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Anchoring Bias and Financial Security: A Study of KSE Markets

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Abstract

Business anomalies such as overreaction and underreaction are affected by a variety of psychological causes. The use of anchors or baseline values, known as the anchoring effect, causes market underreaction and overreaction. This research used nearness to 52-week high and nearness to historical high as proxies for under and over-reaction, respectively, to analyze the psychological causes for under and over-reaction. On the KSE-100 and KSE-30, the findings revealed that proximity to the 52-week peak positively predicts future returns, whereas proximity to the historical high negatively predicts future returns. KSE-100 was used for the key time series research., while KSE-30 was used for rigorous testing. There is no substantial gap between the KSE-100 and KSE-30 scores, according to the findings. Similarly, the three macroeconomic variables used as control variables are the exchange rate, inflation rate, and interest rate in order to provide a more robust model of strong prediction capacity. The findings revealed that proximity to the 52-week maximum and proximity to the historical high, as well as other macroeconomic factors, had a forecast capacity of around 62 percent. Similarly, focused on volatility clusters, the GARCH (1, 1) model was used to measure the association between potential and past returns. The results show that in the GARCH (1, 1) model, there is a first order autoregressive function. The findings also show that when the study's individual variables are moved from everyday to annual horizons, their predictive capacity decreases.

Keywords: Behavioral prejudices, investment decision, stock exchange Over reaction, Anchors, GARCH

1. Introduction

With varying levels of psychological anchors, investment choices would most definitely vary. The influence of framing/anchor on human decision-making was highlighted by (Elhussein, Hussein, Elhussein, Nabi, & Abdelgadir, 2020). Behavioral prejudices, such as anchoring biases, have become well-known as essential factors that influence market participants' behavior, (Ishfaq & Anjum, 2015), and these factors are accompanied by asset price behavior. Since behavioral biases like momentum and reversals of asset returns trigger mispricing, trading strategies that leverage these biases may produce trading income. In this sense, foreign exchange pricing can be influenced by market participants' framing/anchoring. As a result, the current research hypothesizes that the results of currency momentum/reversal and the relationship between equity and currency returns may be influenced by the states of psychological anchors in the currency and stock markets if informed/smart investors manipulate the states of behavioral preferences of other investors (Westerhoff, 2003a).

The aim of this analysis is to see how the relationship between Pakistani Currency futures returns and subsequent equity returns differs depending on the condition of the currency and stock markets' psychological anchors. Many international finance analysts concentrate on the foreign exchange sector to have enough proof of currency momentum and reverse impacts (Mcmillan, 2004). These studies show business inefficiency (Waweru, Munyoki, & Uliana, 2008) and the potential for creating a plan that generates good returns (Thi Bich Ngoc, Bien Phu Street, Thanh District, & Chi Minh, 2014). In addition, the partnership between stock and currency markets has gotten a lot of coverage (Njeri Wamae, 2013). Since investments in foreign securities ultimately require investments in foreign currencies, understanding the connection between international equity returns and currency returns is critical to international fund management. The analytical research on the relationship between equity and currency returns, on the other hand, has not yielded a unanimous conclusion. On the one side, (Njeri Wamae, 2013) suggest that if investors cannot perfectly hedge their foreign exchange rate exposure, foreign currency would depreciate due to portfolio rebalancing when a foreign stock market outperforms domestic equities. In the other side, several studies suggest that investors often raise their stakes in markets that have recently outperformed (Rajesh Babu, 2020), resulting in a strong association between foreign stock returns and currency returns due to the impact of investor return-chasing. Since the indication of the association between equity returns and currency returns can be positive or negative, as previous literature has shown, relative stock market success is a crucial factor in deciding foreign exchange returns.

Financial economists have been trying to find factors that can predict overall capital market returns. The potential of nearness to the PSE 52-week high and nearness to the PSE historical high to forecast market returns is investigated in this research. The psychological anchoring and small investor interest predictors we suggest in this analysis are based on empirical proof. (George, Hwang, 2391455, & 2015, n.d.) propose that traders use the 52-week high as an anchor while measuring the increase in market value indicated by new knowledge in an interesting analysis. They contend that a stock whose price is at or above its 52-week high is a stock that has recently received positive news, and that this may be the height of traders' underreaction to good news. As a result, proximity to the 52-week peak is correlated with higher predicted returns in the cross section. (Westerhoff, 2003b), on the other hand, indicate that investors' reduced focus contributes to category-learning behavior, in which investors process more market-wide information than firm-specific information. Investors are expected to use the KSE index as a guide when analyzing new industry-wide knowledge since it is arguably the most commonly accessible information regarding the market. We believe that proximity to the KSE 52-week high catches the degree of underreaction and can be used to predict overall market returns. Individuals can underreact to sporadic news, but overreact to a long history of salient results, whether good or poor, according to (Chang, Luo, the, & 2011, n.d.). We also hypothesize that traders could use the KSE historical high as an anchor when evaluating facts, based on (Galen V. Bodenhausen, Gabriel, & Lineberger, 2000) (GV Bodenhausen, …, & 2000, n.d.). The result of this anchor, on the other hand, is predicted to be the polar opposite of the KSE 52-week high anchor. When the current price is well below its historical average, traders' overreaction to negative news could be at its highest. Since there has likely been a string of negative news in the past, markets tend to overreact to extended news. As a result, we believe that proximity to the KSE's historical peak catches the magnitude of overreaction and can be adversely correlated with potential stock returns. Investors, on average, overreact to various pieces of news when underreacting to a single piece of random news (S. D. Campbell & Sharpe, 2007). In other terms, whether a stock's price is at or at a 52-week peak, it indicates that the market has received some positive reports regarding the stock and that buyers are reacting to it. Although (Waweru et al., 2008) used the historical Dow jones high as an anchor, they discovered that when a stock price is far from the historical Dow jones high, the investor is overreacting to a variety of bad or good news. As a result, a stock price close to a 52-week high may suggest an investor's underreaction when anticipating positive returns. More proximal equity values to a historical high, on the other hand, reflect an investor's overreaction to a pessimistic potential return forecast.

In developed nations, behavioral biases are less studied; in particular, existing study is restricted to primary measures, resulting in less generalizable findings. The current research aims to close this void. As a result, this research is intended to serve as a foundation for future research and contribute to the existing body of knowledge. Furthermore, unlike lagged returns, our predictors have a high prediction capacity in forecasting potential returns for short term horizons up to one year, according to our research. Similarly, in order to determine the effect of anchoring bias in market reactions in Pakistan, the current study examines both the KSE-100 and KSE-30 indexes simultaneously for key time series analysis and rigorous testing.

