), the causality-in-quantile hypothesis can be expressed as

$$H_0: \; P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{3}$$

$$H_1: \; P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{4}$$

A causality in a fat tail is different from that at the center of the distribution (Lee and Cheng, 2007) .[4]

4. Data and descriptive statistics

To investigate the distributional predictability between the Consumer Sentiments Index (CSI) and the sectoral stock returns of Australia in order to ascertain the perceptions of economic agents on stock returns, we obtain monthly indices of Australia's aggregate Consumer Sentiments index and components of the aggregate index which includes CSI Rural Australia, CSI-Aged 18–24; CSI – Aged 25 to 44, and CSI–Aged 45 and above. For our measure of sectoral stock returns, we consider the following nine sectors: Health Care, Financials, Real Estate, Consumer Discretionary, Consumer Staples, Utilities, Industrials, Basic Materials and Energy. Our data obtained from Datastream spans the period from October 1974 to October 2020.

Table 1 reports the statistical properties of the monthly returns for the nine sectoral stock price indices and our five sentiment measures of CSI: CSI- Overall, CSI Rural Australia, CSI Aged 18–24; CSI – Aged 25 to 44, and CSI – Aged 45 and above. Comparing the mean returns of the nine sectoral stocks, we find that the daily mean returns of all the stock sectors are positive, with the Consumer Discretionary sector recording the highest mean return, which is equal to 0.921, followed by the Health Care sector (0.901). The least mean return which is equal to 0.601 was recorded by the financial sector. We note that the mean of all the sentiment indices is positive with the exception of CSI Aged 18–24, which recorded a negative mean of −0.001. Concerning the standard deviation of the sectoral stocks and the consumer sentiment indices, the results illustrates a considerable number of fluctuations in all series under examination, even though the extent of volatility and variability is low for all the series.

On skewness, we see a negative skewness for all the series except that of CSI Rural Australia, which is mostly affected by conditions in urban Australia. Negative (positive) skewness implies the tendency of higher negative (positive) returns without matching the tendency of positive (negative) returns. For kurtosis, all the series examined in this study recorded a kurtosis which exceeds the threshold 3 which is for the normal distribution. This surmises that the return series for the period have flatter tails, compared to what one could expect from a normally distributed series. We use the Jarque-Bera (JB) test to check for the normality assumption in the series. We reject the null hypothesis of normality for all the series under investigation at the 1% level. We use Dickey and Fuller's (1979) ADF test, Philips and Parron's PP test, the KPSS stationarity test and the ZA tests to test for the stationarity/nonstationarity of all the variables examined. Our results show the series are integrated of order one i.e., they are log first difference stationary.

Fig. 1 shows the graphical outlook of the overall distribution of the data together as well as the pairwise correlations between sectoral stock returns and consumer sentiment indices. Once again, Fig. 1 confirms that the data used in this investigation is normally distributed. We focus our analysis here on the correlation between the nine sectors and our overall measure of consumer sentiments. The highest correlation between the Overall CSI for Australia and any of the sectoral stock

[3] The exposition in this section closely follows Nishiyama et al. (2011) and Jeong et al. (2012).

[4] We have made use of the bandwidth h = 0.05 and the kernel type used both for (•) K and (•) L is Gaussian.

Table 1
Summary statistics.

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP	KPSS	ZA	Obs.
Health. Care	0.901	1.028	17.519	−44.726	5.077	−1.367 *	14.493 *	3215.9 *	−7.29022	−524.784	0.084436	−8.152 *	553
Financials	0.601	1.089	26.101	−40.032	5.499	−1.008 *	11.489 *	1754.1 *	−8.12039	−536.455	0.401358	−7.575 *	553
Real. Estate	0.623	0.864	27.435	−47.517	5.672	−1.752 *	17.337 *	5018.8 *	−7.47508	−551.809	0.500582	−6.564 *	553
Consumer. disk.	0.921	1.319	28.091	−61.623	7.036	−1.399 *	15.663 *	3875.2 *	−7.01359	−494.566	0.547212	−6.541 *	553
Consumer. Staples	0.538	0.911	22.918	−58.068	7.295	−1.357 *	12.605 *	2295.3 *	−7.24875	−618.75	0.292138	−7.110 *	553
Industrials	0.609	1.287	18.954	−38.457	5.57	−0.969 *	8.364 *	749.3 *	−7.39916	−496.16	0.378097	−7.461 *	553
Basic. Materials	0.681	1.108	19.378	−45.291	6.25	−0.876 *	8.633 *	801.9 *	−7.72626	−525.624	0.102599	−7.309 *	553
Energy	0.612	0.689	23.498	−44.038	7.137	−0.703 *	6.690 *	359.3 *	−7.7247	−508.861	0.288453	−6.999 *	553
Utilities	0.684	0.659	32.788	−49.644	6.977	−0.24823	10.554 *	1320.5 *	−7.66389	−512.329	0.268958	−7.049 *	553
CSI.OVERALL	0.027	0.087	16.551	−19.512	5.218	−0.331 *	4.251 *	46.1 *	−9.27422	−556.953	0.015123	−8.565 *	553
CSI.RURAL	0.042	0	27.793	−20.289	5.99	0.094709	4.310 *	40.4 *	−8.85577	−597.787	0.017798	−8.586 *	553
CSI.AGED18TO24	−0.001	0.018	62.421	−48.221	8.179	0.277 *	11.411 *	1637.3 *	−10.1585	−590.013	0.015157	−8.829 *	553
CSI.AGED25TO44	0.038	0.078	19.841	−25.44	6.396	−0.350 *	4.394 *	56.1 *	−9.23014	−623.293	0.015074	−8.705 *	553
CSI.AGED45andOVER	0.035	−0.01	19.268	−19.468	5.828	−0.06685	3.696 *	11.6 *	−9.10355	−558.813	0.015638	−8.887 *	553

Notes. The table reports the summary statistics for the indices examined in this study. Std.Dev denotes the standard deviation. JB denotes the Jarque-Bera test for normality.
* denotes significance at the 1% level.

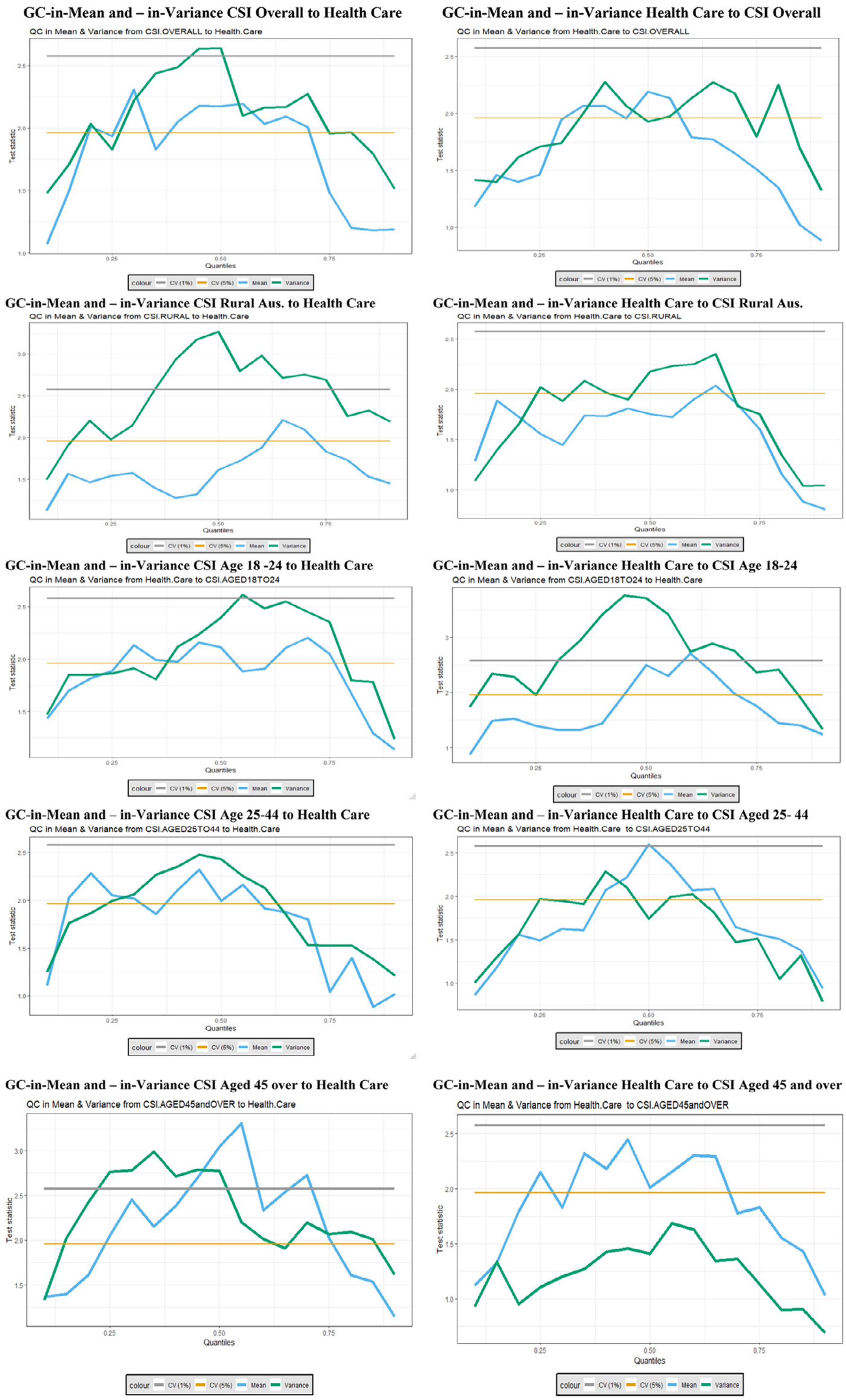

Fig. 1. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Health Care Sector market returns. *Notes*: The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

sectors is seen for the case of the Overall CSI and Real Estate sector which is equivalent to 0.22. Focusing on the components of Overall CSI and the sectors under examination, we observe the highest significant correlation between CSI Rural Australia and the various sectors is seen for the case of CSI Rural Australia and the Basic Materials sector (0.14). For the remaining sentiment indices, we find a significant correlation between the CSI Aged 18–24 and Industrials (0.12); the CSI Aged 25–44 and Real Estate (0.22) and the CSI Aged 44 and above and Financials (0.18) and Basic Materials (0.18).

The low pairwise correlation displayed in Table 1.1 between the various sectors and the sentiment indices is not surprising since the sectoral stock returns are impacted by several factors within the broader economy. However, we argue that this lays a solid foundation to do further tests, using robust methodologies to examine the extent of the distributional predictability among the series.

5. Discussion of the empirical results

5.1. Linear and nonlinear causality tests

The tests for causality provide a mechanism of testing for the dependence between the measures of sentiment and the returns of stocks under consideration in Australia. Table 2 describes the tests of the linear and nonlinear causality tests between the aggregate/overall CSI Australia and the nine sectoral stocks and vice versa. Schmeling (2009) reports that there is a two-way causality in which the sentiments depend on the lagged returns, and the returns depend on the lagged sentiments. Focusing on the causality between the aggregate CSI measure and the sector returns, we find no statistical dependency for many of the relationship. However, three directional dependencies are identified. First, from the linear causality tests, we find that changes in the overall consumer sentiments influence the health care sector returns, financial and industrials sectors. Second, most importantly the result from the nonlinear tests shows that the stock returns of the health care sector and financial sector are influenced by the changes in the overall sentiments of consumers in Australia, but the reverse causality is not true.

We find that most of the sectoral stock returns are not dependent on the overall consumer sentiments, which suggests that the aggregate CSI is not an important measure driving returns. This initial finding agrees with the findings of Salmes (2017) who established that the consumer sentiments in Australia have a direct or an undeviating effect on the returns of certain sectors including the financials and industrials sectors where the valuations of firms in these sectors are highly subjective and not easy to arbitrage.

Next, we focus on the causal relationship between the disaggregate components of Australia's overall CSI and the returns of sectoral stocks. Table 3 reports the results for the case of the causality between the Rural Australia Consumer Sentiments and the sectoral stocks returns. We observe from the linear causality test that the sentiments of consumers in the rural Australia cause returns of the health care, financial, real estate and industrial sectors. For the non-linear causality tests, we observe that the CSI Rural Australia granger causes the Energy, Utilities and Basic Materials sectors, in addition to the Health Care, Financial, and Real Estate sectors, a result that is similar to what we obtained from the linear causality tests.

On the reverse causality test, we find a bidirectional causality only for the case of the CSI Rural Australia and the Industrials sector under the test of linear causality, and the case of the CSI Rural Australia and the Real Estate and Industrials sectors, using the nonlinear tests. Thus, changes in the returns of the industrial sector significantly influence the sentiments of the consumers across rural Australia. This result is not surprising for some varying reasons. For example, the spillover effects of activities of the firms in the industrial sector, which include automobile, clothing, food services and mining firms, can extend themselves to the rural settings. This is because the consumers in the rural settings also depend on products from the industrial sector.

