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RESEARCH PAPER

Predictability of Return in Pakistan Stock Market through the Application of the Threshold Quantile Autoregressive Models

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Abstract
Stock market behavior is a contentious matter among researchers in the field of finance. In literature, various conventional and behavioral explanations exist to the real-life stock market behavior. This study considered and incorporated all three schools of thought on the matter and applied a nonlinear model namely a threshold quantile autoregressive model as a contribution to exploring the behavior of the Pakistan stock market from 2000 to 2018. The findings of the study indicate that autocorrelation exists in the KSE 100 index and has a significant impact on both higher and lower regimes. The results also point out that the investors overreact and underreact in different states of the stock market. During the examination of the impact of stock characteristics and behavioral factors on the existence of stock market autocorrelation. It is concluded based on empirical evidence that these factors cause a significant impact on autocorrelation in the index. The study is of the view that behavioral biases are among the prime reasons for violation of efficient market behavior and need further exploration.
Keywords: Autocorrelation, Stock returns, Market Sentiments, Pakistan Stock Market.
JEL Classification: G1, G2, G4, G14.

Introduction

Stock markets in a country are considered to be a reflection of a country's economic condition. Stock markets are vital as a source of financing for business organizations in a country provided by investors who invest their funds to get appropriate returns. Investors are the source from where stock markets derive its importance and hence study of stock market behavior is very important in context of understanding an economy. Pakistan is one of the emerging economies. Initially, in Pakistan, there were three stock exchanges of which the premier was the Karachi Stock Exchange established in 1949, the second-largest exchange in the Lahore Stock exchange which came into being in 1970 and the last one was in Islamabad which was established in 1989. These markets continued to trade separately until recently on 11th January 2016 all these three markets merged to form one market and started operating as Pakistan Stock Exchange Limited (PSX) with KSE 100 as an Index. This was done under Stock Exchanges Demutualization and Integration Act 2012 and this merger completed the second phase of the

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Act, which was passed by a joint session of parliament, aimed to facilitate economic growth and have a stable market in the country. After this Pakistan Stock Exchange has also become a listed company with forty percent of its shares with the brokers whereas forty percent of the markets shares are offered to foreign buyers and the remaining twenty percent of the shares are to be offered to the general public through an initial public offering (IPO).

Predictability of future expected return of the stock market from its past values remained a challenge for researchers (Chabi-Yo, 2019). According to the conventional view of the efficient market hypothesis (EMH) as proposed by Fama in 1970, these stock markets are ordered into three categories which include weak-form market, semi-strong form efficient market, and strong form efficient market. Even in a weak-form efficient market all the available past information are reflected in today’s value, making the stock completely unpredictable from past prices (Xue and Zhang, 2017). In other words in an efficient market, the market follows the random walk hypothesis (Chakraborty, 2006). Whereas in the real-world stock markets, we can witness that market efficiency fails to hold.

The financial theory attributes this inefficiency to market frictions which include transaction costs and limited dissemination of information (Campbell et al., 1997; Cohen et al., 1986; Keim and Stambaugh, 1986). According to Rapach, Strauss and Zhou (2013) and Hong, Torous and Valkanov (2007) the frictions of information and behavioral factors including biases, heuristics, and sentiments are significant determinants of the stock market predictability (Barber and Odean, 2008; DeBondt and Thaler, 1995; Kahneman and Riepe, 1998; Rasheed and Tariq, 2017; Tversky and Kahneman, 1974). In real life investors follow a patterned behavior due to behavioral factors including overconfidence, herding behavior, and other psychological factors. All these factors led investors to inadequate response or overreaction to the available information resulting in the predictability of stock return form the past data (Xue and Zhang, 2017). Based on the discussion the study aims to establish the impact of behavioral factors alongside the conventional explanations of stock market autocorrelation for a better understanding of real-life stock market behavior.

Pakistan is one of the emerging economies. For international investors also Pakistan is an outstanding spot to invest, with investors throughout the globe eyeing Pakistan as their future venture and this study may be extremely relevant for them. Harvey (1995) reported that return correlation and its predictability in emerging stock markets e.g. Pakistan is even higher than the developed countries. Khilji and Nabi (1993) explored the monthly behavior of return of the stock market in Pakistan and found the existence of autocorrelation in return. The predictability of stock return is also tested there are various factors that are significant determinants of return and dividend payout of a stock (Khan and Ahmad, 2017).