1.2 Contribution

The current research adds to the existing body of knowledge in two ways. For starters, this is the first research to look at whether PSE and their related country-level stock indices have an effect on their price activity. This study presents the significant effects of psychological anchors of stock markets on stock price behavior. This research expands the stock market's anchoring literature to the currency market and investigates whether the states of currency price anchors and their related country-level stock indices influence momentum and reversal impacts, as well as the relationship between equity and currency markets. Our empirical findings add to our knowledge of the nature of currency price behavior. Second, this is the first analysis to see whether using anchors for KSE 100 and KSE 30 and the corresponding country-level market indices as partitioning/states variables in a linear-regression-based tree model will increase the forecasting efficiency of the return direction. Instead of predicting the absolute returns of PSE, this analysis employs ARCH and ARIMA model to forecast the trajectory of returns. For practitioners and risk management, our methodology offers another helpful tool for developing trading techniques for carry trades and hedging. To begin, we want to see whether the use of anchors will accurately forecast potential returns either used alone or in conjunction with other macroeconomic variables. Second, to see whether using anchors causes underreaction or overreaction in the Pakistani stock market. Finally, the current research looks at the predictive capacity of anchors and macroeconomic factors at various period frequencies. Fourth, to see if the GARCH model, after taking into account the risk factor in returns, produces stronger outcomes than the NLS-ARMA model and linear regression. Finally, to see whether there is a substantial gap between the KSE-100 and KSE-30 scores.

The remainder of the research is organized as follows: 2, Literature Review 3 The methodology clarified the data and methodology Preliminary data analysis and data. The empirical findings are presented in Section 4. The conclusions are summarized in Section 5.

2. Literature Review

In the literature, the impact of psychological anchors on price activity has gotten a lot of coverage. Individuals can underreact to sporadic news, but overreact to a long history of salient results, whether good or poor, according to (Rajesh Babu, 2020). (Westerhoff, 2003a) offer proof that stock market psychological anchors influence price action. According to (Nafila & Wibowo, 2020), the 52-week high ratio is linked to intermittent reporting, while the historical high ratio is linked to a long history of noteworthy results. Although the existing literature suggests that currency returns are linked to relative stock market performance (Jaksic, Steel, Moore, & Stewart, 2020), and psychology is a key driver of stock market price behaviour (Cho & Yang, 2018), as well as the foreign exchange rate (Hesketh, Griffin, Dawis, & Bayl-Smith, 2015), no research has been done to see whether the relationship between equator returns and stock market performance is causal. This research aims to fill the gap.

Traditional finance is founded on the assumption that in a stock economy, all financial players, including individuals and institutions, are fair. These stakeholders make impartial judgments and optimize their gains as a group. Every unreasonable decision by a financial stakeholder will have negative consequences. Market investors must eventually understand how to behave rationally, otherwise they would exit the market. Any pitfalls in these members' financial decision-making have no reciprocal partnership, so they are unlikely to distort market equilibrium.

Investor behavior in capital markets, on the other hand, has been governed by the familiar EMH (Efficient Market Hypothesis) for nearly 45 years, among many other realms. (Elhussein et al., 2020) suggested the EMH, which states that stock values essentially represent any accessible knowledge in the economy. It shows that passive traders' tactics, such as holding the stock index, cannot be beaten by aggressive traders. In a highly competitive sector, achieving an abnormal return will be difficult. Throughout the past five decades, the EMH has remained a magnet for scholars. Jensen (1978) claimed, for example, that EMH is backed up by the best scientific evidence available. The effective market theory gives investment and regulatory plans and initiatives a solid foundation.

Many experiments have generated contradictory conclusions over time, contributing to consumers and academicians being misled in their decision-making (Ishfaq & Anjum, 2015). The subprime mortgage crisis, which lasted from December 2007 to June 2009, raised serious concerns about the EMH and necessitated the creation of an alternate explanation to understand asset valuation. Behavioral finance is one such choice, which claims that an investor's irrationality distorts real protection prices (which represent its intrinsic value) (Shin, Journal, & 2018, n.d.). According to behavioral finance, the overall rationality of the financial market is governed by various underlying investor behaviors, which are responsible for the aggregate market anomalous behavior. One such motivation pursued by investors is anchoring. In 1974, Kahenman and Tversky were the first to demonstrate anchoring prejudice. Individuals predict values by starting with a base value and refining it to arrive at the final answer. The initial value or starting point may be suggested by the formulation of a problem or based on some calculations. The modifications or refinements vary depending on the original value, which is converged against the initial value in any scenario. Anchoring Effect refers to this kind of convergence to the original value or some other base value.

Anchoring is most important in financial decision-making when it is reliable and decides the correct direction; otherwise, it can drive an investor astray. Corrections are rendered to the original estimation in order to arrive at a final value so assumptions are focused on a reference point or initial estimate (Rajesh Babu, 2020), but these changes are insufficient. In comparison to firm-specific knowledge, publicly accessible industry information is more confidently processed by an individual (Ishfaq & Anjum, 2015). Investors are most interested in stocks whose shares have fallen from their record or all-time highs and they see them as an asset. Since an investor bases their decision on a stock's past success and hopes for a reversion to previous high values, those stocks are seen as investing opportunities. If, on the other hand, the fall in equity values is attributed to overall business behaviour rather than some one company's irrationality, so the investor's judgement would pay off and the purchase was a positive one. An investor can still use anchoring to the lowest price for a stock to be purchased, although in this situation, the investor may forfeit the chance to lose. Similarly, an investor can hold a stock until it hits a certain price before selling it.

Many studies explored the anchoring impact in several domains since Tversky and Kahneman's (1974) work, leading to the presence of robust and significant anchoring effects. Furthermore, (Cho & Yang, 2018) investigated the anchoring effect of international institutional investment and came to the conclusion that previous foreign ownership has an impact on the traction of foreign investments. The anchoring influence has also been investigated in a variety of financial markets, including horse race betting (Stone & Cooper, 2001), real estate investing (Conti, Frühwirth-Schnatter, Heckman, & Piatek, 2014; Hundleby & Nunnally, 1968)(Ishfaq & Anjum, 2015). Analysts' earnings forecasting (Elhussein et al., 2020) and macroeconomic releases have also been shown to benefit from the anchoring impact (Gurdgiev, Experimental, & 2020, n.d.). (Chang et al., n.d.) do a thorough and thorough analysis of all major research on the anchoring impact. By narrowing the form of demand and anchor, this analysis attempts to advance Furnham and Boo's research. This thesis conducts a comprehensive analysis of the literature on the anchoring impact in individual investment decision-making, especially in the stock market.

