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Research Article

Anchoring and Stock Market Reactions: Evidence from Pakistani Stock Exchange

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Abstract: Anchoring effect is basically the use of anchors or baseline values which leads to market under and over reaction. In order to investigate the existence of anchoring bias in Pakistani stock market, this study uses nearness to 52 weeks high and nearness to historical high as proxies for under reaction and over reaction respectively. The results show that the nearness to 52 weeks high positively predicts the future returns while on the other hand, nearness to historical high negatively predicts future returns on KSE-100 and KSE-30. The study uses KSE-100 for main time series analysis while KSE-30 for robust checking. It was found that there is no significant difference between the KSE-100 and KSE-30 results respectively. The results show that nearness to 52 weeks high and nearness to historical high being two major anchors, along with other macro-economic variables have a prediction power of approximately 62 percent. Similarly, GARCH (1, 1) model has been used to assess the relationship between future and past returns based on volatility clusters. The results indicate the existence of first order autoregressive feature in GARCH (1, 1) model respectively. The results further explain that the predictive power of the individual variables of the study declines while moving from daily to annual horizons respectively.

Keywords: Over Reaction, Under Reaction, Anchors, GARCH
JEL Classification Codes: G11, G14, G41

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1 Introduction

Traditional finance is based on the notion that all financial stakeholders, including individuals and institutions are rational in a financial market. In aggregate these stakeholders take unbiased decisions to maximize their profits. Any irrational move from a financial stakeholder would result in adverse outcomes. In long run, market participants would learn how to act rationally or otherwise leave the market place. Any sorts of pitfalls in financial decision-making of these participants have no mutual relationship and hence these may not distort the market equilibrium.

On the other hand, among many other domains, investor behavior in financial markets is governed by the famous EMH (Efficient market hypothesis) for almost a period of four five decades. The EMH was proposed by Fama (1981) indicating that the stock prices effectively demonstrate any available information in the market. It reflects that strategies used by passive traders like holding market index, cannot be overcome by the active traders. An abnormal return would therefore be quite hard to achieve in a highly competitive market. During the past five decades, EMH remained a center of attraction for the researchers. For instance, Jensen (1978) stated that EMH is supported by the strongest empirical evidence available. The efficient market hypothesis provides a firm basis for the investment and regulatory policies and strategies.

Over a period of time, many studies have produced contradicting results hence misleading the investors and academicians in their relative decision making (Malkiel, 2003). Specially, the subprime mortgage crisis from December 2007 to June 2009 posed some serious questions on the EMH and demanded for an alternating theory to explain the asset pricing. Behavioral finance is one such alternative which assumes that irrationality on part of an investor distorts the true security prices (depictive of its intrinsic value) (Akerlof and Shiller, 2010). Behavioral finance proposes that various underlying investor behavior govern the overall rationality in the financial market that is responsible for the aggregate market anomalous behavior.

Anchoring is one such motive undertaken by investors. Tversky and Kahneman (1974) explained anchoring bias for the first time. Individuals predict values by starting from a base value that is refined as the ultimate answer. Such starting point or the initial value may be proposed by the formulation of a problem or it may be based on some calculations. The adjustments or refinements are different for different initial values which in either case is converged towards the initial value. Such convergence to the initial value or any other base value is called the 'anchoring effect.'

In financial decision making, anchoring is most relevant only when it is accurate; it determines a right direction or otherwise it may also lead an investor astray. As the decisions are based on a starting point or the initial estimate (Tversky and Kahneman, 1974), corrections are made to the initial estimate in order to arrive at a final value but yet these adjustments are inadequate (Lichtenstein and Slovic, 1971).

The widely available information in the market is more confidently processed by investors in contrast to the firm-specific information (Peng and Xiong, 2006). Those stocks whose prices have declined from their historical or all-time high, are more attractive to investors because they look at such stocks as an opportunity. It is because that the investors anchor previous performance of stock and hope for a reversion to the previous high prices, and that's why the investors look at such stocks as an investment opportunity. However, if the decline in stock prices is due to the aggregate market behavior and not due to any company specific irrationality, the investor decision pays back and the investment is regarded as a good decision. Anchoring to a lowest price for a stock to be bought may also be used by an investor but in such case the investor may lose the opportunity to lose. Similarly, an investor may hold the stock to sell till the stocks reaches a certain price.

Generally, investors overreact to multiple news while they under react to a single random news (Griffin and Tversky, 1992). In other words, if a stock price is somewhere near to or at a 52-week high, it implies that some good news about the stock has hit the market and therefore the investors currently under react to such news. While Li and Yu (2009) used the Dow Jones historical high as an anchor and found that when a stock price is somewhere far from the historical Dow Jones high, it reflects that the investor is overreacting to an array of good or bad news. Therefore, a stock price proximity to a 52-week high may indicate an investor under reaction while expecting a positive return. On the other hand, more proximal stock price to a historical high represents an investor's overreaction with an expectation of negative future returns.

Firstly, our study is aimed to investigate whether the use of anchoring successfully predict future returns solely and with a combination of certain macroeconomic variables Secondly, the study tries to determine whether the use of anchoring lead to under reaction or overreaction in Pakistani stock market. Thirdly, the present study attempts to investigate the predictive power of anchoring and macroeconomic variables at different frequencies of time. Fourthly, to find out whether GARCH model, after incorporating the risk factor in returns, yield better results as compared to the NLS-ARMA model. And lastly, to conclude whether any significant difference exists in the results for KSE-100 and KSE-30?

