

Predicting Stock Returns and Volatility with Investor Sentiment Indices: A Reconsideration using a Nonparametric Causality-in-Quantiles Test[#]

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ABSTRACT

Evidence of monthly stock returns predictability based on popular investor sentiment indices, namely S^{BW} and S^{PLS} as introduced by Baker and Wurgler (2006, 2007) and Huang *et al.* (2015) respectively are mixed. While, linear predictive models show that only S^{PLS} can predict excess stock returns, nonparametric models (which accounts for misspecification of the linear frameworks due to nonlinearity and regime changes) finds no evidence of predictability based on either of these two indices for not only stock returns, but also its volatility. However, in this paper, we show that when we use a more general nonparametric causality-in-quantiles model of Balcilar *et al.*, (forthcoming), in fact, both S^{BW} and S^{PLS} can predict stock returns and its volatility, with S^{PLS} being a relatively stronger predictor of excess returns during bear and bull regimes, and S^{BW} being a relatively powerful predictor of volatility of excess stock returns, barring the median of the conditional distribution.

JEL Codes: C22, C32, C53, G02, G10, G11, G17

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1. INTRODUCTION

Stock returns and its volatility (often identified as a measure of uncertainty) are among the most important indicators for capital budgeting and portfolio management decisions as they directly reflect companies' financial health and future prospects (Poon and Granger, 2003; Rapach and Zhou, 2013). Hence, predicting stock returns and volatility is of paramount importance to practitioners in finance. Variety of macroeconomic and financial variables has been used to predict stock returns (see Rapach and Zhou (2013) for a detailed literature review). In this regard, there is also a related literature that has analyzed the role of behavioral variables, like investor sentiment, in predicting stock returns (see for example, Gebka (2014); Lutz (2015, 2016) for detailed literature reviews in this regard), as market agents tend to make overly optimistic or pessimistic judgments and choices (Huang *et al.*, 2015). While

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variety of investor sentiment indices have been developed (as described in detail in Lutz (2015, 2016)), one of the most popular investor sentiment index is derived from the works of Baker and Wurgler (2006, 2007).

Note that, trader behaviour and investor sentiment is not directly measurable or observable. Given this, Baker and Wurgler (2006, 2007) constructed a novel sentiment index, which aggregates information, based on the first principal component derived from six proxies: close-end fund discount rates, share turnover, number of initial public offerings (IPOs), first-day returns of IPOs, dividend premium and equity share in new issues. Recently, Huang *et al.*, (2015) using the same proxies of Baker and Wurgler (2006, 2007) developed a new “aligned investor sentiment index”, which separates out the information in the proxies that is relevant to the expected stock returns from the error or noise, utilizing a partial least squares (PLS) method. Importantly, Huang *et al.*, (2015) showed that their modified index can predict aggregate stock market returns at a monthly frequency, as opposed to the findings of Baker and Wurgler (2007) and Baker *et al.*, (2012). As is standard practice in the literature on predicting stock returns, Huang *et al.*, (2015) derived their results based on a linear predictive regression framework.

However, Bekiros *et al.*, (forthcoming) highlighted that a linear framework relating stock returns with the investor sentiment indices of Baker and Wurgler (2006, 2007, S^{BW}), as well as that of Huang *et al.* (2015, S^{PLS}), is misspecified due to the existence of uncaptured nonlinearity and structural breaks. Given this, Bekiros *et al.*, (forthcoming) compared the predictive ability of S^{BW} against S^{PLS} not only for the aggregate stock market returns, but also for its volatility, using the nonparametric causality test of Nishiyama *et al.* (2011). This test is developed to incorporate higher-order interrelationships inherently based on the nonlinear dependence structure between the investigated variables in question. Bekiros *et al.*, (2015) indicated that once this nonparametric test is employed, even the S^{PLS} index developed by Huang *et al.*, (2015) fails to predict either stock returns or its volatility, just like the S^{BW} index of Baker and Wurgler (2006, 2007).

Against the backdrop of this startling result of non-predictability of stock returns and volatility based on investor sentiment indices once nonlinearity is accounted for, and given the importance of predicting these two variables, the objective of this paper is to revisit the issue using a recently proposed nonparametric causality-in-quantiles test by Balcilar *et al.*, (forthcoming). This test combines the frameworks of k -th order causality of Nishiyama *et al.*, (2011) and nonparametric quantile causality of Jeong *et al.*, (2012), and hence, can be considered to be a more general version of the former. The causality-in-quantile approach employed in our study is characterized by the following novelties: Firstly, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series; this could prove to be particularly important, as it is well known (and as we also show below) that stock returns display nonlinear dynamics. Secondly, via this methodology, we test for

causality that may exist in the tails of the joint distribution of the variables, thus not only for causality-in-mean (1st moment). Finally, we are also able to investigate causality-in-variance thereby volatility spillovers, as some times when causality in the conditional mean may not exist, yet higher order interdependencies may emerge. To the best of our knowledge, this is the first paper to employ a causality-in-quantiles approach to study the predictability of both stock returns and its volatility based on investor sentiment indices. Understandably, our paper can be considered to be an extension of the work of Bekiros *et al.*, (forthcoming).

