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The impact of Twitter-based sentiment on US sectoral returns

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ABSTRACT

This paper scrutinizes the effect of Twitter-based sentiment on US sectoral returns using data from between 21 June 2010 and 13 April 2020. We apply causality in quantiles as a non-parametric measure, followed by a rolling window wavelet correlation. The former measures the manifestation of causality directed from Twitter-based sentiment towards US sectoral returns, whereas the latter measures the correlation of returns across decomposed series that correspond to different time horizons. Our results highlight symmetric changes in US sectoral returns that vary across different sectors. The healthcare, communications, materials, consumer discretionary, energy, staples, and information technology sectors are more sensitive to changes in Twitter-based sentiment across all quantiles. Our findings from the rolling window wavelet correlation point to low correlation values for all decomposed series (i.e., long-, medium-, and short-run). Our findings have value for investors in the US sectoral market because they may be helpful for constructing and rebalancing portfolios based on varying levels of correlation across different quantile distributions and investment periods.

1. Introduction

Due to the popularity of behavioural finance in academia and the investment community, the literature regarding the association between investor sentiment and stock returns has increased significantly (see, e.g., Joseph, Wintoki, & Zhang, 2011; Rao & Srivastava, 2012; Sul, Dennis, & Yuan, 2017; Kranefuss & Johnson, 2021, among others). Indeed, understanding the importance of the sentiment–returns relationship is useful to practitioners for several reasons. First, investor sentiment represents the attitude of investors towards a financial market or specific security, which in turn drives the prices of securities away from their fundamental values and induces changes in investment opportunities (Edelen, Marcus, & Tehranian, 2010). Second, the feelings or attitudes of investors are dynamic, and they can change irrationally, leading to mispricing and making investment decisions more complicated. Such mispricing can become more pronounced during extreme market conditions when sentiments are high, and therefore bearing high risk would not be rewarded by high returns, i.e., a more complex investment environment (Yu & Yuan, 2011; Wang, Su, & Duxbury, 2021). Third, sentiment spreads rapidly through the market, thus affecting investment behaviours and portfolio choices, regardless of cash flow prospects. Fourth, investor sentiment has been documented to exhibit spill-over effect across different countries. Such spill-over can

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become an effective channel of transmission between the international equity markets (Bathia et al., 2016).

Based on sentiment's capacity to spread quickly, it is vital to quantify the influence of investor sentiment on risk perception and stock prices. Rupande, Muguto, and Muzindutsi (2019) highlighted volatility-driven risk movements and linked them with sentimental noise trading activities whose patterns are not reconcilable with changes in the key factors. McGurk, Nowak, and Hall (2020) highlighted how investor sentiment has a momentous impact on US stock returns. A year later, Fousekis (2020) reported a negative, non-linear, and asymmetric connection between equity and investor sentiment, while Wang, Su, and Duxbury (2021) found that investor sentiment affects emerging stock markets more quickly than developed stock markets, which require a more sustained impact. They reported significant differences in the sentiment–returns relationship for individual stock markets, indicating a degree of heterogeneity in this relationship. For disaggregated stock returns, Khan, Hernandez, and Shahzad (2020) reported that investor sentiment has a substantial influence on the US's financial, technology, healthcare, and consumer discretionary sectors. Similarly, Rehman et al. (2021) tested the connection between investor sentiment and US sectoral returns and found that investor sentiment appears to be an important determining factor for US sectoral returns, although this relationship is asymmetric in nature.

The question is therefore no longer about whether investor sentiment impacts stock returns but rather the extent to which this occurs (Baker & Wurgler, 2007). Recently, trends on social media platforms, such as Twitter and Facebook, have become important considerations in trading decisions. Since 2013, when the US Securities and Exchange Commission proclaimed that firms might utilize social media platforms to publish key information, investors have used social media to gather information for making investment decisions. Investors' thoughts, opinions, and knowledge shared through different online forums have allowed researchers to investigate the role that investors' emotions, moods, and sentiments play in their investment decisions (Duz Tan & Tas, 2020). As a consequence, these behavioural aspects and psychological components provide the opportunity to acquire direct data about human factors, which are viewed as causes of anomalies in the financial markets (Baker & Wurgler, 2006). Existing studies have documented the importance of social media for extracting investor sentiment. For instance, Bollen, Mao, and Zeng (2011) used Twitter messages to derive six social mood dimensions, and they reported a significant improvement in predicting the Dow Jones Industrial Average returns. Similarly, Sprenger, Sandner, Tumasian, and Welphe (2014) applied computational linguistics to 400,000 S&P 500 stock-related Tweets to identify bad and good news, and they reported that social media news has an impact on stock returns. Yang, Lin, and Yi (2017), meanwhile, built a binary logit model to analyse the impact of social media on investor sentiment and showed that social media causes significant variation in investors' sentiment and consequently their trading decisions. Accordingly, the greater the degree of pessimism on social media, the more active the trading behaviour of investors in the financial markets (Tetlock, 2007).

The influence of investor sentiment on equity returns is difficult to measure using conventional linear models because investor sentiment follows irrational emotions that may vary substantially, irrespective of any underlying pattern. These sentiments also highlight reactions to different market conditions, so they can feature structural breaks. Therefore, to measure spill-over from Twitter-based sentiment onto US sectoral returns, we employ a causality-in-quantile, non-parametric approach because this is an effective measure for detecting causality at every point of a given distribution. Utilizing this approach, we capture non-linear causality across all the quantiles of the returns distribution. Moreover, the application of causality in quantiles (CIQs) is also useful in the existence of structural breaks, frequent outliers, and misspecification errors (see Balcilar et al., 2017). Following this, we use the rolling window wavelet correlation (RWWC) technique proposed by Polanco-Martínez et al. (2018) because this is useful for measuring multi-dimensional correlation (MDC) in the time and incidence domain. This technique has been found to be beneficial when analysing correlation patterns across distinct time intervals, which is why Ranta (2010) initially proposed it.

The contributions of our study are as follows. First, we use a sentiment index based on discussions about happiness on Twitter as a proxy to measure investor sentiment. This differs from the earlier works of Apergis and Rehman (2018) and Rehman et al. (2021), which used Baker and Wurgler's (2006) and the AAII Investor Sentiment Survey indices, respectively. The measure used in the present study, based on social media information, is selected due to the increasing influence and popularity of social media in recent years. Investors make judgements based on different social media trends, highlighting how they tend to make decisions that are more sentimental rather than rational in nature. According to Baker and Wurgler (2006), there are two types of investor sentiments. The first type concerns rationale traders, whereas the second type is related to non-rationale (irrational) traders or noise traders. For informed decision-making, the sentiments of rationale investors represent more accurate information than those of noise traders who follow random walk behaviour. Twitter-based investor sentiments are more related to informed investors who follow and track current trends and any subsequent changes. According to Shen (2019), Twitter-based sentiments reflect the sentiments of informed traders, which also support our idea of using Twitter-based sentiments in explaining stock returns.

The second contribution comes in the form of examining the relationship between investor sentiment with sectoral, as well as disaggregated, US stock returns. Such a comparison could highlight the heterogeneous response of different US sectors to investor sentiment, which is hard to quantify for aggregated stock returns. This may have several implications for investors involved in making sector-based investments. Since sentiments are based on rationale or stock fundamentals (Baker & Wurgler, 2006), their significance to US sectoral returns may help investors to construct new portfolios and re-evaluate existing ones. The third contribution is based on examining the effect of investor sentiment on US sectoral returns across different quantiles. Measuring this relationship with conventional regression models would provide mean results, thus precluding the opportunity to examine the results across different quantiles. However, examining the relationship across different quantiles could help investors to adjust their portfolios based on typical as well as extreme returns distributions. Results based across different quantile distributions could also help determine the response of US sectoral returns to investor sentiment under normal and extreme market conditions. The final contribution concerns measuring the rolling window correlation between Twitter-based sentiment and US sectoral returns under short-, medium-, and long-run periods. Our analysis is based on a decomposition of an original series into sub-components based on a time and frequency scale. This could help investors to measure the MDC between US sectoral returns and Twitter-based sentiment over various investment horizons (e.g., long-, medium-, and short-run).

