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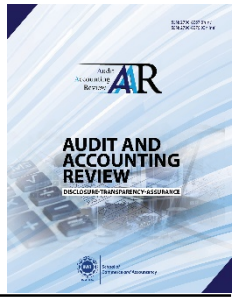

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Nexus between Investor Sentiment and Equity Returns in Pakistan Stock Exchange

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Abstract

The term Investor Sentiment (IS) depicts the mental activities of investors and reflects their expectations towards the market. It plays a crucial role in their decision making process, which ultimately affects the stock market. The current research attempted to examine the nexus between IS and Equity Returns (ER) of 61 financial and non-financial firms of the KSE-100 index of Pakistan Stock Exchange (PSX). Data was collected from the official website of PSX and the published annual reports of the companies for the period 2008–2019. Vector Auto Regression Model (VAR) was used to determine the relationship between dependent and independent variables. The findings revealed that the Share Turnover (SHT) and Money Flow Index (MFI) indicated a significant positive relationship with ER for the KSE-100 index. Similarly, the Price Earnings Ratio (PER) was found to be significantly inversely related to ER. The current study is important both for investors to predict stock trends and for the government's formulation of policies to prevent excessive stock market volatility. It also suggests some important implications for policymakers and investors in order to improve investment policies and make good investment decisions.

Keywords: Investor Sentiment (IS), money flow index, price earnings ratio, share turnover

JEL Codes: E41, E43, E42, E31

Introduction

Investor Sentiment (IS) is considered as a significant topic in the field of behavioral finance which depicts mental activities of the investors. It also reflects investor's expectations towards the market and plays a crucial role in investor's decision making process (Corredor et al., 2015). The idea of IS was first introduced by (Shleifer & DeLong et al., 1990). Investor's feelings and expectations towards market conditions are normally referred to as IS. Baker and Wurgler (2006) defined IS as "the propensity to

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speculate." Antoniou et al. (2015) defined sentiment as an overall inclination or attitude of investors towards specific financial markets or assets, which is independent from rudimentary information. Fluctuation in IS reflects the variation in stock prices and returns which ultimately reflects the stock market behavior. Therefore, to obtain comprehensive knowledge of IS and its contributing factors is an important area in recent research.

IS, one of the major concept under behavioral finance, is defined as "the study of human fallibility in the competitive markets" (Shleifer, 2000). Behavioral finance emerged as a retaliation to traditional finance, which claimed that the investor's investment behavior might be influenced by some cognitive biases, therefore, the complete rationality of investor is not accepted anymore. The behavioral portfolio theory presented by Shefrin and Statman (2000) replaced the concept presented by mean-variance portfolio theory presented by Markowitz (1952) with the supposition that investor decisions are sometimes subjected to their behavioral biases. Therefore, it is not possible for the investors to always think and act rationally. In addition to the rudimentary risk, behavioral portfolio theory acknowledges the effect of behavioral prejudices on investors' decisions related to investment (Kapoor & Prosad, 2017).

Classical finance typically leaves no room for existence of IS. However, economists have been struggling to undertake the market variations that may not be justified by underlying fundamentals. In recent times, financial economists attempted to understand how investors' decisions were impacted by their psychology. Behavioral finance, a new area of financial research, consists of two basic ideas, that is, psychology and limits to arbitrage that was first pioneered by Shleifer and Summers (1990) where psychology highlighted the presence of cognitive biases, such as IS and irrationality of investors.

In the literature related to behavioral finance specifically IS, the most renowned research was conducted by Baker and Wurgler (2007). Their research investigated that how stock market's behavior was impacted by IS. They constructed sentiment index and by utilizing that index, the impact of IS on stock market return and volatility was explored which challenged the ignorant beliefs of traditional finance theories regarding IS.