The problem with earlier studies is that they applied linear models to estimate stock return autocorrelation (Xue and Zhang, 2017). This makes it challenging to predict the stock market using historical data (Chabi-Yo, 2019). Another problem with such an approach is that the stock return distribution is skewed and asymmetric in financial time series (Khilji and Nabi, 1993). Furthermore different market conditions like bull and bear market cause differential effects and asymmetrical behavior in the stock markets (Harvey and Siddique, 1999; He et al., 2008). This makes financial time series data unsuitable for linear models and needs to be explored and tested using nonlinear econometric models. Therefore to offer an appropriate and comprehensive insight into the Pakistan stock market and overcome this mythological deficiency in the previous literature, the current study followed the methodology proposed by Galvao et al. (2011) and applied threshold quantile autoregressive model. This study will employ data of the KSE 100 index from 2000 to 2018. The advantage associated with this methodology is that it can provide better results as it considers both asymmetries and skewness (Xue and Zhang, 2017). It can also predict stock returns which are innately having different distribution features. Resultantly this model has a better capacity than linear models. This study will also provide a new perspective about stock return predictability and autocorrelation in an emerging economy. A country like Pakistan where existing literature on the topic is already limited apart from its contribution to the econometrics strand. The current work will focus on how return autocorrelation changes with selected characteristics of the stock market including behavioral factors and further extend the analysis by considering the stock market behavior among different regimes, alienated by different thresholds which will produce a better and in depth model for understanding.

Literature

The Efficient Market Hypothesis (EMH) advocates that in an efficient market stock predictability is not possible based on the historical return but this model of traditional finance is widely criticized by the researchers because there is an obvious autocorrelation and predictability of stock return found in the previous researches (Amini et al., 2013). In some empirical research on return autocorrelation, Poterba and Summers (1988) along with Conrad and Kaul (1988) concluded that the earnings of the stock are positively autocorrelated in a short time horizon. MacKinlay (1997) also finds significant autocorrelation of all the daily, weekly, monthly stock indices in NYSE, AMEX, and NASDAQ.

In their work, Boudoukh et al. (1994) summarized the different school of thoughts existed on the reasons for the presence of returns autocorrelation from the literature. The factors which cause the behavior of stock market to deviate as expected under the traditional theories of finance includes three explanations. The first school of thought advocated in the studies of Lo and MacKinlay (1990) and Scholes and Williams (1977) also known as loyalists tend to attribute this return autocorrelation to the market frictions. Which includes price spreads and nonsynchronous trading. Cost and time of transaction taken by investors for decision results in slow adjustment of information which lead to return autocorrelation (Mech, 1993). Apart from that, it is evident from the studies of Rapach et al. (2013) that the autocorrelation is caused partly by the information friction.

The second school of thought or the revisionist including Fama and French (1988) and Conrad and Kaul (1988) believed this return autocorrelation is due to the variation in the risk factors and is in line with the time fluctuating economic risk premiums. According to Gębka and Wohar (2013), the characteristics of stocks can significantly impact the return autocorrelation including the size of the stock, the associated trading volume of it and return volatility, etc. Similar results are obtained in Indian stock market (Narayan and Bannigidadmath, 2015) and Chinese stock market (Westerlund et al., 2015). McKenzie and Kim (2007) find that there is a noteworthy relationship between autocorrelation in the stock market and volatility. Similarly bid-ask bounce, nonsynchronous trading, time-varying risk premium, and partial price adjustment effects the autocorrelations in returns not only for individual stocks but portfolios also (Anderson et al., 2013). Similarly, Tang et al. (2019) concluded that different economic factors including monetary policy, trading volume, and monetary policy are significant determinants of stock market predictability

The third school on the matter is of the view that the reason behind autocorrelation in return is due to the psychological factors and the fact that the investors are not perfectly rational. The predictability of returns exit since market participants either over or under-react to the available and often irrelevant information (Xue and Zhang, 2017). There are many biases reported in the prior research that significantly impact the investors' behavior including overconfidence, availability, representativeness, framing effects, and self-attribution bias, etc. (Kudryavtsev et al., 2013; Tversky and Kahneman, 1974; Waweru et al., 2008). By deriving on to the prospect theory by Kahneman and Tversky (1979) that states that investors behave differently to good and bad news, Veronesi (1999) established that investors are inclined to overact to the adverse information during the period of market flourishing and underreact to the same in the periods of depression. This under-reaction and overreaction to the news lead to the return autocorrelation in the stock market (Bondt and Thaler, 1985). According to the findings of Daniel, Hirshleifer and Subrahmanyam (1998), this is attributed to overconfident behavior and self-attribution of the investors. They also believed and attributed the positive autocorrelation to the overreaction in the market, whereas because of the market adjustment to the overreaction, the negative autocorrelation is caused. Herding behavior causes this autocorrelation to be higher in the stock markets (Amini et al., 2013). This linkage of overreaction and the existence of autocorrelation in stock returns is confirmed by Lewellen (2002) and Baur et al. (2012). Based on the discussion, the current study will also consider investors' sentiments as a proxy for behavioral factors to be considered as a reason for stock market autocorrelation alongside traditional factors.