Our findings from the non-parametric, causality-in-quantile analysis highlight how investor sentiment triggers symmetric changes in US sectoral returns, although the results are not homogeneous across all sectors. The healthcare, materials, communications, information technology, consumer discretionary, staples, and energy sectors are more sensitive to changes in investor sentiment across all quantiles, whereas the changes in the financial, real estate, industrial, and utilities sectors appear only across certain quantiles. The results of the rolling wavelet analysis show low correlation across all decomposed series (e.g., long-, medium- and short-run). In particular, the materials sector is negatively correlated with investor sentiment only during 2019, whereas the financial, industrial, technology, staples, and utilities sectors are negatively correlated in 2018 and 2019. The US consumer discretionary, energy, financial, industrial, healthcare, real estate, utility, and technology sectors correlate with investor sentiment in the long-run period (i.e., D4) with a relatively strong magnitude in 2014. For aggregated US returns, we find traces of a negative correlation during 2010 and between 2018 and 2020, compared to a strong positive correlation, at least in the long-run period, during 2014. The remainder of this paper is arranged as follows. Section 2 reviews the related literature. Section 3 provides details about the data and the applied methodologies. Section 4 then discusses the data analysis and interprets the results. Finally, Section 5 concludes this work by presenting some implications for investors and policymakers.

2. Literature review

Since the earlier work of Keynes (1937), investor sentiment has been considered as a significant factor in financial markets (see also Ranco et al., 2015; Renault, 2017; Duz Tan & Tas, 2020). Different proxies for measuring investor sentiment have been used, based on market fundamentals (Baker & Wurgler, 2006), a market-wide investor sentiment index (Stambaugh, Yu, & Yuan, 2012; Sibley et al., 2016), and a consumer confidence index (Fisher & Statman, 2003; Hsu, Lin, & Wu, 2011). Recently, a few researchers have measured investor sentiment based on prevailing attitudes on social media platforms (Chen, De, Hu, & Hwang, 2011; Sul, Dennis, & Yuan, 2017). Yang, Mo, and Lui (2015) and You, Guo, and Peng (2017) highlighted how investor sentiment based on social media can be important in predicting stock returns, while Gu and Kurov (2018) showed that Twitter-based investor sentiment provides useful information about investors' recommendations, price targets, and earnings, which in turn have predictive ability for stock returns. However, the existing literature remains silent on how Twitter-based investor sentiment predicts the returns of different US sectoral returns. Another gap that exists in the present literature is the sensitivity of returns across different investment periods, i.e., short- and long-run or across different investment windows. A good knowledge of the short- and long-run effect of sentiments from this social media platform can help in the timely rebalancing and adjustment of portfolios.

Although the concept of behavioural finance is new in the context of conventional finance, the current literature provides valuable insights regarding the relationship between investor sentiment and returns on stock. Among existing studies, one of the earliest works on investor sentiments is by Baker and Wurgler (2007), who used six fundamental proxies to measure investor sentiment. This sentiment proxy has since been used in various studies, including those of Rehman et al. (2022), Apergis et al. (2018), and Apergis and Rehman (2018), among others. Another sentiment proxy is the AAII Investor Sentiment Survey (https://www.aaii.com/sentimentsurvey), which is founded on the opinions of individual investors regarding their thoughts about where the market is heading and how it has been doing in the past. The AAII Investor Sentiment Survey differs from Baker and Wurgler's (2006) sentiment index in that the latter is based on fundamental measures, whereas the former is based on an opinion-based survey. Another work employing investor sentiment to examine its effect on stock returns is that of Sun et al. (2016), who computed investor sentiment using a comprehensive textual analysis from Internet news sources, news wires, as well as social media. Among the recent strand of studies, Wang et al. (2022) used turnover ratio to measure investor sentiment by using "generalized autoregressive conditional heteroscedasticity" (GARCH) models; although this resembles the AAII Investor Sentiment Survey index in terms of measuring optimistic and pessimistic sentiments, the AAII Investor Sentiment Survey index is based on a survey methodology. More recently, another sentiment measure is proposed by Smales (2022), who used implied volatility as a measure of fear and examined its effect on the global stock market.

Our work is comparatively different in terms of measuring investor sentiment. The power of social media has increased significantly over the past five years, therefore acting as a strong transmission channel. Our measure of sentiments using Twitter, as one of the strongest social media platforms, contributes to the existing strand of literature related to investor sentiment. There are a few studies that have documented the use of the Twitter platform in measuring investor sentiment; for example, Shen et al. (2019) used Twitter to measure the number of times the word "Bitcoin" had been Tweeted. It can be seen that our work is distinct from the existing strand of literature as it uses the Twitter platform to estimate investor sentiment and then uses this index to explain the variance in stock returns. Although the current literature has used various sentiment proxies, our work adds to the literature by using Twitter-based sentiment to predict US stock returns.

The existing literature also features studies that highlight the association between investor sentiment and US sectoral returns. Mao et al. (2012) measured the connection between investor sentiment and S&P 500 sectoral returns and found that the US's financial, energy, healthcare, and materials sectors strongly are correlated with daily Twitter data. Sayim, Morris, and Rahman (2013), meanwhile, documented the significant impact of investor sentiment on the US's auto, finance, oil, and utility sectors. They also reported that the rational positive component of individual US investor sentiment tends to increase stock returns at a sectoral level, but that an unanticipated escalation in the rational constituent of investor sentiment negatively impacts the volatility of the auto and financial sectors. According to Huang, Yang, Yang, and Sheng (2014), investor sentiment positively correlates with Chinese industry returns for the current period but negatively correlates with one-lagged returns. Later, Souza et al. (2015) reported Twitter-based sentiment as a significant predictor of stock returns for the US retail industry. According to Curatola, Donadelli, Kizys, and Riedel

(2016), there is an economic linkage between sports sentiment and sectoral stock returns in the US; only sports-based investor sentiment impacts the US financial sector, while none of other sectors significantly respond to changes in investor sentiment. According to these authors, this significant relationship can be attributed to high liquidity making the financial sector more attractive to investors who are sensitive to sports sentiment than it is to local US investors.

Rehman and Shahzad (2016), in another work, studied the time–frequency link between investor sentiment and US sectoral returns and found a cyclical, in-phase relationship between investor sentiment and US sectoral returns. According to Oliveira, Cortez, and Areal (2017), Twitter-based sentiment is not only important for predicting aggregated S&P 500 returns but also the returns of the energy, business equipment, and telecommunication sectors. For renewable energy stocks, however, Reboredo and Ugolini (2018) found that Twitter-based sentiment had no significant impact, suggesting that such sentiment is not important for predicting stock prices.

Most recently, research into the relationship between US sectoral returns and investor sentiment has included the period of the COVID-19 pandemic, thus yielding interesting results. According to Teti, Dallocchio, and Aniasi (2019), a strong relationship exists between Twitter-based investor sentiment and the US technology sector. Lee (2020), meanwhile, used Google Trends data and the Daily News Sentiment Index to analyse the relationship between COVID-19-related sentiment and US sectoral returns and found that COVID-19-related sentiment has a significant effect on the US's communication services, industrial, consumer discretionary, materials, and energy sectors, as well as a limited effect on the utility sector. Similarly, Reis and Pinho (2020) argued that COVID-19-based investor sentiment is negatively connected with returns for the US global index and the real estate and tourism sectors. The above-mentioned literature regarding the nexus of stock returns and investor sentiment at aggregated and sectoral levels suggests that investor sentiment's effect on equity returns is crucial for investors. Different sectors respond in a heterogeneous way, however, which provides some rationale for investigating the impact of Twitter-based sentiment on US sectoral returns.