Various studies have been conducted by different researchers in different countries to study and explore the effect of IS on stock market

behavior. These studies have been helpful to prove the association of IS with stock returns, however there exists a great dispute over whether there is positive or negative association between IS and stock returns. Some researchers suggested significant positive linkage of sentiment-returns nexus (Baker & Wurgler, 2006; Corredor et al., 2015; Schmeling, 2009), while some other found that IS and ER were negatively related (Brown & Cliff, 2005; Ryu et al., 2017). The developed world has recognized the importance of IS as an important indicator related to stock market performance and conducted various studies in the western and developed markets in this area (Baker & Wurgler, 2006; Concetto & Ravazzolo, 2019; Finter et al., 2012; Kim & Park, 2015; Sinha, 2016). Despite the fact that investors in developing markets, specifically Asians may experience behavioral biases to a greater extent as compared to other cultures. However, literature related to IS on emerging markets is not as extensive as compared to the developed markets (Kim & Nofsinger, 2008; Yates et al., 1997). Similarly, it has been proved that the investors in developing markets exhibit noticeable irrational behavior as compared to the investors in developed markets (Frugier, 2016; Maitra & Dash, 2017). Pakistan Stock Exchange (PSX) is a developing market and is considered to be one of the leading exchanges in the world. It is one of the best performing stock exchange in Asia with an objective to provide investors with safe, efficient, and permanent marketplace where they may trade in common stock of listed companies and other securities. Therefore, on the basis of mixed results of the previous studies and lack of research in emerging markets, the current study shed light to securitize the impact of IS on ER in KSE-100 index of Pakistan. KSE-100 index was selected for the current study, because it is considered as one of the most acknowledged index of PSX. It consists of largest companies representing all market sectors on the basis of market capitalization. KSE-100 index represents 85% of market capitalization of PSX.

Previous studies have shown that many researchers around the globe used different proxies to measure IS. Finter et al. (2012) claimed that, proxies if used isolated may not portray a whole picture as different stocks exhibit different sensitivity level towards IS. The previous studies identified proxies that included direct and indirect measures. Baker and Wurgler (2006) stated that the direct measures of IS may exhibit biased behavior, as sometimes investors are not consistent with their answers in surveys and their actions in the market. Therefore, the current study would use some

indirect proxies to measure the sentiments of investors, such as Price Earnings Ratio (PER), Share Turnover (SHT), and Money Flow Index (MFI). These indirect measures were also used in some well-known previous studies (Baker & Stein, 2004; Baker & Wurgler, 2006, 2007; Chen et al., 2010; Chong et al., 2017; Statman et al., 2006).

The current study attempted to investigate the relationship between IS and ER in KSE-100 index. Therefore, the major objective of this study was to examine the relationship between IS and ER in KSE-100 index.

Literature Review

Behavioral finance contradicts the concept of investors' complete rationality by proposing that investors sometimes take biased investment decisions for which they are influenced by their own sentiments. It has been evidenced that IS, an inborn element, impacts the stock's equilibrium price with the noise trader model. Security prices tend to show divergence from their underlying value due to the presence of IS (Shleifer & Summers, 1990). Similarly, Huang et al. (2015) argued that IS could be considered as a systematic risk factor that impacts the stock prices.

Although, various renowned papers used the concept of "investor sentiment" including (Baker & Wurgler, 2006, 2007; Barberis et al., 1998; Qiu & Welch, 2006), however, still there is no general definition of IS that could be used as a universal definition. Therefore, to find a clear definition still remains a challenge. IS has itself a range of meanings. For instance, IS was defined by some researchers as investors' propensity to trade on noise rather than information (Baker & Wurgler, 2006, 2007; Shleifer et al., 1990). While others considered it as excessive optimism (bullish) and pessimism (bearish) among investors towards the current and future prices of stock market (Brown & Cliff, 2004, 2005). Additionally, IS could be measured by using wide range of methodologies as there is no universally accepted proxy used to measure IS. Previous research used two primary methods to measure IS that were direct method involving surveys and indirect method which used observable economic variables (Brown & Cliff, 2004, 2005).

The most famous and prior research related to IS was conducted by Baker and Wurgler (2006). They utilized various proxies, such as SHT, number of IPOs, IPO first day return, dividend premium, closed-end fund discount, and the equity share in new issues and developed sentiment index.

They used it to measure the sentimental effect on US stock market return and volatility. Their results also challenged the traditional finance by proving the presence of direct relationship between IS and US stock market.

Grigaliūnienė and Cibulskienė (2010) considered the effect of IS on market returns of Scandinavian countries (Sweden, Denmark, Norway and Finland) by using consumer confidence index and economic sentiment indicator as a measure of IS. It was concluded that an inverse linkage is present between sentiment of investors and ER at different predicting periods between 1989 to 2009. Finter et al. (2012) constructed an IS index and used that index to inspect the effect of IS on ER of German stock market. Their findings revealed that sentiment weakly influenced the returns, because German stock market was mainly based on institutional investors who were not influenced by sentiment variations. Another research related to IS was carried out by Chi et al. (2012), in which mutual funds flow were used as an indirect measure of IS, leading to the exploration of the relationship between IS and Chinese stock market returns. It was concluded that IS and ER were positively related. It was concluded that the Chinese stock market was an emerging stock market. Lack of experienced investors, therefore showed a huge impact on stock returns.