The propensity to make choices based on a comparison point that has little objective significance to the judgement is known as anchoring bias. As a result, consumers depend on statistics and statistics that have little bearing on their decision-making. In reality, investors invest in businesses whose prices are declining in the hopes that the price decline will be temporary and that the stock will inevitably recover. As a result, buyers are willing to buy certain securities at cheap rates, because they are relying on the existing low prices. When making investment choices, such a pattern is calculated by holding an eye on reputable stocks and taking seasonal market cycles into account (Cen, Hilary, Analysis, & 2013, n.d.).

Anchoring bias is described as an investor's dependence on prior knowledge, past pricing, a lack of attention to recent facts, or market fixing prior to actual trading. Anchoring is analysed in stock market returns by using the 52-week high and low as anchors. The premise behind such anchors is that a stock would never fall below its 52-week low or rise beyond its 52-week peak (Nafila & Wibowo, 2020). The use of a historical high as a calculation of anchor for estimation is becoming more popular (Mcmillan, 2004). Similarly, as previously discussed, the 52-week high has been used as a reliable indicator of the anchoring impact (Duclos, 2014). Since past knowledge is integrated into present values, potential planning is dependent on the past collection of data (Ishfaq & Anjum, 2015).

Nearness to a 52-week peak has far higher predictive ability for potential returns than the historical high index (Nafila & Wibowo, 2020). It was also discovered that 52-week high returns do not reverse in the long term, implying that a 52-week high is a more reliable indicator of underreaction to new facts. A 52-week peak is the strongest predictor of anchoring for valuation in stock price increments since under reaction reflects the sluggish exposure of buyers to relatively new facts in the sector. When researching the behavioural effects of the anchoring hypothesis, (George et al., n.d.) argue that proximity to the 52-week peak is a stronger predictor of potential returns since the present price level will best calculate the momentum effect in comparison to any price increases. They claim that a 52-week peak should be seen as a reference point for making changes to a predicted return estimate. Some stock returns are close to a 52-week peak, indicating that positive news has recently reached the industry. And if the knowledge expects a market increase in the future, consumers would not trade those stocks. In the end, the knowledge contributes to exorbitant costs. Similarly, if a stock's valuation is close to its 52-week low, buyers are more likely to buy it rather than sell it. As a result of the spread of knowledge, prices are falling. (Cen, Hilary, Wei, et al., n.d.) conducted a report on the Helsinki stock exchange and found the same findings. Stock values that are close to a 52-week high do well when investors use the 52-week high as an anchor for stock valuation. Regardless of the advent of fresh positive news, investors are not willing to buy those stocks. As a result, while equity markets are near their 52-week highs, investors appear to overreact. As a result, stocks near 52-week highs are undervalued, contrary to market expectations.

(Westerhoff, 2003b) considers anchoring to be an essential component in behavior-based asset pricing . Because of its built-in function of prediction, anchoring plays a crucial position in the financial sector. Individual investors use heuristics, which are cognitively controllable decision mechanisms, to cope with dynamic circumstances (S. D. Campbell & Sharpe, 2007). Heuristics are often known as behavioural shortcuts because they turn difficult choices into reasonably straightforward and less time-consuming tasks. This behavioural shortcuts may also lead to unbalanced results. As previously said, investors use anchoring to shape calculations depending on any reference value known as anchors. As a result of incomplete calculations or by some other method, such a reference value can emerge. The asset's inherent value is not always represented by the final value after required changes. Since the adjustment mechanism would not reliably provide a representative asset price.

As an effective anchor, the previous highest-priced job. Investors' decision-making is influenced by their tendency to anchor market buying rates to the most current high prices. (Khan, Bibi, & Tanveer, 2016) justifies this strategy by arguing that current market values which be close to previous prices if recent rates are used as a reference for new prices. Furthermore, stocks with more uncertain values are more likely to be priced using investor anchors. Such a proposal will undoubtedly elucidate the unfavourable return-on-investment relationship. As a result, buyers would regard such stocks as inexpensive if their prices decline, whereas those stocks would be regarded as costly if their prices increase. (George et al., n.d.) reported a 52-week high momentum and linked it to anchoring and change prejudice, proposing a 52-week high anchor influencing decision making. As a result, investors are unable to accurately bid rates, especially when they are near their previous highest value, which is influenced by positive news. In a nutshell, owing to anchoring bias, investors' forecasting is heavily skewed by the historical time series order of market markets when measuring the true intrinsic value, which depicts new sets of facts.

A analysis of 300 Scandinavian finance professionals and 213 university students found that students have major anchoring effects for long-term stock return goals, whereas finance professionals have a negligible anchoring impact. In forecasting, it was also discovered that financial experts are unaffected by prior principles (Njeri Wamae, 2013). (Malik, Butt, Din, & Aziz, 2020) used primary data to investigate the role of anchoring in the Malaysian and Pakistani capital markets. When forecasting a company's results, most analysts use its historical average as an anchor (S. Iqbal, Chaudry, & Iqbal, 2015). (S. Campbell & Sharpe, 2007) find strong proof of an anchoring impact using monthly data from 1990 to 2006. The findings also revealed an expert opinion that was skewed against the previous month's evidence. A clear indicator of bond returns' response to an unpredictable portion of knowledge was also discovered, implying that bond yields are unrelated to the calculation error caused by anchoring. (Njeri Wamae, 2013) investigated the effect of anchoring bias in financial indicator forecasting in Brazil. Anchoring prejudice, in addition to the inclination effect, was found to have a substantial impact on financial indicator estimation.

(Thi Bich Ngoc et al., 2014) looked at how behavioral factors influenced investor decision-making on the Tehran stock exchange. The main behavioral influences analyzed were anchoring, gambler's fallacy, overconfidence, mental accounting, failure aversion, representativeness, and regret aversion. Behavioral factors have a significant impact on an investor's decision-making, according to the findings. Additionally, the gambler's error and anchoring have the greatest effect on investor decision-making.

Several experiments in the behavioral finance literature look at mood as another element in determining an investor's actions. Weak or depressive moods, for example, are observed to have a lower proportion of anchoring bias and more accurate measurement of protection prices (N. Iqbal & Mohsin, 2019). In contrast, (Mohsin et al., 2020) discovered that depressive moods result in a higher proportion of anchoring bias than positive or strong moods. (Chang et al., n.d.) investigated the actions of capital market investors in Vietnam. Anchoring prejudice, overconfidence, mood influence, and gambler's fallacy were discovered to be more influential influences on investor decision-making. In terms of anchoring bias measurement., the following table describes numerous research that have utilized various anchoring bias tests.