There are few studies that have used social media sentiments to explain variations in stock returns. For example, Ho et al. (2017) used Bayesian dynamic linear models to examine the effect of investor sentiment on stock returns. They reported the time-varying behaviour of sentiments on stock returns and also found that social media sentiment remains more stable during turbulent periods. Broadstock and Zhang (2019) analysed Twitter messages in the context of constructing general sentiments and sentiments specific to firms. These authors examined the effect of such sentiments on intra-day stock returns and reported that the effect of media sentiment is significant. The pricing dynamics are sensitive both to firm-specific as well as market-wide sentiments. Fang et al. (2021) employed FinTech approaches to create a sentiment variable to measure the effect of investors' pessimism and optimism on equity returns. Their results highlighted that firms with optimism investor sentiment enjoy higher returns than the firms with pessimism sentiment, which have opposite effects. According to Alomari et al. (2021), news sentiment has a significant influence on volatility, while social media exhibits a pronounced effect on the stock and bonds correlation. Al-Nasseri et al. (2021) used the textual classification of online Tweets to measure the predictability of DJIA stocks using quantile regression. Their results highlighted a positive association between stock returns and sentiment at higher quantiles; however, sentiment acted as negative predictor of future returns across lower quantiles. Their results also highlighted that sentiment mainly affects assets' valuation during extreme market circumstances, therefore being consistent with previous behavioural theories. In another interesting work, Wang et al. (2022) used an innovative methodology for constructing sentiment using a large panel of online messages as a controlled experiment with no fundamental information. The authors reported causality running from sentiment to returns on stock on the same day, which diminished the next day. More recently, Liu et al. (2022) investigated the synergetic pattern between equity prices and sentiment using the social media messages of investors. The authors reported a positive bidirectional relationship between stock returns and sentiment, which diminished over a specific time period. Such synergy is, however, affected by an external anxiety, such as the recent COVID-19 pandemic. Similarly, Du et al. (2022) examined media coverage premium in the Chinese equity market. These authors reported that longing firms with no bad (negative) news and shorting firms with high bad (negative) news earned abnormal returns after adjusting for well-known risk factors. These authors also reported that abnormal returns are earned for portfolios with a holding period of more than three months. They also concluded that short-run momentum effects do not result in news sentiment anomalies and are robust in the Chinese equity market. Karampatsas et al. (2022) examined firm-specific investor sentiment on equity returns for positive and negative earnings shocks and found that such sentiment has a greater effect on equity returns for negative compared to positive earnings surprises. These authors also reported the reversal of returns after the announcements period.

On the basis of the strand of literature discussed above regarding investor sentiment, our work fills an existing gap by employing non-linear estimation techniques to measure the influence of investor sentiment on US sectoral as well as aggregate returns. We use an extension of conventional wavelet techniques, namely RWWC, which decomposes the original returns into decomposed returns over different investment periods. In this way, we analyse the effect of investor sentiment on US sectoral returns across different investment windows. We also add to the existing literature on investor sentiment by analysing its causal effect on US sectoral returns across market conditions (normal and extreme). In this way, the upside and downside risks to US sectoral returns due to investor sentiments can provide rich insights.

3. Data and methodology

3.1. Investor sentiment index

Our paper uses Twitter-based investor sentiment, which is different from sentiment measures used in past studies. Other sentiment indices include, but are not limited to, fundamental proxies (Baker & Wurgler, 2007), the AAII Investor Sentiment Survey (https://www.aaii.com/sentimentsurvey), comprehensive textual analysis (Sun et al., 2016), and implied volatility (Smales, 2022). The use of Twitter, therefore, adds to the existing body of literature on measuring investor sentiment. Additionally, this measure provides a twofold benefit compared with the other sentiment measures. First, keeping in view the immense volume of activity on social media, this measure can provide timely information and updates regarding the prevailing sentiments of investors regarding any particular investments, and therefore can help in rebalancing the portfolios in a timely fashion. Second, this measure offers an easy way to calculate sentiment. Conventional measures require a good knowledge of traditional finance to estimate an updated index of sentiment or rely on the updating of such measures on timely basis. On the contrary, the Twitter-based sentiment index is easy to calculate, and the information regarding how to obtain it is presented below.

Our work uses daily returns data for 11 US sectors, namely communications, consumer discretionary, financial, energy, healthcare, industrial, real estate, materials, utilities, technology, and staples. We also extract daily data for the S&P 500 as a proxy for aggregated US market returns. The data covered a period from 21 June 2010 to 13 April 2020. The data for pricing for all US sectors are obtained from Thomson Reuters DataStream. The natural logarithm of two adjacent price differences is used to calculate the returns. For the same period, our study also includes a Twitter-based sentiment index curated from http://hedonometer.org/api.html. This sentiment index is constructed using an application programming interface (API) to understand the discussions on Twitter by randomly sampling 10 % of the almost 500 million messages that are posted on Twitter per day. Messages with specified words were collected and then assigned a happiness score to measure sentiment.

3.2. Causality in quantiles

In this study, we measure the CIQs between the Twitter-based sentiment index (x_t) and the US sectoral returns (y_t) as a non-linear model based on a contemporary method following the work of Balcilar et al. (2017). We surmise that x_t does not give rise to y_t in the θ quantile for the lag vector of $\{y_{t-1},\cdots,y_{t-p},x_{t-1},\cdots,x_{t-p}\}$, as suggested by Jeong et al. (2012), if:

$$Q_\theta\{y_t y_{t-1},\cdots,y_{t-p},x_{t-1},\cdots,x_{t-p}\} = Q_\theta\{y_t y_{t-1},\cdots,y_{t-p}\} \tag{1}$$

However, we presume the existence of causality between x_t and y_t in the θth quantile with:

$$\{y_{t-1},\cdots y_{t-p},X_{t-1},\cdots X_{t-p}\}\{y_{t-1},\cdots y_{t-p},X_{t-1},\cdots X_{t-p}\}$$

$$\text{if } Q_\theta\{y_t y_{t-1},\cdots y_{t-p},X_{t-1},\cdots X_{t-p}\} \neq Q_\theta\{y_t y_{t-1},\cdots,y_{t-p}\} \tag{2}$$

where $Q_\theta(y_t)$ represents the θth quantile of y_t in Eq. (2). The conditional quantiles of $Q_\theta(y_t)$ and y_t depend on t, and they range from zero to one (i.e., $0 < \theta < 1$). We then describe the vectors $Y_{t-1} \equiv \left(y_{t-1},\cdots,y_{t-p}\right), X_{t-1} \equiv (x_{t-1},\cdots,x_{t-p})$. The conditional distribution functions are $F_{(y_t\, Y_{t-1})}(y_t\, Y_{t-1})$ and $F_{(y_t\, Z_{t-1})}(y_t\, Z_{t-1})$ of y_t, which are conditional of the vector Y_{t-1} and Z_{t-1}, respectively. The distribution $F_{(y_t\, Z_{t-1})}(y_t\, Z_{t-1})$ is assumed to be completely continuous in y_t for almost all Z_{t-1}. Holding probability to unit (one), we define $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t\, Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t\, Y_{t-1})$, which yields $F_{(y_t\, Z_{t-1})}\{Q_\theta(Z_{t-1})Z_{t-1}\} = \theta$. Based on the previous equations (Eqs. (1) and (2)), we define the CIQ as:

$$H_0\text{: } P\{F_{(y_t\, Z_{t-1})}\{Q_\theta(Z_{t-1})Z_{t-1}\} = 1 \tag{3}$$

$$H_1\text{: } P\{F_{(y_t\, Z_{t-1})}\{Q_\theta(Z_{t-1})Z_{t-1}\} < 1 \tag{4}$$

Jeong et al. (2012) utilized the distance measure $J = \{\varepsilon_t E(\varepsilon_t Z_{t-1}) f_Z(Z_{t-1})\}$, where the regression error is denoted by ε_t and the marginal density function of Z_{t-1} is denoted by f_Z (Z_{t-1}). The unknown regression error estimator is defined as:

$$\widehat{\varepsilon}_t = 1\{y_t \leq \widehat{Q}_\theta(Y_{t-1})\} - \theta \tag{5}$$

The quantile estimator $\widehat{Q}_\theta(Y_{t-1})$ shown is Eq. (5), which denotes the θth conditional quantile of y_t as Y_{t-1}. The non-parametric kernel method for computing $\widehat{Q}_\theta(Y_{t-1})$ is defined in Eq. (6) as follows:

$$\widehat{Q}_\theta(Y_{t-1}) = \widehat{F}^{-1}_{(y_t\, Y_{t-1})}(\theta Y_{t-1}) \tag{6}$$

The Nadarya–Watson kernel estimator $\widehat{F}_{(y_t\, Y_{t-1})}(y_t\, Y_{t-1})$ is defined as:

$$\widehat{F}_{(y_t\, Y_{t-1})}(y_t\, Y_{t-1}) = \frac{\sum_{s=p+1,S\neq 1}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right) 1\{y_s \leq y_t\}}{\sum_{s=p+1,S\neq 1}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \tag{7}$$

where L in is the kernel function, while h symbolizes the bandwidth in the procedure. As the refusal of “causality in moment” m fails to insinuate non-causality in moment k for $m < k$, we similarly measure causality in variance in the same way as the second moment, as illustrated below:

Table 1
Descriptive statistics.