Behavioral biases are relatively less researched in developing countries; especially the extant research is limited to primary measure which leads to less generalizable results (Asad et al., 2018; Islam et al., 2020; Parveen and Siddiqui, 2018; Rehan et al., 2021). The study at hand is aimed to fill such gap. This study is therefore expected to form basis for further studies and adds to the extant literature. The research is also aimed to validate the predictive power of anchoring variables in contrast to lagged returns. Moreover, such predictive power of X52w and XHH is analyzed while moving from short to long-term horizons. Similarly, in order to assess the role of anchoring bias in market reactions in Pakistan, this study attempts to analyze both of the KSE-100 and KSE-30 indices simultaneously for main time series analysis and robust checking respectively.

2 Literature Review

Anchoring bias can be defined as the tendency to take decisions on the basis of some reference point which has no logical relevance. So, investors rely on facts and figures which are irrelevant to the decision making. Most of the recent studies conducted on Pakistani stock market are based on primary data, where such studies focus on behavioral and psychological biases in relation to stock prices, investment patterns, investment returns, and market anomalies (Asad et al., 2018; Islam et al., 2020; Rehan et al., 2021).

As a matter of fact, investors invest in those companies whose stocks are falling with a hope that such fall in price is shortterm and eventually they will rise again. So the investors are able to purchase those shares on low prices, i.e. investors are anchoring on current low prices. Such trend is measured through keeping an eye on reputed stocks and considering seasonal cycles in prices while making investment decisions (Parveen and Siddiqui, 2018). Shin and Park (2018) examined anchoring bias with special emphasis on the contribution of foreign investors. The study was conducted on stocks listed on Korean stock exchange. It was found that the anchoring proxy had a positively significant association with post-earning announcement drift. Moreover, it was found that the positive relationship among anchoring bias and post earnings announcement drift did not exist for those stocks which were held by foreign investors. This indicated that international investors are able to overcome the anchoring bias.

Anchoring bias can be perceived as the investor's reliance on previous experience, past prices, lack of due attention to the recent information or fixation of prices before actual trading. Anchoring depicted in stock market returns is studied by taking 52 weeks high and 52-weeks low as anchors. Such anchors are based on the assumption that a stock will never go below its 52-week low and above 52-week high (Ben, 2009). A historical high is more frequently used as a measure of anchor for estimation (Li and Yu, 2009). Similarly, as mentioned earlier, 52-week high has also been used as robust measure for anchoring effect (George and Hwang, 2004; Li and Yu, 2009). Since past information is incorporated in current prices, future forecasting depends upon the past set of information (Campbell and Sharpe, 2009).

The estimation power of nearness to a 52-week high for future returns is much better than the historical high measure (George and Hwang, 2004). It was also found that the 52-week high returns do not revert back in long run which indicates that a 52-week high is a more robust measure of under reaction in relation to some new information. As, under reaction represents the slow response of investors to relatively new information in the market, a 52-week high is the best measure of anchoring for valuation of stock price increments. George and Hwang (2004) suggest that nearness to 52-week high is a better measure of future returns because the current price level can best determine the momentum effect in contrast to any price changes while studying the behavioral impact of the anchoring theory. They argue that a 52-week high act as an anchor to make corrections for a future return forecast.

Proximity to a 52-week high by return of some stock indicates that good news has recently hit the market. The investors will not engage in trading of such stocks even the information predicts a hike in future prices. Ultimately, the information leads to high prices. Similarly, if a stock price is near to the 52-week low, investors will tend to purchase the stocks rather than selling at a low price, while the prices fall due to spreading of the information. A study on Helsinki stock exchange by Grinblatt and Keloharju (2000) also revealed the same results. Stock prices near to a 52-week high perform better as investors use 52-week high as anchor, which forms the basis for valuation of stocks. Investors are not open to purchase such stocks irrespective of the arrival of new good news. Consequently, investors tend to overreact when stock prices are near to the 52-week high. Therefore, opposed to investor's expectations, stocks near to 52-week high are undervalued.

Anchoring is considered as an important constituent of behavior-based asset pricing by Hirshleifer (2001). Anchoring has the key role in the financial market because of its built-in feature of estimation. It is proposed by Tversky and Kahneman (1974) that heuristics being the cognitively controllable decision strategies, are used by individual investors in order to deal with complex situations. These heuristics reduce the complex decisions into relatively simple and less cumbersome activities for which reason heuristics are called mental shortcuts. Sometimes, these mental shortcuts also result into unbalanced outcomes. As mentioned earlier, anchoring is used by investors to form estimates based on some reference value called anchors. Such reference value may come out as result of incomplete calculations or through any other mechanism. The final value after necessary adjustment does not necessarily represent the intrinsic value of the asset, as the adjustment process does not work accurately to come up with a representative price of the asset.

As the previous highest price work as an important anchor, Investors tend to anchor stock purchase prices with recent highest prices which affects their decision making. Such approach is justified by Shiller (1999) by stating that nearness of new prices of stocks to the past prices may occur if previous prices are taken as a proxy for the new prices. Furthermore, securities which prices are more ambiguous, are relatively more prone to be valued on investor anchors. Such proposition would definitely elaborate the negative return-flow relationship as investors shall consider those stocks as cheap, whose prices fall while those stocks as costly whose prices rise. Similarly, George and Hwang (2004) observed a 52-week high momentum and attributed it to anchoring and adjustment bias, and proposed 52-week high anchor affecting the decision making. Subsequent to that, investors are unable to bid the prices adequately especially when the prices are somewhat near to the past highest value, which in turn is affected by good news. In a nutshell, it can be inferred that while calculating the true intrinsic value which depicts new sets of information, investor forecasting is highly influenced by the historical time series order of stock prices due to anchoring bias.

A study conducted on 300 Scandinavian finance professionals and 213 university students showed significant anchoring effects on students for a long term stock return expectations and an insignificant anchoring effect for the finance professionals. It was also found that finance professionals are not highly affected by the previous values in forecasting (Kaustia et al., 2008). A study conducted by Khan et al. (2017) in Malaysian and Pakistani stock market through primary data also showed anchoring effect. Most investors use the past average of a firm as an anchor while predicting the performance of a firm (Cen et al., 2013).