The existence of this autocorrelation in stock returns leads to stock return predictability. Kim et al. (2011) tested this predictability empirically and find that this predictability is statistically significant. The predictability of stock exists even during the periods of low autocorrelation (Hudson, 2010). Kinnunen (2013) conducted a similar study and concluded the same in the Russian context therefore it save to say that the return autocorrelation reflects predictability of return (Xue and Zhang, 2017). Bannigidadmath and Narayan (2016) concluded with similar results in India and find strong evidence of market predictability. In the Pakistan stock market (PSX) likes of Khilji and Nabi (1993) and Khan and Ahmad (2017) studied the stock return using linear regression models and concluded that return correlation exists in the market. In the research on the comparison of return autocorrelation among developing and developed countries, Harvey (1995) reported that the return correlation and predictability in emerging stock markets like Pakistan is even higher than the developed countries.

So in methodology, many scholars studied the return autocorrelation and tried to explore the reasons behind this deviation of the market from standard behavior as explained by efficient market hypothesis but most of this work employed linear models to estimate the return autocorrelation and its antecedents. This includes the work of Baur et al. (2012), Lehmann (1990), Poterba and Summers (1988), Säfvenblad (2000), and Shen and Wang (1998). The linear approach is not suited for such type of data, because the variance is not constant and asymmetry and skewness exits in the data (Xue and Zhang, 2017). As Kahneman and Tversky (1979) established empirically that investors evaluate gains differently from the losses. Chang (2009) also investigated that predictability of stock returns change over time and that predictability is stronger in bad times as compared to the good times. Therefore because of this difference in the behavior of investors in different market situations, researchers like McMillan (2004) and Xue and Zhang (2017) are now adopting nonlinear models to overcome the problem of asymmetric stock returns and to understand the autocorrelation more precisely and deeply.

Methodology

Linear time series models have proven of limited or inadequate value when analyzing the macroeconomic and financial time series data (Galvao et al., 2011). Such data is effected with nonlinear characteristics like positive and negative shocks, different tail behavior and heteroscedasticity of data. To overcome these nonlinearity problems in the data many models have introduced, among which the model that enjoyed the most popularity is the linear threshold autoregressive model (TAR) (Galvao et al., 2011). But the said model failed to incorporate the nonlinearity caused by heterogeneity hence the idea that time-series data may behave differently as explained by Koenker and Bassett (1978) is focused by researchers in theory like Koenker and Xiao (2006) and the reference therein, which then lead to a natural extension of the existing different regimes in threshold regression model based on different quantiles of time series. The model then advanced and combined quantile technique with the threshold models adding both model's advantages, known as threshold quantile autoregressive processes (T-QAR). As the distribution of the Pakistan stock market index (KSE) returns is not expected to be normal. Therefore after exploring existing literature threshold quantile autoregressive model is considered best suitable for the paper.

Model

Quantile Regression is a statistical technique that provides insight about the relationship of covariates (x) with the response distribution (y) depending on different tails of that response distribution (y) where $Q_y\ (\tau/x)$ is the value of Y at any given quantile (τ) of the dependent variable (y) given the independent variable (x) hence.

$$Q_y\ (\tau/x)\ =\ x'\beta(\tau)$$

where $\beta(\tau)$ is the regression coefficient for the given quantile hence we can get a clearer picture of the behavior of Y by considering different quantiles values (Koenker and Bassett, 1978). Galvao et al. (2011) considered the threshold quantile autoregressive model which can be written as

$$Q_{y_t}(\tau/\Im_{t-1}) = \begin{cases} \theta_{01}(\tau)\ +\theta_{11}(\tau)(y-1)+\cdots+\theta_{p1}(\tau)(y-p)\,, & q_t \leq \gamma(\tau) \\ \theta_{02}(\tau)\ +\theta_{12}(\tau)(y-1)+\cdots\ +\theta_{p2}(\tau)(y-p)\,, & q_t > \gamma(\tau) \end{cases}$$

where q_t a threshold variable and the model allows different values of $\gamma(\tau)$ across different quantiles of the dependent variable(y).