	SP500	Comm.	Disc.	Energy	Financial	Healthcare	Indus.	Material	Realest.	Tech.	Utilities	Staples	Sentiments
Mean	0.0004	0.0002	0.0005	−0.0002	0.0002	0.0005	0.0003	0.0002	0.0003	0.0006	0.0003	0.0003	6.0083
Maximum	0.0897	0.0880	0.0829	0.1511	0.1243	0.0731	0.1200	0.1100	0.0871	0.1130	0.1232	0.0808	6.3260
Minimum	−0.1277	−0.1103	−0.1288	−0.2242	−0.1507	−0.1053	−0.1216	−0.1215	−0.1809	−0.1498	−0.1227	−0.0969	5.7127
Std. Dev.	0.0106	0.0108	0.0112	0.0156	0.0140	0.0104	0.0121	0.0129	0.0126	0.0127	0.0108	0.0086	0.0529
Skewness	−0.9116	−0.6085	−1.0493	−1.7856	−0.7327	−0.4395	−0.7870	−0.5885	−1.2866	−0.6084	−0.3353	−0.4494	−0.0946
Kurtosis	23.1864	14.2287	17.7099	33.2107	20.3874	13.6952	18.9155	13.6966	27.7569	19.5024	29.3124	22.0843	7.3941
JB Test	43837.2	13612.3	23559.5	98751.8	32489.3	12288.5	27294.0	12357.0	66108.4	29217.7	73926.5	38950.6	2064.2
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Correlation	0.0312	0.0373***	0.0374***	0.0503**	0.0317	0.0076	0.0460**	0.0376***	0.0307	0.0174	0.0294	0.0295	1

Note: Std. Dev. denote standard deviation of series, whereas JB Test stands for the Jarque Bera test. ***, ** and * represents significance level at 1, 5 and 10 percent respectively.

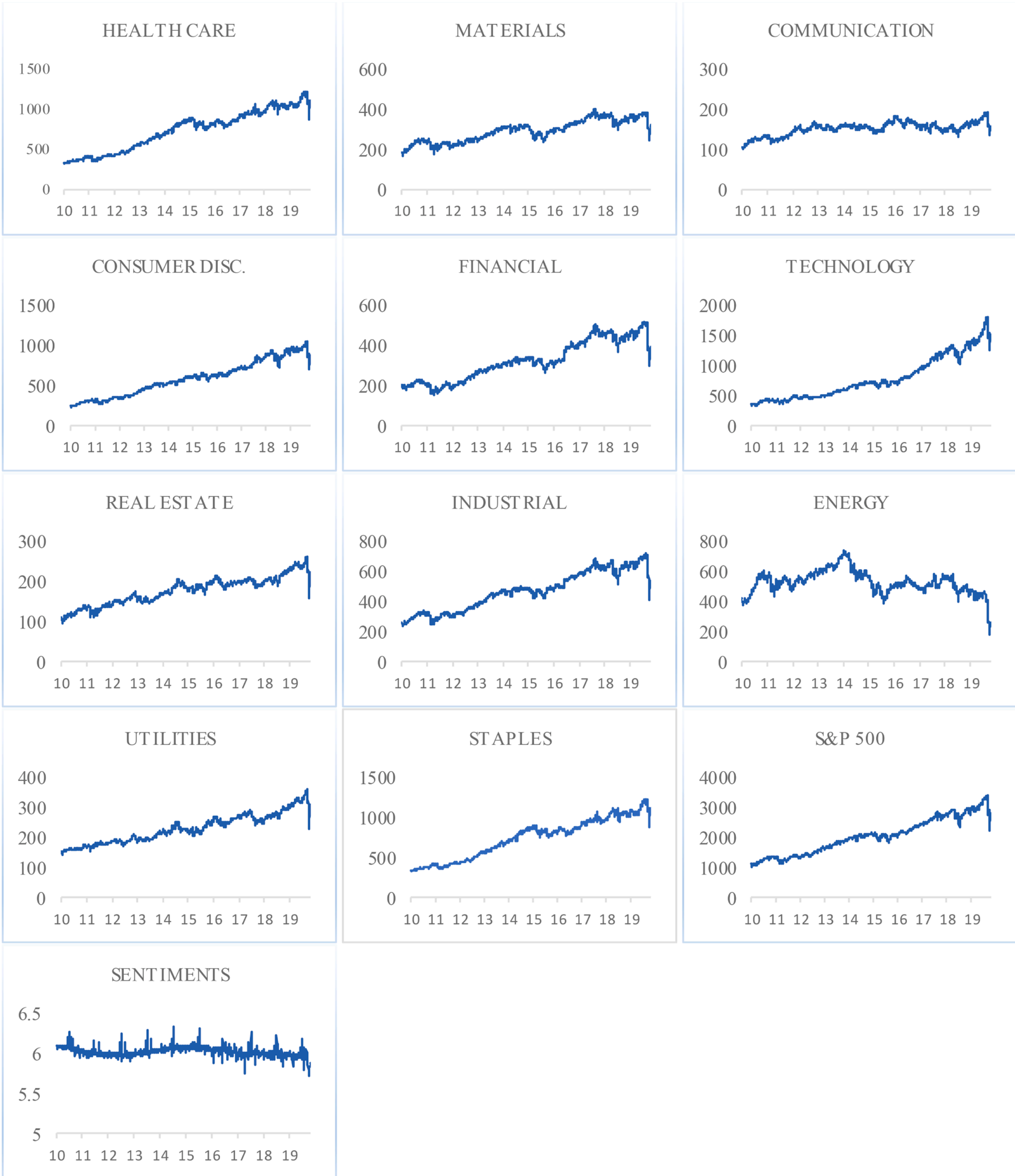


Fig. 1. Pricing trend of returns.

$$y_t = g\left(X_{t-1}, Y_{t-1}\right) + \varepsilon_t \tag{8}$$

We test CIQs in upper order as follows:

$$H_0 : P\left\{F_{(y_t^k Z_{t-1})}\{Q_\theta(Y_{t-1})Z_{t-1}\} = \theta\right\} = 1 \text{for} k = 1, 2, \cdots, K \tag{9}$$

$$H_1 : P\left\{F_{(y_t^k Z_{t-1})}\{Q_\theta(Y_{t-1})Z_{t-1}\} = \theta\right\}\langle 1 \text{ for} k = 1, 2, \cdots, K \tag{10}$$

Table 2
BDS test.

	m				
	2	3	4	5	6
S&P500	0.0261***	0.0572***	0.0802***	0.0943***	0.1007***
	−0.0021	−0.0033	−0.0039	−0.0041	−0.004
DISCRETIONARY	0.0235***	0.0499***	0.0683***	0.0797***	0.0842***
	−0.002	−0.0031	−0.0037	−0.0038	−0.0037
ENERGY	0.0179***	0.0389***	0.0536***	0.0609***	0.0631***
	−0.0019	−0.003	−0.0035	−0.0037	−0.0035
FINANCIAL	0.0260***	0.0545***	0.0727***	0.0825***	0.0860***
	−0.002	−0.0031	−0.0037	−0.0039	−0.0038
HEALTHCARE	0.0199***	0.0410***	0.0561***	0.0635***	0.0663***
	−0.0019	−0.003	−0.0035	−0.0037	−0.0036
INDUSTRIAL	0.0201***	0.0445***	0.0620***	0.0721***	0.0759***
	−0.002	−0.0031	−0.0037	−0.0038	−0.0037
MATERIALS	0.0205***	0.0444***	0.0613***	0.0714***	0.0752***
	−0.0019	−0.003	−0.0035	−0.0037	−0.0036
REALESTATE	0.0229***	0.0484***	0.0651***	0.0738***	0.0774***
	−0.0019	−0.003	−0.0036	−0.0037	−0.0036
COMMUNICATION	0.0166***	0.0300***	0.0376***	0.0410***	0.0415***
	−0.0017	−0.0028	−0.0033	−0.0035	−0.0033
TECHNOLOGY	0.0217***	0.0446***	0.0611***	0.0705***	0.0733***
	−0.002	−0.0031	−0.0037	−0.0039	−0.0037
UTILITIES	0.0164***	0.0313***	0.0392***	0.0422***	0.0434***
	−0.0017	−0.0027	−0.0033	−0.0034	−0.0033
CONSUMER STAPLES	0.0214***	0.0430***	0.0579***	0.0646***	0.0661***
	0.0018	0.0029	0.0034	0.0036	0.0034
SENTIMENTS	0.1091***	0.1852***	0.2337***	0.2636***	0.2830***
	−0.0014	−0.0021	−0.0025	−0.0026	−0.0025

Notes: m presents parameter m in the embedding dimension whereas ε denote epsilon values.