Using the monthly data from 1990-2006, Campbell and Sharpe (2009) found substantial evidence of anchoring effect. The results also showed an inclined expert opinion towards past months data. A strong indication of the reaction of bond returns to unexpected component of information was also found which implied that yields related to bond are not associated with the estimation error resulted by anchoring.

Masomi and Ghayekhloo (2011) studied the influence of behavioral aspects on investor's decision making in Tehran stock exchange. Anchoring, gambler's fallacy, overconfidence, mental accounting, loss aversion, representativeness and regret aversion were the key behavioral factors studied. The results concluded that behavioral factors have a significant impact on the investor's decision making. Furthermore, gambler's fallacy and anchoring had the most significant impact in investor's decision making.

Luppe and Fávero (2012) studied the role of anchoring bias in forecasting of financial indicator in Brazil. It was found that estimation of financial indicators is significantly influenced due to anchoring bias in addition to the disposition effect.

Mood as yet another factor in defining the investor's behavior is also investigated by several studies in the literature of behavioral finance. For instance, bad moods or depressed moods are found to exhibit relatively less proportion of anchoring bias and more precise estimation of security prices (Bodenhausen et al., 2000). On the other hand, Englich and Soder (2009) found that depressed moods lead to a high proportion of anchoring bias as compared to that of pleasant or good moods.

Ngoc (2014) studied the stock market investor's behavior in Vietnam. Anchoring bias, over-confidence, disposition effect and gambler's fallacy were found to be more relevant factors influencing investor's decision making. As far as measuring of the anchoring bias is concerned, the following table summarizes various studies which have used distinct measures for anchoring bias.

Based on literature, it can be inferred that anchoring bias is one of the important psychological traits which leads to market reactions in aggregate. It is therefore, hypothesized that nearness to historical high and nearness to 52-week high being two measures of anchoring bias, negatively and positively predict future returns in Pakistani stock exchange respectively. Table 1 summarizes the literature on different measures used for anchoring bias.

Table 1: Summary of Anchoring Measures

Anchor	Studies
Chart Pattern	It was found by Ducles (2015) that a specific trading is considered as peak day if the closing price is higher than the opening of the specific day. Therefore, the next day is expected to be a higher returns day hence attracting more investments on that very day. Similarly, Mussweiler and Schneller (2004) proposed that owing to salient high on the chart, investors purchase more and sell less.
Moving Averages	Park (2010) found that in order to predict the future returns, the moving averages of the proportions of 50 days to 200 days can be used. Furthermore, if such proportions are used in addition to the 52 week high values, these may work as an anchor for the prediction of momentum profits on both short term and long term horizons.
52 weeks high & low , 5-days week high and low stockprice	George and Hwang (2004) found that nearness to 52week high and nearness to historical high can act as anchors for estimating future returns but only in short horizons. Grinblatt and Keloharaju (2001) using the nearness to 52 weeks high and nearness to historical high anchors found that investors tend to sell those stocks whose prices are near to the historical high. Similarly, investors will buy those stocks whose prices are near to the 52-week low in prospect of price appreciations. Li and Yu (2012) found that nearness to the historical high negatively predict future returns while nearness to 52 weeks high positively predicts the future market returns. George, Hwang and Li (2013) found that post earnings announcement drift is heavily reliant on the nearness or farness from 52 week high specially when the earnings surprises arrive.
Initial Values/ Prices	Kaustia, Alho and Puttonen (2008) concluded that regardless of any investment experience, initial prices act as anchors for the management graduates.

Anchor	Studies
Recent Prices	Baker, Pan and Wurgler (2012) found that at the time of valuation, recent prices act as a useful anchor. Chang et al (2011) found a strong positive association between past day and current day prices. Similarly, past month values are also used as anchors and consensus forecasts are inclined towards the previous month's values suggested by Campbell and Sharpe, (2009). While, Torngern and Montogomery (2004) stated that recent prices or past movements in prices are only used by common individual investors.
Nearness to Week High	Parveen et al, (2018) used nearness to the 5-days week time high as an anchor in their study of anchoring , disposition and over-confidence bias.

3 Research Methodology

Li and Yu (2009) suggest that proximity to 52-week high act as a proxy for underreaction with predicting positive future returns, while proximity to historical high act as a proxy for over-reaction, predicting negative future returns in a short span of time (1-12 months). These mentioned proxies if added with macro-economic variables estimate 46% of market returns all due to underreaction of stock market to discontinuous information while overreaction to an array of news. The existing price of a stock closer to the 52-week high represents market underreaction to some positive news while stock prices far from 52-week high represents market underreaction to some bad news. While any stock price close to or far from historical high represent market overreaction to a series of positive or negative information.

The daily and monthly stock indices have been obtained for the Karachi stock exchange (KSE-100 and KSE-30) for the period January 2009 to December 2018. The KSE-100 index shows the aggregate returns of market regardless of the fact, that after announcement of dividends and bonus shares, the index needs to be adjusted. The KSE-30 index was introduced in the year 2006 which constitutes of the top 30 most liquid stocks listed on the Pakistan stock exchange (PSX). Since it provides free-floating market value in contrast to the full capitalization, as a consequence, the oil and gas stocks are not misrepresented in the KSE-30 index. Moreover, the KSE-30 index is adequately adjusted for right shares and dividends.