Given that the objective of our paper is to extend the work of Bekiros *et al.*, (forthcoming), it makes sense to use the same indices of investor sentiments in our paper as in Bekiros *et al.*, (forthcoming). Having said this, it is also important to point out that there are indeed various other measures of investor sentiments that have been used in the literature (Gebka, 2014; Lutz, 2015; 2016). At this stage, it is important to provide a discussion of these measures, with empirical studies using both direct and indirect approaches to capture investor sentiments. The direct measures are mostly based on stated, or explicitly expressed, opinions regarding future stock market movements. Fisher and Statman (2000) used an index compiled by Merrill Lynch to capture sentiment of very large investors. Specifically, the Wall Street sell-side strategists were surveyed monthly regarding their portfolio recommendations, and the mean portfolio recommendation was used as a measure of prevailing sentiment. Solt and Statman (1988), Clarke and Statman (1998), Fisher and Statman (2000), Lee et al. (2002), Brown and Cliff (2004, 2005), and Verma et al. (2008) aims to capture the sentiment of medium-size investors. These studies do so by surveying recommendations issued by writers of diverse investors newsletters, like the ‘Investors Intelligence’ (II) which is published weekly by the investment services company Charikraft. This company classifies the news into three categories: bullish, bearish, and waiting for a correction, and a sentiment index is constructed as a ratio of bearish to all newsletters. Data on sentiment of small investors is usually derived from the Association of Individual Investors (AII) which has been conducting weekly survey of its members since July 1987. In this survey, the AII’s members are asked to classify themselves as bullish, bearish, or neutral. As indicated in Brown (1999), Fisher and Statman (2000), Brown and Cliff (2004), and Verma et al. (2008), the fraction of bullish investors can be used as a measure of individual investors’ sentiment. Alternatively, consumer sentiment measures, like that of the Conference Board’s Index of Consumer Confidence (CBIND) or the Index of Consumer Sentiment (ICS) constructed by the University of Michigan Survey Research Center have also been proposed proxy for the individual investor’s sentiment as in Fisher and Statman (2003), and Lemmon and Portniaguina (2006). These indices are based on the surveys of a large number of households on their personal financial situation, their expectations regarding the economy, and their propensity to consume major household items.

Since the direct survey measure of investor sentiment has several limitations, such as likelihood of errors in the stage of data collection and processing, its limited scope of generalisation, unscalability, and so on, many recent studies have used market-related implicit proxies as indicators of investor sentiment (Naik and Padhi, 2016). Unlike the direct survey, the market-related proxies have advantages of representing the mood of the economy, they can be easily generalized, and often available from the most authentic sources (Naik and Padhi, 2016). However, there are no specific numbers of factors to represent these market-related implicit proxies. As a result, a plethora of proxies based on the observed market outcomes has been used. These include: (a) levels of discounts on closed-end funds (Zweig 1973; Neal and Wheatley 1998; Bathia and Bredin 2012); (b) the ratio of odd-lot (transactions involving less than 100 shares) sales to purchases (Neal and Wheatley 1998); (c) net mutual fund redemptions (Neal and Wheatley 1998; Beaumont et al. 2008; Bathia and Bredin 2012); (d) the volatility index (VIX: Simon and Wiggins 2001); (e) the put–call ratio (Simon and Wiggins 2001; Wang et al. 2006; Bathia and Bredin 2012); (f) the trading index (TRIN) for Standard & Poor’s (S&P) 500 futures returns (Simon and Wiggins 2001); (g) stock turnover (Baker and Stein 2004); (h) IPO’s related measures (Brown and Cliff 2004; Baker and Wurgler 2006); (i) the share of equity issues in total equity and debt issues (Baker and Wurgler 2000); (j) the dividend premium (Baker and Wurgler 2004), and; (k) the traders’ current aggregate positions as well as their extreme historical values (Wang, 2001).