Dalika and Seetharam (2014) examined the impact of IS on South African stock market returns over the period from 1999 to 2009. They used volatility premium, market turnover, total volume of IPOs, and their initial first day returns to measure IS. Their findings revealed that IS and stock returns were positively related. Alrabadi (2015) examined the connection between sentiments of investors and stock returns of Amman Stock Exchange by using daily data from 2004-2013. He used order imbalance as a measure for IS and concluded that there exists bi-directional causal relationship between IS and stock returns. Dash and Maitra (2018) examined the influence of IS on Indian stock market returns by incorporating wavelet method. The findings revealed a strong effect of IS on both short and long-run returns. They used put-call-ratio, advance decline ratio, SHT. Moreover, India implied volatility index to measure the sentiments of investors. Aggarwal and Mohanty (2018) investigated the existence of interrelationship between IS and ER of Bombay Stock Exchange and National Stock Exchange of India. They used principal component analysis by using PER, price to book ratio, dividend yield, RSI, and MFI to measure IS from 1996 to 2017. The results expressed that IS

positively and significantly impacts the stock returns of both stock exchanges.

Concetto and Ravazzolo (2019) investigated the relationship between IS and ER of US and EU stock markets and evaluated the predictability power of sentiment indices on US and EU stock market returns. They used SHT, number of IPOs, IPO first day return, dividend premium, closed-end fund discount, and the equity share in new issues as indirect measures of IS. The research concluded that IS positively impacts stock market returns. The results further explained that sentiments have strong predictability power on stock returns of US market and weak predictability power on ER of EU stock market. Another research was conducted to investigate the linkage between IS and Taiwan stock market returns during the period from December 2012 to June 2016 (Lee, 2019). IS index, the consumer confidence index, and the market volatility index were employed to measure IS and the findings exhibited that IS significantly impacts ER.

Another research study was carried to investigate the cross-sectional and asymmetric relationship of IS with the ER and volatility in India. The investor sentiment was captured using a market-based measure Market Mood Index (MMI) and a survey-based measure Consumer Sentiment Index (CSI). The findings revealed that IS caused stock returns at extreme quantiles (Chakraborty & Subramaniam, 2020). McGurk et al. (2020) proved the predictive ability of IS for ER by investigating the linkage between both variables. Researchers employed textual analysis on social media posts and concluded significant positive impact of IS on stock returns. Jiang and Jin (2021) utilized the data of Shanghai Stock Exchange ranging from Jan 2012 to Dec 2018 developing a spatio-temporal dynamic panel model. Their study concluded that there exists direct association between IS and ER. Wang et al. (2021) investigated the influence of IS on future ER in 50 global stock markets using consumer confidence index as measure of IS. They documented inverse relationship between underline variables at global level. They further elaborated that IS has more prompt impact on emerging markets as compared to developed markets as developed markets exhibit long-lasting impact of IS. Muguto et al. (2022) conducted their research on Johannesburg Stock Exchange by utilizing daily sentiment composite index, constructed via set of proxies from July 2002 to June 2018. The findings indicated the presence of significant

linkage between IS and ER, demonstrating that behavioral finance could considerably explain the ER fluctuations.

Previous studies related to IS and equity market returns showed mixed outcomes. As Pakistan stock market mainly comprises of retail investors who actively perform their duties on daily basis. Therefore, it may be hypothesized that IS has a significant relationship with ER in KSE-100 index of PSX.

H_1: There is a relationship between price earnings ratio and equity returns.

H_2: There is a relationship between share turnover and equity returns.

H_3: There is a relationship between money flow index and equity returns.

Methodology

This section focuses on the research methodology regarding the measures of the variables by briefly explaining research design, research population, sampling techniques, data collection methods, and computation of dependent and independent variables used to examine the association between IS and ER.