The present study has employed both KSE-100 index and KSE-30 index because of its more frequent and widespread use by the investors. It is also proposed by Li and Yu (2012) that investors tend to utilize market and sector-wise information more than the firm-specific information. KSE-100 and KSE-30 are relatively more readily visible and available to investors. Therefore, investors are expected to utilize the KSE-100 and KSE-30 indices as a yardstick while assessing the new information. As proposed by Li and Yu (2009), this study has also used several macroeconomic variables like the real interest rates, inflation rates and exchange rate as control variables where Inflation rate (i) is calculated from the monthly Consumer Price Index (CPI) values obtained from Pakistan Bureau of Statistics. The interest rate and the monthly exchange rates are taken from the digital archives. The above stated macro variables are used as control variables for the historical high and 52-

week high in the predictive regressions. In running the daily regressions, monthly and yearly values of the macro variables are extrapolated for the daily values. As a time series analysis is used in this study, the main focus is to investigate whether the results for KSE-100 index significantly differentiates from those of KSE-30 index respectively.

As evident from table 1, nearness or proximity is the most frequently used measure in literature. The same has also been used in some recent studies for instance, Parveen and Siddiqui (2018) used nearness to 5-days week time high as an anchor in their study to validate disposition effect, anchoring, and over-confidence bias. Similarly, nearness to 52-week high is also used by Shin and Park (2018) to study its relationship with post earnings announcement drifts.

The 52-week high is computed simply as the maximum share price of a stock over the last one-year period while the historical high value is calculated from the available computerized data within the sample period.

The proxies for overreaction and under reaction i.e. nearness to historical high and nearness to the 52-week high are computed from the following formula.

$$X_{(HH)} = \frac{P_t}{P_{max,t}} and X_{(52w)} = \frac{P_t}{P_{52,t}} \tag{1}$$

Where,
$X_{(52w)}$ = Nearness to 52-Week high (Henceforth)
$X_{(HH)}$ = Nearness to Historical high (Henceforth)
P_t = Index point at time t
$P_{52W,t}$ = 52-Week high value on the index
$P_{max,t}$ = Historical high on index

The daily returns are calculated from the index as:

$$R_t = ln(\frac{P_t}{P_{t-1}}) \tag{2}$$

Where,
R_t= Return on time t
P_t = Closing price at time t
P_{t1} = Closing price at last trading time (Day, week, month, quarter, year)

The present study has used KSE historical high indicator as a dummy variable (Dt) and the dummy variable when historical high equals to the 52-week high (It) respectively. Dt is calculated as 1 when the KSE indices equals or reaches above the historical high or 0 otherwise. Whereas, It is calculated as 1 when historical high equals to the 52 week high, and 0 otherwise. In the study, conducted by Yuan (2008), Dt was used as a proxy for attention-grabing events. It was also found that Dt was negatively correlated with next day returns due to the selling pressure after capitalizing gains from the event. Since, stock returns and the macroeconomic variables of the study possess random-walk feature due to time dependency, therefore, before running regression, stationarity of stock returns and the macro economic variables is checked through the Augmented Dickey Fuller (ADF) test expressed as:

$$\Delta y_t = \cap_0 + \gamma y_{t-1} + \cap_0 t + \sum_{i=1}^{p} \beta_i \Delta y_{t-1} + e_t \tag{3}$$

Where, Δy_{t-1} is represents the stationary process while t is the white-noise process.

Similarly, the ARCH effects is measured by employing the Lagrange multiplier test expressed as:

$$Var_{(\mu_t)} = {\sigma_t}^2 = \gamma_0 + \gamma_1 \mu_t^2 \tag{4}$$

Where, no auto correlation is found when γ_1 is 0 and σ_{2t} = γ_0

Box et al. (1970), initially introduced the ARMA models for time series analysis of estimating returns on the basis of past values. The ARMA model proposes that future market returns are dependent on several factors including past values and the white noise disturbance terms.
The ARMA(m,n) and GARCH (p,q) model is presented as:

$$R_t = \alpha_0 + \sum \alpha_1 R_{t-1} + \sum \alpha_2 k \varepsilon_{t-k} + \varepsilon_t \tag{5}$$

$\varepsilon_t \approx N(0, h_t)$

$$h_t = \beta_0 + \sum_{j=1}^{p} \beta_{1j} h_{t-j} + \sum_{i=1}^{q} \beta_{2i} \varepsilon_{t-i}^2 \tag{6}$$

Where, R_t is the market returns and α1, α2k represents the autoregressive and moving average terms. In our case, initially, past returns (R_{t-1}) is regressed against the future market returns in order to know about the predictive power of lagged return through the following equation.

$$R_t = \alpha + \beta_1 R_{(t-1)} + \mu \tag{7}$$

Where,
R_t= Returns at time t
R_{t1} = Return at time t1
β = Coefficient of variables
μ= Error term
At the second step, nearness to the 52 week high (X_{52w}), nearness to the historical high (X_{HH}), Dummy variable for historical high (D_t) and dummy variable when historical high equals to the 52week high (I_t) have been added to the equation in order to know about the predictive power of the model, given as:

$$R_t = \alpha + \beta_1 R_{(t-1)} + \beta 2 X_{52w} + \beta 3 X_{hh} + \beta 4 D_t + \beta 5 I_t + \mu \tag{8}$$

Where,
R_t = Returns at time t
R_{t1} = Return at time t1
X_{52w}= Nearness to 52-week high
X_{HH}= Nearness to historical high
D_t= Dummy variable (indicator for historical high)
I_t= Dummy variable when 52w high equals to historical high
β = Coefficient of variables
μ = Error term

In the final stage, three macro-economic variables that influences the discount rate and the business conditions of an economy are added to the regression equation. These variables are the interest rate (Intr), Inflation rate (Infr) and Exchange rate(ER) respectively. The regression equation can be expressed as:

$$R_t = \alpha + \beta_1 R_{(t-1)} + \beta 2 X_{52w} + \beta 3 X_{hh} + \beta 4 D_t + \beta 5 I_t + \beta 6 Intr + \beta 7 Inflr + \beta 8 ER + \mu \quad (9)$$