Recently, Da et al. (2015) developed an investor sentiment index using daily Internet search data from millions of households in the U.S by focusing on particular ‘economic’ keywords that reflect investors’ sentiment towards economic developments. As pointed out by Da et al., (2015), the market-based measures have the disadvantage of being the equilibrium outcome of many economic forces other than investor sentiment, even though they are quite readily available and that too at relatively high frequency. Also, when compared to survey-based measures of investor sentiment, the search-based sentiment measure seems to have an advantage in terms of frequency, i.e., daily relative to monthly or quarterly frequency of the former. Furthermore, search-based measures reveal attitudes rather than inquire about them, and hence, are more likely to be more accurate due to relatively less measurement errors. Finally, a search based measure is not susceptible to the concern that it may be driven by answers in survey data that have not been cross-verified with data on actual behavior by some objective external assessment. Underlining these potential issues, Da et al. (2015), claim their approach to be relatively more transparent to the two other general alternatives of market and survey-based approaches.

In sum, while there are multiple ways of capturing investor sentiment, our decision to use the recent index developed by Huang et al., (2015) is aligned with our objective of extending the work of Bekiros et al., (forthcoming), who in turn had also used this data. The rest of the paper is organized as follows: Section 2 presents the empirical methodology, while Section 3 discusses the data and presents the results. Finally, Section 4 concludes.

2. METHODOLOGY

We present here a novel methodology, as proposed by Balcilar *et al.*, (forthcoming), for the detection on nonlinear causality via a hybrid approach based on the frameworks of Nishiyama *et al.* (2011) and Jeong *et al.* (2012). We denote excess stock returns as (y_t) and S^{BW} or S^{PLS} as (x_t) . Following Jeong *et al.* (2012), the quantile-based causality is defined as follows:¹

x_t does not Granger cause y_t in the θ -quantile with respect to the lag-vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if

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

x_t is a prima facie cause of y_t in the θ -th quantile with respect to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if

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

where $Q_\theta(y_t|\cdot)$ is the θ -th quantile of y_t depending on t and $0 < \theta < 1$.

Let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1} , respectively. The conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all Z_{t-1} . If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. Consequently, the hypotheses to be tested based on definitions (1) and (2) are:

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

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

Jeong *et al.* (2012) employs the distance measure $J = E\{\varepsilon_t E(\varepsilon_t|Z_{t-1})f_Z(Z_{t-1})\}$, where ε_t is the regression error and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1} . The distance measure is convenient to use because $J = E\{[E(\varepsilon_t|Z_{t-1})]^2 f_Z(Z_{t-1})\} \geq 0$ and $J = 0$ holds only if the null H_0 is true.

¹ The exposition in this section closely follows Nishiyama *et al.* (2011) and Jeong *et al.* (2012).

Therefore, J is quite useful for testing of the null non-causality in Eq. (3). The regression error ε_t emerges based on the null in Eq. (3), which can only be true if and only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or equivalently $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Therefore, we see that $E(\varepsilon_t|Z_{t-1}) = F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta$ in our case and based on this Jeong *et al.* (2012) specify the distance measure as follows:

$$J = E \left[\left\{ F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta \right\}^2 f_Z(Z_{t-1}) \right] \quad (5)$$

In Eq. (5), it is important to note that $J \geq 0$, i.e., the equality holds if and only if H_0 in Eq. (3) is true, while $J > 0$ holds under the alternative H_1 in Eq. (4). Following Li and Wang (1998), Jeong *et al.* (2012) obtains a feasible kernel-based test statistic \hat{J}_T using the density weighted sample analogue of J . The feasible kernel based test statistic is obtained by replacing ε_t and $E(\varepsilon_t|Z_{t-1})f_Z$ with $\hat{\varepsilon}_t$ and $E(\varepsilon_t|Z_{t-1})\hat{f}_Z(Z_{t-1}) = \frac{1}{(T-1)h^{2p}} \sum_{s=p+1, s \neq t}^T K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right) \hat{\varepsilon}_s$, respectively, which gives:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1, s \neq t}^T K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \quad (6)$$

where $K(\cdot)$ is the kernel function with bandwidth h while $\hat{\varepsilon}_t$ is the estimate of the unknown regression error. Jeong *et al.* (2012) establish that the re-scaled statistics $Th^p \hat{J}_T / \hat{\sigma}_0$ is asymptotically distributed as standard normal, where $\hat{\sigma}_0 = \sqrt{2\theta(1-\theta)} \sqrt{1/(T(T-1)h^{2p})} \sqrt{\sum_{t \neq s} K^2((Z_{t-1}-Z_{s-1})/h)}$. The most crucial element of the test statistics \hat{J}_T is the regression error $\hat{\varepsilon}_t$. In our particular case, $\hat{\varepsilon}_t$ is obtained as follows:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta \quad (7)$$

where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ -th conditional quantile of y_t given Y_{t-1} . Below, we obtain $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as:

$$\hat{Q}_\theta(Y_{t-1}) = \inf\{y_t: \hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) \geq \theta\} \quad (8)$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by:

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right) \mathbf{1}(y_s \leq y_t)}{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \quad (9)$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