Table 4 depicts the linear and non-linear causalities for the relationship between the Consumer Sentiments for the age group 18–24 and the nine sectors. Interestingly, we find that variations in sentiments for this age group do not affect the returns of any of the nine sectors examined in this study. This outcome can be attributed to the fact that this age group does not have much money to invest in stocks. However, for the case of the reverse causality, we observe that the returns of the following sectors: health care, financial, real estate, industrials, energy and utilities impact the perceptions and feelings of consumers in Australia within the age bracket of 18–24 years for both linear and non-linear causality tests. This result is interesting since the behavioral theorists suggest that this age of the people in this bracket is the time of the lifespan when very little is normative. It is a period of frequent changes and explorations that covers many aspects of the life of this group from home, family, work, school, resources, and roles in society (Johnson and Naka, 2014). Hence, it is not surprising that variations in returns of several sectors affect the sentiments of this age group. This result is a unique contribution to the literature since this paper is the first to examine sentiments of diverse age groups and stock prices.

Table 5 presents the causality test for the case of the sentiments for the age group 25–44 and the nine sectors. We find a bidirectional relationship between the sentiments for this age group and the real estate, industrials, basic materials, and utilities sectors. It is surprising that we find no dependency between the sentiments of this age group and the variations in stock prices for sectors such as the financial, energy and utilities. This is perhaps because this age group constitutes the adult consumers who are active in the labor force with varied needs spanning from health to energy to financing, among other sectors. Hence, it is expected that changes in sectors such as the financial, energy and utilities will affect the overall perceptions and sentiments of individuals within this age group. Our findings are not in agreement with the conclusion of Salmes (2017).

Table 1.1
Pairwise correlations.

	Health Care	Financials	Real Estate	Consumer Disk	Consumer Staples	Industrials	Basic Materials	Energy	Utilities	CSI Australia	CSI Rural Australia	CSI AGED 18 to 24	CSI AGED 25 to 44	CSI AGED 45 and Over
Health Care	1													
Financials	0.742	1												
Real Estate	0.587	0.903	1											
Consumer Disk	0.733	0.968	0.910	1										
Consumer Staples	0.538	0.675	0.711	0.731	1									
Industrials	0.766	0.869	0.875	0.873	0.887	1								
Basic Materials	0.704	0.865	0.701	0.845	0.601	0.732	1							
Energy	0.680	0.904	0.722	0.874	0.643	0.759	0.969	1						
Utilities	0.739	0.968	0.843	0.954	0.696	0.843	0.916	0.942	1					
CSI Australia	−0.073	0.166	0.188	0.179	−0.019	0.005	0.086	0.086	0.147	1				
CSI Rural Australia	−0.069	0.138	0.140	0.144	−0.087	−0.048	0.073	0.062	0.119	0.961	1			
CSI AGED 18 to 24	0.090	0.357	0.368	0.378	0.205	0.223	0.266	0.280	0.341	0.841	0.769	1		
CSI AGED 25 to 44	−0.018	0.153	0.173	0.176	0.002	0.025	0.078	0.072	0.144	0.975	0.934	0.797	1	
CSI AGED 45 and Over	−0.054	0.228	0.219	0.223	−0.019	0.027	0.156	0.163	0.203	0.966	0.942	0.768	0.905	1

Table 2
Linear and nonlinear causality: Overall CSI Australia and sectoral stocks returns.

H0: non causality **H1: causality**	**Linear** **Causality Test**		**Non-Linear** **Causality Tests**		
Sectoral Stocks	Linear Granger	General Taylor-based	Semi-additive Taylor-based	P-General Taylor based	ANN-based
H0: Overall CSI does not cause sectoral stock returns					
Health Care	2.0696 [0.0677]***	1.8841 [0.0525]***	0.8903 [0.5338]	2.0696 [0.0677]***	0.9671 [0.4667]
Financials	2.5431 [0.0274]**	1.1359 [0.3287]	1.1056 [0.3572]	2.5431 [0.0274]**	1.5363 [0.1326]
Real Estate	1.5867 [0.1620]	4.1866 [0.0000]*	1.7314 [0.0797]***	1.5867 [0.1620]	0.9044 [0.5212]
Consumer Disk	0.7121 [0.6145]	1.3179 [0.2399]	0.6366 [0.7659]	0.7121 [0.6145]	0.6177 [0.7822]
Consumer Staples	1.4502 [0.2046]	2.3696 [0.0290]**	0.8346 [0.5845]	1.4502 [0.2046]	0.8333 [0.5857]
Industrials	4.4663 [0.0005]*	2.2794 [0.0033]*	2.0204 [0.0357]**	4.4663 [0.0005]*	2.2302 [0.0193]**
Basic Materials	1.7702 [0.1171]	1.3414 [0.1855]	1.0631 [0.3890]	1.7702 [0.1171]	1.0065 [0.4338]
Energy	0.7080 [0.6176]	0.9690 [0.4778]	0.7412 [0.6711]	0.7080 [0.6176]	0.4281 [0.9200]
Utilities	1.3064 [0.2596]	4.4594 [0.0000]*	0.5658 [0.8252]	1.3064 [0.2596]	0.7820 [0.6332]
H0: Sectoral stock returns do not cause Overall CSI-Australia					
Health Care	0.7306 [0.6007]	0.2084 [0.9589]	0.0793 [0.9886]	0.7306 [0.6007]	0.9716 [0.4628]
Financials	0.5190 [0.7620]	0.1551 [0.9785]	0.1496 [0.9801]	0.5190 [0.7620]	0.2444 [0.9877]
Real Estate	1.1940 [0.3107]	0.3089 [0.9076]	0.3686 [0.8701]	1.1940 [0.3107]	0.9379 [0.4918]
Consumer Disk	1.6186 [0.1532]	0.1667 [0.9747]	0.1704 [0.9734]	1.6186 [0.1532]	0.5792 [0.8144]
Consumer Staples	1.7711 [0.1170]	0.3141 [0.9045]	0.3364 [0.8909]	1.7711 [0.1170]	0.9621 [0.4709]
Industrials	0.9770 [0.4311]	0.3960 [0.9046]	0.2531 [0.9382]	0.9770 [0.4311]	0.5682 [0.8233]
Basic Materials	0.2764 [0.9261]	0.2414 [0.9439]	0.2736 [0.9275]	0.2764 [0.9261]	0.4740 [0.8921]
Energy	0.9834 [0.4272]	0.2893 [0.9188]	0.3098 [0.9071]	0.9834 [0.4272]	0.6844 [0.7232]
Utilities	1.5970 [0.1591]	0.2223 [0.9529]	0.2602 [0.9346]	1.5970 [0.1591]	1.3734 [0.1977]

Notes. This table presents the linear and nonlinear granger causality tests between CSI and sectoral stock returns. The figures in the curry brackets are the *p*-values. *, ** and *** denote significance at the 1%. 5% and 10% levels.

Table 3
Linear and nonlinear causality: CSI- Rural Australia and sectoral stocks returns.

H0: non causality H1: causality	**Linear** **Causality Test**		**Non-Linear** **Causality Tests**		
Sectoral Stocks	Linear Granger	General Taylor-based	Semi-additive Taylor-based	P-General Taylor based	ANN-based
H0: CSI-Rural Australia does not cause sectoral stock returns					
Health Care	3.0788 [0.0095]*	2.2340 [0.0078]*	1.3170 [0.2255]	3.0788 [0.0095]*	1.5309 [0.1344]
Financials	3.0384 [0.0103]**	1.3212 [0.1797]	1.3463 [0.2107]	3.0384 [0.0103]*	1.8784 [0.0533]**
Real Estate	2.2054 [0.0524]***	2.9399 [0.0004]*	1.6783 [0.0919]***	2.2054 [0.0524]***	1.2288 [0.2752]
Consumer Disk	0.8134 [0.5403]	1.5732 [0.1207]	0.6566 [0.7482]	0.8134 [0.5403]	0.5312 [0.8519]
Consumer Staples	1.2906 [0.2664]	1.5363 [0.1237]	0.7596 [0.6540]	1.2906 [0.2664]	0.5377 [0.8471]
Industrials	5.3026 [0.0001]*	2.5443 [0.0003]*	2.0762 [0.0304]**	5.3026 [0.0001]*	2.4000 [0.0116]**
Basic Materials	1.8416 [0.1030]	1.6905 [0.0416]**	1.3360 [0.2158]	1.8416 [0.1030]	0.8133 [0.6042]
Energy	0.9528 [0.4463]	1.6202 [0.0603]**	0.7486 [0.6643]	0.9528 [0.4463]	0.5491 [0.8384]
Utilities	1.5323 [0.1779]	3.2125 [0.0000]*	0.5962 [0.8004]	1.5323 [0.1779]	0.8940 [0.5305]
H0: Sectoral stock returns do not cause CSI-Rural Australia					
Health Care	0.7676 [0.5734]	0.6620 [0.6525]	0.6969 [0.5944]	0.7676 [0.5734]	0.9418 [0.4883]
Financials	1.7092 [0.1306]	0.5394 [0.7464]	0.6071 [0.6946]	0.5394 [0.7464]	0.8482 [0.5720]
Real Estate	2.2342 [0.0497]**	0.9657 [0.4384]	1.1301 [0.3435]	0.9657 [0.4384]	1.8248 [0.0619]***
Consumer Disk	1.6905 [0.1350]	0.6897 [0.6314]	0.7109 [0.6155]	1.6905 [0.1350]	0.8772 [0.5456]
Consumer Staples	2.2566 [0.0476]**	1.1241 [0.3467]	1.1591 [0.3285]	2.2566 [0.0476]**	1.5564 [0.1261]
Industrials	2.7724 [0.0175]**	1.4649 [0.1585]	1.2531 [0.2833]	2.7724 [0.0175]**	1.6823 [0.0909]***
Basic Materials	0.7208 [0.6080]	0.7944 [0.5541]	0.8825 [0.4926]	0.7208 [0.6080]	0.5096 [0.8677]
Energy	1.5859 [0.1622]	0.5982 [0.7319]	0.7458 [0.5896]	1.5859 [0.1622]	0.6794 [0.7278]
Utilities	3.0176 [0.0107]**	0.6763 [0.6416]	0.7005 [0.6233]	3.0176 [0.0107]**	1.6864 [0.0899]***

Notes. This table presents linear and nonlinear granger causality tests between CSI and sectoral stock returns. The figures in the curry brackets are the *p-values*. *, ** and *** denote significance at the 1%. 5% and 10% levels.

Table 6 denotes both the linearity and nonlinearity tests of causality for the sentiments for the age group 45 years and above and the nine sectors. We observe some interesting results in this table, demonstrating that perceptions and sentiments of elderly consumers granger cause the returns of all nine sectors under examination. However, the reverse is not true. This is an insightful finding but is not surprising because the individuals in this age group arguably are more concerned about wealth. Otoo (1999) concludes that stock returns can increase consumer sentiments since the stock returns bring wealth which boosts consumer confidence in the economy. In addition, Otoo (1999) asserts that changes in wealth including the wealth from the stock markets are likely to affect sentiments less than changes in income because changes in wealth affect consumption much less than changes in income.

Table 4
Linear and Nonlinear causality: CSI – AGED 18 TO 24 and Sectoral Stocks Returns.

