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Sensitivity of US equity returns to economic policy uncertainty and investor sentiments

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A R T I C L E I N F O

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A B S T R A C T

This paper examines the sensitivity of major US sectoral returns to economic policy uncertainty and investor sentiments. Our analysis is based on weekly frequency and ranges from January 1995 to December 2015 covering a span of 20 years. Considering existing, however limited evidence of non-linear structure exhibited by investor sentiments and economic policy uncertainty and on the basis of our non-linear diagnostics, we use novel technique of non-parametric causality in quantiles approach proposed by Balcilar, Gupta, and Pierdzioch (2016). Our results highlight that economic policy uncertainty and investor sentiments act as driving factors for US sectoral returns. The nature of relationship is reported as asymmetrical for stock returns and symmetrical for variance of returns with an exception of Healthcare sector for economic policy uncertainty and bullish market sentiments. Our study carries implications for portfolio diversification and policy makers for forecasting market efficiency and economic trends.

1. Introduction

Last two decades have witnessed an increasing amount of literature regarding determinants of stock returns. Such studies range from addressing asset pricing models to the inclusion of major macro-economic variables that influence international stock markets. Among many, two factors i.e. Economic Policy Uncertainty (EPU) and Investor Sentiments are reported in recent strand of literature. The discussion of these two factors and their impact on stock prices address questions like whether EPU or investor sentiments affect stock prices, and "if they do, how?" Such questions are of long-standing interest to policy-makers, market participants and academics. The classical finance remains silent in explaining the sentiment based concepts since most of the assumptions of classical finance (i.e. efficient market hypothesis, CAPM, three factor model, etc.) are based on rational and efficient markets. Likewise, Economic policy uncertainty possess the power to affect the decision-making processes and their implementation by different firms and investors. High uncertainty may adversely influence an economy as a whole which was clearly observed during the 2008–09 Global Financial Crisis

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(GFC) and 2012 European Sovereign Debt Crisis (ESDC) periods. Moreover, the Brexit decision of UK, and the US presidential elections in 2016 demonstrated how an increase in the EPU may create wide fluctuations in different financial markets. Existing literature also documents the effects of uncertainty on different economic variables. For example, according to Bernanke (1983), when firms face uncertainty, they prefer the wait-and-see approach rather than to engage in investment because investment costs are irreversible.[1] Few studies also document that EPU can influence asset prices, directly or indirectly, through several channels. First channel is through the firms or investors who may change or delay their important decisions such as employment, investment, consumption, and saving (Gulen & Ion, 2015). Second channel is through supply and demand channels, leading to increased financing and production costs, which would discourage investors (Gilchrist, Sim, & Zakrajšek, 2014). Third, EPU may reduce the value of protections provided by government for markets, yielding an increased risk in the financial markets (Pastor & Veronesi, 2012). Fourth, EPU might affect macroeconomic variables such as inflation, interest rate and expected risk premiums leading towards economic contractions (Pástor & Veronesi, 2013).

Though there are many studies that address the importance of economic policy uncertainty and its effect on different variables,[2] its relationship with sectoral equity returns presents itself an avenue for further research. This gap is also motivated by the non-linear behavior of economic policy uncertainty as highlighted earlier by Bekiros, Gupta, and Majumdar (2016) and Rehman (2018). In this aspect of non-linear behavior of economic policy uncertainty and its impact on sector equity returns, studies focusing on EPU–-stock return relationship are relatively limited, with a general conclusion that EPU has a negative effect on stock returns. For example, government policy uncertainty is measured by Pastor and Veronesi (2012) as a measure of variation in policy and report its negative effect on the US equity returns.

With the recent advent of behavioral finance and its acceptance since the last couple of decades by academic community and practitioners, investor sentiments are considered as important phenomena in international financial markets. Since Keynes (1937), several authors have considered the possibility that sentiment-driven investors can cause prices to depart from their fundamental values and therefore, tried to examine this hypothesis through different theoretical as well as empirical studies. The classical argument on investor sentiment is that rational traders would eliminate any mispricing trying to exploit the profit opportunities. However, if they cannot fully exploit such opportunities due to limits of arbitrage, for instance due to unexpected demand shock, the sentiment effects become more likely.[3] De Long, Shleifer, Summers, and Waldmann (1990) report that within a theoretical perspective, limits to arbitrage and variations in noise traders leads to deviation in equity pricing from their fundamentals, thereby resulting in their volatile behavior. In another study, Barberis, Shleifer, and Vishny (1998) highlight that investor sentiments are capable in underreacting as well as overreacting to news. According to Antoniou, Doukas, and Subrahmanyam (2013), rise in the momentum profits are attributed to investor optimism whereas changes in subsequent returns are relative to investor sentiments (see Baker & Wurgler, 2006). There is an existing strand of literature that reporting that investor sentiments can influence pricing level of different assets (see Renault, 2017) however recent work by Apergis, Cooray, and Rehman (2018) report evidence of reverse causality running from US energy prices towards investor sentiments. They report significant association between energy prices and investor sentiments after controlling number of financial and macro-economic factors.

There are several attempts to introduce asset pricing models for capturing the role of investor sentiments. Yang and Zhang (2013a) introduce a sentiment asset pricing model showing that stock prices have wealth-weighted average structure and that investor's wealth proportion could amplify sentiment shocks on asset prices. In another work, Yang and Zhang (2013b) propose a dynamic asset pricing model with diverse sentiments and report that equilibrium in equity pricing results from the wealth-share weighted average of stocks with an assumption of the economy comprising only of investor sentiments (see Mehra & Sah, 2002; Yang, Yan, & Zhang, 2013). More recently, Apergis and Rehman (2018) investigate the role of investor sentiments in asset pricing proposing that investor sentiment is a priced factor, overlooking of which may result in imperfect depiction of asset pricing.

The theories in traditional or neo-classical finance are based on market efficiency under numerous assumptions however, remains silent in addressing the human or investor sentimental aspect regarding various investment decisions. Therefore, besides rationality and market efficiencies, the sentiment or behavioral aspect of investors play a key role in addressing asset pricing, mostly at disaggregate level. Likewise, the presence of uncertainties in economic environment are also capable to affect the decisions made by at individual as well at institutional level. Our work is also motivated by the non-linear exhibition of the model comprising of assets and sentiments and policy uncertainties since the effect of investor sentiments and economic policy uncertainties are hard to predict the

[1] For other early examples related with the effect of uncertainty on economic activity, see Scheffel (1990), Romer (1991), Bertola and Cabellero (1994), Dixit, Dixit, and Pindyck (1993), Abel and Eberly (1996), Balcilar et al. (2016).

[2] These studies analyze the effect of EPU on crucial topics such as corporate governance (Zhang, Han, Pan, & Huang, 2015), firm's cash holdings (Diks & Panchenko, 2017), Al-Yahyaee examine the effectos of differnet uncertainty indices on cryptocurrencies, investment behavior (Gulen & Ion, 2015), IPO activity (Çolak, Durnev, & Qian, 2017), economic development (Schmeling, 2016), unemployment (Castelnuovo, Lim, & Pellegrino, 2017), monetary policy (Aastveit, Natvik, & Sola, 2013), yield curve (Lemmon & Portniaguina, 2015), sovereign risk (Yang & Zhang, 2015), financial stress (Tsai, 2017), inflation and output (Kahneman & Tversky, 2013), real economy (Chang et al., 2017), bank lending (Brock, 2016), housing sector (Chung, Hung, & Yeh, 2017), commodity markets (Wisniewski & Lambe, 2015), forex markets (Ko & Lee, 2016), relationship between stock and bond markets (Liu & Zhang, 2015), co-movement of stock markets (Li, Zhang, & Gao, 2017), stock market volatility (Malkiel & Fama, 2015), and global stock market risk (Wang, Zhang, Diao, & Wu, 2017).

[3] Kahneman and Tversky (1979) porposed an alternative work as behavioral economic theory (also commonly known as loss aversion or prospect theory). They postulated that by valuing losses and gains differently, individuals undergo decision making on the basis of peceived gains rather than perceived losses. So, in case of two choice with equal probability, where one present potential losses and the other presenting potential gains, an investor will choose the later.

magnitude of change in equity returns.

The novelty of our work is to examine the causal relationship between different US sectoral returns and economic policy uncertainty and investor sentiments. Investment community is widely influenced by the market sentiments about the performance of stocks. On one hand these are the sentiment which tend to influence investors decisions whereas on the other hand, economic uncertainties tend to change the way business perform. However, this causal relationship between US sectoral returns and EPU and bearish and bullish sentiments may not only yield significant results under the linear model. Therefore, based on our non-linear diagnostics and existing evidences about the non-linear relationship between investor sentiments, EPU and sectoral returns, we aim to capture the presence of underlying non-linear causality between investor sentiments, EPU and sectoral returns.

Looking at the aforementioned work, we are motivated by a large number of studies documenting that economic uncertainties and investment behaviors in financial markets might affect asset prices. We believe that this subject requires further investigation, which led us to contribute in the following aspects. First, we aim to capture the non-linear relationship of US sectoral returns with investor sentiments and economic policy uncertainty. The motivation for this work comes from the fact that though existing literature[4] is rich in estimating asset pricing and its determinants, the gap exists in terms examining causal relationship between stock returns and the related factors. Second, we aim to report the presence of any non-linear relationship of US sectoral returns with EPU and investor sentiments. The testing of this relationship of US sectoral returns with investor sentiments and EPU is supported by the non-linear behavior of stock returns estimated by the BDS test for independent and identical distribution (*i.i.d.*) of residuals. This objective is further motivated by the application of a comparatively new non-parametric, non-linear causality in quantiles estimation model proposed earlier by Balcilar et al. (2016). Third and final objective of this study is to investigate the sensitivity of sector based US returns to EPU and investor sentiments, since gap for investigating the behavior of disaggregate sectoral returns exists in recent literature. Economic policy uncertainty presents itself as a macro-economic risk factor and is considered an important driver of aggregate risk. On the other hand, investor sentiments have been extensively studies for their linear impact on stock returns. Our study however, differentiates from the rest exploring cause and effect relationship under the first (mean) and second moments (variance) of weekly returns. This aspect also carries important implications for sector based investments for the purpose of portfolio diversification. Our results highlight driving role of economic policy uncertainty and bearish and bullish investor sentiments on US sectoral returns. This relationship of EPU and investor sentiments with equity returns is asymmetrical in nature for both returns and variance of returns across the sampled period. These results are in accordance with the findings by Hoque and Zaidi (2019) who highlight the non-monotonic, non-linear and asymmetric nature of the relationship between sectoral returns and EPU. They report that the economic policy uncertainty has the predictive power for stock returns. Furthermore, they are also of the opinion that EPU qualifies as a proxy to systematic risk for different investment decisions and asset pricing. Likewise, our results are also supported by Arouri and Roubaud (2016) who find the non-linear relationship of economic policy uncertainty with US equity returns. However, the results for relationship between equity returns and EPU remains persistent and robust only under extreme volatilities.

The rest of the paper is organized as follows: Section 2 presents related literature. Section 3 provide details about the data, its sources and the results of preliminary analysis. Section 4 explains the methodology with main empirical findings. Finally, Section 5 concludes our work.