Data

In the current study, we analyzed the data of Pakistan stock market index, known as the KSE 100 index. The index comprises 100 firms from 38 sectors. The frequency of the data is from 2000 to 2018. The data is collected from yahoo finance and Khistocks.com. The analysis is going to be conducted with the help of software like Microsoft excel and E-Views.

Variables

Return

The daily stock index is studied in the current study and index return is calculated by taking the log difference between the current and previous index. Which is going to be incorporated as an dependent variable to analyze the return autocorrelation of the KSE index while we are going to take the first lagged return of the index as an independent variable and subsequent lagged return as control variable based on Akaike information criterion (AIC), While considering the first lagged return as a threshold variable also as it will have the highest impact on the current return. The distribution of return during the period under study can be observed in the Figure 1 below.

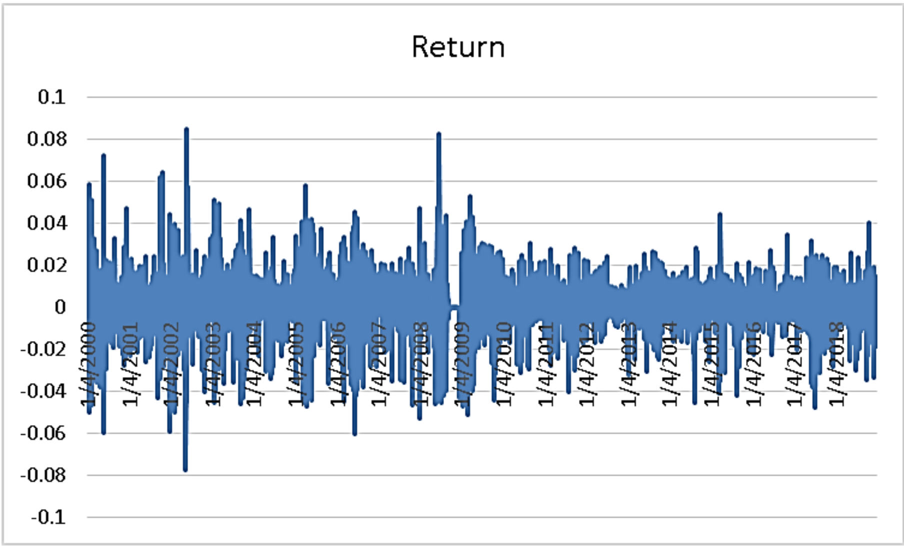

Figure 1: KSE100 Index Return
Source: Research finding.

Also to identify the determinants of the said autocorrelation in the stock market in line with the study of Xue & Zhang (2017) we incorporated market liquidity, market volatility, market's market to book value (MB) ratio along with adding behavioral prospect in the form of investor's sentiment as a proxy for investor's biases as exogenous threshold variables.

Market Liquidity

We are going to incorporate trading volume as a proxy for market liquidity. As trading volume is a widely used and popular proxy for the market liquidity because of the fact the more active tend to be more liquid hence linking directly the trading volume with improved liquidity and also because the measure is simple and data is easily available (Fleming, 2001). The distribution of the variable can be observed in the Figure 2.

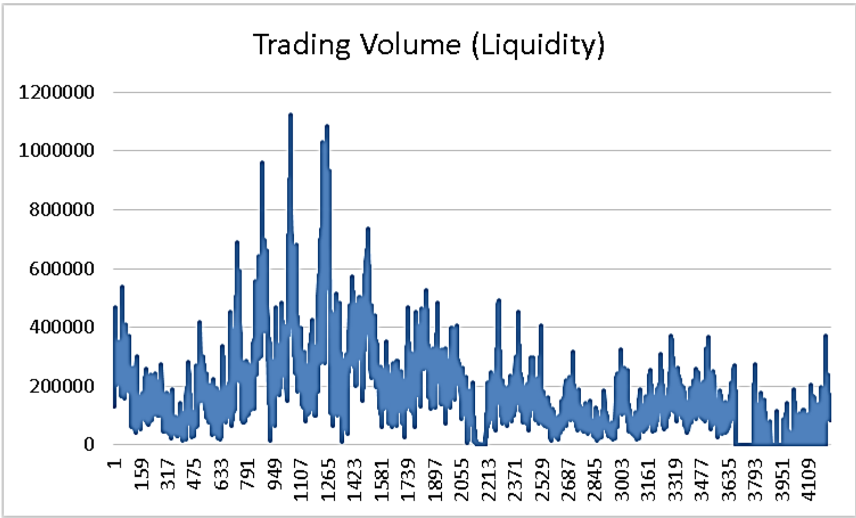

Figure 2: KSE 100 Index Liquidity
Source: Research finding.