3. Research Methodology

According to (George et al., n.d.) , proximity to the 52-week maximum is a proxy for under-reaction, which predicts optimistic future returns, while proximity to the historical high is a proxy for over-reaction, which predicts negative future returns in a limited period of time (1-12 months). These proxies, when combined with macroeconomic factors, predict 46 percent of market returns, all attributable to the equity market's underreaction to discontinuous facts and overreaction to a wide range of news. The current price of a stock above the 52-week high indicates that the market is reacting positively to any good data, while stock values further from the 52-week high indicate that the market is reacting negatively to some poor news. Although any stock price near or far from a record peak indicates investor overreaction to a sequence of favorable or negative events.

3.1 Data Collection

For the period January 20010 to December 2019, regular and monthly stock indices for the Pakistan stock Exchange (KSE-100 and KSE-30) were obtained. The KSE-100 index represents the market's total returns, notwithstanding the fact that the index must be updated after dividends and incentive shares are announced. The KSE-30 index, which includes the top 30 most liquid stocks listed on the Pakistan stock exchange, was launched in 2006. Since it has free-floating market prices rather than absolute capitalization, oil and gas stocks are no longer misrepresented in the KSE-30 index. Furthermore, the KSE-30 index is well-adjusted for appropriate securities and dividends.

Because of its more common and popular usage by investors, the KSE-100 and KSE-30 indexes were used in this analysis. (N. Iqbal, Arijo, & Iqbal, 2019) often say that investors choose to use business and sector-specific details over firm-specific information. The KSE-100 and KSE-30 are more widely known and accessible to investors. As a result, when evaluating new material, investors are required to use the KSE-100 and KSE-30 indices as a yardstick. This research has used many macroeconomic variables as control variables, such as actual interest rates, inflation rates, and the exchange rate, as suggested by (George et al., n.d.).

The monthly Consumer Price Index (CPI) values derived from the Pakistan Bureau of Statistics are used to measure the inflation rate I The monthly share rates and the interest rate are taken from the digital archives. In the statistical regressions, the above-mentioned macro variables are used as control variables for the historical high and 52-week maximum. Monthly and annual values of the macro variables are extrapolated for the daily values while performing daily regressions. The key goal of this report, which employs a time series approach, is to see how the findings for the KSE-100 index vary greatly from those for the KSE-30 index.

The 52-week high is actually the highest market price of a company in the previous year, while the historical high value is measured using computerized data accessible over the sampling era.

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.

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

Where,

$X_{(52)}$ w =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:

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

(2)

Where,

R_t = Return on time t

P_t = Closing price at time t

P_{t-1} = Closing price at last trading time (Day, week, month, quarter, year)

The PSE historical high predictor was used as a dummy variable (D_t) in the current analysis, as well as a dummy variable when historical high equaled 52-week high (I_t). When the KSE indices match or exceed the historical high, D_t equals 1; otherwise, it equals 0. When the historical peak matches the 52-week high, it is counted as 1; otherwise, it is calculated as 0. Dt was used as a proxy for attention grabbing activities in an analysis undertaken by Yuan (2008). Due to the selling pressure after capitalizing profits from the case, D_t was also observed to be negatively associated with next day returns.

Because of their time dependence, stock returns and macroeconomic variables in the sample have a random-walk function. The stationarity of stock returns and macroeconomic variables is then tested before running regression using the Augmented Dickey Fuller (ADF) measure, which is represented as:

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

Where, Δyt-1 is represents the stationary process while εt is the white-noise process.

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

$$\mathrm{Var}(\mu_t) = \sigma^2{}_t = \gamma_0 + \gamma_1 \mu^2{}_t \quad (4)$$

Where, no autocorrelation is found when $\gamma 1$ is 0 and σ2t = γo

The ARMA models for time series analysis of calculating returns on the basis of past values were first proposed by Box and Jenkins (1970). According to the ARMA model, potential market returns are influenced by a number of variables, including previous prices and white noise interference words.

The ARMA (m,n) and GARCH (p,q) model is presented as:

R t □ □0 □ □□1*Rt*□ *1* □ □□ 2*k* □ *t* □*k* □ □ *t* (5)

$\varepsilon t \approx N(0, h_t)$

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

(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.

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

Where,

R_t = Returns at time t

R_{t-1} = Return at time t−1

β = Coefficient of variables

μ = Error term

At the second step, nearness to the 52 week high (X_{52}w), nearness to the historical high ($_{XHH}$), 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:

$$R_t = \alpha + \beta_1 R_{t-1} + \beta 2X52w + \beta 3Xhh + \beta 4Dt + \beta 5It + \mu \quad (8)$$

Where,

R_t = Returns at time t

R_{t-1} = Return at time t−1

X_{52w}= Nearness to 52 week high

$_{XHH}$= 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:

$$R_t = \alpha + \beta_1 R_{t-1} + \beta 2X52w + \beta 3Xhh + \beta 4Dt + \beta 5It + \beta 6Intr + \beta 7Inflr + \beta 8ER + \mu \quad (09)$$

Where,

R_t = Returns at time t

R_{t-1} = Return at time t−1

$X_{52}w$= Nearness to 52 week high

$_{XHH}$= 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 buyers underreact to recent good news, and current prices are close to the 52-week peak, the 52-week high is supposed to accurately forecast potential returns. In contrast, when buyers or traders overreact to poor data when the market price is very far from the historical peak or very close to the historical low, the historical high is suggested to expect unfavorable potential returns. Only one anchor will affect the investor whether the historical peak equals the 52-week high, and the investor is more likely to underreact in reaction to the positive news.

4. Results and Discussion

Using firm specific as well as macro-economic factors, the current research sought to examine the impact of anchoring on the equity market at various frequencies of time. The plotted graph between returns and historical peak (XHH) and 52-week peak (X52w) for the KSE-30 index and the KSE-100 index from January 2010 to December 2019 is seen in Figure 01. For the time frame under consideration, both indexes show a mixed pattern. The all-time highs for the KSE-100 and KSE-30 were 52,877 on April 24th, 2017 and 28,173 on May 25th, 2017, respectively. From 2012 to 2015, a reasonably consistent trend can be seen. The upward trajectory only lasted until 2017, when political unrest began after the disqualification of the prime minister in July 2017. Both indices have a clear positive trend until April 2017 due to sustained inflation over the sampled era.