Research Design

Sekaran and Bougie (2003) stated that the research design helps to determine the nature of study. It also shows whether the study is exploratory or descriptive and causal or correlational in nature. The current study is descriptive in nature as it utilized data in mathematical form and employed quantitative research methodology based on extensive literature revised(Hair et al., 2006).

Research Population, Sampling, and Data Collection

Van Blerkom (2017) defined population as the total number of observations and respondents, whereas samples were defined as the number of observations drawn from population for statistical analysis. Population of the current study comprised PSX as it is an active Asian market and considered as the small, opaque, and highly volatile emerging market of Asia (Sheikh & Riaz, 2012). KSE-100 index was taken as a sample for the current study. KSE-100 index was taken as a sample because of largest market capitalization and representation of all sectors of market.

Stratified Random Sampling technique was selected with consideration of heterogeneity to analyze the sample data. This sampling technique certified that the sample distribution pattern was same as population (Bryman & Bell, 2007). Additionally, Thornhill et al. (2009) noticed that larger sample size was the better representative of the population as it generated reliable results. The current study utilized yearly data for analysis from the time period 2008 to 2019, which covered the time span of twelve years. The reason to select this time period was to exclude the impact of Global financial crisis of 2008 and COVID-19 from the data set. The data availability and access to data on hand was another reason to select this time period. In order to achieve the stated objectives, the current study mainly relied on secondary data. This data was collected from the official website of PSX (www.psx.com) and audited annual reports published by leading financial and non- financial companies listed in PSX, specifically from KSE-100 index. The study also eliminated the firms that were de-listed by KSE-100 index or in state of merger or acquisition during the specified time period. Firms having no or incomplete information in the given time period were also disqualified from the sample.

Variables Calculation

The details of variables used in the current study along with the methods to calculate them are as under:

Equity Returns (ER)

ER is dependent variable of the current study and is considered as one of the important indicator to measure company's stock performance which consequently depicts the financial performance of a company. ER is gained on an investment, produced by the investor through trading of shares. Investors normally gain two types of returns from stocks. Stocks may provide capital gain/loss due to fluctuation of stock price or provide profits in form of cash dividends (Sheikh & Riaz, 2012). Statman et al. (2006) used this variable to calculate security returns. Annual data was used in the current study which was calculated by taking average of daily frequencies from January 2008 to December 2019 on monthly basis and then averaged annually. The ER of companies listed on KSE-100 index has been calculated by:

$$ER_{i,} = \ln (p_{i,}/p_{i,t-1})$$

where ER$i,t$ and pi,t is return and closing price of industry *i* at time *t*.

Price Earnings Ratio (PER)

PER indicates the price which market was willing to pay for each share with respect to earning on share. Fisher and Statman (2006) claimed that PER is used as indirect measure of IS as it provides combination of sentiment and values. PER may be defined as the ratio of market price per share and earnings per share (Anderson & Brooks, 2006). The current study used Anderson and Brooks (2006) method to calculate PER.

PER= Market Price per Share/ Earnings per Share

Share Turnover (SHT)

SHT measures the trading activity of stock market and is considered as an important indicator of IS. SHT represents the ratio of transactions volume and number of shares outstanding (Baker & Stein, 2004). SHT of individual stock is computed by dividing stock's trading volume on outstanding shares, mathematically;

SHT = Volume/Outstanding Shares

Where, Earnings per share is used to find outstanding shares by formula used by (Statman et al., 2006).

Outstanding Shares = Net Income/Earnings per Share

Money Flow Index (MFI)

MFI is an important indicator of IS as it reflects the liquidity of stock market by determining the short term price movements caused by investors (Bernard & Thomas, 1990). To construct the MFI, it is important to define the following:

Typical Price=high + low + close/3

The daily typical price is the simple average of daily high, low and close prices. The money flow is defined as:

Money Flow= Typical Price * Turnover:

Money flow is considered as positive if the current typical price is greater than the previous typical price and vice versa.

Money Ratio = Positive Money Flow/Negative Money Flow

The MFI is calculated as follows:

MFI = 100 – 100/1 + Money Ratio

It can also be expressed as

MFI=100*Positive Money Flow/Positive Money Flow+ Negative Money Flow

The reference equation that exhibits the relationship between IS and ER is written as follows:

$$ER_{i,t} = \beta_0 + \beta_1 PER_{i,t} + \beta_2 SHT_{i,t} + \beta_3 MFI_{i,t} + \mathcal{E}_t$$

where Ɛ, t and i represents error term, time (years) and number of firms respectively.