Where,
R_t = Returns at time t
R_{t1} = Return at time t1
X_{52w}= Nearness to 52-week high
X_{HH}= Nearness to historical high
D_t= Dummy variable (indicator for historical high)
I_t=Dummy variable when 52w high equals to historical high
Intr=Interest rate
Infr=inflation rate
ER=exchange rate
β = Coefficient of variables
μ = Error term
If traders or investors underreact to the existing good news, where the current prices are somewhat near to the 52week high, then the 52-week high is expected to predict the future returns positively. Conversely, investors or traders who overreact to bad news when the stock price is somewhere very far from the historical high or near to the historical low, then the historical high is proposed to predict negative future returns. As long as the historical high equals to the 52-week high, only one anchor will influence the investor, the investor is most likely to underreact in response to the good news.

4 Findings

The present study has attempted to analyze the effect of anchoring on stock market at different frequencies of time by employing firm-specific as well as macro-economic variables respectively. The historical high on the KSE-100 and KSE-30 is observed to be 52,877 on April 24th 2017 and 28,173 on May 25th, 2017 respectively. A relatively stable pattern is observed from 2012 till 2015. The upward trend is only till 2017, a downward pattern is seen afterwards when the political instability started after the disqualification of the prime minister in July 2017. Due to persistent inflation over the sampled period, both indices have a strong positive trend till April 2017.

The summary statistics of the respective variables are reported in Table 2 and table 3 respectively. Due to an increasing trend on both indices, the average values of X52w are somewhat near to 1 while the average value for XHH is somewhat near .5 and most of the predictor variables are negatively skewed. The kurtosis values for most of the variables are near to or higher than 3, representing flat-tail or leptokurtic distribution. Similarly, the Jarque-bera (JB) test has been also used to check the normality of the variables. The JB results and the corresponding p-values confirms the leptokurtic distribution of our major variables.

Table 2: Summary Statistics for KSE-100

Frequency	Variables	Mean	S.D	Skewness	Kurtosis	JB-test	P-value	Obs
Daily								
	Returns	0.01	0.01	-0.27	6.56	1326.39	0	2458
	Exch.Rate	0.01	0	0.03	2.79	5	0	2459
	Infl.Rate	7.79	3.72	0.31	1.72	206.25	0	2459
	Intr.Rate	7.79	3.72	0.31	1.72	206.25	0	2459
	X52w-kse100	0.8	0.2	-1.8	5.28	1863.67	0	2459
	XHH-kse100	0.48	0.26	0.17	1.61	209.24	0	2459
Weekly								
	Returns	0	0.01	-0.26	4.35	42.92	0	492
	Exch.Rate	0.01	0	0.02	2.79	0.91	0	492
	Infl.Rate	7.79	3.72	0.31	1.73	41.22	0	492
	Intr.Rate	3.66	3.23	-1.01	3.07	84.52	0	492
	X52w-kse100	0.8	0.2	-1.81	5.3	376.94	0	492
	XHH-kse100	0.48	0.26	0.17	1.61	41.96	0	492
Monthly								
	Returns	0	0	-0.18	6.13	47.06	0	114
	Exch.Rate	0.01	0	-0.08	2.94	0.15	0.04	114
	Infl.Rate	7.79	3.72	0.31	1.74	9.42	0.01	114
	Intr.Rate	3.65	3.23	-1.02	3.08	19.65	0	114
	X52w-kse100	0.8	0.2	-1.8	5.28	86.51	0	114
	XHH-kse100	0.48	0.26	0.15	1.59	9.82	0.01	114
Quarterly								
	Returns	0	0	0.47	2.97	1.41	0.49	38
	Exch.Rate	0.01	0	-0.05	2.86	0.05	0.98	38
	Infl.Rate	7.79	3.75	0.31	1.74	3.15	0.21	38
	Intr.Rate	3.65	3.23	-1.01	3.02	6.4	0.04	38
	X52w-kse100	0.8	0.2	-1.85	5.32	30.25	0	38
	XHH-kse100	0.48	0.26	0.14	1.58	3.33	0.19	38
Annually								
	Returns	0	0	-0.2	2.31	0.27	0.88	10
	Exch.Rate	0.01	0	-0.23	2.67	0.14	0.93	10
	Infl.Rate	7.79	3.76	0.35	1.8	0.81	0.67	10
	Intr.Rate	3.66	2.87	-0.66	2.04	1.11	0.57	10
	X52w-kse100	0.81	0.15	-2.25	6.79	14.41	0	10
	XHH-kse100	0.5	0.27	0	1.43	1.02	0.6	10

The results reported in table 3 indicates that the two anchors (X52w and XHH) are not significantly correlated with the given macroeconomic variables. Inflation rate and exchange rate have a relatively higher correlation with X52w on both indices on different horizons. X52w and XHH have a correlation of .35 and .30 for KSE-100 on daily horizon. Although, both anchors are somewhat correlated with each other, (as evident from table 03), their predictive power is not affected after all. It can be observed from Table 04 that the correlations among the variables of the study get stronger while moving from daily to annual horizons. The predictive power of the variables is not compromised. Since we have used the least square regression method and the least square method is a more suitable technique in case of collinearity in the predictor variables (Stewart, 1987).