Figure 01: Daily Returns vs X52w and XHH

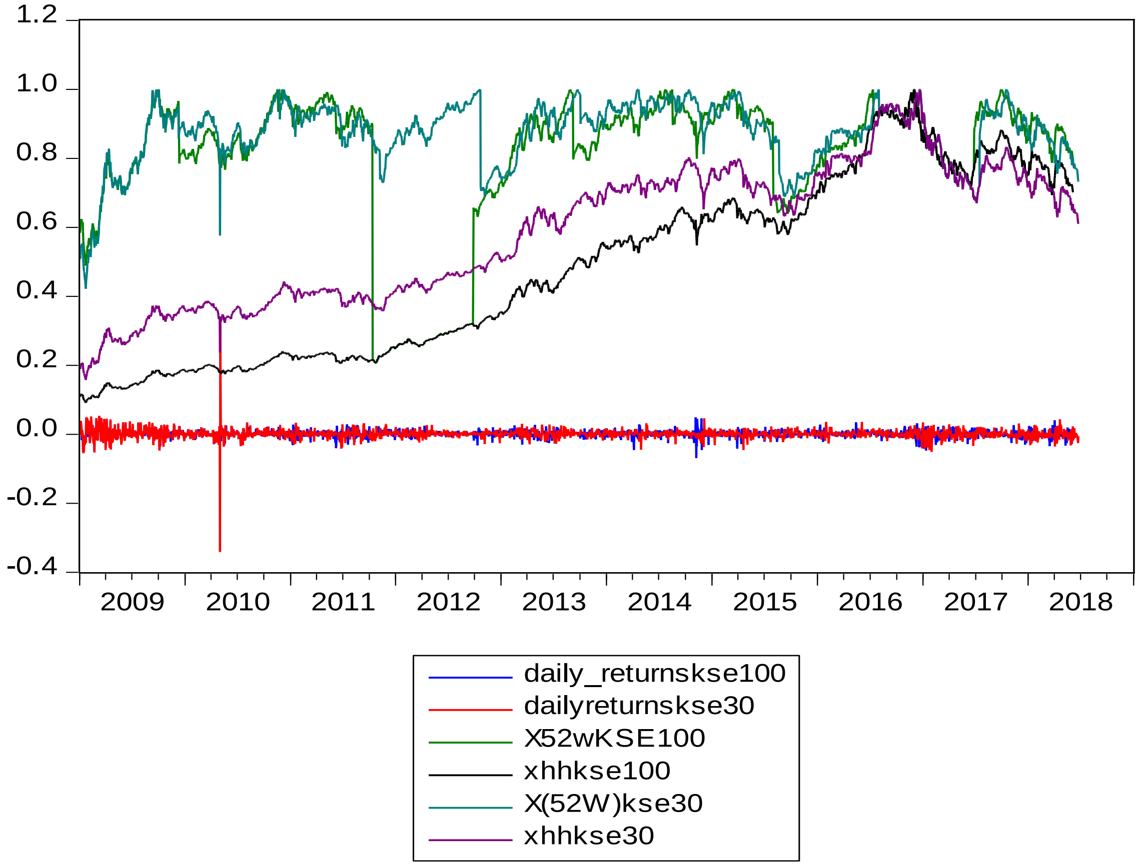
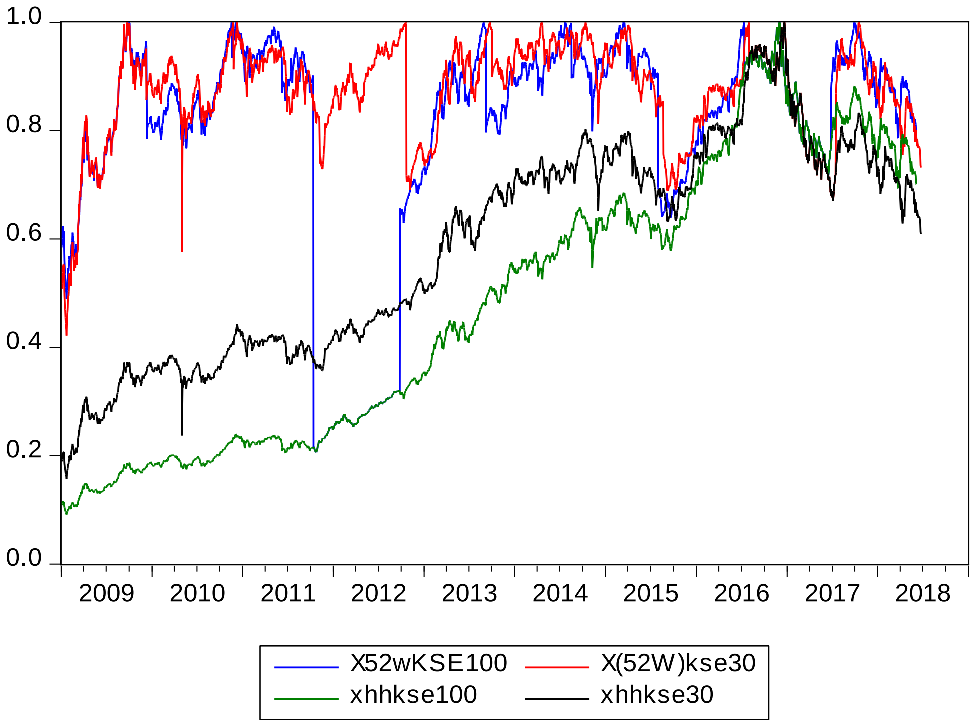


Figure 02: Comparison of XHH and X52w for KSE-30 and KSE-100



Tables 01 and 02 provide the summary figures for the corresponding factors. The average values of X52w are very near 1, whereas the average value of XHH is somewhat near.5, and most of the indicator variables are negatively biassed due to a growing tendency on both indices. Most of the variables have kurtosis values close to or greater than 3, indicating a flat-tail or leptokurtic distribution. Similarly, the Jarque-bera (JB) test was used to ensure that the variables were standard. The leptokurtic distribution of our main variables is verified by the JB findings and related p-values.