In an extension of the Jeong *et al.* (2012) framework, we develop a test for the 2nd moment. In particular, we want to test the causality in variance between S^{BW} or S^{PLS} and excess stock returns. Causality in the k -th moment generally implies causality in the m -th moment for $k < m$. In order to illustrate the causality in higher order moments, we assume:

$$y_t = g(Y_{t-1}) + \sigma(X_{t-1})\varepsilon_t \quad (10)$$

where ε_t is a white noise process, and $g(\cdot)$ and $\sigma(\cdot)$ are unknown functions that satisfy certain conditions for stationarity. However, this specification does not allow for Granger-type causality testing from x_t to y_t , but could possibly detect the “predictive power” from x_t to y_t^2 when $\sigma(\cdot)$ is a general nonlinear function. Hence, the Granger causality-in-variance definition does not require an explicit specification of squares for X_{t-1} . We re-formulate Eq. (3)-(4) into a null and alternative hypothesis for causality in variance as follows:

$$H_0: P \left\{ F_{y_t^2|Z_{t-1}} \{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta \right\} = 1 \quad (11), \text{ or}$$

$$H_1: P \left\{ F_{y_t^2|Z_{t-1}} \{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta \right\} < 1 \quad (12)$$

To obtain a feasible test statistic for testing the null in Eq. (11), we replace y_t in Eq. (6) - (9) with y_t^2 . A problem may arise with the definition of causality given in Eq. (11) when there exists causality both in the second moment (variance) and the first moment (mean). We can illustrate this with the following model:

$$y_t = g(X_{t-1}, Y_{t-1}) + \varepsilon_t \quad (13)$$

Thus, higher order quantile causality in relation to Eq. (13) can be specified as:

$$H_0: P \left\{ F_{y_t^k|Z_{t-1}} \{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta \right\} = 1 \quad \text{for } k = 1, 2, \dots, K, \quad (14), \text{ or}$$

$$H_1: P \left\{ F_{y_t^k|Z_{t-1}} \{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta \right\} < 1 \quad \text{for } k = 1, 2, \dots, K. \quad (15)$$

Integrating the entire framework, we define that x_t Granger causes y_t in quantile θ up to K -th moment utilizing Eq. (14) to construct the test statistic of Eq. (6) for each k . However, it can be shown that it is not easy to combine the different statistics for each $k = 1, 2, \dots, K$ into one statistic for the joint null in Eq. (14) because the statistics are mutually correlated (Nishiyama *et al.*, 2011). To efficiently address this issue, we include a sequential-testing method as described Nishiyama *et al.* (2011) with some modifications. Firstly we test for the nonparametric Granger causality in the 1st moment ($k = 1$).

Rejecting the null of non-causality means that we can stop and interpret this result as a strong indication of possible Granger quantile causality-in-variance. Nevertheless, failure to reject the null for $k = 1$, does not automatically lead to non-causality in the 2nd moment. Thus, we can still construct the tests for $k = 2$.

Finally, we can test the existence of causality-in-variance, or the causality-in-mean and variance successively. The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h , the lag order p , and the kernel type for $K(\cdot)$ and $L(\cdot)$ in Eq. (6) and (9), respectively. In our study, the lag order of 1 is determined using the Schwarz Information Criterion (SIC) under a VAR comprising of excess returns and S^{BW} or S^{PLS} respectively. The choice of this lag-length is also in line with predictive regression framework in the stock returns predictability literature discussed in the introduction. The bandwidth value is selected using the least squares cross-validation method.² Lastly, for $K(\cdot)$ and $L(\cdot)$ we employ Gaussian-type kernels.

3. DATA AND EMPIRICAL ANALYSIS

The aggregate stock market returns are estimated as the excess returns of a market index, which is common in the relevant literature. Specifically we calculate the continuously compounded log-returns of the S&P 500 index (including dividends) minus the risk-free rate. The return (*exsr*) of the S&P 500 and its volatility (*exsv*) measured as the squared values of the returns, are derived from the Center for Research in Security Prices (CRSP). The data on both the value-adjusted CSRP for the S&P500 index and the risk free rate can be found on the website of Professor Amit Goyal at: <http://www.hec.unil.ch/agoyal/>, while the sentiment indices by Baker and Wurgler (2006, 2007; S^{BW}) and Huang et al., (2015; S^{PLS}) can be downloaded from the website of Professor Guofu Zhou at: <http://apps.olin.wustl.edu/faculty/zhou/>.