Market Volatility

Realized volatility is considered to be a benchmark proxy for market volatility (De Vilder and Visser, 2007) which is calculated by using intraday data. It is simply the square root of the squared realized return and is shown in the graph below.

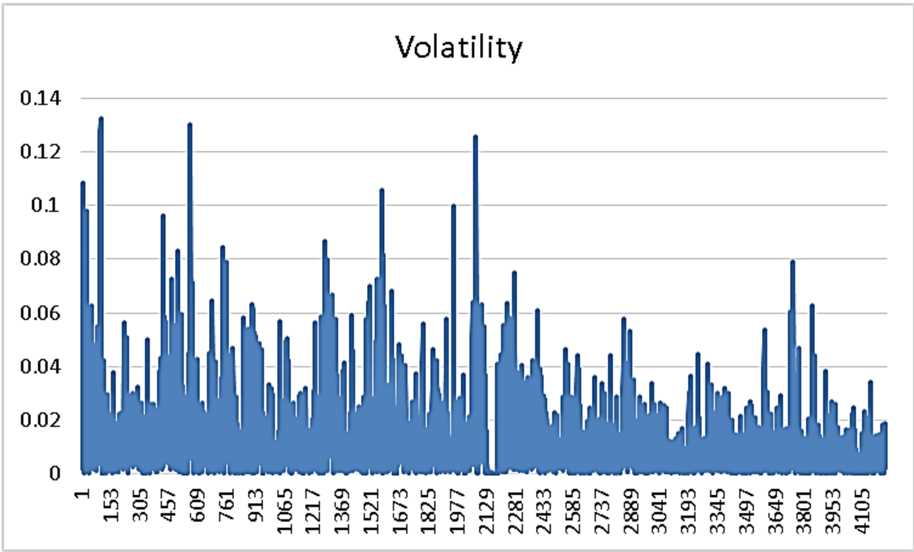

Figure 3: KSE 100 Index Volatility
Source: Research finding.

Market to Book Ratio

The market index itself is a market to book value ratio of the market with a base of 1000 hence market to book ratio for KSE 100 index is going to be calculated by dividing the index by 1000 which is represented in the Figure 4 below.

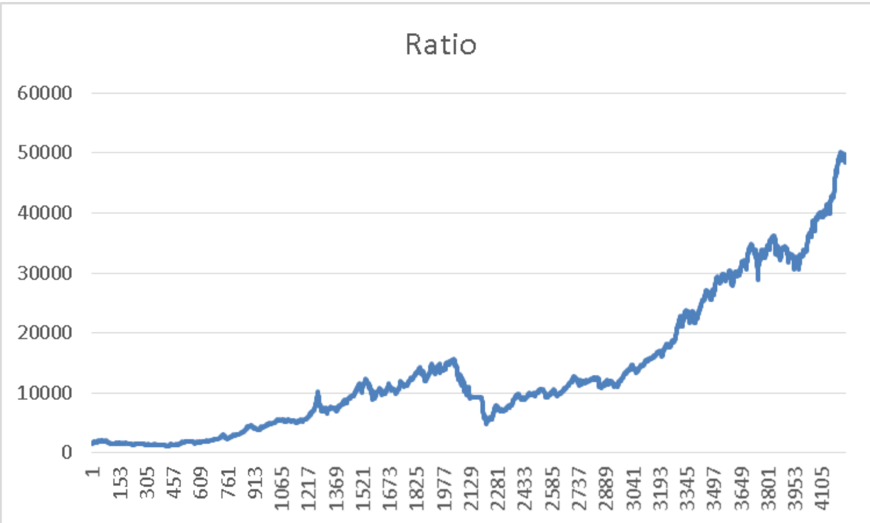

Figure 4: KSE 100 Markets to Book Ratio
Source: Research finding.