H0: non causality H1: causality	**Linear Causality Test**		**Non-Linear Causality Tests**		
Sectoral Stocks	Linear Granger	General Taylor-based	Semi-additive Taylor-based	P-General Taylor based	ANN-based
H0: CSI –Aged 18 to 24 does not cause sectoral stock returns					
Health Care	0.7271 [0.6033]	0.7116 [0.5843]	0.7105 [0.5851]	0.7271 [0.6033]	1.1763 [0.3083]
Financials	0.8179 [0.5372]	0.3598 [0.8372]	0.3596 [0.8373]	0.8179 [0.5372]	0.9967 [0.4419]
Real Estate	0.8962 [0.4832]	0.0937 [0.9844]	0.0914 [0.9851]	0.8962 [0.4832]	0.8354 [0.5837]
Consumer Disk	1.1195 [0.3488]	0.3248 [0.8614]	0.3140 [0.8686]	1.1195 [0.3488]	0.8654 [0.5563]
Consumer Staples	1.2600 [0.2798]	0.0285 [0.9984]	0.0290 [0.9984]	1.2600 [0.2798]	0.7606 [0.6531]
Industrials	1.0201 [0.4049]	0.2543 [0.9070]	0.2535 [0.9075]	1.0201 [0.4049]	0.9112 [0.5152]
Basic Materials	0.7162 [0.6115]	1.1505 [0.3322]	1.1291 [0.3421]	0.7162 [0.6115]	0.8229 [0.5952]
Energy	0.7966 [0.5524]	0.4942 [0.7400]	0.4875 [0.7449]	0.7966 [0.5524]	0.6592 [0.7459]
Utilities	0.6683 [0.6477]	0.4452 [0.7759]	0.4381 [0.7811]	0.6683 [0.6477]	0.7013 [0.7078]
H0: Sectoral stock returns do not cause CSI – Aged 18 to 24					
Health Care	2.0765 [0.0668]***	1.7441 [0.0970]***	0.1503 [0.9628]	2.0765 [0.0668]***	0.8017 [0.6149]
Financials	4.0015 [0.0014]*	7.0641 [0.0000]*	0.0832 [0.9948]	4.0015 [0.0014]*	0.5124 [0.8658]
Real Estate	2.3430 [0.0404]**	3.2360 [0.0014]*	0.1080 [0.9905]	2.3430 [0.0404]**	0.3637 [0.9518]
Consumer Disk	1.2514 [0.2837]	0.1507 [0.9798]	0.1434 [0.9819]	1.2514 [0.2837]	0.5421 [0.8438]
Consumer Staples	1.0572 [0.3832]	0.2640 [0.9326]	0.2741 [0.9272]	1.0572 [0.3832]	0.9197 [0.5077]
Industrials	2.5380 [0.0277]**	5.7848 [0.0000]*	0.1779 [0.9708]	2.5380 [0.0277]**	0.5850 [0.8096]
Basic Materials	2.7183 [0.0194]**	7.0490 [0.0000]*	0.2326 [0.9481]	2.7183 [0.0194]**	1.5429 [0.1304]
Energy	0.4928 [0.7817]	3.7805 [0.0000]*	0.0804 [0.9952]	0.4928 [0.7817]	0.9114 [0.5150]
Utilities	2.0040 [0.0765]***	1.8066 [0.0739]***	0.1708 [0.9733]	2.0040 [0.0765]***	1.2719 [0.2499]

Notes. This table presents linear and nonlinear granger causality test between CSI and sectoral stock returns. The figures in the curry brackets are the *p-values*. *, ** and *** denote significance at the 1%. 5% and 10% levels.

Table 5
Linear and Nonlinear causality: CSI – AGED 25 TO 44 and Sectoral Stocks Returns.

H0: non causality H1: causality	**Linear Causality Test**		**Non-Linear Causality Tests**		
Sectoral Stocks	Linear Granger	General Taylor-based	Semi-additive Taylor-based	P-General Taylor based	ANN-based
H0: CSI –Aged 25 to 44 does not cause sectoral stock returns					
Health Care	1.4797 [0.1946]	1.4226 [0.1847]	1.0214 [0.4189]	1.4797 [0.1946]	0.7968 [0.6194]
Financials	1.5046 [0.1865]	1.2585 [0.2518]	1.3653 [0.2097]	1.5046 [0.1865]	0.9351 [0.4941]
Real Estate	0.8927 [0.4856]	4.1548 [0.0000]	2.0939 [0.0352]	0.8927 [0.4856]	0.8588 [0.5623]
Consumer Disk	0.3028 [0.9112]	1.1448 [0.3359]	0.6950 [0.6961]	0.3028 [0.9112]	0.4737 [0.8923]
Consumer Staples	0.7554 [0.5823]	2.7673 [0.0179]	0.5459 [0.8218]	0.7554 [0.5823]	0.6986 [0.7103]
Industrials	2.6363 [0.0228]	2.4704 [0.0030]	1.8983 [0.0586]	2.6363 [0.0228]	1.7742 [0.0710]
Basic Materials	2.7654 [0.0177]	1.6872 [0.0736]	1.8308 [0.0696]	2.7654 [0.0177]	1.7920 [0.0677]
Energy	0.9193 [0.4679]	0.9375 [0.5039]	0.5885 [0.7875]	0.9193 [0.4679]	1.0333 [0.4122]
Utilities	0.4423 [0.8189]	2.9947 [0.0028]	0.4367 [0.8989]	0.4423 [0.8189]	0.2457 [0.9874]
H0: Sectoral stock returns do not cause CSI – Aged 25 to 44					
Health Care	1.3561 [0.2393]	0.1127 [0.9895]	0.0796 [0.9886]	1.3561 [0.2393]	0.9727 [0.4620]
Financials	0.7642 [0.5759]	0.2460 [0.9417]	0.1208 [0.9877]	0.7642 [0.5759]	0.2938 [0.9764]
Real Estate	1.8356 [0.1041]	0.2342 [0.9474]	0.2108 [0.9579]	1.8356 [0.1041]	1.0871 [0.3709]
Consumer Disk	1.5204 [0.1816]	0.0640 [0.9972]	0.0662 [0.9970]	1.5204 [0.1816]	0.6231 [0.7775]
Consumer Staples	1.3672 [0.2350]	0.2688 [0.9301]	0.3226 [0.8994]	1.3672 [0.2350]	0.9740 [0.4608]
Industrials	1.2856 [0.2685]	0.7420 [0.6364]	0.0894 [0.9939]	1.2856 [0.2685]	0.6429 [0.7603]
Basic Materials	0.4089 [0.8427]	0.0378 [0.9992]	0.0463 [0.9987]	0.4089 [0.8427]	0.5582 [0.8312]
Energy	1.1798 [0.3178]	0.2588 [0.9353]	0.1523 [0.9793]	1.1798 [0.3178]	1.0290 [0.4157]
Utilities	1.7857 [0.1139]	0.1134 [0.9894]	0.1768 [0.9712]	1.7857 [0.1139]	1.2381 [0.2696]

Notes. This table presents linear and nonlinear granger causality test between CSI and sectoral stock returns. Figures in curry brackets are *p-values*. *, ** and *** denote significance at the 1%. 5% and 10% levels.

5.2. Causality- in-quantile tests

Post to the establishment of the unstable nature of the causality parameters of the linear causality, as well as the existence of the non-linearity causality tests in the relationship between the Australian consumer sentiments and sectoral stock returns, we extend our analysis with the application of the unique causality-in-quantile methodology of Balcilar et al. (2016), deemed as robust to the aforesaid economic issues under examination.

Table 6
Linear and Nonlinear causality: CSI – AGED 45 and above Sectoral Stocks Returns.

H0: non causality H1: causality	**Linear Causality Test**		**Non-Linear Causality Tests**		
Sectoral Stocks	Linear Granger	General Taylor-based	Semi-additive Taylor-based	P-General Taylor based	ANN-based
H0: CSI –Aged 45 and above does not cause sectoral stock returns					
Health Care	1.3176 [0.2549]	1.8523 [0.0500]	1.1965 [0.2952]	1.3176 [0.2549]	0.7900 [0.6258]
Financials	2.7738 [0.0174]	1.4985 [0.1017]	2.2486 [0.0183]	2.7738 [0.0174]	2.1729 [0.0229]
Real Estate	2.6706 [0.0213]	5.0062 [0.0000]	3.6436 [0.0002]	2.6706 [0.0213]	1.6113 [0.1095]
Consumer Disk	1.0789 [0.3710]	0.9014 [0.5151]	1.3385 [0.2146]	1.0789 [0.3710]	0.7856 [0.6299]
Consumer Staples	2.3831 [0.0374]	2.3729 [0.0288]	1.0816 [0.3749]	2.3831 [0.0374]	1.4590 [0.1608]
Industrials	5.9822 [0.0000]	3.1884 [0.0000]	3.8198 [0.0001]	5.9822 [0.0000]	3.2952 [0.0007]
Basic Materials	1.3368 [0.2471]	1.3684 [0.1649]	0.9691 [0.4650]	1.3368 [0.2471]	0.7883 [0.6273]
Energy	1.0994 [0.3596]	2.0883 [0.0097]	0.7439 [0.6686]	1.0994 [0.3596]	1.2671 [0.2527]
Utilities	2.4757 [0.0312]	4.8017 [0.0000]	2.2522 [0.0181]	2.4757 [0.0312]	1.6965 [0.0875]
H0: Sectoral stock returns do not cause CSI – Aged 45 and above					
Health Care	0.4807 [0.7907]	0.1005 [0.9920]	0.0566 [0.9940]	0.4807 [0.7907]	0.6966 [0.7121]
Financials	1.1447 [0.3355]	0.1940 [0.9648]	0.1915 [0.9657]	0.1940 [0.9648]	0.6643 [0.7414]
Real Estate	1.3257 [0.2516]	0.3912 [0.8549]	0.4509 [0.8126]	1.3257 [0.2516]	1.5311 [0.1344]
Consumer Disk	1.4322 [0.2109]	0.0892 [0.9939]	0.0896 [0.9939]	1.4322 [0.2109]	0.5776 [0.8157]
Consumer Staples	1.8633 [0.0990]	0.1112 [0.9899]	0.1334 [0.9846]	1.8633 [0.0990]	0.9649 [0.4686]
Industrials	0.5210 [0.7605]	0.5704 [0.8023]	0.2629 [0.9332]	0.5704 [0.8023]	0.4655 [0.8976]
Basic Materials	0.1625 [0.9761]	0.1183 [0.9883]	0.1328 [0.9848]	0.1625 [0.9761]	0.3594 [0.9536]
Energy	0.7939 [0.5544]	0.2604 [0.9344]	0.2676 [0.9307]	0.2604 [0.9344]	0.4947 [0.8782]
Utilities	0.8817 [0.4930]	0.2626 [0.9333]	0.3465 [0.8845]	0.8817 [0.4930]	1.5009 [0.1450]

Notes. This table presents linear and nonlinear granger causality test between CSI and sectoral stock returns. Figures in the curry brackets are the *p-values*. *, ** and *** denote significance at the 1%. 5% and 10% level.

The causality-in-mean (denoted in blue) and the causality-in-variance (denoted in green) are predicted in a time-varying context. This is conditioned on the states of the markets represented by the corresponding quantiles found in the distribution of the dependent variable. Grounded on the distribution quantiles, the markets have been classified as normal (average market), bullish (good market) and bearish (bad market). These classifications correspond to the 50th (average), 90th (higher) and 10th (lower) quantiles, respectively. The quantiles are presented on the x-axis and the nonparametric causality test statistics are shown on the y-axis. The dark horizontal yellow line represents the 10% critical values, and the gray lines are representative of the 5% critical values. The center of the distribution focuses on the normal markets, whereas the lower and higher extreme quantiles show the bearish and bullish markets as indicated. The nature of the causality curve is indicative of the strength of the causality and the degree of the predictableness that exist between the sentiments and the sectoral stock returns across the quantiles which correspond to particular conditions of the market, be they bear, bull and normal market conditions. The finding replicates three varieties of asymmetry in causality. This is an affirmation of the choice of the methods, causality- in-quantile, over other existing and prior linear and non-linear models that are employed in the estimation of the average conditional causality. The hump-shaped curvature of the causality is indicative of a strong conditional causality at the average. Again, this shows that the strength of the causality fades or loses strength towards the extreme quantiles considered far away from the mean or the median. The inverted hump -shaped curve suggests evidence of causality with an altered degree at the quantiles distant from the average. The left tail (which shows a hump towards the right) and the right tail (showing a hump towards the left) are indicative of an asymmetric causality, which the causalities of linearity and non-linearity do not capture.

5.2.1. Relationship between consumer sentiments and the health care sector stock returns

The results of the causality-in-quantile between the aggregate/overall and disaggregate components of the consumer sentiments index in Australia and the health care sector's market returns are presented in Fig. 1. These results show a clear difference between the quantile causality in the mean and the variance analyses. The causality-in-mean is bidirectional with its presence seen only in the normal market conditions. This suggests a presence of a sturdy predictability around only the normal market condition. Issue of no causation in the bearish and bullish market conditions implies a failure of consumer sentiments to lead the stock returns of the health care sector. Hence, for policy decisions in terms of investments and also risk management, the quantile causality bears or provides more information in different market circumstances. Thus, this finding upholds that the sentiments are proficient predictors of the health care sector stock price as applied in the asset pricing model around the normal market condition.

The causality-in-variance is also bidirectional around the conditions pertaining to a normal market. The no causation in the bear market and bull market suggests the inability of the sentiments in playing their economic roles as a transmission of risk and an effective predictor of the health care sector's returns in the bad and good conditions of the market. The causality-in-variance running from aggregate sentiments to the health care sector returns is indicative of a transfer of risk from sentiments to the health care sector market in the normal market condition. This suggests that sentiments lead the health care sector in the issue of the efficiency in information and the discovery of price in the condition of the market deemed as normal but not in the bearish and bullish market conditions. The reverse is also true, running from the health care sector to the overall sentiments in the normal market condition.