2. Literature review

2.1. Economic policy uncertainty and the stock market

The EPU – stock return nexus has gained much popularity in the last decade, with ample evidence of the importance of economic policy uncertainty for capital markets. Kang and Ratti (2013) employ a VAR model and find that increasing level of EPU causes a drop in US equity market returns. Antonakakis, Chatziantoniou, and Filis (2013) estimate dynamic correlations between US stock market returns, volatility and economic policy uncertainty over time using the DCC model and show that an increase in EPU decreases stock market returns. The state-dependent relationship between EPU and equity pricing has also been highlighted in existing literature: Pástor and Veronesi (2013) introduce a theoretical model to examine the relationship between EPU and risk premia. They highlighted that political uncertainty commands risk premium however its effects on volatility, correlation, and risk premia are stronger when the economy is weaker. In another study, Bijsterbosch and Guérin (2013) find that high uncertainty episodes are associated with a sharp decline in security pricing.

In terms of methodological aspect while measuring the impact of economic policy uncertainty, existing literature documents many alternative methodologies. For example, Ko and Lee (2015) analyze link between EPU and stock prices in both time and frequency domain using wavelet analysis and highlight time varying negative relationship ranging from low frequency-high frequency cycles. Moreover, timings of such changes in frequencies overlays when there exists a co-movement between the EPU of US and other countries. In another study, Ajmi, Aye, Balcilar, El Montasser, and Gupta (2015) investigates the relationship of equity market uncertainties with EPU in US and report significant predictive relationship directed from equity market uncertainties to economic policy uncertainty compared with similar relationship from economic policy uncertainty to equity market uncertainties. Brogaard and Detzel

[4] According to Baker et al. (2016), policy uncertainty is related with the volatility of US sectors which are more related to policy related issues. i.e. defense, finance, healthcare, infrastructure construction etc. In a similar pursuit, Arouri, Estay, Rault, and Roubaud (2016) investigate the sensitivity of US stocks due to EPU and report an inverse relationship between EPU and equity US returns with more intense relationship during economically turbulent periods.

(2015) use EPU index of Baker, Bloom, and Davis (2016) to capture its forecasting power regarding the excess market returns and report significant positive forecasting power. Chang, Chen, Gupta, and Nguyen (2015) investigate seven OECD countries to examine whether economic policy uncertainty is linked with their respective equity markets and with the oil prices and highlight that high levels of EPU in both, US and the UK, lead stock prices. Later, Bekiros et al. (2016) employ a quantile predictive regression model to find if economic policy uncertainty is capable to forecast premium on US stocks and report that EPU possess substantial out-of-sample forecasting ability under normal and bullish market conditions. Later, Chen, Jiang, and Tong (2017) study the relationship between Chinese EPU and their equity market returns with results suggesting that under several control variables, the Chinese EPU negatively predict their equity returns. In another study, Peng, Huiming, and Wanhai (2018) uses quantile regression to estimate dependence structure between equity returns and EPU in G7 and the BRIC economies. Their results suggest that increasing EPU hinders equity returns except UK and France. In a more recent work, Rehman, Asghar, and Hussain (2019) examine the sensitivity of US sectoral returns to economic policy uncertainty and find that IT, utilities, industrials and telecommunications sector highlight no changes to US EPU.

2.2. *Investor sentiment and the stock market*

Existing literature entails important theoretical as well as empirical studies on investor sentiment–stock returns relationship highlighting that investor sentiment can persist and affect stock prices. Earlier studies start with theoretical approaches. For example, De Long et al. (1990) introduce two types of investors in the stock market, namely rational investors and noise traders. Rational investors contribute to fundamental value whereas noise traders cause premium risk. By imposing limit on arbitrage process, noise traders lead towards the deviation of equity returns from their fundamentals. According to Barberis et al. (1998), overreaction towards the good news and underreaction towards bad news represents investor sentiments. The work by Fisher and Statman (2000) highlights positive correlation of investor sentiments with mispricing in the equity market which is further followed by predictable reversal trends. According to Brown and Cliff (2004), there exists a contemporaneous relationship between the US stock returns and changes in investor sentiments where stock valuation is affected by investor's subject belief thereby leading towards the biased expectations like optimism and pessimism. However, a year later Brown and Cliff (2005) report that companies that are new, have high book to market ratio with less profits, have small size and pay no dividends are affected by investor sentiments due to the associated difficulty in valuing such companies. On the contrary, companies with stable earning and consistent dividend paying ability are less sensitive to investor sentiments thereby confirming the results of Lemmon and Portniaguina (2006) and Baker and Wurgler (2006).

Although there are many studies[5] that highlight the importance of investor sentiments in influencing asset returns, the assumption is based on the presence of underlying linear relationship only. However, there are few studies that investigates the non-linear behavior of investor sentiments. In one of the late studies, Ni, Wang, and Xue (2015) apply quantile panel regression framework to investigate nonlinear relationship between investor sentiment and Chinese stock returns and report the influence of investor sentiment over 1-month to 24-months' period. Rehman and Shahzad (2016) apply time–frequency relationship between US sectoral returns and investor sentiments and report cyclical and in-phase relationship between investor sentiments and industry returns. In another recent work, Sun, Najand, and Shen (2016) and Renault (2017) use proprietary datasets of high-frequency investor sentiments extracted from news, social media and various internet sources and highlight the predictability of S&P 500 intraday returns from 30 min lagged investor sentiments. These results suggest that investor sentiments become more influential at high frequency data.

The abovementioned literature on EPU-stock market and investor sentiment-stock market nexus shows us that both of these factors are crucial to analyze. However, few studies tend to capture their underlying non-linear relationship with sector based returns. Since efficient markets returns are more susceptible to sentiments, we examine the US stock returns at sectoral level to provide much richer findings on the subject.

3. Methodology, data and preliminary analysis

3.1. *Methodology*

To test the presence of any non-linear behavior of investor sentiments and economic policy uncertainty with US sectoral returns, we use nonlinear causality in quantiles method which was proposed by Balcilar et al. (2016). This method was proposed earlier by Nishiyama, Hitomi, Kawasaki, and Jeong (2011) followed by Jeong, Härdle, and Song (2012) and presents itself as a useful technique for detecting the non-linear causal behavior via hybrid approach. Our work is based on detecting the causality running from investor

[5] According to Hoque and Zaidi (2009), inclusion of investor sentiments increases explanatory power of the asset pricing models for equity returns. Shahbaz, Balcilar, and Ozdemir (2009) also reports sensitivity of equity returns to investor sentiments in 18 countries over 20 years' period. Similar findings are reported by Zhang et al. (2011) suggesting that investor sentiments affect the US stocks return-volatility relationship. Baker, Wurgler, and Yuan (2012) contruct a global sentiment index along with six local indices and find that all these indices act as a contrarian determinants of cross section of equity returns. According to Sun et al. (2012), investor sentiments play an important role during high sentiment regimes and therefore remain as anomalies for equity returns. Çolak et al. (2017), report the presence of an an asymmetric relationship between investor sentiments and cross-section of equity returns under various recessionary and expansion states of an economy. They conclude that investor sentiments fades away under economic recessions however remains significant during economic expansions. Antoniou et al. (2013) report that during high sentiment periods, noise traders become more bullish and reponsive to stocks with high beta values.

sentiments and EPU x_t towards US weekly sectoral returns y_t. We follow Jeong et al. (2012) and therefore, the resultant quantile-based causality is explained below[6]

x_t does not cause y_t in the θ-quantile with regards to the lag- vector of $\left\{y_{t-1}, \cdots, y_{t-p}, x_{t-1}, \cdots, x_{t-p}\right\}$ if

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

x_t is presumably cause of y_t in the θ^{th} quantile with regards to $\left\{y_{t-1}, \cdots, y_{t-p}, x_{t-1}, \cdots, x_{t-p}\right\}$

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

Here, $Q_\theta(y_t \bullet)$ is the θ^{th} quantile of y_t. The quantiles of y_t, $Q_\theta(y_t \bullet)$ depends on t and $0 < \theta < 1$.

For the purpose of presenting the causality-in-quantiles test, we define the following vectors as

$Y_{t-1} \equiv \left(y_{t-1}, \cdots, y_{t-p}\right), X_{t-1} \equiv \left(x_{t-1}, \cdots, x_{t-p}\right)$ and $Z_t = (X_t, Y_t)$. $F_{(y_t|Z_{t-1})}\left(y_t|Z_{t-1}\right)$ and $F_{(y_t|Y_{t-1})}\left(y_t|Y_{t-1}\right)$ are defined as the conditional distribution functions signifying the distribution functions of y_t conditioned on vectors Z_{t-1} and Y_{t-1}, respectively. The conditional distribution $F_{(y_t|Z_{t-1})}\left(y_t|Z_{t-1}\right)$ is presumed to be completely continuous in y_t for nearly all Z_{t-1}. By defining $Q_\theta(Z_{t-1}) \equiv Q_\theta\left(y_t|Z_{t-1}\right)$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta\left(y_t|Y_{t-1}\right)$, it is clear that $F_{(y_t|Z_{t-1})}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, which holds with a probability equal to 1. Hence, hypotheses based on Eq. (1) and Eq. (2) for the causality-in-quantiles are presented as follows

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

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

For defining the measurable metric for the purpose of practical implementation of causality-in-quantiles tests, Jeong et al. (2012) propose the use of the distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\}$, where ε_t represents error of the regression and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The estimators of unknown regression are defined as

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

where quantile estimator $\widehat{Q}_\theta(Y_{t-1})$ yields an estimate of the θ^{th} conditional quantile of y_t given Y_{t-1}. The term $\widehat{Q}_\theta(Y_{t-1})$ is estimated using the nonparametric kernel approach[7] as below.

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

where $\widehat{F}_{(y_t|Y_{t-1})}\left(y_t Y_{t-1}\right)$ denotes the Nadarya-Watson kernel estimator given by:

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

where $L(\bullet)$ denotes a known kernel function and h represents the bandwidth used in kernel estimation.

In the next step, we examine causality in variance because the rejection of causality in moment m does not imply non-causality in the moment k for $m < k$, from EPU and investor sentiments (both bearish and bullish) to the US sector based returns. This is explained by the below mentioned model:

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

We present the higher order causality-in-quantiles as

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

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

Overall, we investigate whether x_t Granger causes y_t in quantile θ up to K^{th} moment using Eq. (9) and formulate feasible kernel-

[6] The statements in this section is based on Pastor and Veronesi (2011) and Jeong et al. (2012).

[7] We perform non-linear Granger causality test using the feature space of suitable kernel functions by assuming the arbitrary degree of non-linearity. We generalize the Granger causality to non-linear case by using the theory of kernel Hilbert spaces. We perform linear Granger causality in the feature space of suitable kernel functions by assuming the arbitrary degree of non-linearity. This new strategy helps in coping with the issue of overfitting, which is based on the geometry of reproducing kernel Hilbert spaces.

based test statistics following Jeong et al. (2012), for each k. For the joint density-weighted nonparametric tests for all $k = 1, 2, \cdots, K$, the sequential testing approach is followed used earlier by Nishiyama et al. (2011). We select lag order of 1 based on the Schwarz Information Criterion (SIC) whereas least squares cross-validation techniques are used for selecting the bandwidth value. Finally, for $K(\bullet)$ and $L(\bullet)$, we employ Gaussian-type kernels.

3.2. Data and preliminary analysis

We source data ranging from December 8, 1995 to December 8, 2020 for our sampled variables i.e. US sectoral based returns, economic policy uncertainty and investor sentiments. Data for US sectoral returns[8] consists of nine major sectors including Healthcare, Consumer discretionary, Financials, Industrials, Telecom, Materials, Information Technology, Utilities and Automobiles. Data for these sectoral returns is extracted from Thomson Reuters Data Stream on daily frequency. Daily data for economic policy uncertainty[9] is based on the work of Baker et al. (2016) and is extracted from www.policyuncertainty.com. Data for investor sentiments comprises of the bearish and bullish market. American Association of Individual Investors (AAII) is used as a proxy[10] of bearish and bullish investor sentiments with weekly data frequency.