Baker and Wurgler (2006, 2007) constructed a novel sentiment index, which aggregates information, based on the first principal component derived from six proxies: close-end fund discount rates, share turnover, number of initial public offerings (IPOs), first-day returns of IPOs, dividend premium and equity share in new issues. From the perspective of econometrics, the first principal component is the best combination of the above six proxies that optimally represents the total variations of these variables. Given that all the six proxies may have approximation errors to the true but unobservable investor

² For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

sentiment, with these errors being parts of their variations, the first principal component can potentially contain a substantial amount of common approximation errors that are not relevant for predicting movements in stock returns (and its volatility). Given this, Huang *et al.*, (2015) using the same proxies of Baker and Wurgler (2006, 2007) developed a new “aligned investor sentiment index”. The main idea behind their new index is to align the investor sentiment measure with the objective of explaining the stock returns (and volatility) by extracting the most relevant common component from the six proxies. From the view point of economic intuition, this essentially means that Huang *et al.*, (2015) separates out information in the proxies that is relevant to the expected stock returns (and volatility) from the noise or error. In this regard, the statistical approach of partial least squares (PLS) method, originally developed by Wold (1966, 1975) and extended later by Kelly and Pruitt (2013, 2015), can achieve exactly this objective. In sum, Huang *et al.*,’s (2015), aligned investor sentiment index extracted using PLS, incorporates efficiently all the relevant predictability information from the six proxies by separating out the information in the proxies that is relevant to the expected stock returns from the error or noise.

To ensure comparability of predictability across these two sentiment indices, we standardize the data by dividing with their respective standard deviations. Our monthly sample covers the period 1965:07 - 2014:12 (i.e., 594 observations), with the start and end date being purely driven by availability of data on the variables of concern. The distribution of *exsr* was found to be negatively skewed (-0.4252), and have excess kurtosis (4.7527), yielding a Jarque-Bera statistics of 93.9311, whereby the null of normality was overwhelmingly rejected at 1 percent level of significance. This, in turn, is indicative of a heavy left-tail for *exsr*, and provides an initial motivation to look at the effect of the sentiment indices over its entire conditional distribution of *exsr*, rather than just in the conditional-mean.³

We start off with the standard linear Granger causality test for the sake of comparability and complementarity reasons. To ensure that our results will be comparable vs. the nonparametric test, we use a lag-length of 1 in the vector autoregressive (VAR) models, as selected by the SIC criterion. As it is demonstrated from Table 1, the null hypothesis that S^{BW} and S^{PLS} does not Granger cause *exsr* can be strongly rejected only for the latter case, thus confirming the results of Huang *et al.* (2015), and Bekiros *et al.*, (forthcoming).

³ The Jarque-Bera test rejected the null of normality at 1 percent level of significance for both S^{BW} and S^{PLS} , with the both the indices being positively skewed and having excess kurtosis. Complete details of the summary statistics of the *exsr*, S^{BW} and S^{PLS} are available upon request from the authors.

TABLE 1: LINEAR GRANGER-CAUSALITY TESTDependent Variable: *exsr* (1965:7-2014:12)

S^{BW}	1.1951
S^{PLS}	11.3452***

Note: *** indicates rejection of the null hypothesis of absence of Granger causality at 1% level.

Next, we conduct the Bai and Perron (2003) test for detecting multiple structural breaks in case of an autoregressive AR(1) model for *exsr*, as well as for the *exsr* equation of the bivariate VAR(1) including S^{BW} or S^{PLS} respectively. We were able to detect three structural breaks for the AR(1) (1982:08, 2000:04 and 2009:03) model of *exsr*, five breaks each were obtained by the VAR model between *exsr* and S^{BW} (i.e., 1970:07, 1974:10, 2002:04, 2006:10 and 2009:03), and between *exsr* and S^{PLS} (i.e., 1972:05, 1974:10, 2000:01, 2002:10 and 2009:03).⁴ In the presence of these breaks, the assumption of parameter constancy over the entire sample as used by the linear Granger causality test is strongly violated, and consequently cannot be deemed conclusive.

TABLE 2: BDS TEST

Dimension	AR(1)	S^{BW} - based VAR(1)	S^{PLS} - based VAR(1)
2	0.0003	0.0003	0.0006
3	0.000	0.0001	0.0001
4	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.0000

Note: Entries are *p*-values for the null of serial independence in the error structure of *spr* after using an AR(1) filter or two VAR(1) model specifications i.e., [*exsr*, S^{BW}] and [*exsr*, S^{PLS}] respectively

Furthermore, we use the Brock *et al.* (1996, BDS) test for the non-*iid* null hypothesis on the residuals of the *exsr* AR(1) model and to those of the *exsr* equation of the VARs comprising *exsr* and S^{BW} and *exsr* and S^{PLS} respectively. As illustrated in Table 2, the BDS test overwhelmingly rejects the null of *iid* structure for all of the embedding dimensions concerned, and hence, implies an omitted nonlinear structure.⁵ Given the evidence of structural breakpoints and nonlinear interdependencies, we