Concerning the causation between the sentiments of rural Australia and the sectoral returns, we observe that the bidirectional results spilling over from the causality-in-mean and the causality-in -variance are similar to the findings we observed concerning the overall CSI Australia and the health care sector returns. Thus, in the normal market condition, the sentiments of consumers dwelling in the rural Australia impact the price levels of the health care sector but with no evidence of causation around the good and bad market conditions. Thus, the causality is not asymmetric, and that the potency of this causality is strong only in the normal condition of the market, something the linear and nonlinear causality tests fail to account for.

The causation is bidirectional both the in mean and the in variance running from the sentiments of age group 18 to 24 to the healthcare sector. There are no causality- in variance in the lower and upper quantiles from the sentiments of consumers within the age group of 18–24 to the health care sector indicates that sentiments of this age group is inefficient in information in a bad market and a good market. Regarding the causality between the sentiments for the age group 25 to 44, we observe a similar outcome just like in the case of the relationship between the sentiments of age group 18–24 and the health care sector returns. However, for the causation between the sentiments of age group 45 and above, we find a bidirectional causation for the causality- in- mean running from the bad market to the normal market, while for the causality-in-variance, we observe a unidirectional relationship from the bearish market to the normal market conditions for sentiments to the health care sector.

Overall, the findings align with the asset pricing theory that the sentiment is a systemic risk and an efficient predictor of the stock returns in this case which is the health care sector. The observed causality seen in both the mean and variance in the normal market condition supports the adoption and the usage of the non-parametric causality in quantile models instead of the linear and nonlinear granger causality tests.

5.2.2. Relationship between consumer sentiments and the financial sector stock returns

Fig. 2 presents the quantile causality between sentiments and the financial sector returns. We document some interesting findings. For the case of the overall CSI and financial sector returns, we note the causality-in-mean is bidirectional which occurs only in the bearish to normal markets, but with no causation in the market conditions seen as bullish. The causality-in-variance is also bidirectional and left tailed, and the shaped (humped towards the right) causality-in-variance curvature indicates that the causality is not symmetric, implying that there exists a near accurate predictability around the normal conditions of the market and that the strength dwindles as we move towards the bullish market condition. The implication drawn is that the efficiency of information about the aggregate consumer sentiments in leading the financial sector markets falls in the extreme bullish condition.

Focusing on the causation between the rural Australia sentiments and the financial sector stock returns, the findings show a one-directional causality running from CSI rural Australia to the financial sector around the bearish market to the normal market conditions. However, for the reverse causality, we find no evidence of causation exists under all the market conditions for both the causality-in-mean and in-variance. This connotes that variations in the financial sector's stock prices do not impact the sentiments of consumers in rural Australia. This result is surprising since spillover effects from the financial sector impact the overall broader economy (Otoo, 1999). Another possible reason for this results is that economic agents in rural Australia may not be exposed to too much media coverage of the traumatic financial events/news in the financial sector and as result their feelings are not impacted by what pertains to the financial sector. We make this claim because Collimore et al. (2008) suggest that the exposure to media reportage on sensitive matters generates increasing levels of anxiety. Arguably, residents in rural Australia are likely not to be active users of Twitter and other social media platforms to access adequate information concerning financial markets.

As evidenced in Fig. 2, a unidirectional causality-in-mean is seen from the financial sector returns to the sentiments of individuals within the age group of 18–24, which runs from the normal market condition to the extreme bullish market situation. In the case of the causality-in-variance, there exists a significant causation from sentiments to the financial sector returns during the normal to bullish market conditions. However, for the reverse causality-in-variance, there exists a causation at the lower quantiles. Thus, we find a transfer of risk from the financial sector to consumers within the aged bracket of 18–24 years. From the CSI aged 25–44 to the financial sector stock returns, the causality-in-mean reveals a unidirectional causality during the normal market condition from the financial sector to the sentiments of individuals aged between 25 and 44 years.

In the case of the causality-in-variance, there exists a causality from sentiments to the financial sector. However, the reverse is untrue. Unlike the results obtained from the linear and nonlinear results reported earlier, there is no causation in the causality-in-mean running from CSI aged 45 years and above, and the causality-in-variance from the financial sector to the sentiments of the aged group 45 years and above. However, we document a one-way directional causality-in- variance running from the financial sector to the sentiments of this aged group. This suggests that there is a transfer of risk from the financial sector to the individuals within the age bracket of 45 years and above. This finding differs from what we recorded by using the linear and nonlinear causality models, which supports the superiority of the quantile-in-causality test.

Consistent with the existing literature, an increase in individual sentiments impacts the financial industry returns and volatility (Brown and Cliff, 2004; Verma et al., 2008; Calafiore, 2010). Overall, in the financial sector we note that the impacts of sentiments of consumers on this sector and vice versa differing in different quantiles. Thus, investors can rely on our findings in their portfolio strategy formation since we observe strong predictability under the normal market condition and to some extent during the bearish market condition.

5.2.3. Relationship between consumer sentiments and real estate sector returns

The causality dynamics between sentiments and real estate sector returns are reported in Fig. 3. For the causation running from the overall sentiment index and the real estate sector, the causality-in-mean is unidirectional and runs from the normal to the bullish market conditions. The stock price variations in the real estate sector are intense; hence, it is not surprising that we find no causation during the bearish market conditions, which also holds for the reverse causality. One would have expected the reverse causality running from the real estate price variation to influence the sentiments of consumers. However, that is not the case for the Australian market.

Regarding the causality-in-variance analysis, we find evidence of a bidirectional causation during the normal market conditions. This is in alignment with the existing studies which argue that risk transfer from the real estate sector impacts household consumption. This further shows that the effects of price pressure (noise traders' pressure on the stock prices

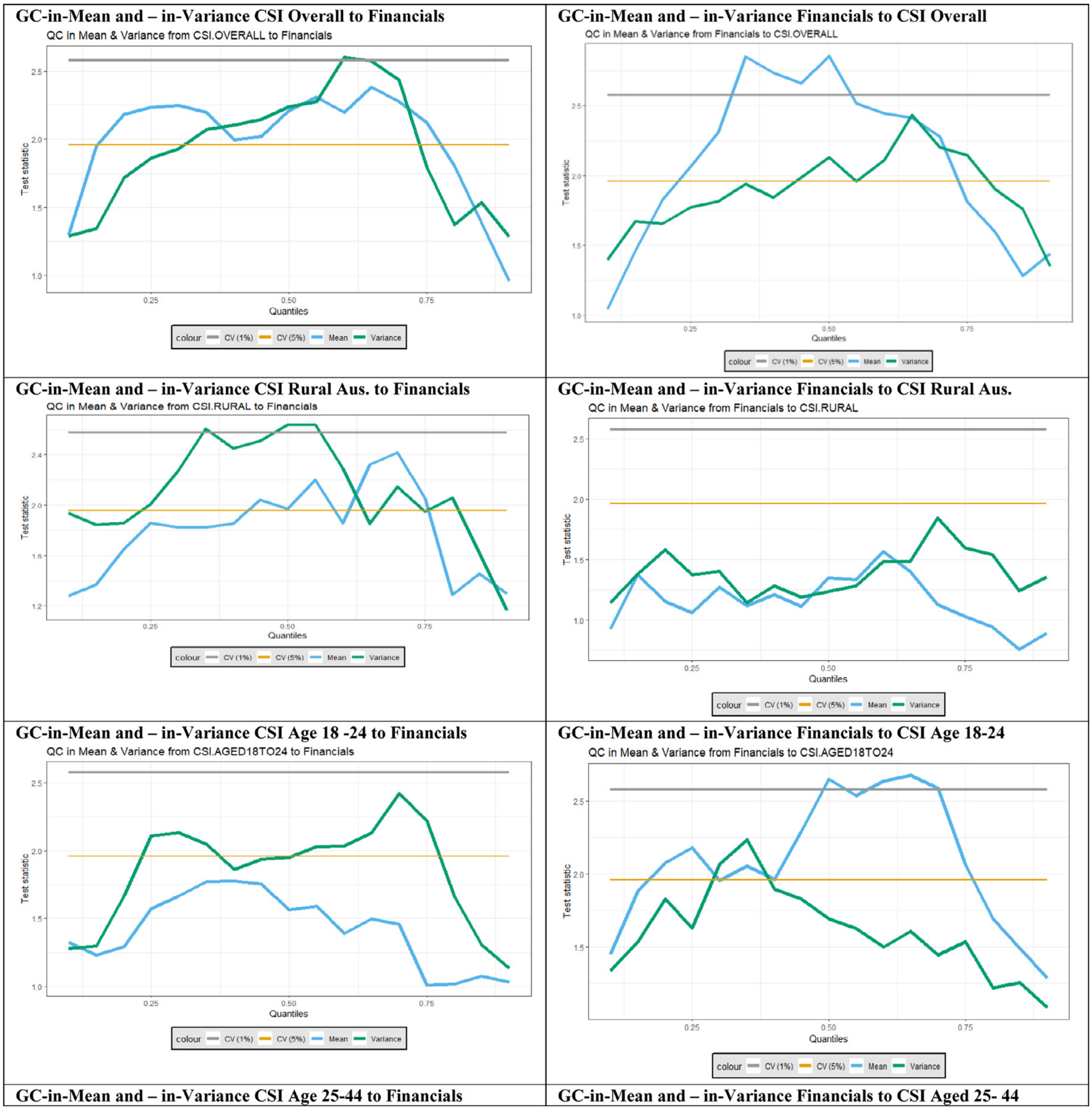

Fig. 2. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Financial Sector market returns. *Notes*: The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

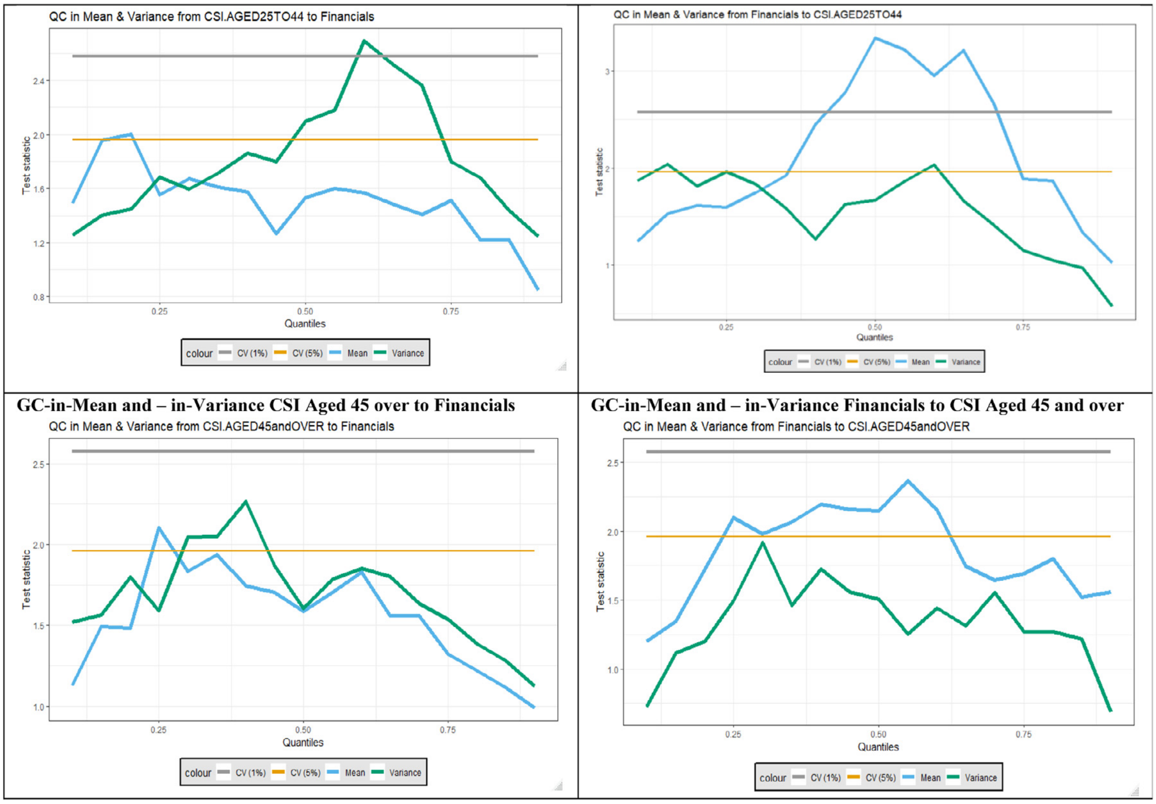

Fig. 2. Continued

reduces the expected return) don't dominate the markets and that noise traders don't benefit from the market during the extreme market conditions where sentiments are high (Haritha & Rashid, 2020).