In applying the appropriate kernel-based test to determine causality between both y_t and x_t in quantile θ up to the Kth moment, we again follow Jeong et al. (2012). In addition, we use Nishiyama et al.'s (2011) sequential testing approach to estimate the joint density-weighted non-parametric tests for $k = 1,2,\cdots,K$. After this, we select the lag order criterion of 1 using the Schwarz information criteria. In addition, we use least squares cross validation (LSCV) methods to identify the Gaussian type and the bandwidth value for K and L.

3.3. Rolling window wavelet correlation (RWWC)

To inspect the connection between the Twitter-based sentiment index and US sectoral returns across different periods, we apply RWWC as a dynamic measure. We compute the "maximal overlap discrete wavelet transform" (MODWT) following Gençay et al. (2002). The "unbiased wavelet correlation" (UWC), for scale λ_j between series X and Y, is then defined as follows:

$$\widetilde{\rho}XY = \frac{cov\left(\widetilde{W}_{Y,jt}, \widetilde{W}_{Y,jt}\right)}{\sqrt{var\left\{\widetilde{W}_{X,jt}\right\}var\left\{\widetilde{W}_{X,jt}\right\}}} = \frac{\widetilde{\gamma}XY(\lambda_j)^2}{\widetilde{\sigma}_X^2(\lambda_j)\widetilde{\sigma}_Y}(\lambda_j) \tag{11}$$

where $\widetilde{\gamma}XY$ stands for the unbiased coefficient of the wavelet covariance between the $\widetilde{W}_{Y,jt}$ and $\widetilde{W}_{Y,jt}$market coefficients. The unbiased estimators $\widetilde{\sigma}_X^2(\lambda_j)$ and $\widetilde{\sigma}_Y^2(\lambda_j)$ of wavelet variances X and Y are correlated with the scale λ_j. Afterwards, we present the unbiased wavelet variance estimator based upon decomposition following MODWT as:

$$\widetilde{\sigma}_X^2(\lambda_j) = \frac{1}{\widetilde{N}}\sum_{t=L_{j-1}}^{N-1}\widetilde{W}_{j,t}^2 \tag{12}$$

In the above expression, $\widetilde{W}_{j,t}^2$ refers to the jth level of the coefficient of MODWT for X, while the length of the scale λ_j (wavelet filter) is denoted by $L_j = (2j-1)(L-1) + 1$. The number of coefficients not affected by the boundary is denoted by $\widetilde{N} = N - L_j + 1$. The confidence interval $100(1-2p)\%$ is constructed for wavelet coherence based on the work of Witcher and Onwueghuzie (1999) (for more details, see Gençay et al., 2002; Whitcher et al., 2000).

In order to examine sequential variation in wavelet correlation, we use the RWWC proposed by Ranta (2010). This technique is commonly used in economic and finance fields due to its superior ability to examine different time intervals (see, e.g., Dajcman et al., 2012; Rehman, 2020, among others). Following previous studies (e.g., Ranta, 2010; Dajcman et al., 2012; Benhmad, 2013), with a window of 250 points in a single year, we compute the pairwise rolling wavelet correlation. Moreover, we followed the work of

Table 3
Linear Granger causality test results.

	Linear causality Sentiments causes returns	Non-linear causality Sentiments causes returns
SP500	$\nrightarrow$	$\nrightarrow$
DISCRETIONARY	$\nrightarrow$	$\nrightarrow$
ENERGY	$\rightarrow$	$\nrightarrow$
FINANCIAL	$\nrightarrow$	$\nrightarrow$
HEALTHCARE	$\nrightarrow$	$\nrightarrow$
INDUSTRIAL	$\nrightarrow$	$\nrightarrow$
MATERIALS	$\nrightarrow$	$\nrightarrow$
REALESTATE	$\nrightarrow$	$\nrightarrow$
COMMUNICATION	$\nrightarrow$	$\nrightarrow$
TECHNOLOGY	$\nrightarrow$	$\nrightarrow$
STAPLES	$\nrightarrow$	$\nrightarrow$
UTILITIES	$\nrightarrow$	$\nrightarrow$

Note: F-statistics are provided in the above table stating hypothesis of no causality in a linear vector AR model. *BIC* is the selected criteria for Lag order selection.

Polanco-Martínez et al. (2018) by including five effective wavelets, $J = 5$, and examining only the first four scales and visualizing the decayed correction.

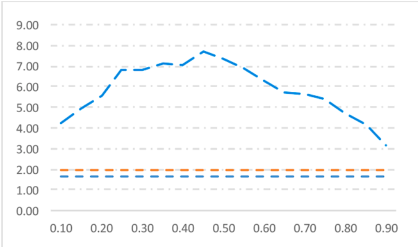
4. Analysis and discussion

We start our discussion with a preliminary analysis. Table 1 presents descriptive statistics for the returns of US sectors, S&P 500 returns, and the sentiment index. All sectors except energy showed positive average returns, with the highest mean returns being provided by the technology sector (0.06 %), followed by the consumer discretionary and healthcare sectors. The poor performance of the US energy sector is attributed to the lowest oil prices mainly after 2015. The oil crisis of 2016 also contributed towards the declining oil prices and added turmoil to the lost decade of the US oil sector. Further havoc for this sector was created during the COVID-19 period, which for the first time resulted in negative oil prices. Notably, the energy sector showed extreme returns, with the greatest return and loss of 15.11 % and 22.42 %, respectively, which shows the extent of volatility exhibited by this sector during the past decade. The variance in returns for all sectors is 1–2 % on a daily basis. All the sectoral returns are negatively skewed with a leptokurtic distribution. This view is supported by Jarque–Bera normality statistics that suggest that our data is not normally distributed. The S&P 500 returns yielded daily returns of 0.04 % on average with a maximum gain of 9 % and a maximum loss of 12.77 %. The variance in S&P 500 returns, as given by the standard deviation, is 1 % with negatively skewed values and a leptokurtic distribution with a fat tail, thus disproving the null hypothesis that our series is normally distributed. These results are again supported by the Jarque–Bera normality statistics. Statistics for the sentiment index provide a mean value of 6.01 with a slight variation in values across the sampling period. These results suggest consistent sentiments across the entire period, which highlights more reliance on fundamentals than speculations. Like all sectoral returns, sentiments exhibit negative skewed behaviour with fat tails. The final rows of Table 1 indicate unconditional correlation between stock returns and investor sentiment, and we see how investor sentiment weakly correlates with the returns of the 11 sectors and the aggregated S&P 500 returns.

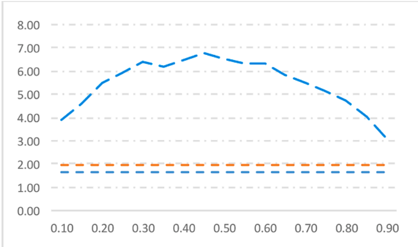
Fig. 1 illustrates the pricing trend of all the US sectoral and S&P 500 returns for the sample period. Although volatility is evident in the US sectoral returns throughout the period, a sharp decline is quite apparent for all sectors towards the end of the sample period as a result of the COVID-19 pandemic affecting the global economy in general and the US economy in particular (Altig et al., 2020). In addition, the energy, materials, and financial sectors are highly volatile throughout the sample period with several breaks, whereas other sectors had relatively consistent pricing patterns. Similarly, the volatility in S&P 500 returns is quite visible towards the end of the period, which is again attributable to the COVID-19 pandemic. Nevertheless, the S&P 500 index shows otherwise consistent pricing trends throughout the period. We can also see the highly volatile nature of Twitter-based sentiment throughout the sample period, with this becoming more pronounced during the COVID-19 period.

We employ a BDS test following Broock et al. (1996) because this is useful for detecting non-linearity in the relationship between different time series. Table 2 shows the results, revealing the presence of non-linearity from various implanted dimensions and suggesting the application of a non-parametric method for scrutinizing the relationship between sectoral returns and investor sentiment. Our results also show significant coefficients across all five embedding dimensions (2 to 6) for all sectoral and aggregated returns. Therefore, conventional linear models may not be able to capture the causal relationship between investor sentiment and returns on stock, so to look for the presence of a causal relationship; we instead applied the non-parametric, causality-in-quantiles method.