⁴ Bekiros *et al.*, (forthcoming) obtained similar results in terms of structural breaks.⁵ Bekiros *et al.*, (forthcoming) obtained similar results in terms of nonlinearity.

next utilize the nonparametric causality test proposed by Nishiyama *et al.* (2011), as in Bekiros *et al.*, (forthcoming), to deal with the misspecification of our linear modelling. The results are displayed in Table 3. As in Bekiros *et al.*, (forthcoming), there is no evidence of predictability emanating from the two sentiment indices for either *exsr* or *exsv*. Though inconsequential, as in the linear model, S^{PLS} is found to be a stronger predictor than S^{BW} in the nonparametric setting as well for both *exsr* and *exsv*. So based on the Nishiyama *et al.*, (2011) test, just as in Bekiros *et al.*, (forthcoming), we tend to conclude that S^{BW} and S^{PLS} cannot predict either excess stock returns or its volatility.⁶ Understandably, in the presence of regime changes and nonlinearity, one would tend to rely more on these results than that from the linear model.

TABLE 3: NONPARAMETRIC CAUSALITY TEST

Dependent Variable: <i>exsr</i> and <i>exsv</i> (1965:7-2014:12)		
	Test statistics	
	$\hat{S}_T^{(1)}$	$\hat{S}_T^{(2)}$
S^{BW}	3.3292	12.8338
S^{PLS}	7.1572	13.8125

Note: 5% critical value is 14.38; $\hat{S}_T^{(1)}$: Test statistic for causality in-mean; $\hat{S}_T^{(2)}$: Test statistic for causality in-variance.

Having confirmed all the findings of Bekiros *et al.*, (forthcoming), we now turn to the primary objective of our paper, namely, revisiting the predictability of S^{BW} and S^{PLS} for *exsr* and *exsv* using the causality-in-quantiles test of Bekiros *et al.*, (2015). As can be seen from Figure 1, both S^{BW} and S^{PLS} predicts *exsr* over the latter's entire conditional distribution. Our results are different from those of the linear model, where only S^{PLS} was found to cause *exrs*, but also that of the nonparametric Nishiyama *et al.*, (2011) test, where neither S^{BW} or S^{PLS} was found to predict *exrs*. Interestingly S^{PLS} is found to be a better predictor than S^{BW} only towards the tails of the conditional distribution of *exrs*, with the latter performing better around the median of the conditional distribution. So S^{PLS} is better suited in forecasting *exrs* when the market is either in bear or bull regimes. Turning now to the cases of stock returns volatility, while S^{BW} predicts *exsv* over its entire conditional distribution, S^{PLS} does so barring some parts at the lower-end of the conditional distribution. In addition, S^{BW} is a stronger predictor of *exsv*, than S^{PLS} , except around the median. Overall, after guarding for possible misspecifications, it can be concluded that both S^{BW} and S^{PLS} can predict stock returns and its volatility, with S^{PLS} being a

⁶ The data used by Bekiros *et al.*, (forthcoming) covered the period of 1965:07-2010:12.

relatively stronger predictor of $exrs$ during bear and bull regimes, and S^{BW} being a relatively powerful predictor of $exsv$, barring the median of the conditional distribution.

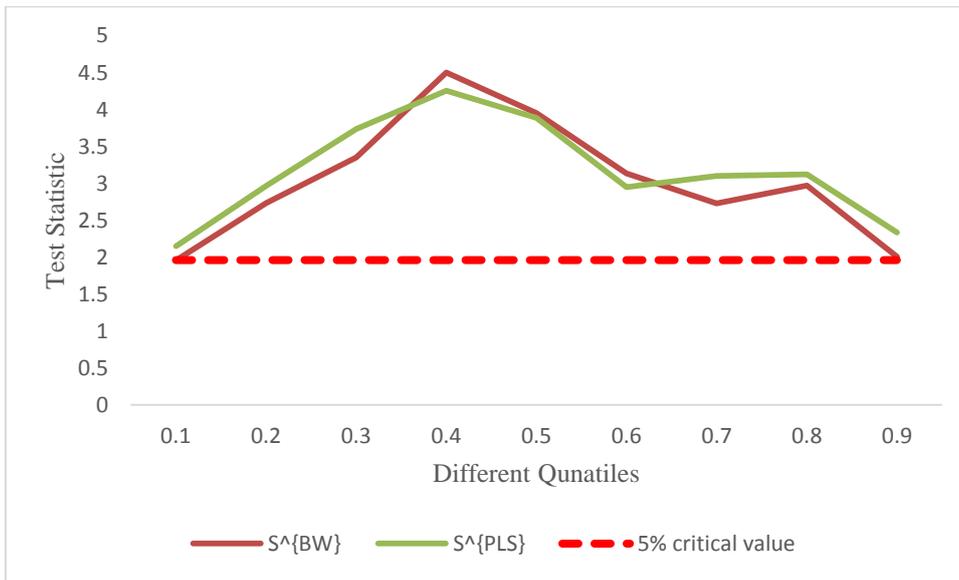


Figure 1. Causality-in-Quantiles of excess stock returns ($exrs$). Note: S^{BW} (S^{PLS}) stands for S^{BW} (S^{PLS}).