Focusing on the causation between disaggregate measures of sentiments and the real estate sector, we find a bidirectional causation for the causality-in-mean as well as the causality-in-variance running from the rural Australia sentiment to the real estate sector during the bearish to normal and bullish market conditions. However, the extent of predictability declines during the good and bad markets conditions. Next, we find that there exists a unidirectional causation in the causality-in-mean for the case of the real estate stock returns to the sentiments of individuals within the age group of 18–24 years, running from the normal to bullish market conditions. However, there is no causation under all market conditions for the causality running from the sentiments of aged group 18–24 years and the real estate sector returns.

For the causality-in-variance from the sentiments of aged group 18–24 years to the real estate sector, the results show the sentiments lead the returns during the normal market conditions. However, once the noise traders start making profits, their expectations on the return and risk will increase. Thus, it may not create a reverse causality because of the information inefficiency which is exactly what we have recorded since the reverse causality is not true for the causality-in-variance analysis. In the case of causation between the sentiments from age group 25–44 and the real estate sector returns, we underscore the existence of a unidirectional causality-in-variance under all market conditions and a directional causality-in-mean during the normal market conditions. The absence of causality- in-variance in the bear market implies an inability of the sentiments in serving its economic role as a fair (transfer of risk) and efficient predictor (efficiency in informational needs) of the real estate stock prices in an unfavorable market condition. We obtain similar findings for the aged group 45 and above and the real estate sector. Similarly, to what we obtained using the linear and nonlinear causality tests, this age group seems to have a dominant impact on the several sectoral stocks since we again have not had a significant causation-in-variance under all market conditions. In brief, the real estate sector is impacted significantly by noise traders under the normal market conditions with a significant reduction in the transfer of risk from the real estate sector to the sentiments in the lower and upper quantiles.

5.2.4. Relationship between consumer sentiments and the sector for consumer discretion

The sector for consumer discretion involves businesses that trade nonessential products and services which consumers may avoid short of any major consequences to their well-being. The sector comprises numerous companies operating in a number of industries which include retail, restaurants, media, consumer durables and apparel. We present the results of the causality-in-quantile between the various components of the consumer sentiments index in Australia and the consumer discretionary returns in Fig. 4. First, we find a causality-in-mean only exists around the extreme market conditions from the overall CSI to consumer discretionary sector, while for the causality-in-variance, the causality exists only in the normal market condition. Thus, during the extreme market conditions, consumers react to the prevailing factors in the sector. The demand for goods based on for consumer discretion is typically much more responsive to demand factors in comparison to the demand for consumer staple goods. The elasticity of demand implies that the demand for such goods can plummet very quickly in response to falls in consumers' incomes or rises in prices of consumer discretionary goods. For instance, during the COVID 19 pandemic lockdown, the decline in income of consumers due to the loss of jobs among other factors affected the returns of firms within the sector. Hence, it is not surprising that we find evidence of a strong predictability only in the normal market condition.

For the relationship between the components of the aggregate sentiment index and the consumer discretionary sector, we note a unidirectional causality both in the mean and the variance from the CSI rural Australia to the consumer discretionary sector under all market conditions. There exist no causality-in-mean and in-variance for the sentiments from the age groups 18–24 and 25–44 to the consumer discretionary sector during the extreme market conditions, which is not surprising. Interestingly, the causality-in-mean and in-variance from the sentiments of the age group 45 and above to the

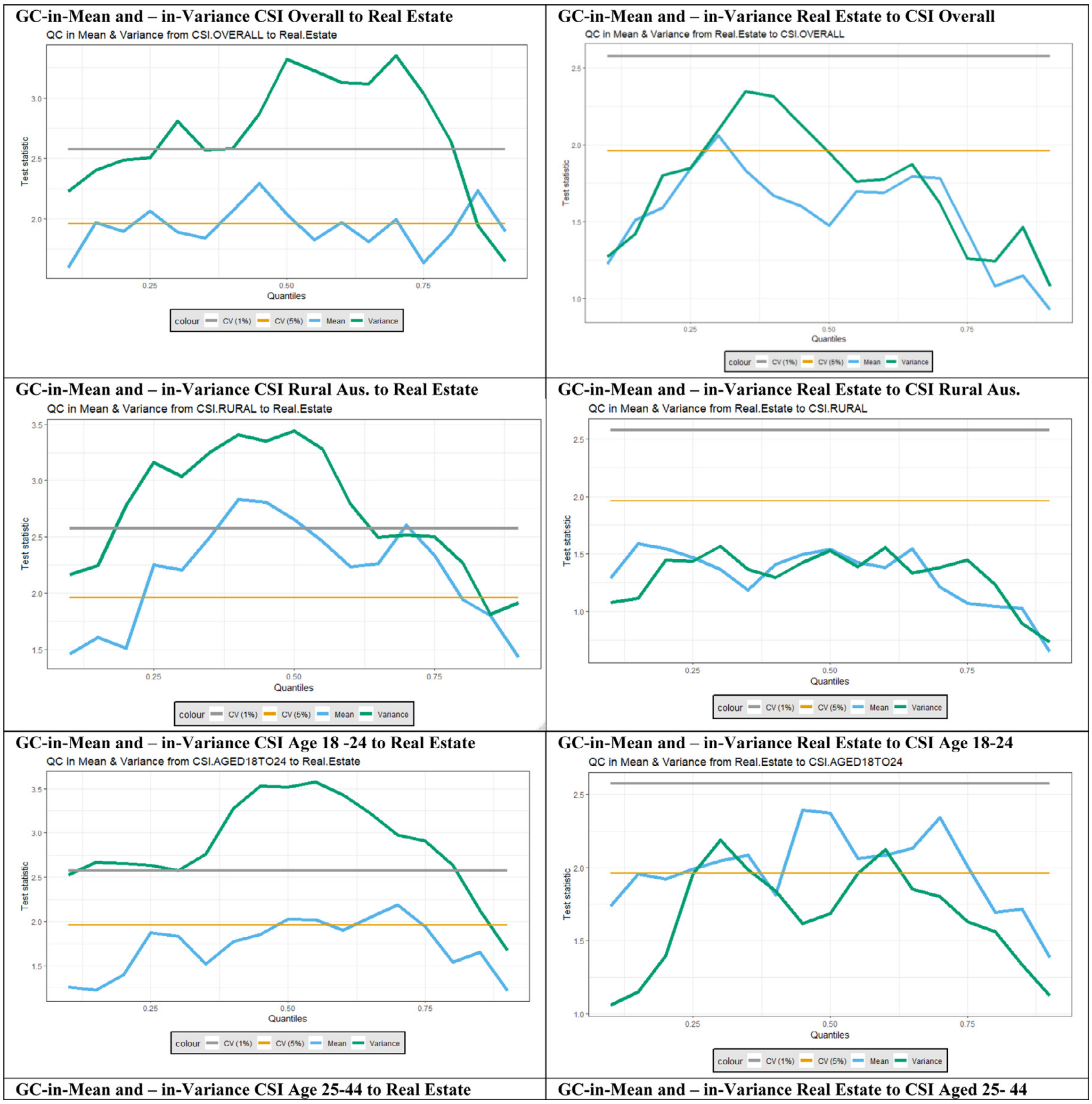

Fig. 3. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Real Estate Sector market returns. *Notes*: The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

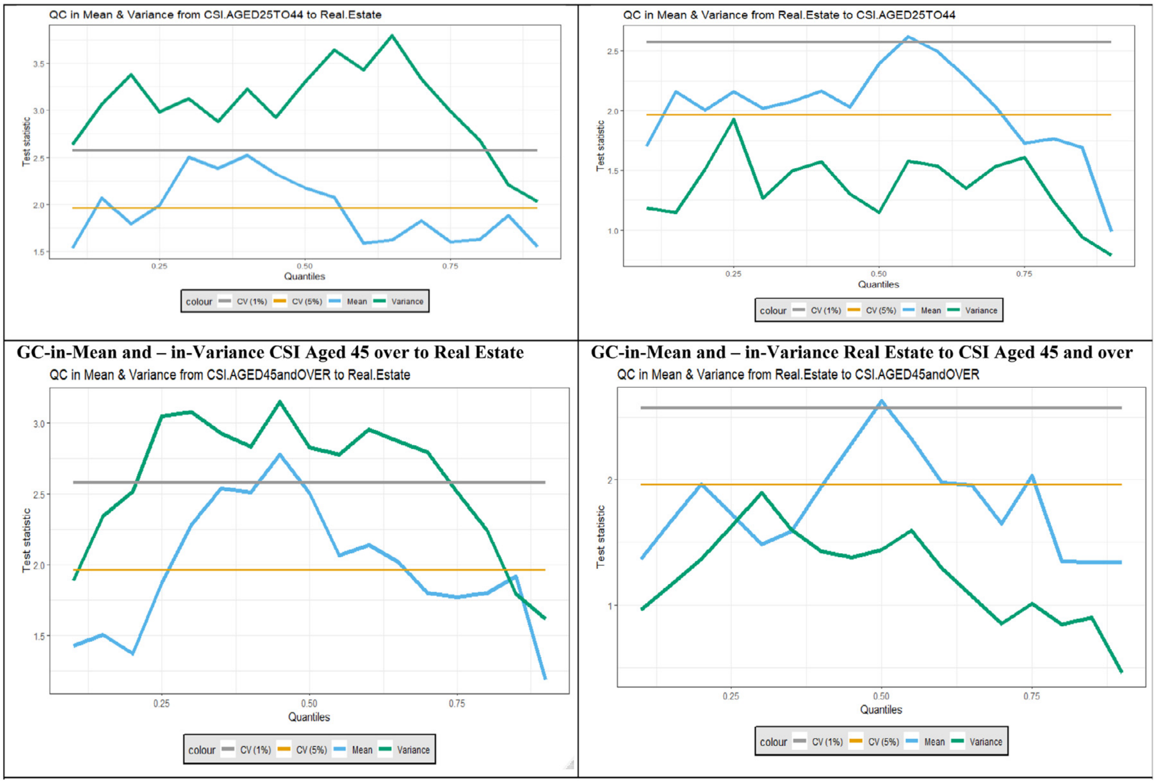

Fig. 3. Continued

consumer discretionary sector is bidirectional for the causality -in-mean with asymmetric features. This signals the existence or presence of a robust predictability around the normal market settings and the strength falls as we approach the extreme quantiles, that is, the 90th and 10th quantiles, which correspond to the bullish markets and bearish markets, respectively.

5.2.5. Relationship between consumer sentiments and the consumer staples sector

Consumer staples are deemed as essential products that consist of typical products such as foods & beverage, household goods, and hygiene commodities. Nevertheless, this category also includes items such as alcohol and tobacco. The staple nature of these goods implies that people are unable or unwilling to cut out of their budgets, regardless of their financial situations. From Fig. 5, we observe a bidirectional causation from the overall sentiments to the consumer staples sector both in the mean and in the variance from the bearish to the normal market conditions. Thus, during the bearish market condition, sentiments of consumers increase until the market conditions stabilize. However, when the conditions are good in the market, we find no transfer of risk from the causality -in-variance analysis. For the causation between disaggregate measures of sentiments and consumer staples both in mean and in variance under the various market conditions, we observe the causation varies depending on the prevailing market condition. It is noteworthy to mention that there exists a significant bidirectional causality under the bearish and normal market conditions for the various categories.

5.2.6. Relationship between consumer sentiments and the industrial sector

We show the results of the causality-in-quantile between the aggregate/overall and the disaggregate measures of the consumer sentiments index in Australia and the industrial sector market returns in Fig. 6. This sector is one of the key sectors that form the economy, and economists are of the opinion that this sector creates wealth unlike the service sector. We argue that the relationship between sentiments and the stock returns in the industrial sector will exist under all market conditions, following the significant role this sector plays in the overall economy. For the causation between the overall sentiments and the industrial sector, the causality- in-mean is bidirectional and runs from the bearish market to the normal market conditions, although the predictability is strong around normal market conditions. There is no causation during bullish market conditions which suggests that consumers in Australia only react when conditions are bad in the industrial sector. This is not surprising because in cases where there is a shortage in a particular product that is essential, one would expect consumer sentiments to increase.