The AAII requires respondents to segregate themselves as bullish, neutral or bearish. The AAII sentiment survey resembles with the Investors Intelligence survey in that both are conducted on weekly basis. On each weekday, AAII mails 100 questionnaires which on each Thursday are tallied, not to be dated earlier than two weeks. In addition to sentiment survey, the AAII also conducts an asset allocation survey by asking individual investors to highlight their actual allocations in portfolios through stocks, cash and bonds. However, this asset allocation survey is on monthly basis unlike the investor sentiment survey. 600 questionnaires are mailed at the beginning of each month which are later tallied with responses received during the month. These responses are returned consistently on monthly basis with central point being the middle of each month. This allows us to consider the mean of weekly AAII sentiment figures during the entire month as a proxy of sentiment corresponding to measuring investment action.

We selected AAII index because of the fact that this sentiment index comprises of the opinions of randomly chosen participants about equity markets over the upcoming six months. Furthermore, these anticipated future directions of equity markets are categorized as bearish, neutral and bullish markets.[11] The categorization among bearish, neutral and bullish sentiments can help investors in predicting the equity pricing behavior for the purpose of sector based investments. Though several authors use different proxies for investors sentiments, our work varies in terms of selection of bearish and bullish sentiments as well as regarding the selection of sector based returns. For example, Schmeling (2009) uses consumer confidence as a proxy of investor sentiments for predicting international stock markets whereas our study uses bearish and bullish sentiments with sector based returns. Similarly, Smales (2017) investigates relationship between FX markets and investor' fear (through implied volatility index) which is quite different from our work in terms of variables, scope and implications. Since data for bullish and bearish investor sentiments is based on weekly basis, we convert daily US sectoral data and the EPU data on weekly frequency to make analysis on weekly basis.

Fig. 1 shows weekly returns of nine major US sectoral indices and the trend of US economic policy uncertainty index and bearish and bullish investor sentiments. It is evident that there are high negative sectoral returns during the 2008 global financial crisis. Almost all of the sectors experienced their lowest return levels during 2008–2009. Likewise, economic policy uncertainty and bearish market sentiments increased substantially during the GFC (2008–09) period however bullish market sentiments exhibited no significant change as a result of financial markets slump.

Table 1 present descriptive statistics of nine major US sectoral returns, US economic policy uncertainty index and bearish and bullish investor sentiments from December 1, 1995 to December 31, 2015 on weekly frequency basis. The average weekly returns are positive for all the sectors. Information technology sector has the highest weekly average returns. Financial sector has the highest return volatilities. Skewness and kurtosis values indicate that all the return series are asymmetric evident by the negatively skewed and leptokurtic distribution with fat tails. Based on these negatively skewed return values, there is a higher possibility of large decreases in sectoral returns (except automobiles sector). The negative skewed and positive excess kurtosis values lead towards non-normal distributions supported by the JB test statistics. The Ljung Box test of residuals Q(20) and squared residuals Q2(20) suggest the presence of serial correlation for the returns in each sector. In addition, ARCH(20) test results indicate that there is ARCH effect in all series. According to our unconditional correlation results, bullish and bearish investor sentiments are strongly correlated with the returns of each sector however on the contrary, economic policy uncertainty exhibit insignificant correlation.

In this study, we apply the quantile covariate unit root test proposed by Galvao (2009) that is based on the quantile autoregression framework with the addition of stationary covariates. Within this quantile covariate framework, the speed of adjustment is dependent on the magnitude as well as direction of a shock. For this reason, we apply quantile based unit root test to each variables across a wide

[8] Our sampled sectoral indices match the normal GICS system. However, the Technology index includes both IT and Telecom sectors.

[9] Economic policy uncertainty index consists of three components. The first component consists of economic uncertainty related to policy related issues data covered by various newspapers. Second component is related to the provisional set of federal tax for future years. Third component highlights disagreement about economic forecasts, thereby acting as a proxy for economic uncertainty.

[10] AAII consists of primary data which is based on a survey asking randomly chosen participants about the likely directions of equity markets during the next six months. These directions are then further categorized as bearish, neutral and bullish markets. Since this index is based on the expectations of individual investors about future directions of equity markets, we use it as an appropriate proxy measure of individual investor sentiments.

[11] For more details, see Galvao (2000).

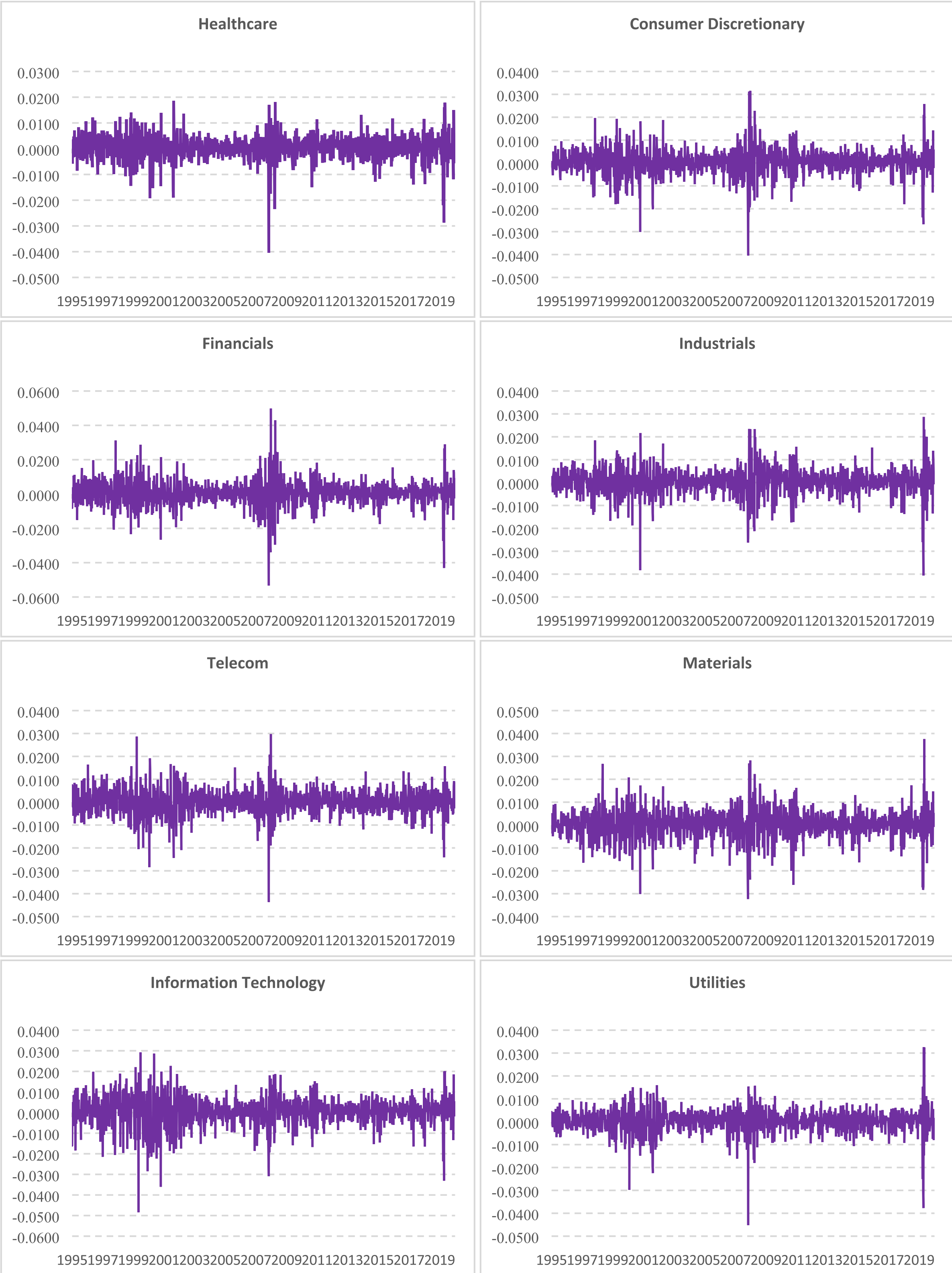

Fig. 1. Sectoral returns with EPU and investor sentiments.

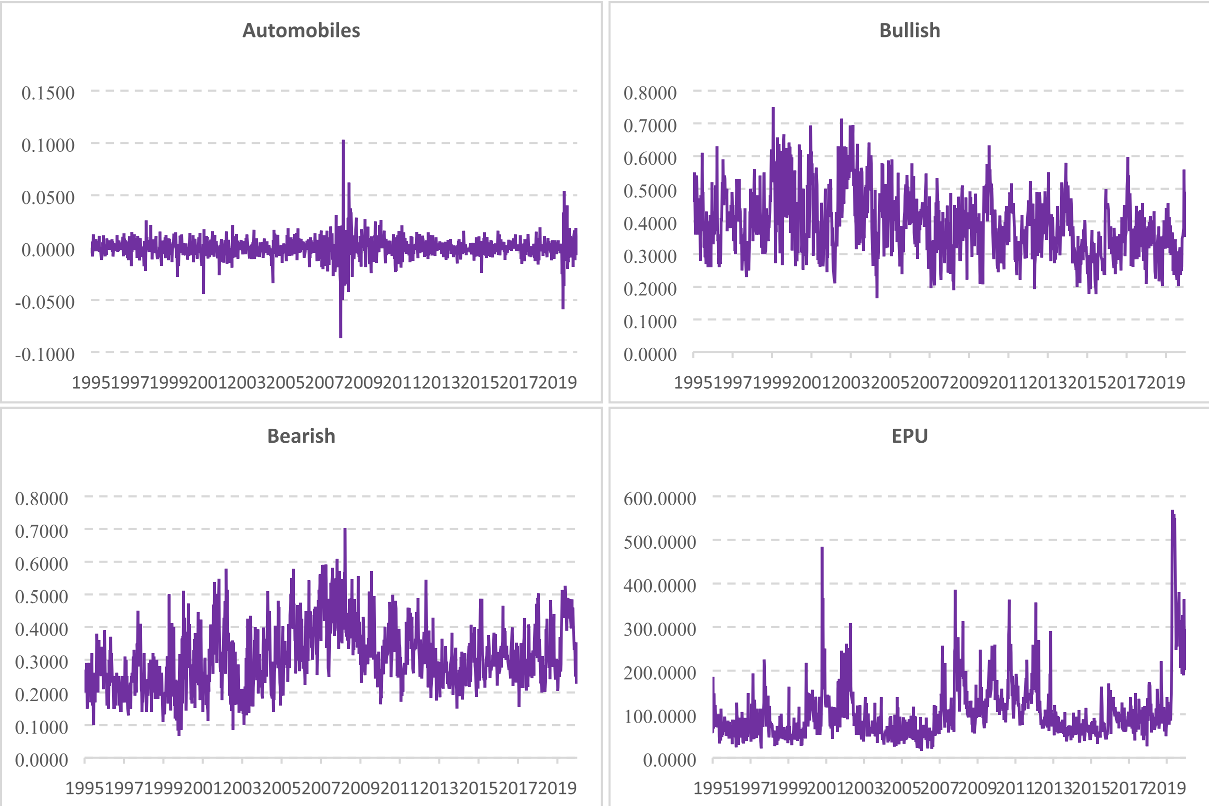

Fig. 1. (*continued*).

range of quantiles which provide estimates not only for conditional mean but also for tail distribution. Results in Table 2 presents statistics for autoregressive coefficient, unit root test statistic ($t_n(\tau)$) and the persistent parameter ($\alpha_1(\tau)$) ranging from 5th to 95th quantile. Our results highlight that the autoregressive statistics show variations consistently across all quantiles for all variables. We report values of $\alpha_1(\tau)$ which are greater than 1 as follows. For Healthcare sector between the range of 75–90%, consumer discretionary and financials at 5–35% range, industrials at 5–30% range, telecom at 5%, materials at 5–35% range, Information Technology at 50–95% range, automobiles at 5–40% range, EPU at 5–15% range and bearish and bullish sentiments both at 60–95% range. Utilities sector is the only one among all US sectors with coefficient value less than one across all the quantiles. The presence of $t_n(\tau)$ highlights rejection of for all variables across majority of the quantiles.