Table 3: Correlation Matrix for KSE-100

Horizon	Variables	Returns	Exch.Rate	Infl.Rate	Intr.Rate	X52w-kse100	XHH-kse100
Daily							
	Returns	1	0.02	0.03	-0.01	-0.02	-0.04
	Exch.Rate	0.02	1	0.28	-0.31	-0.16	-0.49
	Infl.Rate	0.03	0.28	1	-0.4	-0.19	-0.43
	Intr.Rate	-0.01	-0.31	-0.4	1	-0.19	0.37
	X52w-kse100	0.02	-0.16	-0.19	-0.19	1	0.35
	XHH-kse100	-0.04	-0.37	-0.43	0.37	0.35	1
Weekly							
	Returns	1	0.04	0.07	-0.03	-0.07	-0.09
	Exch.Rate	0.04	1	0.31	-0.46	-0.16	-0.41
	Infl.Rate	0.07	0.31	1	-0.8	-0.19	-0.46
	Intr.Rate	-0.03	-0.46	-0.45	1	-0.19	0.42
	X52w-kse100	0.07	-0.16	-0.19	-0.19	1	0.37
	XHH-kse100	-0.09	-0.41	-0.46	0.42	0.37	1
Monthly							
	Returns	1	0.15	0.12	-0.05	-0.13	-0.2
	Exch.Rate	0.15	1	0.35	-0.4	-0.22	-0.42
	Infl.Rate	0.12	0.35	1	-0.49	-0.24	-0.44
	Intr.Rate	-0.05	-0.4	-0.49	1	-0.23	0.45
	X52w-kse100	0.13	-0.22	-0.24	-0.23	1	0.4
	XHH-kse100	-0.2	-0.42	-0.44	0.45	0.4	1
Quarterly							
	Returns	1	0.21	0.19	-0.12	-0.28	-0.34
	Exch.Rate	0.21	1	0.41	-0.52	-0.22	-0.49
	Infl.Rate	0.19	0.41	1	-0.52	-0.2	-0.55
	Intr.Rate	-0.12	-0.52	-0.52	1	-0.19	0.59
	X52w-kse100	0.28	-0.22	-0.2	-0.19	1	0.46
	XHH-kse100	-0.34	-0.49	-0.55	0.59	0.46	1

Horizon	Variables	Returns	Exch.Rate	Infl.Rate	Intr.Rate	X52w-kse100	XHH-kse100
Annually							
	Returns	1	0.35	0.43	-0.27	0.34	-0.64
	Exch.Rate	0.35	1	0.63	-0.56	-0.29	-0.63
	Infl.Rate	0.43	0.63	1	-0.92	-0.26	-0.69
	Intr.Rate	-0.27	-0.56	-0.92	1	-0.1	0.72
	X52w-kse100	0.34	-0.29	-0.26	-0.1	1	0.55
	XHH-kse100	-0.64	-0.63	-0.69	0.72	0.55	1

Before estimation process, the stationarity of the data is tested by employing the Augmented Dickey Fuller (ADF) test. In the first step, the unit root test is run with the intercept at level. And the results showed unit root for four variables out of total eight variables on both indices. So in second step, unit root for all eight variables is tested at first difference against the intercept and trend, this time the results leaded to the rejection of null hypothesis that no unit root exists and the data is now stationary. The results for the unit root test are given in (Annexture-01)

The results showed the existence of ARCH effects (Annexture-01) and autocorrelation in variance of residuals with 1 % of significance level only for daily and weekly horizons. Therefore, according to the Box-Jenkins procedure, the results supports ARMA (1,0) and GARCH(1,1) in explaining the variations in market returns (Daily and Weekly) for both KSE-100 and KSE-30 indices respectively (Annexture-01).

Table 4: Empirical Results: GARCH (1, 1) Model

		KSE-100		KSE-30	
		GARCH (1,1) Daily	GARCH (1,1) weekly	GARCH (1,1) Daily	GARCH (1,1) weekly
Mean Equation	Constant	0	0	-0.018	-0.01
		-1.3	(1.79)**	(3.81)*	(1.66)***
	AR(1)	-0.101	-0.091	-0.09	-0.029
		(5.01)*	-0.59	(4.68)*	-0.66
Variance Equation	Constant	4.16E-06	3.16E-06	8.23E-06	3.03E-06
		(7.54)*	(2.47)*	(5.65)*	(2.40)*
	ARCH effect	0.12	0.11	0.17	0.09
		(12.57)*	(2.16)*	(8.08)*	(2.50)*
	GARCH effect	0.83	0.74	0.77	0.81
		(78.48)*	(8.97)*	(38.25)*	(14.73)*
	$\alpha + \beta$	0.96	0.85	0.95	0.91
Regression Statistics	R^2	0.41	0.38	0.33	0.24
	Log likelihood	7929.2	1808.48	7753.1	1859.64
	SIC	-6.41	-7.21	-6.23	-7.37
	AIC	-6.44	-7.3	-6.26	-7.46
	ARCH-LM Statistics	1.69	13.67	0.24	0.26
	Durbin watson	1.78	1.96	2.16	1.96
	Probability	0.19	0.11	0.62	0.6

Table 4 shows that the AR at lag 1 is significant for daily horizon, indicating that past returns significantly predict future returns for daily returns. The positive sign indicates the positive impact of past return on future returns. The constant for the variance equation is near to zero which indicate that the existing stock volatility is reliant on the square of lagged residuals and past return volatility. The GARCH (1,1) results also indicate the existence of persistent volatility (as $\alpha + \beta$ is somewhat near to 1) hence a relatively stronger ARCH and GARCH effects. Similarly, the Durbin-Watson statistic indicates the threshold value of 1.7-2.3 which shows that there is no first order correlation.

As proposed by Li and Yu (2009), due to the influence of momentum effect in cross section of stocks, it is also tested whether past returns can successfully predict the future returns? For this purpose, using the NLS ARMA, the Returns are regressed with lagged returns on different horizons (Daily, weekly, monthly, quarterly and annually) for both indices. Table 5 shows that past returns do not predict future returns in all horizons except daily horizon for both indices respectively.