Investors Sentiment

Different proxies and measures are implied to measure investor's sentiment which includes direct measures like surveys and indirect measures like trading activity and derivative variables etc. (Chan et al., 2017). we are going to utilize trading volume as a proxy of investors sentiment by creating a high low volume variable (Mazviona, 2015) that will enable us to distinguish between bullish and bearish sentiments. If the trading volume is higher than the previous five-day average it will indicate a bullish trend and will be represented by 1 and otherwise, it will be 0 and will represent a bearish trend in the market.

Results

In this study, we examined the data of the index from the Pakistan Stock Exchange (PSX). This stock index is referred to as the KSE 100 index comprising of 100 top companies. The results are calculated in E-views and detail of the descriptive of the data is discussed below before conducting in-depth statistical analysis.

Descriptive statistics

Table 1 indicates the detail of the descriptive statistics of all the variables of interest of the study but as the main focus of the study is return in the stock market, as the analysis made is to determine the sock return predictability of stock return. The results show that along with all other time series variables, the stock return of the KSE 100 index is also not normal, which is obvious and expected from such data and can be verified from the results of Jarque-Bera test, therefore, the selected methodology of threshold quantile autoregressive model is most appropriate and suited for the study.

Table 1. Descriptive Statistics

	RETURN	**VOLATILITY**	**VARIANCE**	**SENTIMENTS**	**RETURN**	**B.M RATIO**
Mean	0.0007185	0.012177	0.000328	0.872963	0.000814	13539.24
Max	0.0530123	0.132327	0.017510	1.000000	0.085071	49951.60
Min	-0.051312	0	0	0	-0.077414	1101.002
Std. Dev.	0.0104526	0.013410	0.000925	0.333053	0.013475	11460.01
J-Bera	873.39031	28101.70	2514066.	5147.820	2464.908	957.5147
Probability	0.0000000	0.000000	0.000000	0.000000	0.000000	0.000000

Source: Research finding.

After the explanation of the data characteristics, the next step before final analysis is of vital significance to check the data for stationarity and if the data is nonstationary then it must transform in such a way to make it stationary. The term stationary indicates that the statistical properties of the data don't change with time. Nonstationary data have mean and variance value which changes with time and doesn't remain the same across data and indicates that there exists an unpredictable systematic pattern or trend in the data. It is vital to remove any trend from the data to avoid any chances of having biased or misleading results. The trend in data can be removed by taking the log of the variable and due to the transformation caused during stock index return calculation, there is no unit root in the time series as can be observed in Table 2 below.

Table 2. Unit Root Test

	t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic	-44.66887	0.0001
Phillips-Perron test statistic	-44.72133	0.0001

Source: Research finding.

The subsequent table delineates the results of the ordinary least square regression and demonstrates that the threshold points are particularly significant. It shows the first lag return impacts the present returns and that effect ought to be estranged into two regimes to get a progressively thorough and clearer picture. Establishing the significance of the current study against the prior studies which relied on the linear models for the explanation of stock market behavior. The findings of the upper regime show that the coefficients of first lagged returns are positive. This outcome point to the existence of a reversal pattern in stock returns or the existence of a momentum pattern towards intrinsic value in two regimes. Pan (2010) found that the presence of positive autocorrelations in stock returns is analogical to the discovered price momentum and the said can be caused due to of investors' under reaction or continuing overreaction to the information arriving in the market. These outcomes are in line with the investigations of Daniel et al. (1998), Hong and Stein (1999), Barberis et al. (1998) and Lewellen (2002). They inferred that short-run predictability of the stock return is related with positive autocorrelations of returns while long-run inversions are connected to the negative autocorrelations recognized. The outcomes likewise demonstrate that autocorrelations in the higher quantiles are more prominent. The higher coefficients in the progressed quantiles built up the stock exchange's obvious overcompensation to the accessible data. This state can likewise clarify that a higher state of autocorrelation can be related to the upper quantiles and the other way around. Indicating that according to the outcomes in real world the securities exchange overreacts to bad news in good periods and underreacts to good news during bad market conditions. Hence the results established that the stock market doesn't follow random walk hypothesis and there exists certain predictability based on prior returns. It is also established that the stock market behaves differently to the good news and bad news further establishing the presence of behavioral factors as a cause of this predictability and deviation form efficient market hypothesis.