Table 3 reports unidirectional linear Granger Causality test results. Bullish and bullish investor sentiments cause changes in weekly returns of all sectors (except consumer discretionary and financials in case of bullish sentiments) whereas bearish sentiment only induces changes in weekly industrial returns. Likewise, EPU causes change in all the sectoral returns except financial, telecom and information technology sectors. Based on the results of linear granger causality, we further explore the nature of relationship between EPU, sentiments and US sectoral returns.

To further explore the nature of relationship between EPU, sentiments and US sectoral returns, we apply BDS test (see Table 4) in proposed by Brock (1987) and Broock, Scheinkman, Dechert, and LeBaron (1996). This test is quite appropriate for testing nonlinear behavior of model consisting of sectors based returns along with EPU and investor sentiments. Results in Table 4 highlight significant evidence against linearity for all variables. According to BDS test, we reject the null of *i.i.d* residuals at various embedding dimensions (m). Based on these results, we conclude that there is strong evidence of nonlinear relationship between US sectoral returns and our predictive variables i.e. EPU, bullish and bearish sentiments. The null hypothesis of independent and identical distribution is rejected across all the panels comprising of EPU, bullish and bearish market sentiments. This means that Granger causality tests in a linear framework in particular and any parametric estimation technique in general might lead towards unreliable results due to mis-specification errors.

The results of our diagnostic tests comprising of quantile unit root and BDS tests further probe us to investigate the effect of sentiments and policy uncertainty on US sectoral returns using a non-linear framework. The presence of non-linear structure leads us to investigate the presence of causality across various quantiles which provides reliable estimates even in the presence of jumps, structural breaks and outliers.

Table 1
Descriptive Statistics.

	Healthcare	*Con.dis.*	*Fin.*	*Industrials*	*Telecom*	*Materials*	*InfoTech*	*Utilities*	*Automobiles*	*Bullish*	*Bearish*	*EPU*
Mean	0.0003	0.0004	0.0003	0.0003	0.0000	0.0002	0.0004	0.0002	0.0000	0.3915	0.3084	102.0881
Max.	0.0186	0.0315	0.0498	0.0287	0.0298	0.0376	0.0292	0.0325	0.1031	0.7500	0.7027	569.4120
Min.	−0.0404	−0.0404	−0.0533	−0.0406	−0.0436	−0.0333	−0.0484	−0.0452	−0.0866	0.1648	0.0667	15.6580
Std. Dev.	0.0047	0.0058	0.0075	0.0059	0.0057	0.0064	0.0072	0.0052	0.0102	0.0980	0.0969	68.8681
Skew	−0.8826	−0.4574	−0.1892	−0.6647	−0.3888	−0.3760	−0.6379	−1.0164	0.1705	0.4825	0.5068	2.7516
Kurt	10.1273	8.2935	9.4256	8.6854	7.8448	7.0325	6.6120	13.9115	18.6124	2.9890	3.0059	14.1461
JB Test	2931.6*	1569.1*	2252.8*	1853.7*	1309.2*	915.0*	797.9*	6698.6*	13260.1*	50.6*	55.9*	8402.1*
Q(20)	31.349**	33.077**	65.561***	49.865***	25.027***	28.147	26.733	26.659	112.71***	2802.3***	4483.8***	7380.2***
Q2(20)	207.16**	780.60***	976.78***	589.21***	274.15***	567.98***	509.49***	476.97***	820.69***	1039.5***	1008.1***	4185.0***
ARCH(20)	8.4135***	21.296***	121.78***	18.315***	7.7697***	14.261***	10.209***	15.758***	27.169***	21.350***	20.757***	149.13***
Correlation												
Bullish	0.1481***	0.2199***	0.2103***	0.2471***	0.1482***	0.2208***	0.1965***	0.1330***	0.1996***	1.0000		
Bearish	−0.2123***	−0.2411***	−0.2517***	−0.2702***	−0.1549***	−0.2290***	−0.2195***	−0.1684***	−0.2044***	−0.6698***	1.0000	
EPU	0.0177	0.0407	−0.0108	−0.0230	0.0089	0.0060	0.0179	−0.0353	0.0092	−0.1420***	0.3309***	1.0000

Note: Above table represents descriptive and statistical properties of nine major US sectoral returns, US economic policy uncertainty and bearish and bullish investor sentiments from Dec. 1995 to Dec. 2020 based on weekly frequency. Std. dev. represents standard deviation, JB represent Jarque-Bera and SW is the Shapiro Wilk normality test. Autocorrelation test statistics are presented by Ljung Box Q (20) and squared residuals $Q^2(20)$ test statistics and autoregressive conditional heteroscedasticity tests are presented by ARCH (20) results. ***, ** and * represents significance level at 1%, 5% and 10% respectively.

Table 2
Quantile Covariate Unit Root Test.

τ	Health care			Con. dis.			Financials			Industrials			Telecom			Materials		
	t	C	α(τ)	*t*	C	α(τ)	*t*	C	α(τ)	*t*	C	α(τ)	*t*	C	α(τ)	*t*	C	α(τ)
0.05	−0.6644	−2.9888	0.9984	3.6058	−3.1846	1.0100	4.9701	−3.2012	1.0124	5.9985	−2.9507	1.0192	0.7817	−2.9066	1.0018	4.7700	−3.3091	1.0286
0.10	−0.2957	−2.9961	0.9996	4.9243	−3.2458	1.0070	3.5513	−3.1380	1.0052	4.6820	−2.9891	1.0087	−1.3679	−2.9637	0.9981	7.7915	−3.1912	1.0198
0.15	−2.3702	−2.9769	0.9975	4.0305	−3.1628	1.0045	2.6987	−3.1550	1.0026	3.9342	−3.0069	1.0058	−1.9487	−3.0205	0.9980	7.5811	−3.1535	1.0153
0.20	−3.2666	−2.9367	0.9971	2.8702	−3.1836	1.0027	1.7549	−3.1747	1.0014	3.1330	−3.0756	1.0040	−2.7680	−3.1197	0.9976	6.0449	−3.1580	1.0107
0.25	−3.4980	−2.9465	0.9973	1.3651	−3.1079	1.0011	1.4493	−3.0805	1.0010	1.8477	−3.0776	1.0021	−3.1204	−3.1069	0.9976	5.1110	−3.1919	1.0076
0.30	−3.3050	−2.9390	0.9977	1.4145	−3.0652	1.0010	0.4976	−3.0020	1.0003	0.2090	−3.0265	1.0002	−3.2644	−3.0724	0.9977	3.0226	−3.1055	1.0041
0.35	−2.8128	−2.9745	0.9982	0.0301	−3.0086	1.0000	−0.6147	−3.0430	0.9996	−0.8233	−3.0167	0.9993	−2.3853	−3.0565	0.9985	0.8555	−3.0996	1.0011
0.40	−3.3352	−2.9562	0.9981	−0.3369	−2.9555	0.9998	−1.4010	−2.9691	0.9993	−1.3223	−3.0182	0.9991	−2.0511	−3.0217	0.9989	−0.4628	−3.0593	0.9995
0.45	−2.0979	−2.9301	0.9989	−0.5005	−2.8962	0.9997	−1.3493	−2.9459	0.9994	−0.6676	−2.9881	0.9996	−1.2111	−2.9718	0.9994	−1.8122	−2.9692	0.9982
0.50	−1.6439	−2.9602	0.9992	−0.6004	−2.9464	0.9997	−1.7395	−2.8646	0.9992	−2.5358	−2.9896	0.9983	−0.8269	−2.9986	0.9996	−2.1047	−2.9138	0.9979
0.55	−1.9119	−2.9456	0.9990	−1.9320	−2.8559	0.9990	−2.7529	−2.8318	0.9987	−4.2443	−2.9267	0.9971	−1.3987	−2.9830	0.9993	−6.1154	−2.8536	0.9940
0.60	−2.0707	−2.9676	0.9988	−2.1905	−2.7747	0.9988	−3.8964	−2.7472	0.9979	−5.2076	−2.8868	0.9959	−0.0600	−2.9515	1.0000	−6.9238	−2.7756	0.9920
0.65	−0.9693	−2.9537	0.9994	−3.0475	−2.7281	0.9982	−5.0372	−2.6553	0.9970	−5.8600	−2.8687	0.9950	0.0817	−2.8983	1.0001	−7.3713	−2.6795	0.9908
0.70	−0.6687	−2.9093	0.9995	−3.4635	−2.5901	0.9978	−5.4184	−2.5514	0.9966	−6.5487	−2.7916	0.9941	0.7900	−2.7905	1.0005	−9.2554	−2.5934	0.9876
0.75	−0.0139	−2.8623	1.0000	−5.1053	−2.4889	0.9964	−6.0313	−2.4239	0.9959	−8.0870	−2.7041	0.9922	−0.0210	−2.7449	1.0000	−11.2326	−2.4875	0.9841
0.80	0.3682	−2.8044	1.0003	−5.6284	−2.3728	0.9956	−5.6581	−2.3545	0.9957	−8.7803	−2.6201	0.9908	−0.4084	−2.6913	0.9997	−12.1983	−2.3100	0.9807
0.85	0.4002	−2.7796	1.0004	−5.5451	−2.3214	0.9948	−5.4586	−2.3100	0.9950	−9.0553	−2.4988	0.9885	−0.5676	−2.5486	0.9995	−13.6692	−2.3100	0.9761
0.90	0.3912	−2.6871	1.0004	−5.4317	−2.3100	0.9932	−6.9657	−2.3100	0.9917	−10.3750	−2.4687	0.9845	−1.8692	−2.4922	0.9978	−13.0018	−2.3100	0.9718
0.95	−0.2194	−2.4603	0.9996	−5.5819	−2.3100	0.9882	−7.7746	−2.3100	0.9859	−9.6471	−2.3705	0.9783	−1.7032	−2.3100	0.9965	−5.8775	−2.3100	0.9620