Table 5: Empirical results NLS-ARMA(Future returns on past returns)

	KE-100					KSE-30				
Horizon	Daily	Weekly	Monthly	Quarterly	Yearly	Daily	Weekly	Monthly	Quarterly	Yearly
Past returns	0.10*	0.06	0.54	-0 .06	0.46	0.09*	0.03	0	-0.07	0.3
	-5.18	(-1.37)	(-0.55)	(-0.44)	(-1.35)	(-4.68)	(-0.81)	(-0.05)	(-0.50)	(-0.98)
R^2	0.01	0.003	0.002	0.004	0.28	0.008	0.001	0.00002	0.007	0.12

At table 6 we regressed the KSE-100 and KSE-30 index returns (daily, weekly, monthly, quarterly and annually) against lagged returns(past returns), X52w(nearness to 52w high), XHH(nearness to historical high), dummy variable Dt (indicator of historical high) and dummy variable It(indicator when historical high equals 52w high). It was found that XHH has the ability to predict future returns negatively, while the X52 positively predicts future return. As Dt, It, XHH and X52 were added to the equation, the t-statistics insignificantly lowered for past returns. However, the predictive power of these variables improve while moving from short to long horizons (as evident from the values of R^2). It can be inferred that if X52w rises, future returns will also rise proportionately keeping other variables constant. Conversely, an increase in XHH will result into a proportionate decrease in future returns. In other words, where Dt=1 or the indices reach to its historical high values, the future returns are expected to be lower (evident from the negative sign). Li and Yu (2009) and Yuan (2008) argue that such pattern is all due toselling pressure posed to investors after the index climax. However, unlike Li and Yu (2009) our Dt positively predicts future returns in long and short horizons.

Table 6: Empirical results NLS-ARMA (Future returns on past returns, X52w ,XHH, Dt, It)

Horizon	Past returns	X52w	XHH	It	Dt	R^2
Daily KSE-100	.10*	.02*	- .00*	.01*	.02*	0.012
	-5.06	-2.34	(-3.47)	-1.55	-1.18	
Daily KSE-30	.09*	.00*	- .00*	.00***	0.001	0.012
	-4.83	-2.4	(-2.34)	-1.51	(-1.16)	
Weekly KSE-100	0.05	.00*	- .00*	.03***	.00**	0.016
	(-1.21)	-3.4	(-4.60)	-1.51	-1.79	
Weekly KSE-30	0	.00*	- .00*	0.05	0	0.013
	(-1.16)	-3.07	(-3.85)	(-1.462)	(-1.218)	
Monthly KSE-100	0.01	.00*	- .00*	.09**	.00**	0.083
	(- .282)	-3.55	(-4.14)	-1.64	-1.92	
Monthly KSE-30	0	.00*	- .00*	.05***	.00**	0.074
	(- .24)	-2.9	(-3.92)	-1.57	-1.64	
QuartrlyKSE-100	-0.13	.00*	- .00*	.00**	.00*	0.154
	(- .84)	(-4.442)	(-4.69)	(-1.82)	(-2.026)	
QuartrlyKSE-30	-0.17	.00*	- .00*	.08***	.00**	0.137
	(- .63)	-4.04	(-4.16)*	-1.55	-1.87	
Yearly KSE-100	.79**	.00**	- .00*	0.47	0	0.798
	-1.94	-2.04	(-3.39)	(- .96)	(-1.46)	
Yearly KSE-30	0.2	.00**	- .00*	0.39	0	0.587
	(1.77)**	-1.86	(-3.05)	(- .702)	(-1.29)	

Regression results in table 6 shows that the future market returns rise when the existing stock index is somewhat near to its 52 week high and significantly distant from historical high. This implies that good news has recently hit the market, to which the market is under reacting. So the market has higher prospects for even going higher. Owing to this situation, investors can truly benefit from such momentum.

As mentioned earlier, for major period of the sampled time, the indices are observed to be upward trending, therefore, indicator when P52w is equal to Pmax (It) would not be considered as a useful measure for long term good news. So, dummy variable (It) is controlled, table 08 shows that when (It=1), investors are expected to underreact to a recent good news. This also implies that a time when (P52w=Pmax), investors tend to use only one anchor and that is 52-week high while ignoring the historical high. In a nutshell, it is found from the results that investors are expected to underreact to short term good sporadic news (nearness to the 52 weeks high) while they overreact to long term good news (nearness to historical high). So nearness to 52 weeks high and nearness to historical high are the two anchors used by investors to which investors underreact and over react respectively.

As suggested by the literature, various macro-economic variables can also predict market returns therefore, it is ensured that the predictability of variables is not affected by macroeconomic variables. So, future market returns are regressed with X52w and XHH while controlling the macro-economic variables. We have used three major macro-economic variables namely; interest rate, exchange rate and inflation rate.

Table 7 shows an overall regression for both indices, where future returns are regressed on lagged returns, X52w, XHH, It, Dt, Intr, Infla, ER(past returns, index value over 52 weeks high, index value over historical high, pmax is equal to p52w, indicator when index reaches historical high, interest rate, inflation rate and exchange rate respectively). The results indicate that for longer horizons the predictability power of the regression model improves. The future stock returns can be predicted upto 61.5% in the yearly horizon. (As depicted from R-squared value in table 07). Similarly, X52w and XHH have a high predictive power as compared to the macro economic variables. For robustness of results, the study also employs KSE-30 index. The results are given in below in the following tables along with valuesfrom KSE-100. It has been observed that there is no significant difference between the KSE-100 and KSE-30 results which imply that investors use 52 weeks high and historical high as anchors across both indices without any significant discrimination.