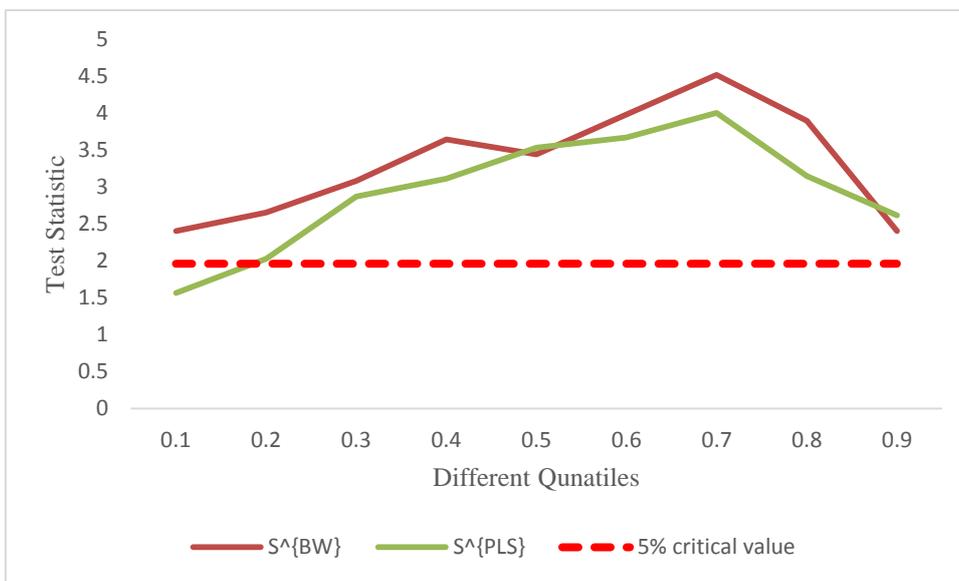


Figure 2. Causality-in-Quantiles of excess stock returns volatility ($exrv$). Note: See Notes to Figure 1.

So when we allow for nonlinearity to prevent econometric misspecification, and study the entire conditional distribution of stock returns and volatility to capture the market position, our results possibly provide support in favor of the existence of “noise traders” in financial markets, which forms an integral part of the behavioural finance literature. A word of caution is warranted at this stage: Our results are based on an athoretical causality analyses, and does not deal with a structural model that directly tests

the noise traders theory. Hence, there is some extent of speculation involved in our conclusions as to the specific theory behind the results that we obtain, which could well be due to some other reasons. Noise traders are defined as investors whose trading decisions are based on what they perceive to be an informative signal but which, to a rational agent, does not convey any information (Black, 1986). Studies by De Long et al. (1990, 1991), Campbell and Kyle (1993), Shefrin and Statman (1994) develop models to demonstrate that even a small group of noise traders, driven by joint unpredictable sentiment rather than by information, and acting in a correlated manner, can create long-lasting inefficient market outcomes. This is due to the fact that, their actions introduce a new type of risk faced by rational investors and limit their ability to fully arbitrage away the emerging price inefficiencies. In these models, the noise traders are also shown, to be able to survive in the long run under certain conditions; thus, making their ever-changing sentiment a persistent determinant of stock returns. Following the above set of studies, subsequent theoretical research has aimed to model the exact driving forces behind the investor sentiment. Barberis et al. (1998) point towards the interplay of conservatism and representativeness; Daniel et al. (1998) suggests overconfidence and self-attribution bias of a representative irrational investor; while Hong and Stein (1999) provide an explanation based on interactions among heterogeneously irrational traders with gradually disseminating information. In general, our results tend to undermine the notion of efficient market hypothesis by highlighting the role of noise traders, which in turn, provides the underlying reason behind investor sentiment being a predictor of stock returns and volatility. However, the possibility of our results being driven by the noise trader theory is only found to hold when we make correct assumptions regarding the econometric framework, by incorporating nonlinearity and especially studying entire conditional distributions of returns and volatility; otherwise, we would incorrectly conclude that markets are characterized primarily by rational investors, who in turn, cannot systematically affect market prices.⁷ Given that we do speculate regarding the noise traders theory, it would be worthwhile to test the hypothesis directly in the future. But in this paper, we were primarily more concerned with the predictability of conditional distributions of stock returns and volatility based on measures of investor sentiment, rather than attempting to explain our results using a certain theory.