τ	InfoTech			Utilities			Automobiles			EPU			Bearish			Bullish		
	t	C	α(τ)	*t*	C	α(τ)	*t*	C	α(τ)	*t*	C	α(τ)	*t*	C	α(τ)	*t*	C	α(τ)
0.05	−3.9477	−2.9277	0.9934	0.6744	−2.9024	1.0021	10.3058	−2.8251	1.0244	3.0549	−2.4568	1.0962	−10.7902	−2.3100	0.9062	−9.4029	−2.3100	0.9173
0.10	−6.6708	−3.0334	0.9921	−1.0516	−3.1033	0.9981	11.0904	−2.9335	1.0169	1.8022	−2.6637	1.0422	−11.8254	−2.3100	0.9333	−11.0276	−2.3100	0.9400
0.15	−7.6161	−3.1398	0.9927	−1.3174	−3.1207	0.9982	9.9712	−2.9732	1.0116	1.2130	−2.7810	1.0238	−11.3073	−2.3683	0.9436	−10.7409	−2.3389	0.9465
0.20	−7.8938	−3.1967	0.9937	−2.1511	−3.1845	0.9976	8.6947	−2.9042	1.0087	−0.0282	−2.8500	0.9995	−9.7485	−2.3843	0.9563	−9.1710	−2.3100	0.9605
0.25	−6.2895	−3.1293	0.9957	−0.9370	−3.1536	0.9991	6.5611	−2.8986	1.0057	−1.5321	−2.9087	0.9752	−9.6372	−2.4790	0.9616	−8.5986	−2.3758	0.9669
0.30	−5.4643	−3.0947	0.9965	−0.5766	−3.1317	0.9995	4.9146	−2.9702	1.0038	−2.9185	−2.9674	0.9565	−8.9878	−2.5231	0.9664	−8.1012	−2.4048	0.9710
0.35	−3.1418	−3.0916	0.9982	−0.4277	−3.0923	0.9997	2.6810	−2.9507	1.0019	−4.2582	−2.9828	0.9393	−8.8873	−2.5535	0.9684	−7.9331	−2.4252	0.9723
0.40	−2.0884	−3.0584	0.9990	−0.5880	−3.0223	0.9996	0.5487	−2.9239	1.0003	−5.3315	−2.9844	0.9243	−7.1921	−2.5688	0.9741	−6.2022	−2.4294	0.9783
0.45	−0.2870	−3.0109	0.9999	−0.8153	−2.9941	0.9994	−1.3247	−2.9020	0.9992	−6.1787	−2.9485	0.9096	−5.9438	−2.5902	0.9789	−5.1369	−2.4424	0.9822
0.50	1.0761	−2.9970	1.0005	−0.9446	−2.9352	0.9994	−1.6966	−2.9234	0.9990	−7.2452	−2.9207	0.8932	−3.4567	−2.6322	0.9875	−2.9640	−2.4998	0.9895
0.55	3.0873	−2.9307	1.0013	−1.4153	−2.8910	0.9991	−5.1517	−2.9290	0.9970	−8.1470	−2.9286	0.8816	−2.1084	−2.6848	0.9923	−1.5326	−2.5325	0.9945
0.60	4.8169	−2.9548	1.0024	−1.1190	−2.8487	0.9992	−8.1742	−2.9440	0.9947	−9.0470	−2.9331	0.8683	0.2100	−2.7533	1.0008	0.4167	−2.5678	1.0015
0.65	5.7602	−2.8926	1.0030	−1.6982	−2.8417	0.9987	−9.3930	−2.8629	0.9931	−9.1271	−2.8960	0.8652	1.7695	−2.7574	1.0068	1.8566	−2.5882	1.0072
0.70	5.9046	−2.8618	1.0032	−2.2192	−2.7726	0.9982	−10.3228	−2.8582	0.9918	−10.0069	−2.8611	0.8484	3.5298	−2.7270	1.0138	2.8722	−2.6099	1.0111
0.75	6.8618	−2.7759	1.0042	−2.3446	−2.7187	0.9980	−11.4510	−2.8867	0.9903	−10.1230	−2.8427	0.8336	5.9904	−2.7302	1.0254	5.0133	−2.6043	1.0205
0.80	7.2293	−2.6886	1.0049	−1.9519	−2.6298	0.9981	−12.2083	−2.8111	0.9881	−10.5182	−2.8419	0.8188	7.2419	−2.6621	1.0336	5.6073	−2.6240	1.0254
0.85	6.1514	−2.6074	1.0048	−1.8664	−2.6603	0.9979	−13.1172	−2.7747	0.9853	−10.7359	−2.7933	0.7891	9.5165	−2.6586	1.0509	7.5649	−2.6132	1.0408
0.90	4.4288	−2.4844	1.0046	−1.6243	−2.4913	0.9978	−15.0112	−2.6643	0.9783	−10.3871	−2.7227	0.7541	10.8879	−2.5934	1.0705	8.4679	−2.5493	1.0539
0.95	2.3723	−2.3100	1.0036	−1.9366	−2.3247	0.9962	−13.4646	−2.5764	0.9702	−8.5802	−2.5482	0.7189	9.4335	−2.5540	1.0921	7.4780	−2.4568	1.0740

Notes: Lag length was chosen by the *BIC* with the maximum lag set to be 12. For $\alpha_1(\tau)$, we examine unit-root null with the $t_n(\tau)$ statistic. Coefficient value is represented by $\alpha(\tau)$, *t* represents *t* statistics and C denotes critical value at 5 percent level of significance. The null of $\alpha(\tau) = 1$ is rejected if *t*-statistic is less than the critical value.

Table 3
Linear Granger Causality.

	H_o: Bullish sentiments does not Granger cause US sectoral returns	H_o: Bearish sentiments does not Granger cause US sectoral returns	H_o: EPU does not Granger cause US sectoral returns
Health care	14.1562**	17.2380***	3.2746**
Con. Discretionary	14.4284	13.7994***	3.9447**
Financials	21.3346	25.7979***	1.8549
Industrials	15.7888***	18.9189***	2.7171**
Telecom	16.6691***	10.8594***	0.0684
Materials	14.2927***	16.6256***	3.8993**
Info Tech	8.1686***	4.0086**	1.4004
Utilities	5.8260***	6.8038***	2.5484**
Automobiles	14.7257***	18.1025***	3.1317**

Note: Above table presents F-statistics for the hypothesis of no causality in linear vector AR framework. Bayesian Information Criteria is used for Lag order selection criteria. ***, ** and * represents significance level at 1,5 and 10 percent respectively.

Table 4
BDS Test Statistics.

	M				
	2	3	4	5	6
Panel 1 with EPU:					
Health care	0.0188*	0.0360*	0.0478*	0.0523*	0.0532*
Con. Discretionary	0.0283*	0.0551*	0.0761*	0.0876*	0.0929*
Financials	0.0278*	0.0565*	0.0756*	0.0874*	0.0914*
Industrials	0.0248*	0.0467*	0.0636*	0.0717*	0.0740*
Telecom	0.0156*	0.0322*	0.0441*	0.0505*	0.0510*
Materials	0.0202*	0.0408*	0.0565*	0.0672*	0.0708*
Info Tech	0.0275*	0.0559*	0.0793*	0.0929*	0.0992*
Utilities	0.0230*	0.0450*	0.0576*	0.0628*	0.0657*
Automobiles	0.0208*	0.0413*	0.0553*	0.0631*	0.0657*
Panel 2 with Bullish:					
Health care	0.0186*	0.0357*	0.0478*	0.0525*	0.0535*
Con. Discretionary	0.0256*	0.0491*	0.0692*	0.0801*	0.0848*
Financials	0.0252*	0.0527*	0.0723*	0.0839*	0.0878*
Industrials	0.0224*	0.0432*	0.0598*	0.0682*	0.0700*
Telecom	0.0155*	0.0318*	0.0425*	0.0483*	0.0486*
Materials	0.0222*	0.0434*	0.0598*	0.0701*	0.0726*
Info Tech	0.0256*	0.0535*	0.0767*	0.0904*	0.0971*
Utilities	0.0213*	0.0420*	0.0532*	0.0571*	0.0591*
Automobiles	0.0192*	0.0375*	0.0498*	0.0563*	0.0573*
Panel 3 with Bearish:					
Health care	0.0188*	0.0352*	0.0474*	0.0527*	0.0534*
Con. Discretionary	0.0268*	0.0506*	0.0713*	0.0835*	0.0890*
Financials	0.0254*	0.0507*	0.0693*	0.0804*	0.0844*
Industrials	0.0233*	0.0442*	0.0607*	0.0692*	0.0709*
Telecom	0.0154*	0.0321*	0.0424*	0.0481*	0.0484*
Materials	0.0201*	0.0399*	0.0562*	0.0680*	0.0718*
Info Tech	0.0259*	0.0534*	0.0776*	0.0922*	0.0997*
Utilities	0.0196*	0.0396*	0.0507*	0.0554*	0.0579*
Automobiles	0.0212*	0.0400*	0.0529*	0.0603*	0.0626*

Notes: M denotes parameter in the embedding dimension. * represents significance level at 5 percent or less.

4. Analysis and discussion

We present results of non-parametric causality in mean and variance for first returns and higher order moments. Results for causality in mean running from bullish sentiments, bearish sentiments and EPU to US sectoral returns are depicted in Figs. 2A, 2C and 2E whereas for causality in variance are shown in Figs. 2B, 2D and 2F, respectively.[12] We document results as follows.

- Results of causality in mean running from bullish sentiments to US sectoral returns are shown in Fig. 2A exhibiting asymmetric behavior across all quantiles. We witness that bullish market sentiments cause changes in the US sectoral returns across all quantiles however telecommunication and information technology sectors sector remains an exception in which no causal relationship is present. These results suggest that these sectors might not be influenced by the sentiments rather by the tangible innovations in technology field. Among other sectors, consumer discretionary, financial, industrials and utility sectors remains sensitive to bullish investor sentiments only under median quantile distribution (0.4–0.7 quantile range) suggesting that basic amenities are not affected to investor's bullish behavior compared with rest of the sectors. However, for healthcare and industrial sectors, bullish investor sentiments seem to play a driving role in causing changes in weekly returns. These results are in accordance with the findings of Sun et al. (2016) suggesting that investor sentiments have significant explanatory power for various asset pricing. Causality in variance from bullish sentiments to US sectoral returns is highlighted in Fig. 2B. Results again show asymmetric behavior like causality in mean for all cases except Utility sector. Returns for all sectors highlight sensitivity to changes in bullish sentiments across all the quantiles under higher moments. These results are somewhat similar to the findings of Yu and Yuan (2011) who report that the return-volatility relation is US equity market is sensitive to investor sentiments. An important point to mention here is that for all sectors except utilities and telecommunication, there is a tendency for insensitive behavior of US sectoral returns to bullish sentiments under median quantiles which reverts back to significant causal relationship under higher quantile distribution.
- We show results for causality in quantiles from bearish investor sentiments to mean returns in Fig. 2C. Causality running from bearish market sentiments to US sectoral returns follow asymmetric pattern in all sectors except healthcare sector. These results

[12] The bell shape of the graph implies symmetric relationship whereas sharp upward and downward trends depict the presence of asymmetric relationship. The graph above the orange and purple lines highlight its significance at 5 and 10 percent, respectively.