Table 01: Summary Statistics for Pakistan Stock Exchange (KSE-100)

Frequency	Variables	Mean	S.D	Skewness	Kurtosis	JB-test	P-value	Obs
Daily	Returns	0 .01	0 .01	-0 .26	6.56	1326.38	.00	2358
	Exch.Rate	0.01	0 .00	0 .03	2.68	5.00	.00	2358
	Infl.Rate	6.68	3.62	.31	1.62	206.25	.00	2358
	Intr.Rate	6.68	3.62	.31	1.62	206.25	.00	2358
	X52w-kse100	0 .80	0 .20	-1.80	5.28	1863.66	.00	2358
	XHH-kse100	.38	.26	.16	1.61	208.23	.00	2358
Weekly	Returns	.00	.01	- .26	3.35	32.82	.00	382
	Exch.Rate	.01	.00	.02	2.68	.81	.00	382
	Infl.Rate	6.68	3.62	.31	1.63	31.22	.00	382
	Intr.Rate	3.66	3.23	-1.01	3.06	83.52	.00	382
	X52w-kse100	.80	.20	-1.81	5.30	366.83	.00	382
	XHH-kse100	.38	.26	.16	1.61	31.86	.00	382
Monthly	Returns	.00	.00	- .18	6.13	36.06	.00	113
	Exch.Rate	.01	.00	- .08	2.83	.15	.03	113
	Infl.Rate	6.68	3.62	.31	1.63	8.32	.01	113
	Intr.Rate	3.65	3.23	-1.02	3.08	18.65	.00	113
	X52w-kse100	.80	.20	-1.80	5.28	86.51	.00	113
	XHH-kse100	.38	.26	.15	1.58	8.82	.01	113
Quarterly	Returns	.00	.00	.36	2.86	1.31	.38	38
	Exch.Rate	.01	.00	- .05	2.86	.05	.88	38
	Infl.Rate	6.68	3.65	.31	1.63	3.15	.21	38
	Intr.Rate	3.65	3.23	-1.01	3.02	6.30	.03	38
	X52w-kse100	.80	.20	-1.85	5.32	30.25	.00	38
	XHH-kse100	.38	.26	.13	1.58	3.33	.18	38
Annually	Returns	.00	.00	- .20	2.31	.26	.88	10
	Exch.Rate	.01	.00	- .23	2.66	.13	.83	10
	Infl.Rate	6.68	3.66	.35	1.80	.81	.66	10
	Intr.Rate	3.66	2.86	- .66	2.03	1.11	.56	10
	X52w-kse100	.81	.15	-2.25	6.68	13.31	.00	10
	XHH-kse100	.50	.26	.00	1.33	1.02	.60	10

Table 02: ***Summary Statistics for Pakistan Stock Exchange (KSE-30)***

Horizon	Variables	Mean	S.D	Skewness	Kurtosis	JB-test	P-value	Obs
Daily	Returns	.005	.02	-.66	188.51	3538.00	.00	2362
	Exch.Rate	.01	.00	-.05	2.81	1.65	.00	2362
	Infl.Rate	6.68	3.61	.31	1.63	205.16	.00	2362
	Intr.Rate	3.66	3.22	-1.02	3.08	326.50	.00	2362
	X52w-kse100	.86	.08	-1.32	5.68	1625.56	.00	2362
	XHH-kse100	.58	.20	-.11	1.80	153.01	.00	2362
Weekly	Returns	.00	.01	-.12	5.22	102.63	.00	385
	Exch.Rate	.01	.00	-.06	2.83	.38	.00	385
	Infl.Rate	6.68	3.61	.31	1.63	30.86	.00	385
	Intr.Rate	3.66	3.22	-1.02	3.08	85.62	.00	385
	X52w-kse100	.86	.08	-1.33	5.81	331.81	.00	385
	XHH-kse100	.58	.20	-.11	1.68	31.00	.00	385
Monthly	Returns	.00	.00	.66	6.33	63.30	.00	113
	Exch.Rate	.01	.00	-.08	2.83	.16	.02	113
	Infl.Rate	6.68	3.62	.31	1.63	8.32	.01	113
	Intr.Rate	3.65	3.23	-1.02	3.08	18.65	.00	113
	X52w-kse100	.86	.08	-1.50	6.08	88.32	.00	113
	XHH-kse100	.58	.20	-.12	1.68	6.31	.03	113
Quarterly	Returns	.00	.00	1.13	5.35	16.68	.00	38
	Exch.Rate	.01	.00	-.06	2.82	.03	.18	38
	Infl.Rate	6.68	3.65	.31	1.63	3.15	.21	38

	Intr.Rate	3.65	3.23	-1.01	3.02	6.30	.03	38
	X52w-kse100	.86	.08	-1.56	6.18	31.66	.00	38
	XHH-kse100	.58	.20	- .13	1.65	2.58	.28	38
Annually	Returns	.00	.00	.20	2.66	.12	.83	10
	Exch.Rate	.01	.00	- .28	2.63	.16	.82	10
	Infl.Rate	6.68	3.66	.35	1.80	.81	.66	10
	Intr.Rate	3.66	2.86	- .66	2.03	1.11	.56	10
	X52w-kse100	.86	.05	- .35	3.38	.30	.82	10
	XHH-kse100	.58	.20	- .26	1.61	.82	.63	10

The findings in tables 03 and 04 show that the two anchors (X52w and XHH) are not strongly associated with the macroeconomic variables in question. In all indexes, the inflation rate and the exchange rate have a greater association of X52w on various time horizons. On a regular horizon, X52w and XHH have a ratio of.35 and.30 for KSE-100 and KSE-30, respectively. About the fact that both anchors are quite associated (as seen in tables 04 and 05), their predictive capacity is unaffected. Tables 03 and 04 show that as the analysis progresses from regular to annual horizons, the similarities among the variables become greater. Similarly, as opposed to KSE-30, KSE-100 has higher correlation coefficients. The variables' predictive capacity is not jeopardised. We used the least square regression approach, which is a more appropriate methodology in the case of collinearity in the predictor variables (Stewart, 1987).

Table 03: ***Correlation Matrix for Pakistan Stock Exchange (KSE-100)***

Horizon	**Variables**	Returns	Exch.Rate	Infl.Rate	Intr.Rate	X52w-kse100	XHH-kse100
Daily	Returns	1	.02	.03	- .01	- .02	- .03
	Exch.Rate	.02	1.00	.28	- .31	- .16	- .38
	Infl.Rate	.03	.28	1.00	- .30	- .18	- .33
	Intr.Rate	- .01	- .31	- .30	1.00	- .18	.36
	X52w-kse100	.02	- .16	- .18	- .18	1.00	.35
	XHH-kse100	- .03	- .36	- .33	.36	.35	1.00
Weekly	Returns	1.00	.03	.06	- .03	- .06	- .08
	Exch.Rate	.03	1.00	.31	- .36	- .16	- .31
	Infl.Rate	.06	.31	1.00	- .80	- .18	- .36
	Intr.Rate	- .03	- .36	- .35	1.00	- .18	.32