At this stage, it is also important to intuitively understand the reasons behind why the results from the nonparametric causality-in-quantiles test tend to be so drastically different from the k -the order

⁷ The fact that rational agents will be unable to move market prices is based on several reasons: First, the erratic nature of individuals' irrationality should cause optimism to cancel out pessimism across the investors. Secondly, the systematic impact of irrationality on prices is likely to be short-lived, since arbitrage by rational investors will push back the prices to their fundamental values. Finally, irrational traders will disappear from the market eventually, since they be incurring increasing losses due to their erroneous investment decisions (Friedman 1953).

nonparametric causality test of Nishiyama *et al.*, (2011). Nishiyama *et al.*, (2011) test takes into account the nonlinearity in the conditional mean. When the covariates induce shifts not only in the location and scale of the conditional distribution, but also shifts in the entire shape of the conditional distribution, nonparametric causality-in-quantile regression results might differ from the nonparametric causality regression results over the entire range of the quantiles. In such models, the response distribution pattern will involve changes in central tendency, variance, and shape. In this case, the change in slopes will not mirror the changes in intercepts. The case can be best understood in linear model where intercepts all change systematically towards a central point where slopes also vary but not monotonically with the intercept change. In this case, a linear quantile regression will have a different slope and intercept at each quantile but the change in slope will not mirror the change in intercept. Therefore, a global nonparametric curve will have a flat shape while the nonparametric curves fitted at different quantiles will each have different shape. Therefore, our results indicate that investor sentiment induces shift in the entire shape of the conditional response distribution of the stock returns, which cannot be accounted by simple location- and scale-shift models or global nonparametric curves.

4. CONCLUSIONS

As investor sentiment is not directly observable, Baker and Wurgler (2006, 2007) created a novel investor index (S^{BW}) that aggregates behavioural information from six financial proxy indicators using principal components analysis. More recently, Huang *et al.* (2015) using the same proxies developed a new index (S^{PLS}) which distinguishes information from the observed expected stock returns vis-à-vis error or noise signals in the market, via a partial least squares approach. Based on a linear predictive regression model, these authors showed that S^{PLS} could predict aggregate stock market returns at monthly frequencies, while S^{BW} failed to do so – a finding we confirm as well.

However, Bekiros *et al.*, (forthcoming), showed that due to inherent nonlinearities and structural breaks in the relationship between returns and the two sentiment indices, the linear Granger causality framework upon which Huang *et al.* (2015) relied upon, might lead to misspecification. Given this, Bekiros *et al.*, (forthcoming) employed the k^{th} order nonparametric causality test of Nishiyama *et al.* (2011) to demonstrate that neither of these two indices can predict stock returns or its volatility – a finding we confirm as well.

Against this backdrop of conflicting evidence, though with more reliance on the results from the Nishiyama *et al.*, (2011) test, we revisited the issue of predictability of stock returns and its volatility based on investor sentiment indices, using a newly developed nonparametric causality-in-quantiles test

by Balcilar *et al.*, (forthcoming). This test combines the quantile causality test of Jeong *et al.*, (2012) with that of Nishiyama *et al.*, (2011) nonparametric framework, and hence, can be deemed as more general. Using this test, we observe that both the investor sentiment indices can predict stock returns and its volatility over the monthly period of 1965:07-2014:12. In addition, we observe that, while the index developed by Huang *et al.*, (2015), i.e., S^{PLS} is a relatively powerful predictor of excess stock returns during bear and bull regimes, S^{BW} , i.e., the index developed by Baker and Wurgler (2006, 2007), is a relatively stronger predictor of stock returns volatility, barring the median of the conditional distribution. Overall, our results suggest that, upon controlling for misspecification, both these popular indices have predictive ability for stock returns and its volatility, when one uses a more general (in relation to the linear and k^{th} order nonparametric frameworks) nonparametric causality-in-quantile approach. As part of future research, it would be interesting to extend our study, as in Bonaccolto *et al.*, (2015), to examine if our results for both returns and volatility continue to hold over an out-of-sample, as in-sample predictability does not guarantee favourable forecasting results (Rapach and Zhou, 2013). Note that, since stock price data is available at higher frequency, we can also analyze the role played by the monthly investor sentiment on realized volatility computed (as sum of squared returns) from high (daily) frequency data. One could also use measures of implied volatility, like the VIX. In addition, it would be an interesting exercise to extend our analysis, contingent on data availability, to a set of emerging and mature markets, to check whether the impact of investor sentiment on stock returns and volatility is dependent on the stage of development of an equity market.

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