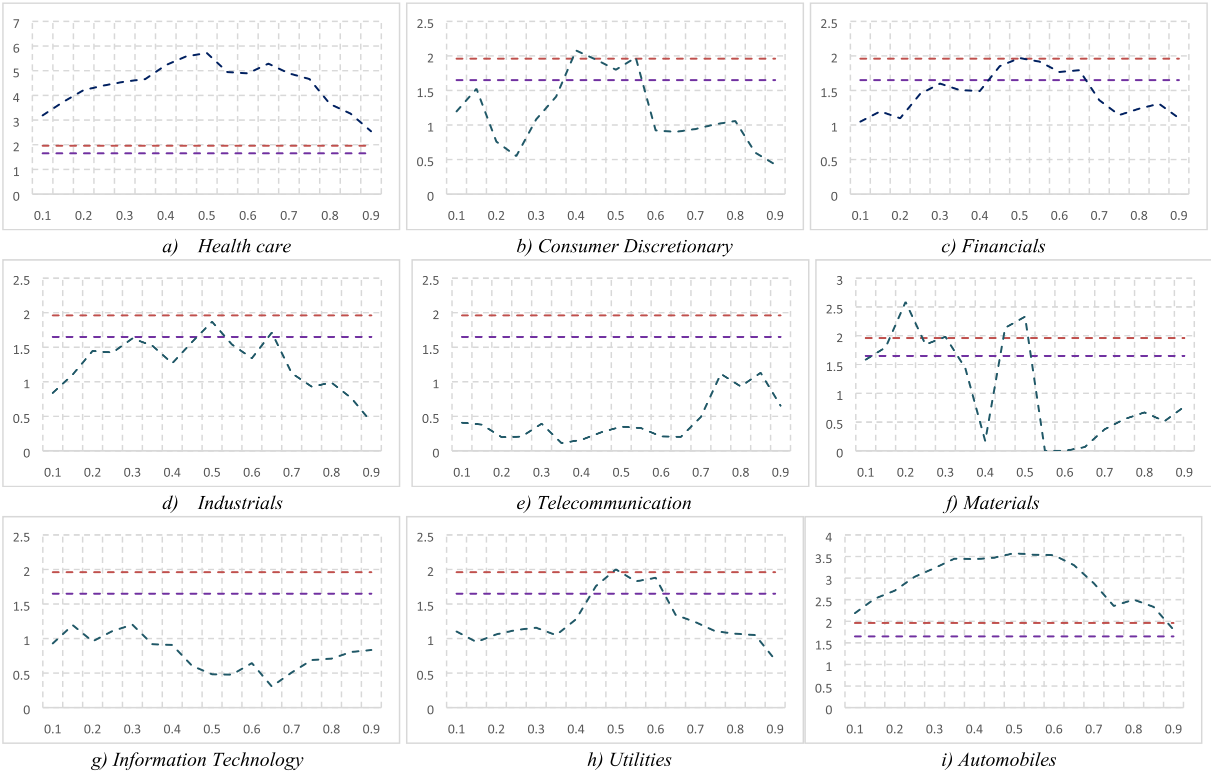

Fig. 2A. Causality in Mean- Bullish Sentiments to US Sectoral Returns. Note: The above figure highlights findings of nonparametric causality tests at different quantiles. We list quantiles of US weekly sectoral returns on x-axis whereas test statistics on y-axis. Dark blue dashed-line shows causality results whereas two dashed purple and red lines highlight critical values (CV) at 5% and 10%, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

suggest that the US sectoral returns are sensitive to the bearish investor sentiments however this sensitivity is not equally distributed across all quantiles. Our results are supported by Baker and Wurgler (2006) that changes in equity returns are relative to investor sentiments. The causality running from bearish sentiments towards US sectoral returns appears significant except telecommunication, material and the information technology sector. However, we witness the absence of symmetry except healthcare sector. Causality from bearish investor sentiments towards remaining US sectors appears significant in the following quantile arrangements. i.e. consumer discretionary (0.4–0.6 quantiles), financial (0.1–0.6 quantiles), industrials (0.4–0.5 quantiles) and utilities (0.2–0.8 quantiles). For causality in variance (see Fig. 2D), we again witness the predictive variance of bearish investor sentiments as fully operational across entire range of quantiles. Any change in the bearish sentiments is fully reflected in the return variances of all sampled US sectoral returns. However, this causal behavior across higher order moment remains asymmetric for all sectors. These significant values of both bearish and bullish investor sentiments confirm the findings of Apergis and Rehman (2018) that investors sentiment is a priced factor, overlooking of which may result in imperfect depiction of asset pricing. However, like our previous results in case of bullish sentiments, majority of the US sectors have the tendency to remain insensitive to bearish sentiments under median quantile distribution except consumer discretionary and telecommunication sectors. However, the causal relationship appears significant under higher quantile arrangements.

- For the effect of EPU on US sectoral returns, we witness quite interesting results. Statistics for non-parametric causality in mean running from EPU to US sectoral returns are shown in 2E. The findings are interesting and quite different from bearish and bullish market results. Across all sectors, asymmetric behavior is observed except healthcare sector however causality results are different across different quantile arrangements. Results for consumer discretionary, financial, telecom, material and the information technology sectors remains insignificant across all quantiles. These results are in line with the findings by Rehman et al. (2019) that IT, industrial, utilities and telecommunication sector remain insensitive to US economic policy uncertainty. Healthcare sector exhibits maximum sensitivity to EPU consistently across all quantiles. According to Pastor and Veronesi (2012), variations in policy uncertainty exhibit negative effect on the US equity returns. This might also be attributed to the fact that the healthcare sector comprises also of private healthcare institutions which depends on the economic conditions. Furthermore, even government health services are dependent on funding and subsidies from the government which may vary under different economic conditions. For industrial and utility sectors, asymmetric causality in mean is observed from EPU in higher order quantiles i.e. 0.60–0.95 for both cases whereas for automobile sector, asymmetric causality in mean is observed from EPU for majority of the distribution i.e. 0.2–0.8 quantiles except in extreme lower and higher order quantiles. Materials sector exhibit significant asymmetric behavior only under

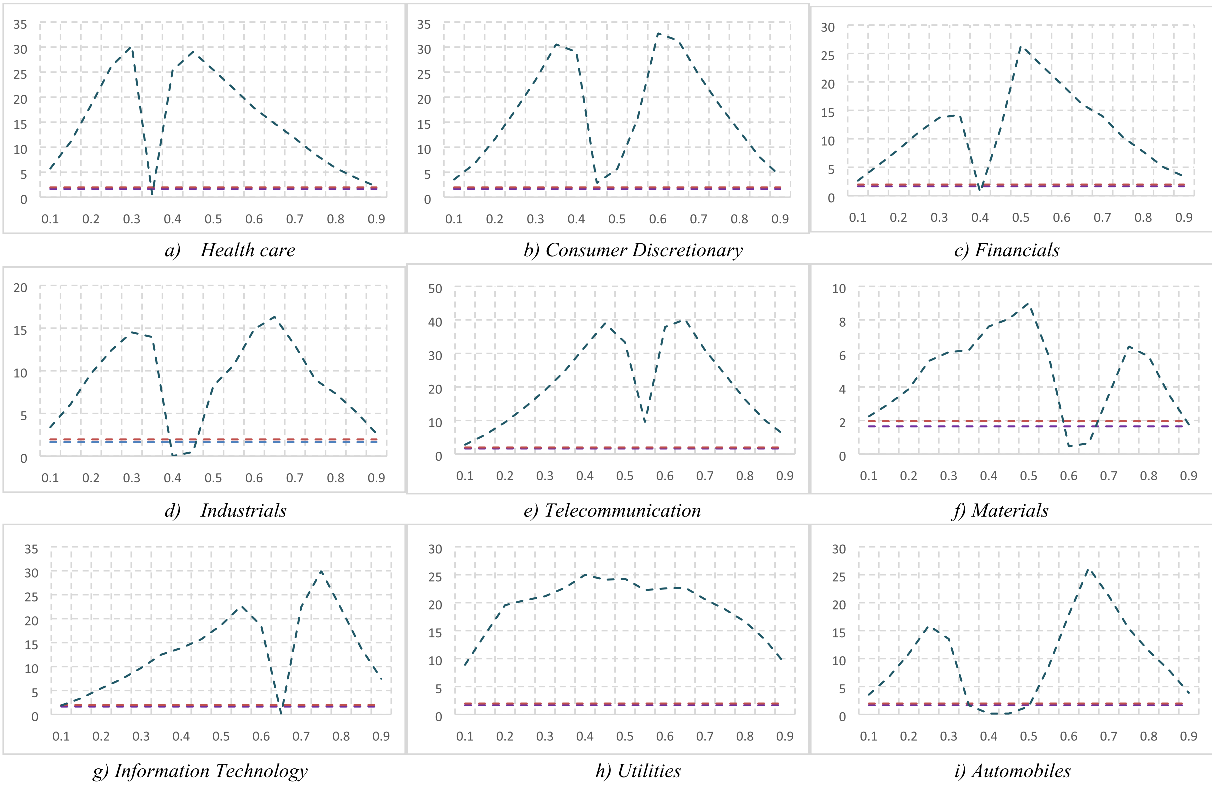

Fig. 2B. Causality in Variance-Bullish Sentiments to US Sectoral Returns. *Note*: Similar to Fig. 2A.

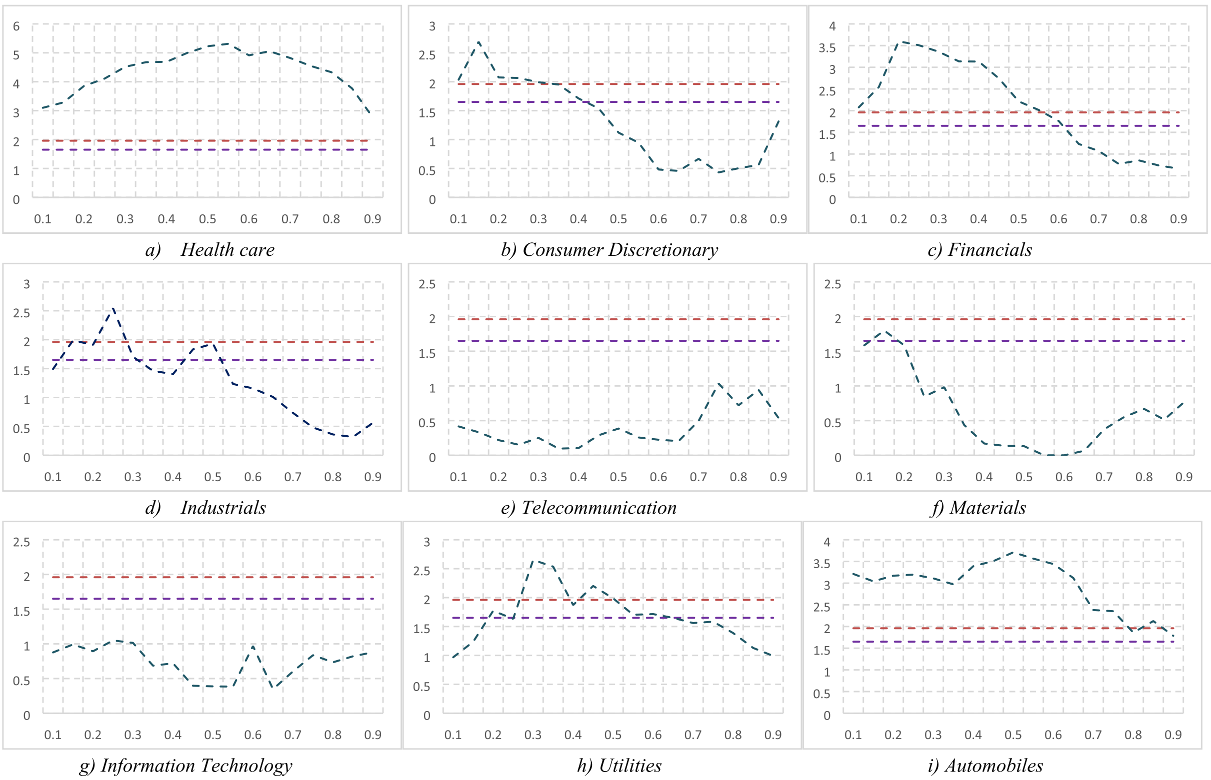

Fig. 2C. Causality in Mean- Bearish Sentiments to US Sectoral Returns. *Note*: Similar to Fig. 2A.