Data Analysis

This section describes the results of some standard diagnostic tests, such as descriptive statistics, unit root test, lag length selection, and Hausman test. Subsequently, some econometric models, such as Fixed Effects Regression Model, Granger causality, and Vector Auto Regression Model (VAR) model are described.

Descriptive Statistics

Descriptive statistics are used to exhibit quantitative descriptions in manageable form. Descriptive statistics provide help in simplification of large data into sensible manner. Descriptive statistics of variables under study for KSE-100 index are presented below to better understand the behavior of variables.

Table 1

Descriptive Statistics of Variables for KSE-100 Index

	ER	PER	SHT	MFI
Mean	-0.727	-0.147	-3.265	0.959
Median	-0.640	-0.096	-3.172	0.932
Maximum	0.751	0.235	0.826	3.381
Minimum	-3.518	-1.564	-5.971	-2.274
Std. Dev.	0.535	0.211	0.898	0.429
Skewness	-1.000	-0.333	-0.202	-0.956
Kurtosis	1.038	0.952	0.603	0.802
Observations	972	972	972	972

Table 1 displays the descriptive statistics results of KSE-100 index for ER, PER, SHT, and MFI. All these variables show 972 annual observations over a sample period of 12 years spanning from 2008 to 2019. The mean value represents average annual value where median exhibits central value of the series. The minimum and maximum values represent the two extreme values of the series. Standard deviation exhibits deviation from the sample mean. Normality of data was measured by skewness and kurtosis, where skewness measures the degree of asymmetry of the series, while kurtosis is a measure of flatness or peakness of distribution of series. The value of skewness and kurtosis between +1 and -1 indicated that the data was normally distributed around its mean (Hair et al., 2016).

Fixed Effects Model

Hausman test was executed to select the suitable model between fixed effects model and random effects model. The null hypothesis showed that the random effects model was appropriate, while alternative hypothesis supported fixed effects model. The observed p-value of Hausman test was 0.001 which showed 1% level of significance leading towards rejection of null hypothesis. It demonstrates that the fixed effects model was preferred for regression analysis of KSE-100 index of PSX.

The fixed effects model is a regression analysis model that considers the connection between independent and dependent variables of various entities (countries, firms, persons etc.) over time. Therefore, it would be preferable to use fixed effects model whenever the impact of variables is analyzed over time within an entity as each entity has its own individual characteristics which may or may not impact dependent variable. The current study used fixed effects model for regression analysis and results are reported below.

Table 2

Regression Results for Equity Returns for KSE-100 Index

Variable	Coefficient	*t*-Statistic	Prob.
Constant	-0.205	-1.698	0.050
PER	-0.190	-3.532	0.020
SHT	0.203	5.363	0.001
MFI	0.118	2.564	0.010
R-squared	0.171		
No. observations	972		

Table 2 reports the regression results for KSE-100 index of PSX by using 972 annual observations for the period of 12 years spanning from 2008-2019. As shown in table, there is a negative relationship between PER and ER, and this relationship is statistically significant at threshold of 5% level. SHT and MFI exhibit significant positive association with ER at 1% level of significance. The value of R-square is 17.1 percent which is not higher, however it is considered good enough in studies focusing on human behavior (Frost, 2014).

Unit Root Test

Augmented Dicky-Fuller test (Dickey & Fuller, 1979) is used to test the stationary of data. This step is essential, prior to perform later analysis. Unit root test with a null hypothesis, representing presence of unit root has been applied to the variables under study and results are expressed below, both in graphical and tabular forms.