	X52w-kse100	.06	- .16	- .18	- .18	1.00	.36
	xHH-kse100	- .08	- .31	- .36	.32	.36	1.00
Monthly	Returns	1.00	.15	.12	- .05	- .13	- .20
	Exch.Rate	.15	1.00	.35	- .30	- .22	- .32
	Infl.Rate	.12	.35	1.00	- .38	- .23	- .33
	Intr.Rate	- .05	- .30	- .38	1.00	- .23	.35
	X52w-kse100	.13	- .22	- .23	- .23	1.00	.30
	xHH-kse100	- .20	- .32	- .33	.35	.30	1.00
Quarterly	Returns	1.00	.21	.18	- .12	- .28	- .33
	Exch.Rate	.21	1.00	.31	- .52	- .22	- .38
	Infl.Rate	.18	.31	1.00	- .52	- .20	- .55
	Intr.Rate	- .12	- .52	- .52	1.00	- .18	.58
	X52w-kse100	.28	- .22	- .20	- .18	1.00	.36
	xHH-kse100	- .33	- .38	- .55	.58	.36	1.00
Annually	Returns	1.00	.35	.33	- .26	.33	- .63
	Exch.Rate	.35	1.00	.63	- .56	- .28	- .63
	Infl.Rate	.33	.63	1.00	- .82	- .26	- .68
	Intr.Rate	- .26	- .56	- .82	1.00	- .10	.62
	X52w-kse100	.33	- .28	- .26	- .10	1.00	.55
	xHH-kse100	- .63	- .63	- .68	.62	.55	1.00

Table 04: Correlation Matrix for *Pakistan Stock Exchange (*KSE-30

Horizon	**Variables**	Returns	Exch.Rate	Infl.Rate	Intr.Rate	X52w-kse100	xHH-kse100
Daily	Returns	1.00	.01	.02	- .01	.02	- .03
	Exch.Rate	.01	1.00	.33	- .28	- .13	- .33
	Infl.Rate	.02	.33	1.00	- .36	- .16	- .38
	Intr.Rate	- .01	- .28	- .36	1.00	- .18	.33
	X52w-kse100	.02	- .13	- .16	- .18	1.00	.30
	xHH-kse100	- .03	- .33	- .38	.33	.30	1.00
Weekly	Returns	1.00	.03	.03	- .03	.06	- .08

	Exch.Rate	.03	1.00	.38	- .35	- .26	- .31
	Infl.Rate	.03	.38	1.00	- .33	- .18	- .38
	Intr.Rate	- .03	- .35	- .33	1.00	- .22	.35
	X52w-kse100	.06	- .26	- .18	- .22	1.00	.38
	xhh-kse100	- .08	- .31	- .38	.35	.38	1.00
Monthly	Returns	1.00	.11	.08	- .06	.13	- .13
	Exch.Rate	.11	1.00	.33	- .38	- .32	- .38
	Infl.Rate	.08	.33	1.00	- .52	- .26	- .55
	Intr.Rate	- .06	- .38	- .52	1.00	- .28	.51
	X52w-kse100	.13	- .32	- .26	- .28	1.00	.36
	xhh-kse100	- .13	- .38	- .55	.51	.36	1.00
Quarterly	Returns	1.00	.13	.16	- .12	.18	- .21
	Exch.Rate	.13	1.00	.52	- .33	- .38	- .55
	Infl.Rate	.16	.52	1.00	- .58	- .26	- .60
	Intr.Rate	- .12	- .33	- .58	1.00	- .31	.55
	X52w-kse100	.18	- .38	- .26	- .31	1.00	.38
	xhh-kse100	- .21	- .55	- .60	.55	.38	1.00
Annually	Returns	1.00	.33	.26	- .26	.33	- .63
	Exch.Rate	.33	1.00	.63	- .56	- .28	- .66
	Infl.Rate	.26	.63	1.00	- .68	- .33	- .60
	Intr.Rate	- .26	- .56	- .68	1.00	- .35	.63
	X52w-kse100	.33	- .28	- .33	- .35	1.00	.55
	xhh-kse100	- .63	- .66	- .60	.63	.55	1.00

Until beginning the estimation procedure, the data's stationarity is verified using the Augmented Dickey Fuller (ADF) test. The unit root test is run first, with the intercept set to level. On both indexes, unit root was found for four variables out of a total of eight variables. So, in the second step, the unit root for all eight variables is evaluated first against the intercept and pattern, and the findings led to the dismissal of the null hypothesis that no unit root exists, indicating that the data is now stationary. The unit root test results are mentioned in table below.

Table 5: Summary of Unit Root Analysis

	KSE-100		**KSE-30**	
	Statistic	Prob.**	Statistic	Prob.**
Daily	2166.58	0	2163.88	0
	-35.2321	0	-35.2268	0
weekly	1208.31	0	1060.02	0
	-32.6503	0	-30.5528	0
monthly	356.533	0	382.323	0
	-16.8008	0	-16.6835	0
Quarterly	118.032	0	112.08	0
	-8.86838	0	-8.68081	0
Yearly	31.565	.0236	33.2003	.0118
	-1.83152	.0266	-2.3532	.0083
Method	*ADF - Fisher Chi-square/ADF-choi z-stat*			

Only for daily and weekly horizons did the findings indicate the presence of ARCH effects as shown in the table and autocorrelation in residual variance with a 1% significance stage. As a consequence, the findings help ARMA (1,0) and GARCH (1,1) in describing fluctuations in market returns (Daily and Weekly) for both the KSE-100 and KSE-30 indices, according to the Box-Jenkins protocol.

Table 6: Summary of ARCH/Heteroskedasticity test for *Pakistan Stock Exchange*

	LM statistic	Prob.**
Daily (KSE-100)	163.63	.00
Daily (KSE-30)	.26	.00
weekly (KSE-100)	116.13	.00
weekly (KSE-30)	68.63	.00
monthly (KSE-100)	1.35	.25
monthly (KSE-30)	3.13	.08
Quarterly (KSE-100)	.66	.38
Quarterly (KSE-30)	.13	.61
Yearly (KSE-100)	.00	1.00
Yearly (KSE-30)	.68	.36

Table 07: *Empirical Results: GARCH (1, 1) Model for Pakistan Stock Exchange*

		KSE-100		KSE-30	
		GARCH (1,1) Daily	GARCH (1,1) weekly	GARCH (1,1) Daily	GARCH (1,1) weekly
Mean Equation	Constant	- .00	.00	- .018	- .01
		(1.30)	(1.79)**	(3.81)*	(1.66)***
	AR(1)	- .101	- .091	- .09	- .029
		(5.01)*	(.59)	(4.68)*	(.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	.12	.11	.17	.09
		(12.57)*	(2.16)*	(8.08)*	(2.50)*
	GARCH effect	.83	.74	.77	.81
		(78.48)*	(8.97)*	(38.25)*	(14.73)*
	α+β	.96	.85	.95	.91
Regression Statistics	R^2	.41	.38	.33	.24
	Log likelihood	7929.20	1808.48	7753.1	1859.64
	SIC	-6.41	-7.21	-6.23	-7.37
	AIC	-6.44	-7.30	-6.26	-7.46
	ARCH-LM Statistics	1.69	13.67	.24	.26
	Durbin watson	1.78	1.96	2.16	1.96
	Probability	.19	.11	.62	.60

*Significance level at 1 %, **Significance level at 5 %,*** Significance level at 10 %.