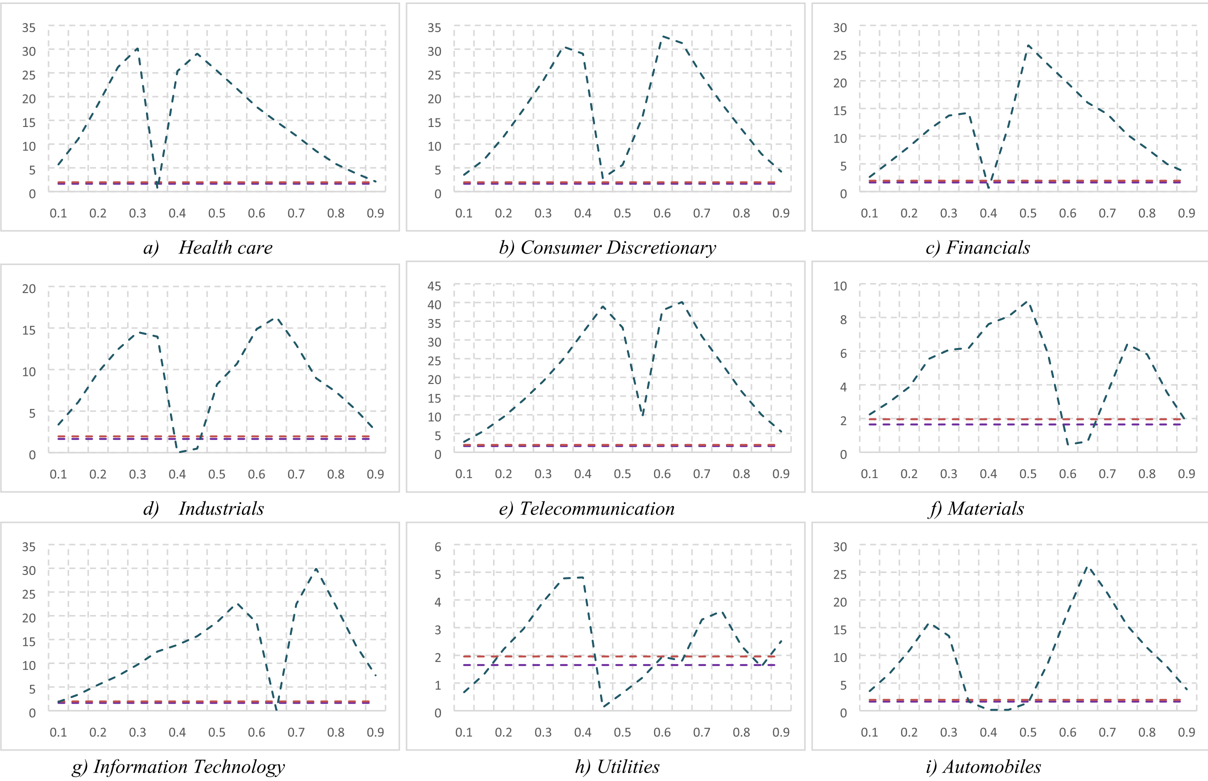

Fig. 2D. Causality in Variance- Bearish Sentiments to US Sectoral Returns. *Note*: Similar to Fig. 2A.

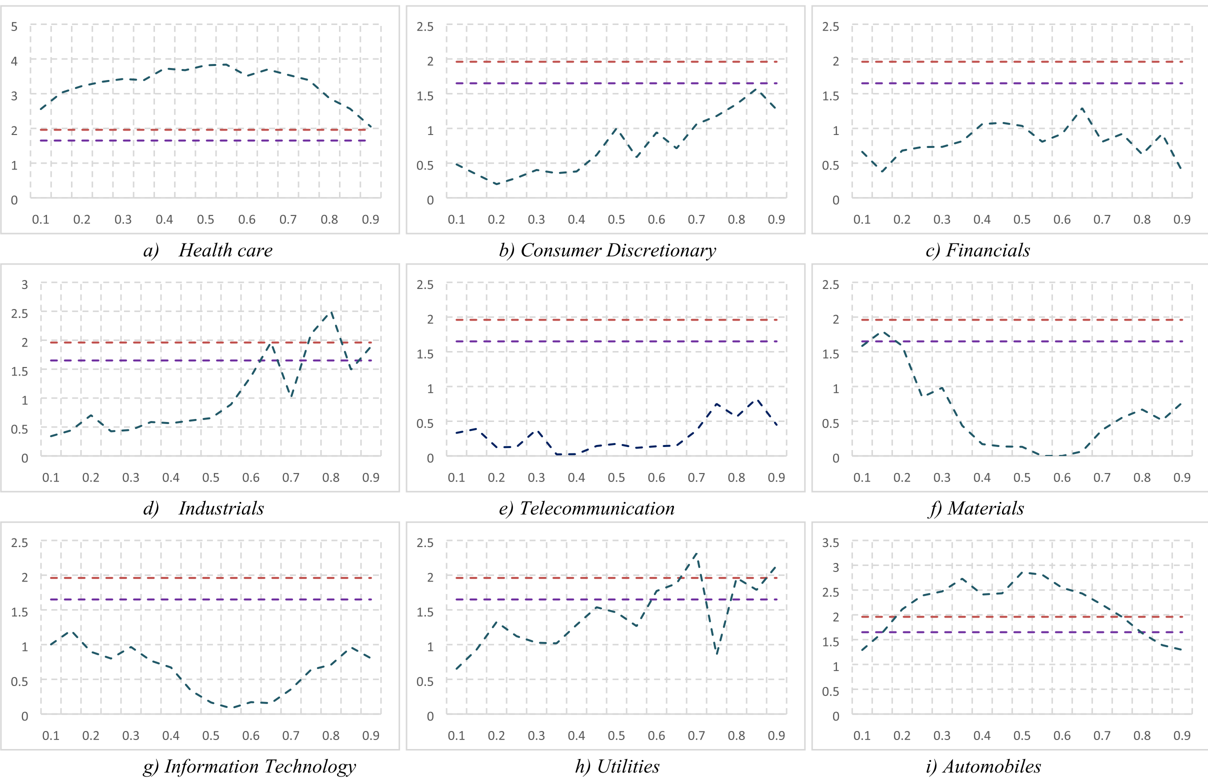

Fig. 2E. Causality in Mean- EPU to US Sectoral Returns. *Note:* Similar to Fig. 2A.

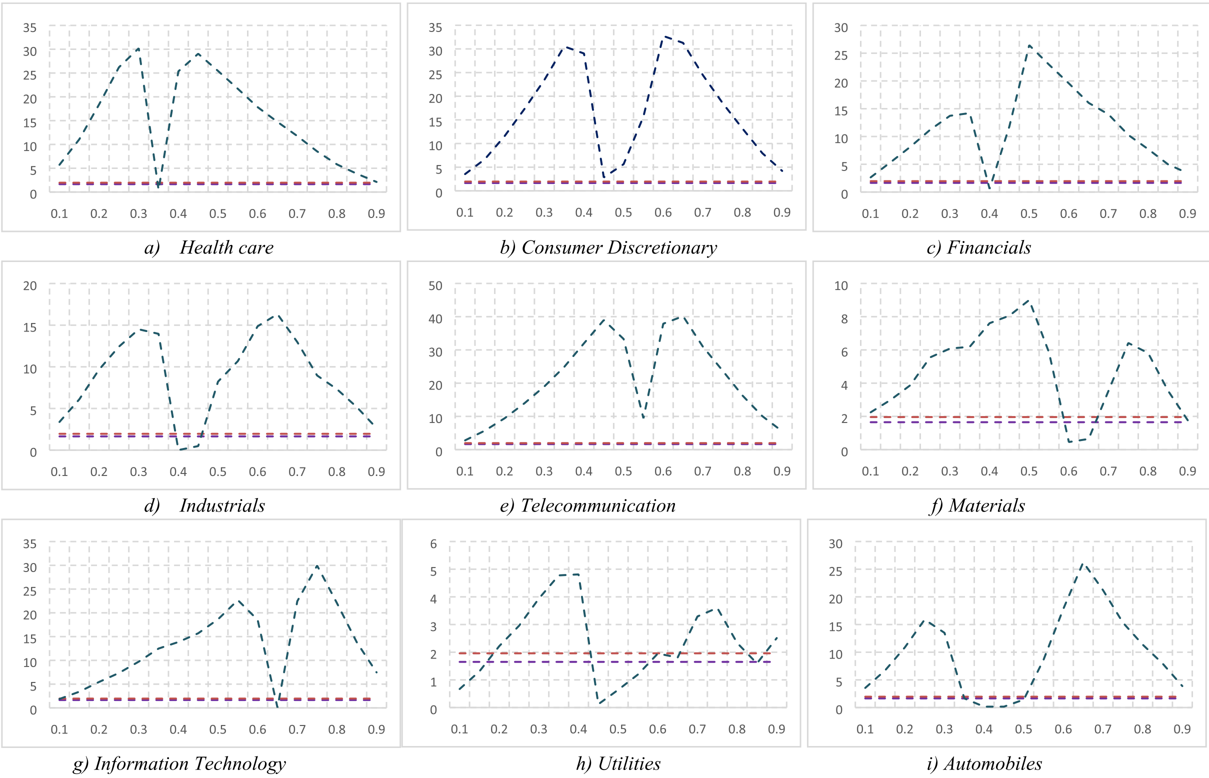

Fig. 2F. Causality in Variance- EPU to US Sectoral Returns. *Note:* Similar to Fig. 2A.

low quantiles ranging from 0.1 to 0.2. These results support the earlier findings by Bekiros et al. (2016) and Rehman (2018) that economic policy uncertainty exhibits non-linear behavior. We present our findings for causality in variance in Fig. 2F. The results for non-parametric causality in variance are no different from the second (variance) order moments results of bearish and bullish investor sentiments. We witness asymmetric causality in variance for majority US sectoral returns across in all quantiles arrangements. Industrial, material, utilities and automobile sectors, however experience insignificant causal behavior from EPU in median quantiles i.e. 0.40–0.60. These results support the findings by Hoque and Zaidi (2019) who signify the presence of non-linear and asymmetric relationship between EPU and sectoral returns.

The above mentioned results highlight the driving role of US equity market sentiments and economic policy uncertainty on weekly sectoral returns. This influential role on US sectoral returns is asymmetrical in nature for equity returns and symmetrical for variance of returns in most of the sectors across sampled period.

We also conduct a robustness measures in the form of quantile regression with sentiment indices and EPU together to investigate their impact on US weekly sectoral returns across different quantile arrangements. In Table 5, we can see that the EPU has significant influence on the returns of consumer discretionary and automobiles across all quantiles whereas telecommunication, materials and information technology sectors show significant results mostly under higher quantiles however remains insignificant for median and lower quantiles. We also have included the OLS results in the first column which also appear significant for both these sectors. The magnitude of relationship of EPU with healthcare and automobiles sectoral returns differentiate from other sectors as in these cases the relationship is strong in magnitude. For other sectors, the relationship appears significant but weak in magnitude. For bullish market sentiments, healthcare and consumer discretionary remains significant across all quantiles whereas financial, industrial, telecom, material, information technologies and automobiles sector remains significant only under higher quantiles. Utilities sector is the only sector which remains significant under lower quantiles unlike rest of the sectors. Regarding bearish market sentiments, healthcare, financial, industrial, telecom, information technologies and automobiles highlight significant coefficients across all quantiles however consumer discretionary is the only sector which yields significant results under higher quantile arrangements. Material and utilities sector however highlight significant results for lower quantiles on consistent basis. These statistics suggest that our sampled US sectors are more responsive to bearish market sentiments compared to the bullish sentiments however EPU seems to have strong results for consumer discretionary and automobiles sector across all quantiles.

5. Conclusion

Our study investigates the driving power of investor sentiment, both bullish and bearish and economic policy uncertainty on US

Table 5
Quantile Regression Statistics.