The results of the self-exiting model in table 3 established grounds for testing of the impact of factors under the school of thoughts on autocorrelation, which are reported in the second part, the result of those exogenous factors are displayed in Table 4 below. According to Gębka and Wohar (2013), the factors relating to stock characters can influence the arrival autocorrelation utilizing some transmission strategies including bid/ask spread and value changes though another approach is of the view that the autocorrelation and the recognition of overreaction and under response is because of exogenous behavioral factors (Bondt and Thaler, 1985). Hence both of these angles are joined as an exogenous threshold in the current study by taking stock and market characters to represent loyalist and revisionist approach of autocorrelation and investors sentiments as a proxy for behaviorist approach of autocorrelation. Results of B.M ratio as an exogenous variable indicated that first lagged returns are very significantly autocorrelated in higher and lower regimes but the coefficient values in the higher regime are significantly low as compared to the lower regimes indicating a weak impact of autocorrelation which as Vassalou (2003) explained is because higher B.M ratio itself indicate news regarding future GDP growth and will result in reduced chances of nonsynchronous trading resulting in weak existence of return autocorrelation. The second exogenous variables are market liquidity and the results are indicating a high and significant autocorrelation coefficient which is decreasing in higher quantiles and increasing coefficient in the higher regimes which is against the traditional explanation of the market liquidity that liquidity motivated trades to result in lower autocorrelation (Amihud and Mendelson, 1987). This behavior can be explained through behavioral finance as in collectivist societies like Pakistan trading based on behavioral factors like herding and panic trading can result in suboptimal decisions and results in higher autocorrelation (Rasheed et al., 2018; 2020). We also employed the stock market volatility as an exogenous variable and it is evident from the results that the autocorrelation coefficient is significant in both higher and lower regimes but the coefficient in the higher regimes is significantly smaller indicating less autocorrelation than the coefficient of the lower regimes. Hence it supports the explanation provided by O'Hara and Oldfield (1986) and Ho and Stoll (1983) that high volatility can be a result of probable losses arising due to nonsynchronous trading resulting in less nonsynchronous trading and weaker autocorrelation. Lastly, the results of investor's sentiments, which we used as a proxy for behavioral biases exhibited significant return autocorrelation in higher and lower regimes with significant higher coefficients in higher regimes indicating overconfidence and herding behavior on part of investors in higher regimes and the significantly low coefficients in lower regime can be contributed to an aversion to loss of investors resulting in lower autocorrelation. This existence of behavioral factors in the stock market are established in the studies of Bondt and Thaler (1985), Rasheed et al. (2018), Waweru et al. (2008) and Xue and Zhang (2017). Wald test is utilized to check the significance of the difference between estimates in lower and higher regimes, all of which are significant at a ten percent level of significance.

Conclusion

The current study focuses on the threshold quantile autoregressive model for exploring the existence of autocorrelation as an indicator of return predictability in Pakistan stock exchange by taking the KSE 100 index. The findings established that the first lagged return is better suited to be studied under two regimes providing a deeper understanding of the stock market behavior than traditional and linear statistical models. The study showed momentum in the stock market index during high and low regimes, indicating the presence of behavioral patterns as investors behave differently to good bad market conditions. Furthermore, this study established that investors tend to overreact in extreme conditions and lower regimes there is a pattern of reversal further enhancing the impact of return predictability. In the second part of the study, we also focused on exogenous variables and market behavior under it. The variables include B.M ratio, market liquidity, market volatility, and investor's sentiments and it was found that higher B.M ratio, market liquidity, and market volatility can result in a reduction in return autocorrelation, lastly, the impact of investors sentiments was also established in both higher and lower regimes showing that behavioral biases do have an impact on the stock market and are one of the causes of stock market's failure to follow random walk hypothesis, resulting in stock market's predictability. The factors that can cause such predictability include overconfidence, herding, and loss aversion, etc. The current study established that even if the stock market behavior can be partly explained by the traditional financial view of loyalist and revisionist but the impact of behavioral factors can't be denied and the significant existence of their impact on stock market autocorrelation implies that even if the markets can overcome the barriers that cause stock markets to deviate from stock markets efficiency. The market efficiency still can't be achieved because investors are irrational which is contrary to the assumptions traditional financial models like random walk hypothesis and stock market efficiency. There is a need to further explore and study these behavioral factors and sentiments to better understand the real-life behavior of the stock market and create models by keeping in view the facts that a human being can never be fully rational. We believe that the unique and dynamic results of this study regarding predictability in stock return of Pakistan stock exchange are of great value for the investors in Pakistan. Investors can take benefit from the findings presented in the paper and utilize the return dynamics presented in the study to devise strategies to earn profit from the Pakistan stock exchange and researchers can devise theories that result in a better understanding of real-life stock markets.