Regarding the causality in the variance analysis, we observe a unidirectional causation from the industrial stock returns to consumers sentiments under all market conditions. Interestingly, this result is in alignment with the notion that the industrial sector creates wealth; hence, the variations in the stock prices of this sector affect the feelings of consumers and

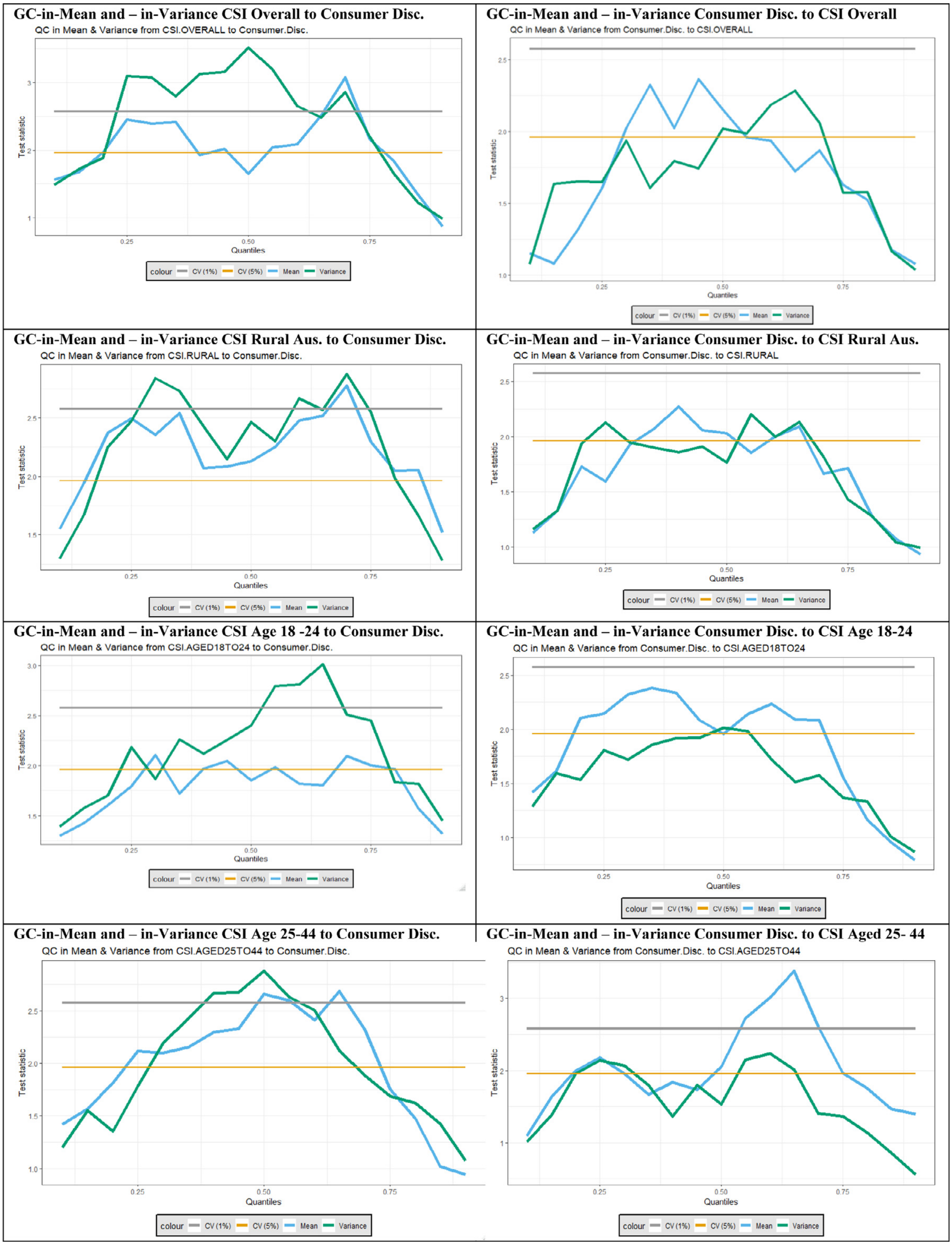

Fig. 4. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Consumer Disk. Sector market returns. Notes. The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

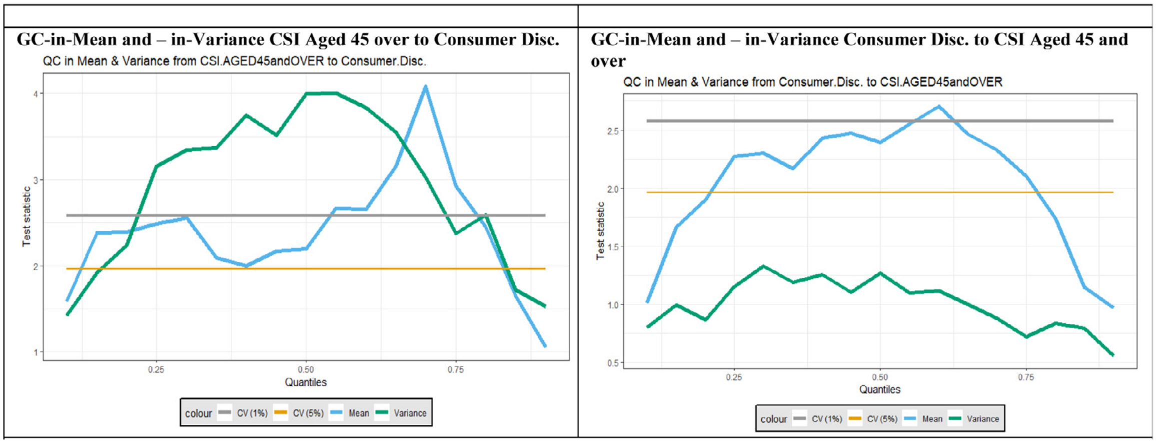

Fig. 4. Continued

noise traders. From the causality-in-mean analysis, sentiments of consumers dwelling in the rural Australia are also seen to be a strong predictor of returns in the industrial sector all through the bearish and normal market conditions, which is not surprising following the significance of this sector in the broader economy.

Comparing the causation between the sentiments of individuals within the age groups of 18–24; 25–44, and 45 and above and the industrial stock returns, the result is interesting. For the age 18–24, the causality-in-mean is unidirectional only during market conditions seen as normal, while the reverse does not hold. Interestingly, for the adult group aged between 24 and 44, the relationship is bidirectional from the causality-in-mean analysis which is not news since the consumers in this bracket are more concerned about making wealth, and as a result, they closely follow this sector in the bearish and normal market conditions. We document similar findings for the consumers within the age group of 45 and above. In addition, for the three age groups under examination, the causality-in-variance analysis shows that sentiments fail to act in its economic role as an unbiased and an efficient estimator of the industrial sector stock returns under the bearish and bullish market conditions.

5.2.7. Relationship between consumer sentiments and the basic materials sector

The basic materials sector comprises companies involved in the discovery, extraction, and the processing of raw materials. The basic materials market is based on the products that make use of such materials. The sub-sectors found within the market for the basic materials include chemicals, metals and mining, and forestry. This causality-in-quality result reported in Fig. 7 for this sector shows that there exists no causality between the overall sentiments of consumers in Australia and this sector from the causality-in-mean point of view. This result is not surprising since the sector is not regarded as a significant sector in the broader financial economy. We find the same results hold for the causation between the disaggregate measures of sentiments and the basic material under all market conditions.

For the causality-in-variance, we find some level of a bidirectional causation from the normal to bull market conditions running from the overall sentiments and CSI Aged 18–24 to the basic material sector. One can argue that a variation in the stock prices or activities of firms in this sector is not of great concern to consumers since the firms in this sector, such as BHP among others, are very strong firms and can bounce back to the normal times even after intense fluctuations.

5.2.8. Relationship between consumer sentiments and the energy sector

The causality dynamics between the sentiments and the energy sector returns are reported in Fig. 8. For the causation running between the overall sentiment index and the energy sector, one finds that the causality-in-mean is bidirectional and emanates from the bearish to normal to bullish market conditions, although the strength of predictability declines during the extreme market conditions that are in the 10th and 90th quantiles. The causality-in-variance analysis is unidirectional running from the energy sector to the overall sentiments under all markets conditions, except at the extreme quantiles. The energy sector is a key contributor to the growth in the broader economy. As a result, it is not surprising that volatility spillovers from the sector predict the sentiments of consumers. Focusing on the causation between the disaggregate measures of sentiments and the energy sector, we find a unidirectional causality for both the causality-in-mean and in-variance running from the stock price fluctuations in the energy sector to the rural Australia sentiment levels during the normal market condition.

Next, we find there exists no causation in the causality-in-mean and for the mean for the case of energy stock returns to the sentiments of individuals within the age group of 18–24. We however find the opposite results for the causation between age groups 25–44 and 45 and above and the energy sector. This is to say that the adult consumers in Australia are concerned about the variations in the activities of the firms in the energy sector, which impacts their feelings and emotions. The perceptions and sentiments of the young adults of consumers of ages18–24 seemed not to be impacted by the energy

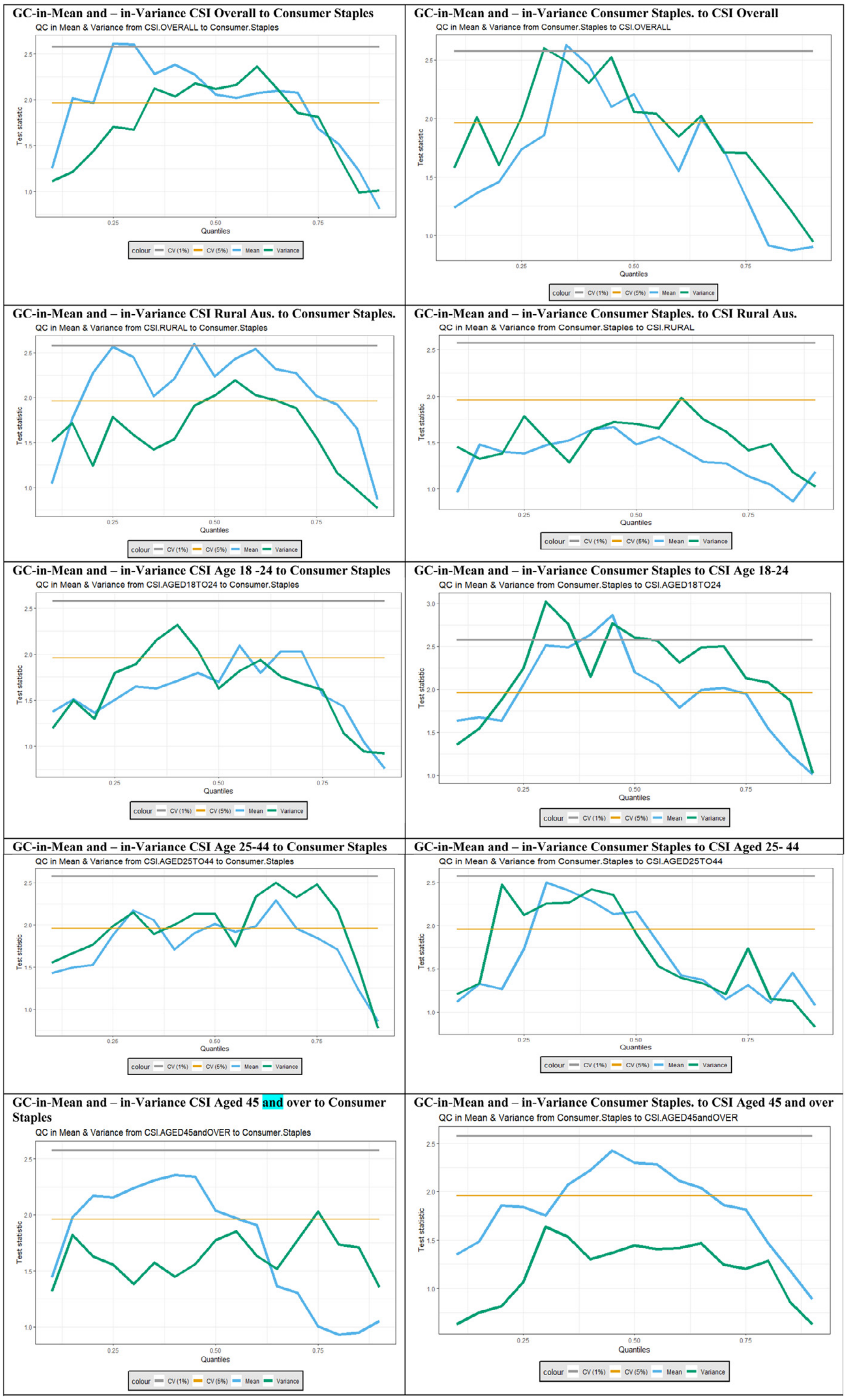

Fig. 5. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Consumer Staples Sector market returns. *Notes*: The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