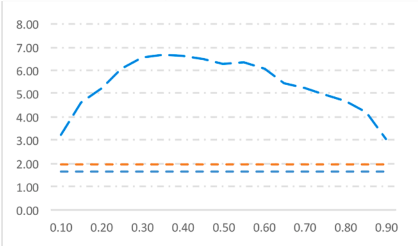
Table 3 presents the results for the linear and non-linear causal relationship between US stock returns and investor sentiment. The first column contains the results for linear causality from investor sentiment to US sectoral returns. Except for energy, no sector is affected by investor sentiment, suggesting that there is no causal relationship between investor sentiment and sectoral returns, thus contradicting existing literature that has found a significant nexus between investor sentiment and stock returns (Apergis & Rehman, 2018; Apergis, Cooray, & Rehman, 2018). Alternatively, it could be the case that conventional linear causality tests are unable to capture such a relationship. The results of the non-linear causality test in the next column also show the absence of any causal relationship between the US stock returns and investor sentiment, suggesting that non-linear models are also unable to detect the presence



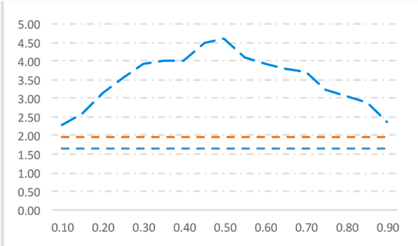
a) Healthcare



b) Materials

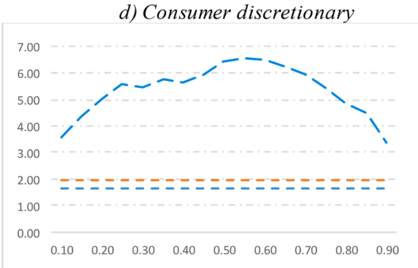


c) Communication services

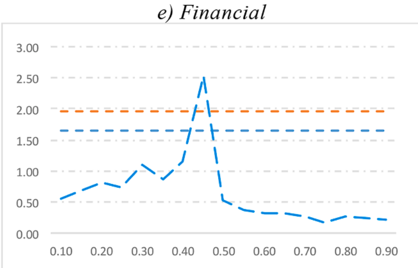


d) Consumer discretionary

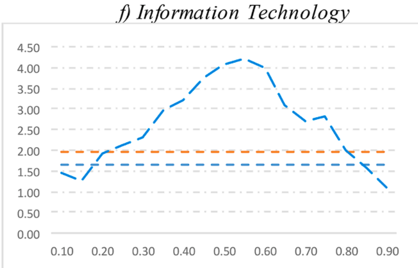
e) Financial



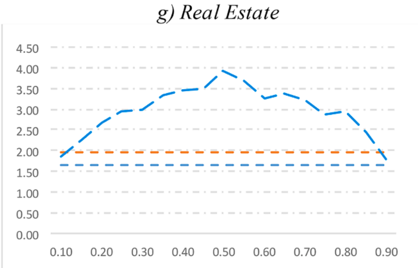
f) Information Technology



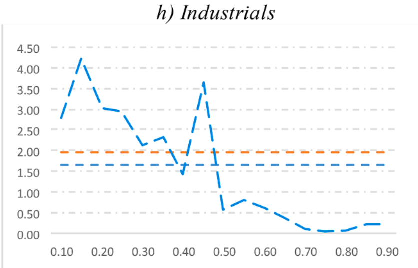
g) Real Estate



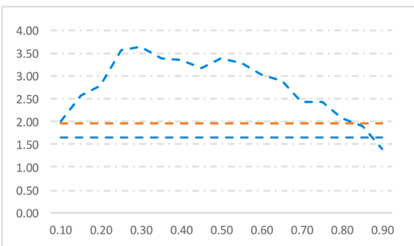
h) Industrials



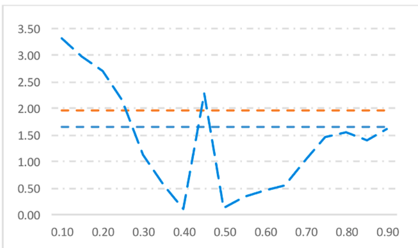
i) Energy



j) Utilities



k) Staples



l) S&P 500

(caption on next page)

Fig. 2. Non-parametric causality-in-quantiles test results.

of causality between investor sentiment and US stock returns. However, such techniques are based on median estimates across the sampling period, which covers normal and turbulent sub-periods, and estimates based on average values are unable to reflect the true underlying relationship. To rectify this, we apply a "non-parametric, causality-in-quantiles" test to capture causality across multiple quantiles rather than the centre of the distribution. In this way, any causal correlation between investor sentiment and US stock returns could be captured during normal and turbulent market conditions.

Fig. 2 illustrates the results of the causality-in-quantiles test for the relationship between investor sentiment and US sectoral and aggregate returns. Overall, they provide evidence that investor sentiment triggers changes in most US sectors across all quantiles, as reflected by the blue-dashed lines. Affected sectors include healthcare, materials, communications, consumer discretionary, information technology, industrials, staples, and energy. The results also suggest that investor sentiment has a predictive power in relation to the returns of these sectors. In contrast, the financial and real estate sectors appear to be insensitive to changes in investor sentiment, even though investments in both these sectors are gaining momentum. In 2021, an increase of almost 30 % is recorded in both sectors, resulting in a market capitalization of approximately USD 11.8 trillion[1]. This finding suggests that these two main sectors, which receive huge investments, are unaffected by changes in investor sentiment on social media platforms. Such insensitivity of the real estate sector to Twitter-based sentiment might be attributed to the fact that investments in this sector are based on the long-run, and therefore returns are not affected by social media sentiment.

Regarding the returns of the US financial sector, its profitability is driven more by fundamentals rather than sentiment. Our CIQ model, however, depicts an asymmetric relationship, which remains significant only during median quantiles, while being insignificant across extreme tail distributions. Therefore, an examination across different investment windows after decomposing the return series will provide more insights for short- and long-run investments. Other sectors are significantly affected by investor sentiment across all quantiles, thus denoting that the effect of sentiment is homogeneous on these sectors under different market conditions. This is consistent with the earlier work of Souza et al. (2015), which found that Twitter-based investor sentiment is important for predicting US retail sector returns. In addition, we can see how the presence of causality is strong in median quantiles, suggesting that sentiment exerts a stronger effect on these sectors during normal market conditions compared to extreme market conditions. We see different results for utilities and S&P 500 returns, for which causality appears significant under bearish market conditions. Furthermore, the causality is also asymmetric in nature, making it difficult to predict and thus creating challenges for investors. These findings insinuate that social media sentiment is a powerful predictor for these sectors, especially while the utilities sector and overall market do not performing so well, suggesting more downside risk for these sectors. However, we go one step further by not relying only on the non-linear causality and investigate further the correlation properties based on rolling window and decomposed series representing different investment windows.

In Fig. 3, we illustrate the results of the RWWC for the relationship between sentiment and stock returns based on different levels of decomposition between D1 and D4. The primary motivation for using different decomposition levels is to investigate the presence of correlation from the short-run to the long-run because this has implications for investors across different investment periods. The strength of the bivariate correlation between investor sentiment and stock returns is depicted in the form of a power bar scale along each figure. The magnitude for this scale ranges from a high correlation value (i.e., top of the scale) to a low correlation value (i.e., bottom of the scale), although this scale is different for each figure as the magnitude of the correlation varies for each pair. The strength of the correlation is depicted by different colour schemes, such that red, yellow, and green represent high, medium, and low bivariate correlation strengths, respectively. Our analysis then started by looking at the correlation between Twitter-based investor sentiment and US sectoral returns.

Overall, we see low correlation values across all decomposition levels and sampling periods, implying that US sectoral returns are not so sensitive to Twitter-based investor sentiment. In particular, we see traces of negative correlation across all sampled sectors during 2010 and 2019 in the long-run. In the case of the materials sector, we see a negative connection between investor sentiment and stock returns only during 2019, whereas the financial, industrial, technology, staples, and utilities sectors are negatively correlated between 2018 and 2019. The US consumer discretionary, energy, financial, healthcare, industrial, real estate, technology, and utility sectors' returns correlated with investor sentiment for the long-run investment horizon (i.e., D4), with this being relatively strong in 2014.

Similar to sectoral stock returns, we see limited relationship between Twitter-based sentiment and the aggregated S&P 500 returns across all decomposition levels, suggesting that the aggregate S&P 500 returns are also insensitive to Twitter-based investor sentiment. However, we also see traces of negative correlation during 2010 and between 2018 and 2020 for long-run investment horizons (i.e., D4). It is worth noting that during 2014, sentiment and S&P 500 returns are strongly and positively associated in the short-run, but the relationship is weak and negative in the medium- to long-run (i.e., D3).