Figure 1

Raw Sentiment Measures KSE-100 Index

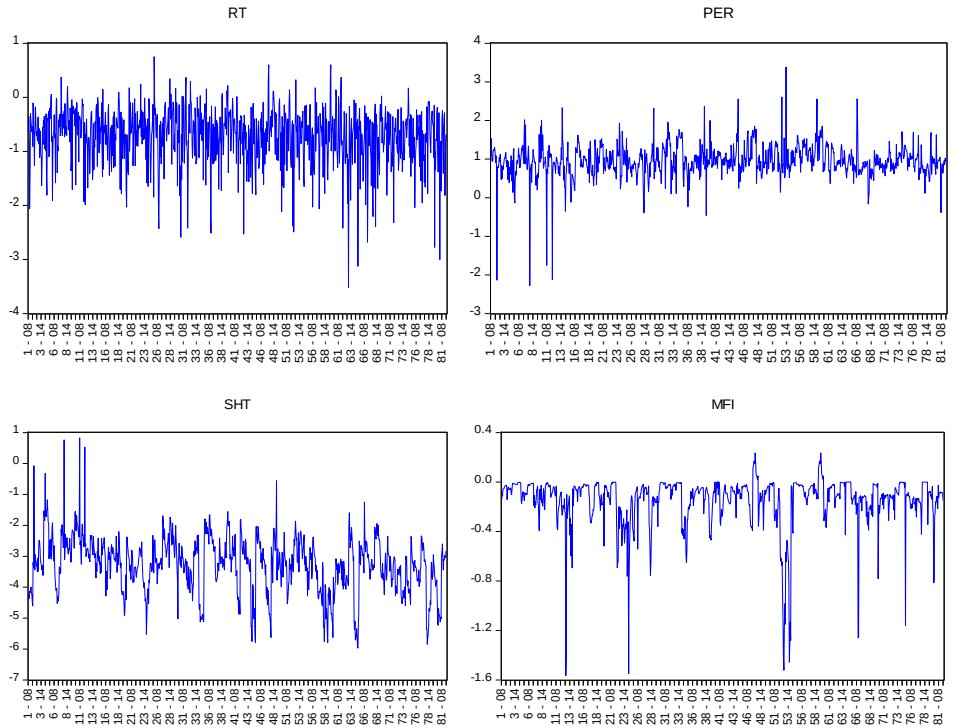

Table 3
Unit Root Analysis of Variables for KSE-100 Index

Variables	Statistic Values	Probability
ER	-13.643	0.00
PER	-10.570	0.00
SHT	-5.042	0.00
MFI	-2.475	0.00

Figure 1 shows the values of ER, PER, SHT, and MFI for KSE-100 index by solid fluctuating lines. Graphical representation and table 4.3 shows that null hypothesis of unit root stands rejected for ER, PER, SHT, and MFI. Hence, all variables were stationary at level and ready for further analysis.

Lag Length Selection

One of the important pre-requisite to estimate the VAR model is to select optimal number of lags for the model. The objective behind selecting appropriate number of lags is to determine whether today's value of underline variable is still impacted by past values (Braun & Mittnik, 1993). In order to determine the optimal number of lags, the VAR lag order selection method, available in E views 10 package was used. Among all provided criterions, the current study used AIC to determine appropriate number of lags in the model. The reason behind the selection of AIC was its widespread acceptance and its high chances to demonstrate true lag length with minimum chances of underestimation of model (Cavanaugh & Neath, 2019; Liew, 2004). The result of optimal lag selection for KSE-100 index is presented below.

Table 4
Optimal Lag Order Selection for Overall KSE-100 Index

Lag	LR	FPE	AIC	SC	HQ
0	NA	0.002033	5.153446	5.200122	5.172077
1	890.5536	0.000138	2.460508	2.693887*	2.553660*
2	27.98213	0.000139	2.470441	2.890524	2.638115
3	49.74832*	0.000131*	2.409244*	3.016030	2.651439
4	22.66061	0.000134	2.434196	3.227686	2.750914
5	17.65892	0.000140	2.474681	3.454874	2.865920
6	21.83862	0.000143	2.500408	3.667304	2.966169
7	23.01976	0.000147	2.521140	3.874740	3.061423

Lag	LR	FPE	AIC	SC	HQ
8	14.79259	0.000154	2.569072	4.109375	3.183876

*indicates lag order selected by the criterion

Table 4 expresses four different lag length selection criterions for KSE-100 index. Three of them, namely LR, AIC, and FPE suggests the use of p=3 lags, while the remaining two HQ and SC suggests p=1 lag. The current study selected lag length 3 for VAR estimation as most of the criterions recommended lag length of three and the selection criteria, AIC suggested 3 lags for the estimation of VAR model.

Vector Auto Regression (VAR) Model

In order to explain the linear interdependencies of multiple series, VAR model has been considered as the most flexible, successful, and easy to use model. VAR estimates helps in order to get better understanding of the relationships between variables. Therefore, general VAR for KSE-100 index was performed and the table 4.5 presented the related VAR estimates.