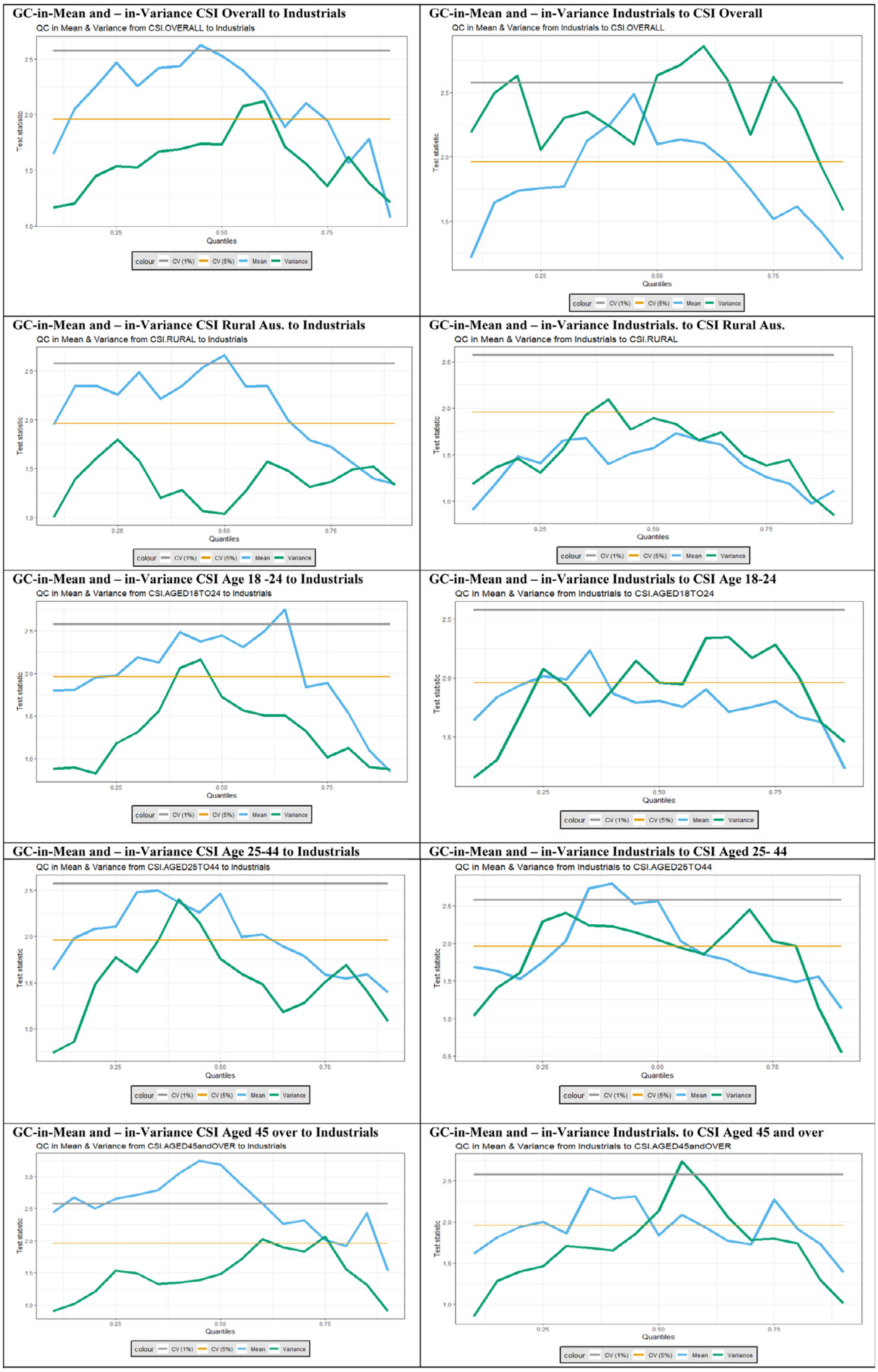

Fig. 6. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Industrials Sector market returns.
Notes. The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

sector under all market conditions. Thus, for policy decision- making regarding investment and the management of risk, the quantile causality bears more information during varied conditions of the market since it is evident that the sentiments of the adult workforce which includes noise traders in Australia are influenced by the energy sector's activities.

5.2.9. Relationship between consumer sentiments and the utility sector

The utilities sector represents a class of companies that provide basic services and essentials, such as water, electricity, sewage services, dams, and natural gas. Investors typically treat the sector for utilities as long-term holdings and use them to generate steady income flows for their portfolios. The results of the causality-in-quantile between the consumer sentiments in Australia and the utilities stock returns are presented in Fig. 9. Regarding the overall CSI and the stock returns in the utilities sector, we find the causality-in-mean and in-variance are bidirectional across the normal states of the markets and the extreme states. The hump-shaped causality- in -mean curvature indicates that the causality is not symmetric. This implies the presence of a strong predictive power around the conditions of a normal market. However, the predictive

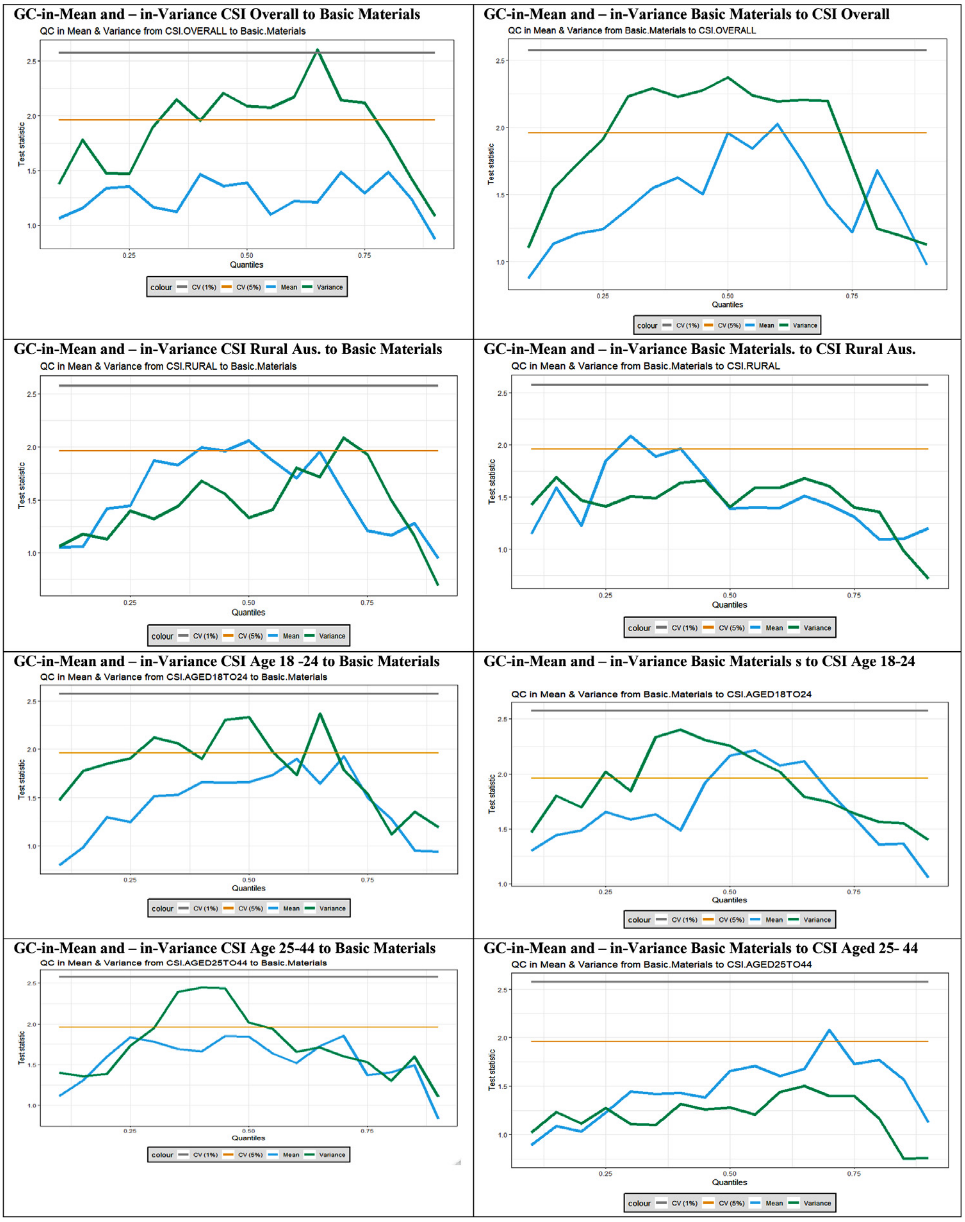

Fig. 7. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Basic Materials Sector market returns.
Notes. The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

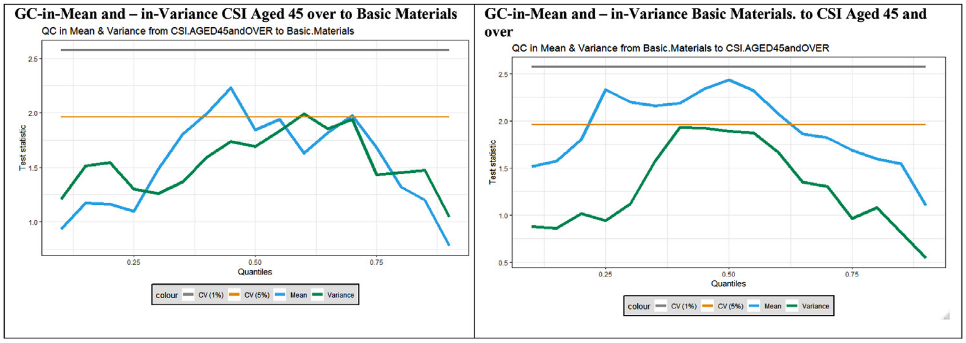

Fig. 7. Continued

strength declines in the approach towards the extreme quantiles, i.e. the 90th and 10th quantiles, respectively, corresponding to the bull and bear markets. This result demonstrates that the role of information efficiency of consumers in the lead of the utilities market dwindles in the extreme bearish and bullish market conditions.

For the aggregate measures of sentiments and the utilities sector, we document several findings. For example, we find evidence of a causation during the normal market conditions for most cases. Fluctuations in the utilities sector in all the market states don't affect the sentiments of the consumers in rural Australia and those within the age bracket of 25–44 and 45 above. No causation also exists between the sentiments of consumers within the age brackets of 18–24 and utilities sector. However, we find a causation running from sentiments of consumers who are within the age of 24–44 and 45 years and above and the utilities sector during the normal markets condition. Since individuals hold the defensive utility stocks for long term purposes, they fail to react even in the extreme market conditions. Our finding that a shock to the Australian consumer sentiments causes substantial or significant changes in returns and volatility of the Australian utility stocks is inconsistent with the findings of Sayim et al. (2013) with regards the effects of sentiments on the US utility stocks.

Overall, considering the sectoral level, this study finds that the energy, financials, industrials, consumer stables sectors are vastly influenced by movements in the sentiments. These sectors can be seen as more idiosyncratic in the valuation. The empirical evidence supports the theory of behavioral finance that sentiments play a vital role in stock pricing. Consumer sentiments seem to lack a predictive power of the subsequent aggregate and most of the sector returns across the bearish and bullish markets states. This result is indicative that any trading strategy set to take advantage of public sentiments needs to be exercised with caution, as the market tends to be informationally efficient during such market conditions.

5.3. Discussion

From the results presented so far, we observe that differences exist in the various age groups' sentiments and industry stock returns, which is consistent with the findings of Johnson and Naka (2014) in the case of the U.S. markets. The results suggest that younger consumers tend to be more optimistic than older generations, which is in agreement with the life cycle investment hypothesis. A possible explanation from the behavioral standpoint would be that younger consumers have more years of their life to participate in the labor force and earn money, subsequently are more hopeful in the current and future savings and consumption, while older consumers have less years to participate in the labor force. Ando and Modigliani (1963) and Johnson and Naka (2014) find that younger consumers have higher propensity to consume, compared to middle and older consumers. In addition, older consumers with children may reduce consumption as their children enter adulthood. With respect to how sentiments of different aged groups predict stock volatility, we observe findings that are similar to what we obtained in the case of the mean returns. We establish that sentiments of different age groups impact industry stocks, which is similar to the findings of Akhtar et al. (2011), Baker and Wurgler (2006), Lemmnon and Portniaguina (2006) among others who established that sentiments affect firms of various sizes and industry differently.

One of the interesting findings we observed has to with the predictive power of sentiments of older consumers on stock returns and volatility. Johnson and Naka (2014) note that older individuals are less likely to have a significant stock market exposure because of their near-term focus on retirement and inclination to possibly hold a larger portion of fixed income securities. However, that is not the case in this paper. For example, we find a causation running from the sentiments of consumers who are 45 years and above and the utilities sector during the normal market condition. A possible factor that may have caused the change could be the older generation's exposure to social media. We make this claim because according to Siganos et al. (2014), Facebook is no longer the exclusive domain of younger people. Kramer and Chung (2011) find that the average age of Facebook users is about 31 years with more than a quarter of Facebook users being older than 45 years. Since the media coverage escalates the level of gloomy attitudes towards investment decisions according to Brigida and Pratt (2017), we hold the view that the older generations in Australia are well informed about market conditions than before.