In summary, we can only see weak co-movement between Twitter-based investor sentiment and US returns during shorter and medium-length investment horizons (e.g., from D1 to D3). We also see few traces of negative correlation between investor sentiment and US equity markets in the short-run. However, for longer investment horizons (i.e., D4), a positive correlation can be witnessed between investor sentiment and the returns of all sectors, except for communications and materials in 2014. Outside 2014, though,

[1] These statistics are sourced from https://www.tradingview.com/markets/stocks-usa/sectorandindustry-sector/ and https://www.schwab.com/resource-center/insights/content/active-trader-market-outlook.

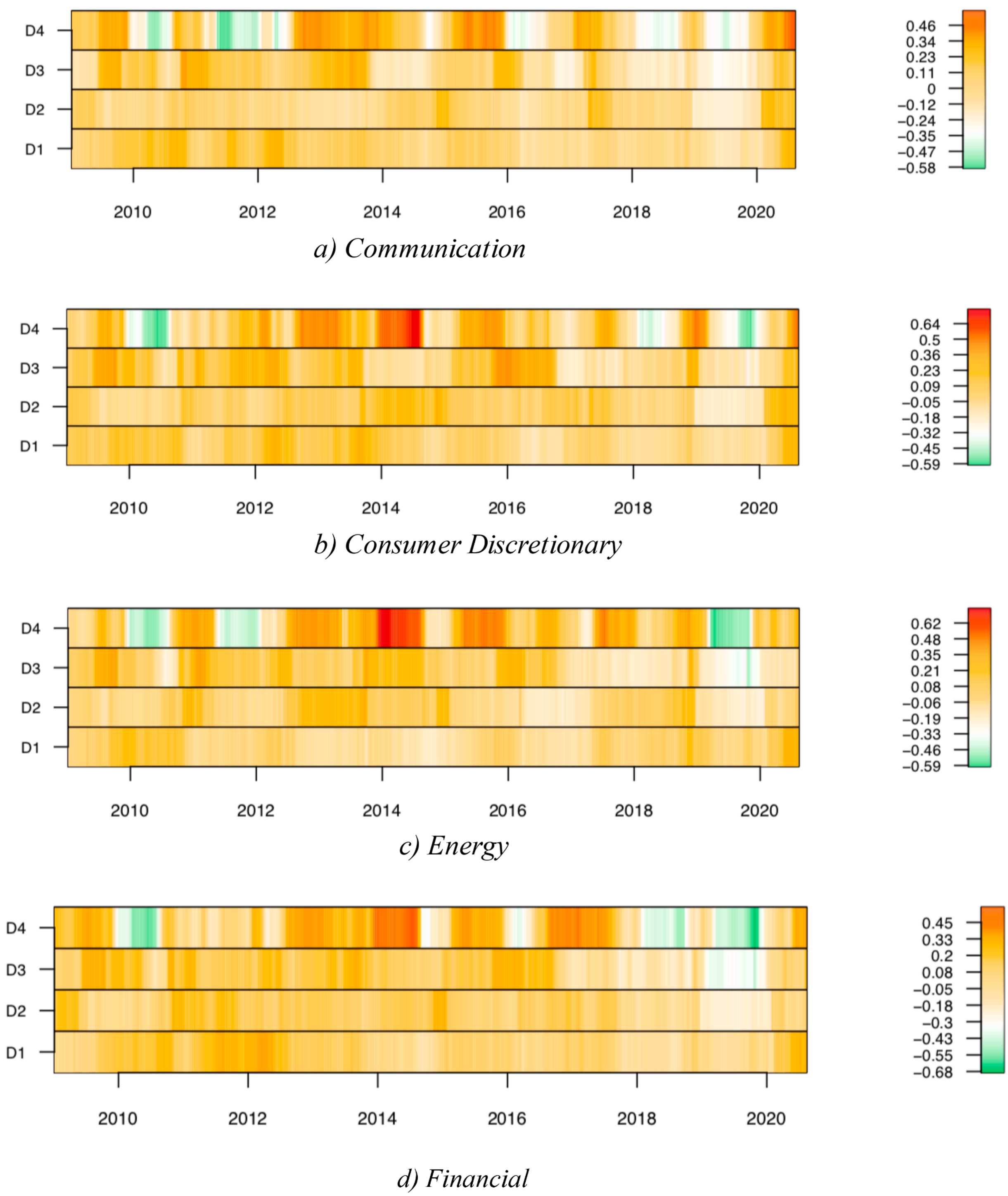
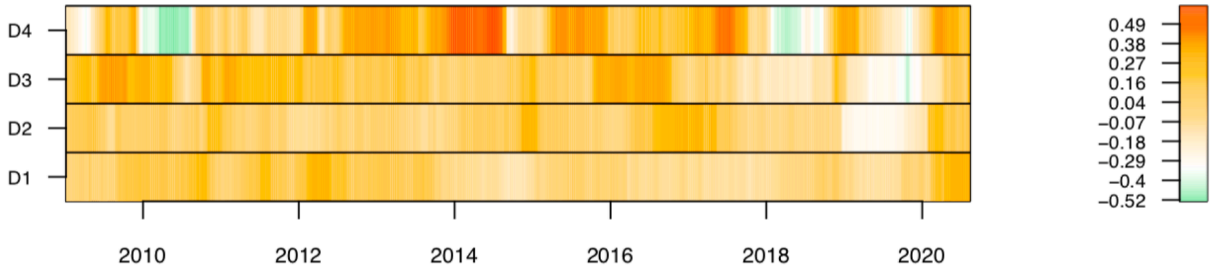
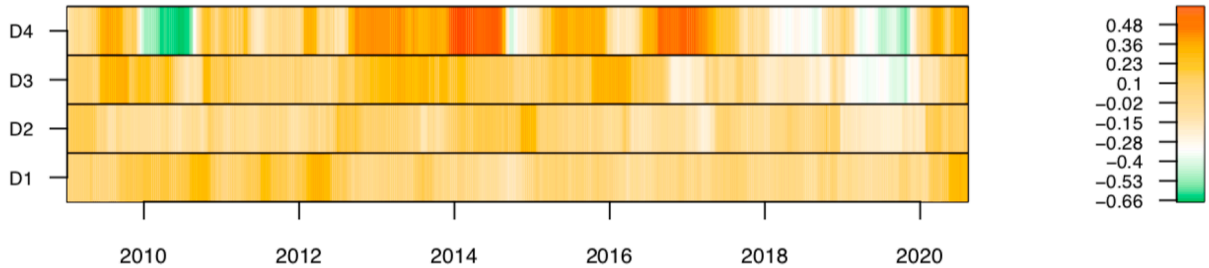


Fig. 3. Rolling window wavelet correlation.

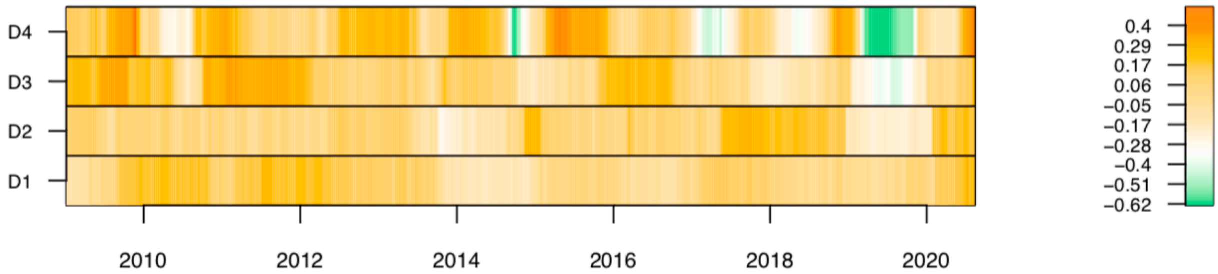
there are no traces of correlation between Twitter-based sentiment and US equity returns. The results of the RWWC for the connection between S&P 500 returns and Twitter-based sentiment follows much the same pattern in highlighting low correlation values. We can also see traces of negative correlation, with these being more pronounced in 2010 and 2019, for long-run investment horizons (i.e., D4). In addition, we can also see traces of a positive association in the long-run period (D4) during 2014, implying that investor sentiment affects S&P 500 returns in the long-run, which may be attributed to the political instability in the US due to elections that year.