Table 7: Empirical results NLS-ARMA (Future returns on past returns, X52w ,XHH, Dt, It,Exch.Rt, Infl.rt, Int.rt)

Horizon	Past returns	X52w	Xhh	It	Dt	Exch.Rt	Infl.rt	Int.rt	R^2
Daily KSE-100	.012*	.00*	- .00*	.01***	0	.00*	- .00**	0.19	0.012
	-4.19	-2.57	(-3.48)	-1.69	(-1.18)	-2.98	(-1.737)	-0.45	
Daily KSE-30	- .09*	.01*	- .00*	0	0	-3.7E-5*	0	0.54	0.013
	(-3.81)	-2.19	(-2.96)	-1.58	(- .89)	(-2.2)	(-1.05)	-1.1	
Weekly KSE-100	0.05	- .00*	- .00*	.03***	- .00*	.00*	2.9E-05*	-0.19	0.0176
	-1.17	(-2.82)	(-3.65)	-1.68	(-2.55)	-3.69	-1.16	(- .71)	
Weekly KSE-30	0	- .00*	.00*	0.05	.00*	1.4E-07*	8.30E-05	-0.02	0.013
	-0.93	(-2.19)	(-3.03)	-1.33	(-2.33)	-3.19	-0.96	(- .04)	
Monthly KSE-100	0.02	- .00*	- .001*	.09***	0	- .12***	-0.01	0.18	0.091
	-0.24	(-2.79)	(-3.42)	-1.53	(- .22)	(-1.65)	(- .84)	-0.35	
Monthly KSE-30	0	- .00*	- .02*	0.04	-0.002	-9.72E-05	-4.50E-05	0.271	0.081
	-0.05	(-2.17)	(-3.34)	-1.2	(- .142)	(-1.12)	(- .15)	-0.17	
QuartrlyKSE-100	-1.74	- .00*	- .00*	0.011	- .00***	0	5.32E-6**	-0.1	0.1848
	(- .91)	(-4.23)	(-5.75)	-1.1	(-1.67)	-1.13	-1.82	(- .19)	
QuartrlyKSE-30	-0.17	0	.00*	0.06	0	0	0	0.31	0.175
	(-1.12)	-0.19	-2.54	-0.53	(-1.24)	-0.93	-0.88	-0.66	
Yearly KSE-100	0.7	.00***	- .00*	0.55	6.80E-06	0	-9.47E+05	-0.88	0.449
	-1.46	-1.87	(-4.06)	-1.16	-0.5	-0.89	(-1.37)	(- .92)	
Yearly KSE-30	0.59	.00***	.01*	0.18	0	0.76	0	0.7	0.615
	-1.34	-1.59	-3.81	-1.1	-0.38	-0.57	(-1.10)	-0.41	

5 Discussion and Conclusion

5.1 Discussion

Most of the behavioral finance studies conducted on Pakistani stock market are based on primary data (Asad et al., 2018; Parveen and Siddiqui, 2018; Rehan et al., 2021; Rinta-Kartano, 2013). Our study is conducted on secondary data, aimed to investigate the role of anchoring bias in aggregate market.

The findings of this study are consistent with previous works conducted on other secondary data across different regions. In other words, as pointed out in George and Hwang (2004); Grinblatt and Keloharju (2000); Kansal and Sing (2015); Li and Yu (2009) and Shin and Park (2018), Our results do indicate that nearness of stock prices to the anchors efficiently help in stocks valuation. Moreover, anchors can be considered as one of the important predictors of stock price dynamics. Moreover, the study validates the existence of inefficient markets driven by behavioral and psychological biases.

5.2 Conclusion

The present study has attempted to analyze the effect of anchoring on stock market at different frequencies of time by employing the two anchors viz 52 week high and historical high along with lagged returns, dummy variable representing when 52w high equals to historical high, dummy variable for historical high indicator and some macro-economic variables viz inflation rate, interest rate and exchange rate respectively. Two anchors namely nearness to 52 weeks high and nearness to historical high have been used to confirm the anchoring effect in KSE-100 and KSE-30. Where, nearness to 52 weeks high represents the market under reaction while nearness to historical high represents the market over reaction. So investors tend to under react to short term good news (nearness to 52 w high) while overreacts to a long term good news (nearness to historical high). It was found from the time series analysis that the nearness to historical high (anchor) negatively predicts while nearness to 52 weeks high positively predicts the future returns. while using the 52-week high anchor the Pakistani stock market underreact while using the historical high anchor, Pakistani stock market over react to any new information. These two anchors have a relatively better predictability as compared to the macro-economic variables. The overall model including the macro-economic variables has almost 62% power to successfully predict future returns. Similarly, the results also showed that the predictive power of the individual variables of the study declines while moving from daily to annual horizons. Furthermore, the results also showed that after incorporating the risk factor in the model through GARCH (1,1), the prediction power of the model is declined to .41 and .33 on daily horizons.

5.3 Implications

It was also concluded that there is no significant difference in the results for KSE-100 and KSE-30 results however, the KSE-100 has relatively better results as compared to KSE-30 indicating its higher popularity among investors.

One implication of this study is that investors can gauge market trends from KSE-100 more efficiently, as compared to the KSE-30 index. Moreover, the study is equally important for policy-makers in general and portfolio managers in specific to become aware of anchoring bias being one of the biases which prevents rational investment decision making. Since, Pakistani stock market is dominated by large institutional investors, this study is expected to enlighten such institutional investors regarding the vicious cycle of inefficient investment decision making, hence leading to market reactions on the aggregate level.

5.4 Limitations and Future Research Implications

Future researches are expected to include longer samples i.e 3-year and 5-year samples for higher statistical robustness. Furthermore, cross sectional research is also encouraged to validate the propositions of this investigation. This study suggests to analyze and evaluate the stock market indices KSE-100 and KSE-30 along with other indices with respect to the firm-specific factors as well as other macro-economic factors that may be considered necessary for stock investment purposes.

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