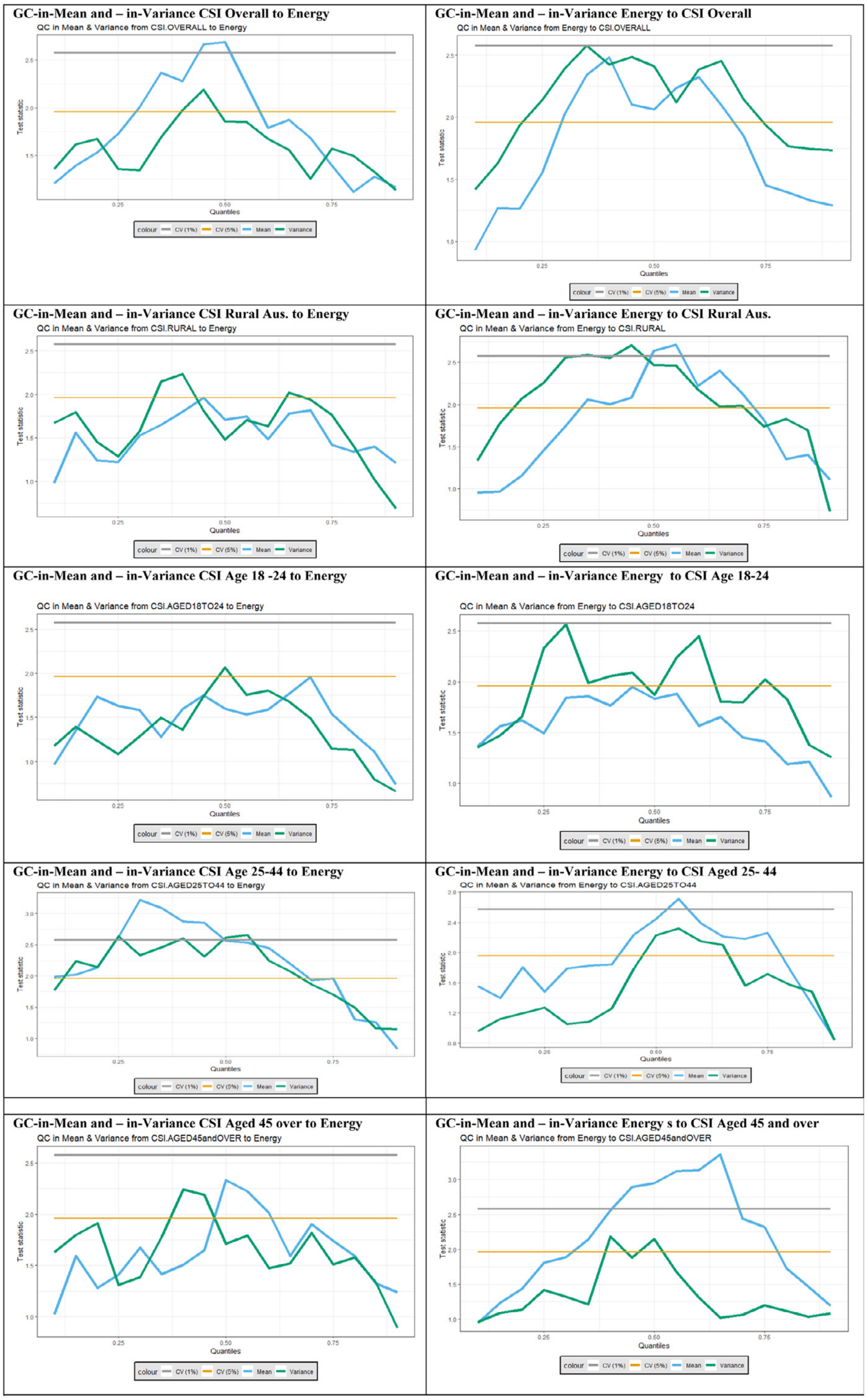

Fig. 8. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Energy Sector market returns. Notes. The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

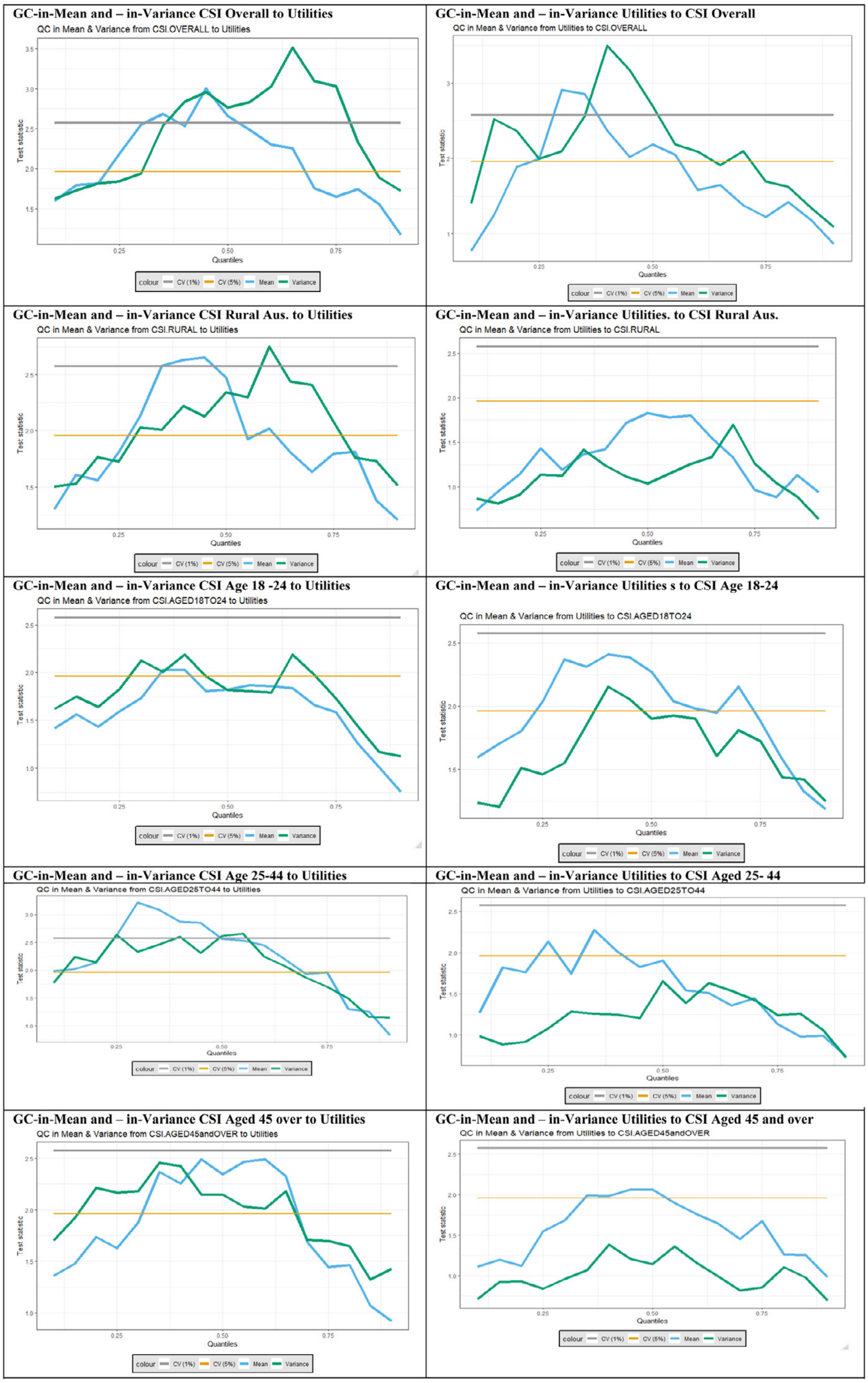

Fig. 9. Causality-in-quantile between Components of Consumer Sentiments Index Australia and Utilities Sector market returns. *Notes*: The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and gray lines represent the 10% and 5% critical values, respectively.

Furthermore, a strand of studies finds a direct relationship between false news and financial markets. Fake news about markets is becoming an issue to many economists. Clarke et al. (2020) find that the equity price reaction to false news is discounted when compared to the authentic news articles. Hence, we argue that consumers' feelings and sentiments in Australia could be impacted by fake news that flows through the media. However, its effect will be dependent on the age of consumers since younger consumers are likely to ignore fake news than older generation. This is because younger generation are more concerned about increasing wealth and as a result may have a strong desire to take more risk compared to older generations.

From the psychological standpoint, news of traumatic events significantly increases consumer's levels of fear and anxiety. Thus, fear and panic are seen as an indirect channel through which media coverage impacts investors' feelings since fear and panic are associated with perceived risk among the market participants. Some studies suggest that people are more prone to being risk averse, the more they perceive about an event (Hanoch, 2002). We can relate this argument to our findings on the differences in sentiments of different age groups and how they impact stock returns since economic decisions of consumers can be impacted by fear and anger among other factors (Lerner et al., 2004).

Another possible explanation for our results could be attributed to the effect of exogeneous factors that can influence the feelings of consumers and their economic decisions. This explanation emanates from the fact that the empirical evidence proves that economic agents and markets are susceptible to exogenous anthropogenic, natural and/or political events (Kaplanski and Levy, 2010; Pástor and Veronesi, 2013). As a case in point, it has been shown that circumstances such as electoral evets, civil unrests, changes in government political regimes, terrorism, geopolitical frictions and tensions, could not directly affect only economic performance and asset markets, but also the cross correlations of the assets, investor sentiments, portfolio allocation and diversification decisions as well (Asteriou and Siriopoulos, 2003; Antonakakis et al., 2017; Drakos and Kallandranis, 2015; Omar et al., 2016).

6. Conclusion

In this paper, we use nonparametric quantile-in-causality tests to examine the relationship between aggregate consumer sentiments and sectoral stock returns in Australia to ascertain the impact of the perceptions of economic agents on stock returns. We obtain monthly indices of Australia's Overall Consumer Sentiments index and the components of this overall index which include CSI Rural Australia, CSI Aged 18–24; CSI – Aged 25 to 44 and CSI – Aged 45 and above, which were obtained from Datastream for the period of October 1974 to October 2020. For our measures of sectoral stock returns, we consider the following nine sectors: Basic Materials, Consumer Discretionary, Consumer Staples, Energy, Financial, Health Care, Industrials, Real Estate, and Utilities.

The findings from the nonlinear causality test reveal the existence of a directional causality between the Overall CSI and the Health Care, Financial sectors; and that the CSI Rural Australia granger causes the Energy, Utilities and Basic Materials sectors. Moreover, the Health Care, Financial, Real Estate, Industrials, and Energy and Utilities sectors impact the perception of consumers in Australia within the age brackets of 18–24. There is also a bidirectional relationship between CSI Aged 25–44 and the Real Estate, Industrials Basic Materials and Utilities sectors, and a causality between CSI for the age group 45 and above and the nine sectors. The results also show the causality-in-return is asymmetric and unidirectional running from consumer sentiments to the sectoral stock returns in some cases, which suggests that the predictability of the sectoral stock returns is robust in the normal market but declines when the consumers' perception is located in the extreme conditions in the bearish and bullish markets. The causality- in -variance is bi-directional and unidirectional in the normal to bull markets, running from consumer sentiments to stock returns and vice versa.

Our study has a number of implications. First, the varied impacts of consumer sentiments on the expected industry returns need to be carefully analyzed by international analysts and investors because the sectors are different and exhibit different features. Second, investors and entrepreneurial firms should consider sentiments as being interdependent with the industry returns in the evaluation of the timing of sector rotations and investments in order to sidestep complications associated with either underinvestment or overinvestment. Third, the study provides practical evidence of the prospect theory from the asymmetric stock return effects of sentiments from the industry perspective. Fourth, the empirical findings endorse the importance of considering different market conditions from the statistical and economical perspectives on the interrelations between sentiments and industry returns. Finally, policy makers and regulatory agents, in the quest to stabilize equity markets and reduce volatility, should be mindful of the different features of sentiments for a specific industry followed by the potential for irrational exuberance. Regarding the implications for the different age brackets, fund managers and analysts can depend on our findings to assist clients in their portfolio formulation strategies, taking into account the ages of those clients since the reactions of consumers to industry stock returns differ across the age groups.

For future research, we only proffer first insights about the effects of public sentiments on equity markets. We suggest that further research be carried out to extend the analysis by exploring how sentiments could impact other markets such as the bond, commodity and exchange rate markets, using the methodology used in our paper. Additionally, we suggest that further studies could be carried out to examine the effects of liquidity variations, economic policy uncertainty and geopolitical risk since these factors can directly impact the sentiments and the behavior of economic agents about equity markets etc.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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