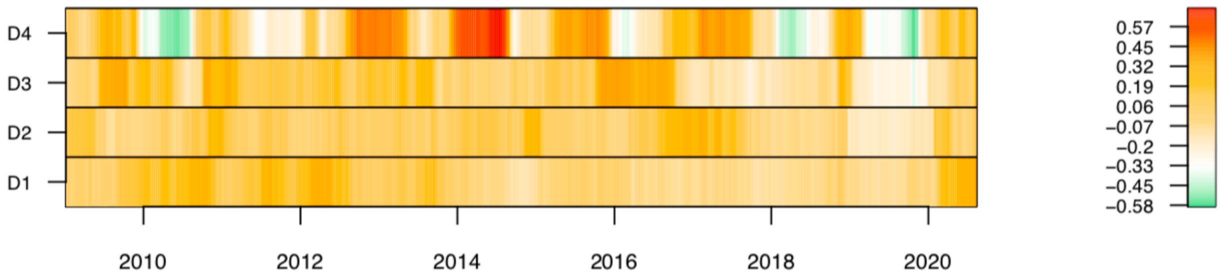
e) Healthcare



f) Industrial



g) Materials

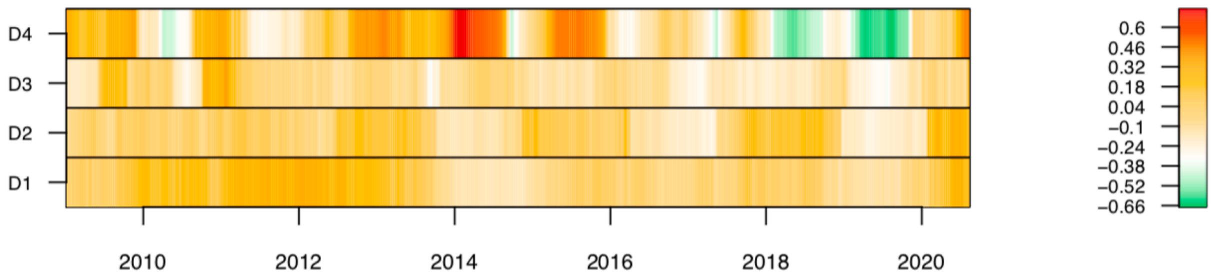


h) Real Estate

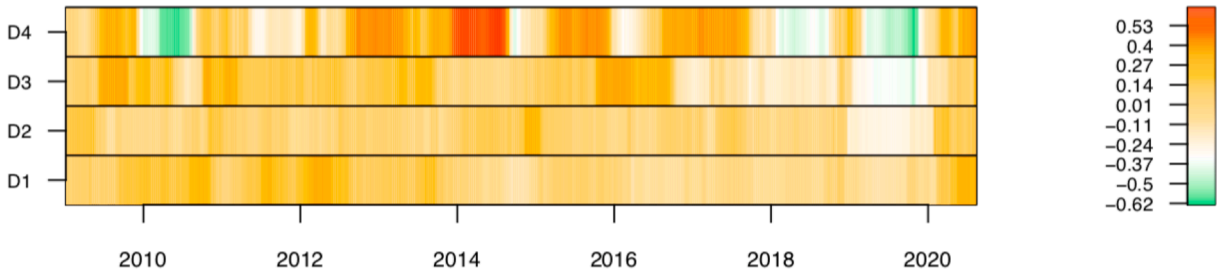
Fig. 3. (*continued*).

5. Conclusion

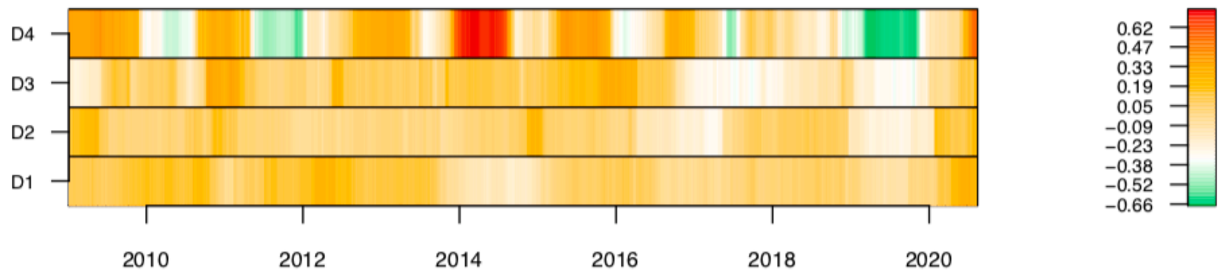
We have examined the influence of Twitter-based sentiment on the returns of 11 US sectors (communications, consumer discretionary, financial, industrial, energy, materials, technology, healthcare, utilities, staples, and real estate), as well as the aggregate S&P 500 returns. To measure sentiment, we sampled data for Twitter-based sentiment through an API. Data for all sampled series is based on daily frequency for the period from 21 June 2010 to 13 April 2020. To capture the non-linear correlation between US sectoral returns and Twitter-based sentiment, we apply a non-parametric, causality-in-quantile analysis, followed by the RWWC method. We



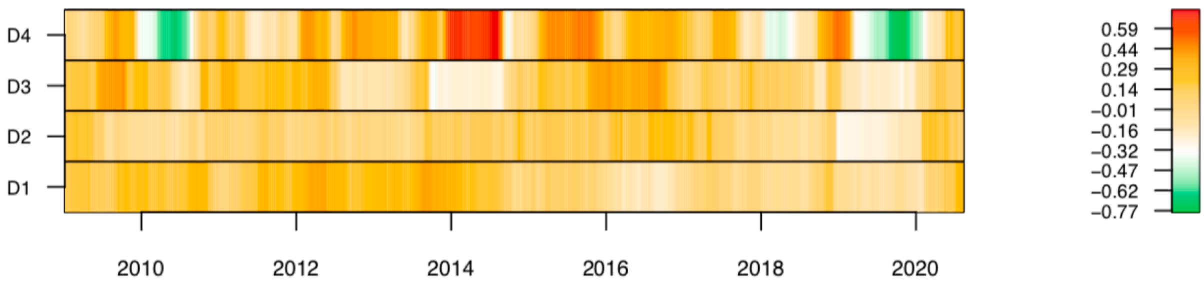
i) Technology



j) Utilities



k) Staples



l) S&P 500

Fig. 3. (*continued*).

show that investor sentiment causes symmetric changes in US equity returns, although this varies across different sectors. The healthcare, communications, materials, consumer discretionary, energy, staples, and information technology sectors seem to be more sensitive to changes in Twitter-based sentiment across all quantiles, while the financial, industrial, real estate, and utilities sectors appear to be affected only in a few quantiles. The RWWC showed low correlation values for all decomposed series (i.e., the short-, medium-, and long-run). Among all the sectors, the returns of the materials sector are negatively correlated with Twitter-based sentiment only during 2019, whereas the returns of the financial, technology, industrial, staples, and utilities sectors showed a negative correlation between 2018 and 2019. The results of the RWWC for the aggregate US returns showed a similar pattern, albeit with weak magnitude. We also observe negative correlation values during 2010 and between 2018 and 2020 for the long-run investment period, as well as a strong positive correlation during 2014 for the long-run decomposed period.

Our findings have significant value and implications for investors in the US sectoral market. First, these investors should be aware of the role of social media in predicting US equity markets at aggregate and sectoral levels. By carefully observing and analysing Twitter-based sentiment and its effect on various US sectors, investors could maximize the returns on their investments by carefully constructing and re-evaluating their portfolios. Second, the heterogeneous effect of Twitter-based sentiment on US sectoral returns calls for the careful placement of sector-based equities in a portfolio based on their sensitivity to such sentiment. Finally, our findings highlight the significant variation in the response of US sectoral returns to Twitter-based sentiment across different levels of decomposition, indicating that investors can overweight or underweight their investment in US sectors based on the magnitude of the underlying correlation. Furthermore, changes in investor sentiment can also result in shifting investment patterns in other sectors. For further research, we suggest using uncertainty and risk measures as control variables, along with investor sentiment for multivariate, time-varying models, because these control variables could provide rich insights concerning the correlation between sentiment and stock returns. Another useful future direction is to analyse industrial returns, since there could be many industries in one sector; for example, the financial sector has three industry groups (banks, diversified financials, and insurance). Such inclusion may provide useful insights, sincesome sectors, like financials, are less sensitive to changes in sentiment, which could be due to the fact that the effect is offset within the sector.

CRediT authorship contribution statement

Rami Zeitun: Investigation, Writing – review & editing, Project administration, Validation. **Mobeen Ur Rehman:** Conceptualization, Methodology, Data curation, Software, Formal analysis. **Nasir Ahmad:** Writing – original draft. **Xuan Vinh Vo:** Conceptualization, Supervision, Resources.

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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