Table 3. Results of Endogenous Threshold Variable

Quantiles	**Lower Regime**				**Higher Regime**				**Threshold**	**Wald-**
	Constant	**R(-1)**	**R(-2)**	**R(-3)**	**Constant**	**R(-1)**	**R(-2)**	**R(-3)**		
10th	-0.000108	1.495602***	0.529718***	0.027125**	-0.000108	0.88165***	0.028851	0.081165	-0.03720931	0.005
20th	-0.0000425	1.493704***	0.519843***	0.021397**	-0.0000425	0.840592***	0.024262	0.129283	-0.02968766	0.000
30th	-0.0000214	1.491508***	0.513833***	0.018462**	-0.0000214	0.930615***	0.015036	0.080078	-0.02440353	0.055
40th	-0.000009	1.491787***	0.511930***	0.016808**	-0.000009	1.043491***	0.054937	0.008552	-0.02027038	0.001
50th	-0.0000037	1.496049***	0.514959***	0.015891***	-0.0000037	1.043801***	0.026751	0.019333	-0.01742467	0.003
60th	-0.0000003	1.496932***	0.515058***	0.015295***	-0.0000003	1.115499***	0.039077	0.155802	-0.0145308	0.005
70th	-0.0000004	1.497684***	0.515377***	0.014933***	-0.0000004	1.264775***	0.095995	0.361227	-0.01298964	0.000
80th	-0.0000088	1.496446***	0.514110***	0.014730***	-0.0000088	1.303021***	0.018901	0.319945	-0.0001386297	0.030
90th	-0.0000073	1.497656***	0.515056***	0.014541***	-0.0000073	1.109542***	0.074372	0.182250	7.980341e-05	0.002
OLS	0.000458	0.083151***	0.056442**	0.074774*	0.000458	0.116160***	0.078528***	0.019624	-0.004167467	0.003

Source: Research finding.

Table 4: Results of Exogenous Threshold Variables

Quantiles	**B.M Ratio**			**Liquidity**			**Volatility**			**Sentiments**		
	L.R	**H.R**	**W.T**	**L.R**	**H.R**	**W.T**	**L.R**	**H.R**	**W.T**	**L.R**	**H.R**	**W.T**
	(R-1)	**(R-1)**		**(R-1)**	**(R-1)**		**(R-1)**	**(R-1)**		**(R-1)**	**(R-1)**	
10th	1.488038*	0.534297*	0.009	1.513576*	0.707469*	0.065	1.584117*	1.239854*	0.044	0.845427*	1.454653*	0.006
20th	1.504658*	0.579358*	0.005	1.533910*	0.771256*	0.001	1.599439*	1.261855*	0.026	0.817595*	1.475456*	0.011
30th	1.513148*	0.627574*	0.053	0.926866*	1.459385*	0.042	1.608133*	1.273632*	0.059	0.845322*	1.486202*	0.000
40th	1.519320*	0.672549*	0.021	0.961307*	1.464329*	0.011	1.614701*	1.285718*	0.006	0.872388*	1.494294*	0.023
50th	1.523674*	0.715827*	0.013	0.994066*	1.467731*	0.023	1.620522*	1.295657*	0.001	0.903198*	1.500479*	0.043
60th	1.527941*	0.761224*	0.052	1.034219*	1.471100*	0.055	1.626968*	1.306126*	0.007	0.935878*	1.506900*	0.005
70th	1.533040*	0.801251*	0.000	1.081878*	1.475111*	0.006	1.634619*	1.317564*	0.061	0.967615*	1.514599*	0.009
80th	1.540240*	0.821872*	0.031	1.130963*	1.480529*	0.033	1.642056*	1.332306*	0.030	1.006679*	1.523890*	0.032
90th	1.552103*	0.808620*	0.043	1.181705*	1.488740*	0.029	1.647849*	1.355778*	0.022	1.022781*	1.536925*	0.000
OLS	0.071843*	0.121712*	0.063	0.265245*	0.073621*	0.030	0.641361*	0.299823*	0.031	0.322401*	0.078364*	0.002

*= Sig.10%, **=Sig. 5%, ***=Sig. at 1%, L.R= Lower Regime, H.R=Higher Regime, W.T=Wald Test. Values in the Wald test are P-value.

Source: Research finding.

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