Table 5

Vector Auto Regression Estimates for Overall KSE-100 Index

	Coefficient	t-value
Constant	-0.527	-4.869*
ER (-1)	0.183	4.815*
ER (-2)	0.019	0.516
ER (-3)	0.030	0.804
PER (-1)	-0.126	-4.737*
PER (-2)	-0.047	-0.210
PER (-3)	0.132	0.735
SHT (-1)	0.245	4.141*
SHT (-2)	-0.252	-3.800*
SHT (-3)	0.023	0.458
MFI (-1)	0.203	3.075*
MFI (-2)	-0.236	-3.621*
MFI (-3)	0.040	0.705

* indicates significance at 5% level

Table 5 exhibits the general VAR estimates for KSE-100 index using 3 lags. Results showed that the current ER has a significant positive relationship with its first two lags at 1% and 5% level of significance

respectively. However, no relationship has been observed between ER and ER (-3). PER (-1) and ER have significant negative relationship at 1% level of significance. However, there was no significant relationship found at PER (-2) and PER (-3). The output of VAR estimates showed the existence of statistically significant relationship between ER and SHT (-1), SHT (-2), and SHT (-3). The first two lags of MFI and ER exhibited relationship at 1% level of significance, which was quite high, however, no significant relationship was found between ER and third lag of MFI.

Granger Causality Test

Individual parameter estimates of VAR model were not considered much reliable to determine the direction of association between variables. Therefore, granger causality test was carried out to evaluate the presence of causal relationship between two variables (Granger, 1969). The ability of one variable to predict the values of other variable is considered granger because of other variable. The results of granger causality test between variables are reported below.

Table 6

Granger Causality Test for Overall KSE-100 Index

Null Hypothesis	Obs	F-Statistic	Prob.
PER does not Granger Cause ER	729	5.806	0.000
ER does not Granger Cause PER		0.378	0.768
SHT does not Granger Cause ER	729	6.589	0.000
ER does not Granger Cause SHT		4.552	0.003
MFI does not Granger Cause ER	729	2.882	0.035
ER does not Granger Cause MFI		0.664	0.574

Table 6 shows the result of causal relationship of dependent and independent variables with respect to KSE-100 index by using lag length of 3. The results exhibited that PER and MFI granger cause ER unidirectional relationship. Whereas, the causal relationship between SHT and ER proved to be bidirectional, as both SHT and ER granger cause each other at 1% significance level.

Conclusion and Recommendations

Behavioral finance considers it impossible for investors to always think and act rationally while making any decision related to investment (Shleifer et al., 1990). Occasionally, while making investment decisions, investors act irrationally following their emotions without focusing on fundamental information. IS, being the focal point of this research, is considered as a significant topic in the field of behavioral finance. It shows the mental activities of investors and reflects their expectations towards the market. Furthermore, it plays a crucial role in the decision making process (Corredor et al., 2015). Various researchers argued that emerging markets, specifically Asian markets, may experience behavioral biases to a greater extent as compared to other cultures (Dash & Maitra, 2018; Frugier, 2016). Therefore, the current study investigated the impact of IS on ER of KSE-100 index. The findings demonstrated a significant relationship between IS and ER. This relationship is stronger for the non-financial sector as compared to the financial sector due to the presence of attractive and giant sectors, such as power, fuel, cement, and chemicals (Raza et al., 2019).

The current study extended the literature on IS in the context of emerging stock markets, such as Pakistan. Additionally, policy-makers and portfolio managers who take IS into account in order to decrease variation in ER and to hedge risk respectively would also benefit from this study. Capital markets authorities would also be guided through the current study regarding the impact of investor behavior on stock market and by ensuring listed companies to provide sufficient information for investors to control and minimize their irrational behaviors. It would be equally important to policy-makers and investors in the stock markets to consider the role of behavioral factors on the investment decisions of investors.

Despite the extensive literature, there are few limitations associated with the current study. Firstly, it focused on the annual data for the time period of twelve years. A large time period may be considered in order to get more generalized results. Secondly, all listed firms of PSX could be used for the purpose of the current study. Another challenge of the current study was the unavailability of a direct measure for IS, as the current study used indirect proxies to measure IS. Finally, as the current study was conducted in the context of PSX; therefore, its findings are regionally restricted and the results may differ for other countries. Hence, it can be proposed that the results may not be generalized to other stock markets in the world.

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