	OLS	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Healthcare										
C	0.0034**	−0.0010	0.0005	0.0019	0.0027*	0.0028***	0.0042***	0.0033***	0.0051***	0.0058***
Bullish	−0.0002	0.0004	−0.0001	−0.0002	−0.0001	0.0008	−0.0006	0.0012	−0.0007	0.0000
Bearish	−0.0121**	−0.0123**	−0.0118***	−0.0124***	−0.0116***	−0.0114***	−0.0111***	−0.0078***	−0.0092***	−0.0090***
EPU	−0.0196*	−0.0109***	−0.0103**	−0.0091***	−0.0099**	−0.0032***	−0.0066**	−0.0033**	−0.0034***	−0.00298**
Consumer Discretionary										
C	0.0014	0.0036	0.0029	0.0015	0.0014	0.0006	0.0004	0.0007	0.0002	0.0004
Bullish	0.0052**	−0.0018***	0.0004***	0.0029***	0.0042***	0.0058***	0.0066***	0.0069***	0.0082	0.0088
Bearish	−0.0135***	−0.0242	−0.0210	−0.0166	−0.0139**	−0.0119***	−0.0104***	−0.0088***	−0.0042***	−0.0019***
EPU	−0.0033***	−0.0001	−0.0001	−0.0021**	−0.0000***	−0.0000***	−0.0000***	−0.0001***	−0.0012***	−0.0022***
Financials										
C	0.0031*	0.0076**	0.0064***	0.0032*	0.0038**	0.0030	0.0030	0.0009	0.0019	0.0021
Bullish	0.0050**	−0.0109**	−0.0047	0.0015	0.0027	0.0049**	0.0056**	0.0098***	0.0119***	0.0147***
Bearish	−0.0182***	−0.0308***	−0.0295***	−0.0212***	−0.0202***	−0.0168***	−0.0157***	−0.0102***	−0.0119***	−0.0105**
EPU	−0.0029***	−0.0003	−0.0003	−0.0023	−0.0014	−0.0001	−0.0023**	−0.0001***	−0.0022***	−0.0013***
Industrials										
C	0.0012	0.0031	0.0010	0.0000	0.0000	0.0002	0.0007	−0.0004	−0.0008	−0.0008
Bullish	0.0066***	0.0010	0.0033	0.0056**	0.0068***	0.0072***	0.0079***	0.0095***	0.0098***	0.0129***
Bearish	−0.0132***	−0.0229***	−0.0160***	−0.0132***	−0.0111***	−0.0106***	−0.0104***	−0.0079***	−0.0047	−0.0033
EPU	−0.0002**	−0.0023	−0.0011	−0.0012	−0.0023	−0.0033**	−0.0011***	−0.0029***	−0.0001***	−0.0004***
Telecommunications										
C	0.0002	−0.0054***	−0.0022	−0.0016	−0.0002	−0.0008	0.0003	0.0010	0.0013	0.0022
Bullish	0.0042**	0.0053	0.0039	0.0049**	0.0035**	0.0054**	0.0057***	0.0061***	0.0070**	0.0074
Bearish	−0.0074**	−0.0062*	−0.0102***	−0.0092***	−0.0092***	−0.0058**	−0.0067**	−0.0051***	−0.0031	−0.0038
EPU	−0.0046**	−0.0021	−0.0120	−0.1300	−0.0023	−0.0431	−0.0023***	−0.0001**	−0.0001**	−0.0002***
Materials										
C	0.0003	0.0034	0.0015	0.0020	0.0014	0.0003	−0.0023	−0.0015	−0.0017	−0.0005
Bullish	0.0072***	−0.0038	0.0017	0.0025	0.0050**	0.0071***	0.0103***	0.0102***	0.0125***	0.0134***
Bearish	−0.0120***	−0.0246***	−0.0189***	−0.0170***	−0.0143***	−0.0113***	−0.0034	−0.0030	−0.0021	−0.0017
EPU	−0.0064***	0.0032	0.0011	0.0031	0.00011	0.0001*	0.0001***	0.0002***	0.0001***	0.0023***
Information Technologies										
C	0.0018	0.0020	0.0008	0.0010	0.0011	0.0017	0.0016	0.0025	0.0039	0.0059
Bullish	0.0056**	−0.0024	0.0018	0.0044	0.0063	0.0077	0.0080	0.0075	0.0089**	0.0087***
Bearish	−0.0149***	−0.0247***	−0.0191***	−0.0157***	−0.0150***	−0.0157***	−0.0135***	−0.0134***	−0.0142***	−0.0151***
EPU	−0.0073***	−0.0000	−0.0001	−0.0001	−0.0021	−0.0001**	−0.0021**	−0.0001***	−0.0021***	−0.0000***
Utilities										
C	0.0018	0.0001	−0.0006	0.0004	0.0002	0.0002	0.0018	0.0020	0.0019	0.0024**
Bullish	0.0017	0.0005	0.0021	0.0015	0.0025	0.0033	0.0019	0.0029	0.0044**	0.0053***
Bearish	−0.0082***	−0.0144***	−0.0090***	−0.0076***	−0.0048**	−0.0031	−0.0033	−0.0030	−0.0026	−0.0026
EPU	−0.0021	−0.00021*	−0.00012	−0.0031	−0.0029	−0.0011	−0.0001	−0.0001	0.0002**	−0.0012***
Automobiles										
C	−0.0001	0.0064**	0.0043	0.0019	−0.0016	−0.0012	−0.0001	−0.0004	−0.0015	−0.0039
Bullish	0.0107***	−0.0029	0.0008	0.0045	0.0100***	0.0101***	0.0092***	0.0106***	0.0131***	0.0194***
Bearish	−0.0170***	−0.0369***	−0.0333***	−0.0241***	−0.0142***	−0.0127***	−0.0141***	−0.0110**	−0.0046	0.0046
EPU	−0.0111***	−0.0158**	−0.0137**	−0.0078***	−0.0069**	0.0008***	−0.0043***	−0.0041**	0.0037***	0.0210**

Note: ***, ** and * represents significance level at 1, 5 and 10 percent respectively.

weekly sector returns over the span 1995–2020. Given the non-linear nature of both these variables i.e. investor sentiments and US economic policy uncertainty and based on our non-linear based preliminary analysis, we applied a comparatively recent and more relevant non-parametric causality on quantiles approach proposed by Balcilar et al. (2016). Our results highlight asymmetric causal behavior of Economic policy uncertainty, bearish and bullish market sentiments on weekly US sectoral returns in across majority of the quantiles under both first and higher moment. We witness symmetric behavior for the healthcare sector for causality in mean. Sector which remain insensitive to any unidirectional causal behavior like Industrials, Telecommunication and Information Technology (IT sector remains significant in case of EPU) sectors for bullish, bearish and EPU. These sectors present an opportunity to investors interested in US sectoral investments purposes due to their insensitivity to changing sentiments and rising economic policy uncertainties.

Overall, we conclude that investor bearish sentiments, bullish sentiments and economic policy uncertainty are helpful drivers in inducing change in the returns and volatility behaviors of US weekly sector returns. This explanation in weekly return values attributable to investors' bearish, bullish sentiments and economic policy uncertainty is witnessed asymmetrically in returns (i.e. across certain quantiles) and in variance (i.e. across all quantiles). Using these results, the investment community may predict the trend of US sectoral returns for investment in these sectors by including the behavior of markets' sentiments and economic policy uncertainty in their information set. Furthermore, as the study is based on US market and sentiments, which is considered as a recipient of strong market efficiency, the results can be of great value to the investors interested in US equity markets. These results can also be useful in devising the portfolio strategies especially among different US sectors and taking investors' sentiments and economic policy uncertainty variables as an extraneous factors or control variables, in particular.

CRediT authorship contribution statement

Mobeen Ur Rehman: Conceptualization, Data curation, Methodology, Writing - original draft. **Ahmet Sensoy:** Methodology, Writing - review & editing. **Veysel Eraslan:** Methodology, Writing - original draft. **Syed Jawad Hussain Shahzad:** Conceptualization, Writing - review & editing. **Xuan Vinh Vo:** Writing - review & editing.

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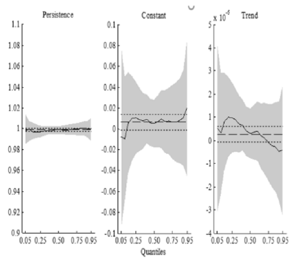
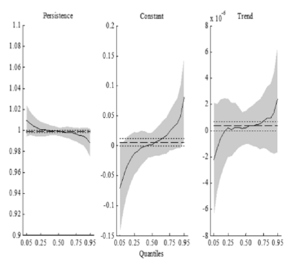
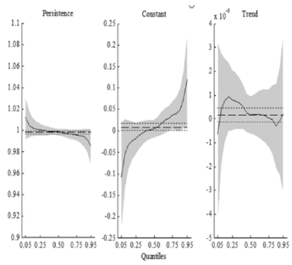
Appendix:. Quantile covariate codes



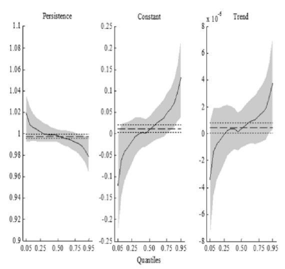
i) Healthcare



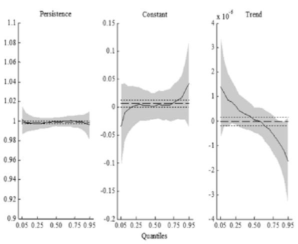
ii) Consumer Discretionary



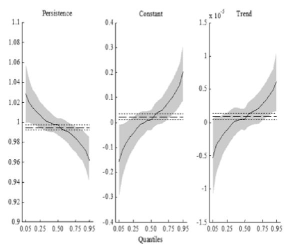
iii) Financials



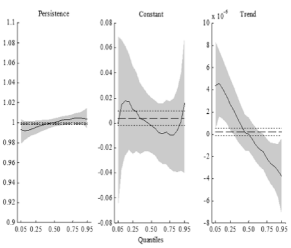
iv) Industrials



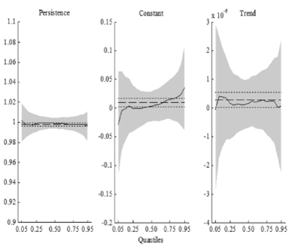
v) Telecom



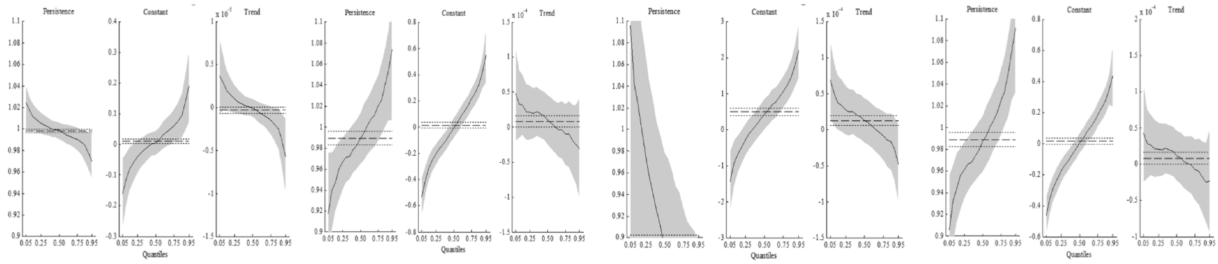
vi) Materials



vii) Information Technology



viii) Utility



ix)Automobiles x) Economic Policy Uncertainty xi) Bullish Sentiments xii) Bearish Senti

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