Table 05 reveals that the AR at lag 1 is important for the regular horizon, implying that past returns are a good predictor of potential returns. The optimistic symbol means that previous returns have a positive effect on potential returns. The variance equation's constant is close to zero, indicating that current market volatility is dependent on the square of lagged residuals and historical return volatility. The GARCH (1,1) findings often suggest that there is constant uncertainty (as + is close to 1), resulting in greater ARCH and GARCH impacts. The Durbin-Watson statistic, on the other hand, suggests a threshold value of 1.7-2.3, indicating that there is no first order association.

Due to the power of the momentum effect in a cross section of stocks, it is also checked if past returns would effectively forecast potential returns, as suggested by (George et al., n.d.). Returns are regressed with lagged returns on various horizons (daily, weekly, yearly, quarterly, and annually) for both indices using the NLS ARMA. For both indexes, Table 06 reveals that past returns do not forecast potential returns in all horizons excluding the regular horizon.

Table 08: ***Empirical results NLS-ARMA for Pakistan Stock Exchange (Future returns on past returns)***

KE-100	KSE-30

Horizon	Daily	Weekly	Monthly	Quarterly	Yearly	Daily	Weekly	Monthly	Quarterly	Yearly
Past returns	.10*	.05	.54	- .05	.45	.09*	.03	.00	- .06	.3
	(5.19)	(-1.36)	(-.55)	(-.44)	(-1.35)	(-4.59)	(-.91)	(-.05)	(-.50)	(-.99)
R^2	.01	.003	.002	.004	.29	.009	.001	.00002	.006	.12

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 of historical high) in table 8. (indicator when historical high equals 52w high). It was discovered that the XHH can forecast future returns negatively, while the X52 can predict future returns positively. The t-statistics for past returns decreased insignificantly when Dt, It, XHH, and X52 were applied to the calculation. However, when you move from small to broad horizons, the predictive strength of these factors improves (as evident from the values of R2). If X52w increases, potential returns would increase proportionately, assuming all other variables remain stable. A rise in XHH, on the other hand, would result in a proportionate drop in potential returns. In other terms, potential returns are predicted to be lower if Dt=1 or the indexes hit their historical highs (evident from the negative sign). According to (George et al., n.d.) and (Nafila & Wibowo, 2020), this trend is attributed to investor selling pressure after the index climax. Unlike (George et al., n.d.), however, our Dt accurately forecasts potential returns for both long and short time horizons.

Table 9: ***Empirical results NLS-ARMA for Pakistan Stock Exchange (Future returns on past returns, X_{52w} ,X_{HH}, D_t, I***

Horizon	Past returns	X52w	XHH	It	Dt	R^2
Daily KSE-100	0 .10*	0.02*	0-.00*	0 .01*	0 .02*	0 .012
	(5.05)	(2.34)	(-3.45)	(1.55)	(1.18)	
Daily KSE-30	0 .08*	0 .00*	- .00*	0 .00***	0 .001	0 .012
	(4.83)	(2.40)	(-2.34)	(1.51)	(-1.15)	
Weekly KSE-100	0 .05	0 .00*	- .00*	0 .03***	0 .00**	0 .015
	(-1.21)	(3.40)	(-4.50)	(1.51)	(1.58)	
Weekly KSE-30	0 .00	0 .00*	- .00*	0 .05	0 .00	0 .013
	(-1.15)	(3.05)	(-3.85)	(-1.452)	(-1.218)	
Monthly KSE-100	0 .01	0 .00*	- .00*	0 .08**	0 .00**	0 .083
	(- .282)	(3.55)	(-4.14)	(1.54)	(1.82)	

Monthly KSE-30	-0 .00	0 .00*	- .00*	0 .05***	0 .00**	0 .054
	(- .24)	(2.80)	(- 3.82)	(1.55)	(1.54)	
QuartrlyKSE-100	-0 .13	0 .00*	- .00*	0 .00**	0 .00*	0 .154
	(- 0.84)	(-4.442)	(- 4.58)	(-1.82)	(- 2.025)	
QuartrlyKSE-30	-0 .15	0 .00*	- .00*	0 .08***	0 .00**	0 .135
	(- .53)	(4.04)	(- 4.15)*	(1.55)	(1.85)	
Yearly KSE-100	0 .58**	0 .00**	- .00*	0 .45	0 .00	0 .588
	(1.84)	(2.04)	(- 3.38)	(0- .85)	(- 1.45)	
Yearly KSE-30	0 .20	0 .00**	- .00*	0 .38	0 .00	0 .585
	(1.55)**	(1.85)	(- 3.05)	(0- .502)	(- 1.28)	

*Significance level at 1 %, **Significance level at 5 %, ***Significance level at 10 %.

Regression is a term used to describe a Table 09 reveals that potential equity returns increase while the current stock index is very close to its 52-week peak but far far from historical highs. This indicates that the market has recently received positive news to which it is responding. As a result, the economy has a better chance of moving any further. As a result of this condition, investors will profit greatly from the current momentum. As previously said, the indexes are found to be upward trending for the majority of the sampled time; thus, the predictor when P52w equals Pmax (It) will not be considered a useful metric for long-term good news. As a result of controlling the dummy variable (It), table 08 reveals that when (It=1), investors are likely to underreact to recent good news. This also means that since (P52w=Pmax), buyers are most likely to use just one anchor, the 52-week high, thus missing the historical level. In a nutshell, the findings show that investors are likely to underreact to short-term positive intermittent news (close to the 52-week high) while overreacting to long-term positive news (nearness to historical high). Investors utilise two anchors: proximity to 52-week high and proximity to historical high, to which they underreact and overreact, respectively.

Since different macroeconomic variables will forecast market returns, as indicated by the literature, the predictability of variables is not influenced by macroeconomic variables. Future market returns are regressed with X52w and XHH whereas macroeconomic variables are regulated. Interest rate, exchange rate, and inflation rate are the three main macroeconomic variables we used.

Table 09 depicts an overall regression for both indexes, with potential returns 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 findings show that the regression model's predictability capacity increases with longer time horizons. In the annual horizon, potential stock returns can be expected up to 61.5 percent. (As seen in table 09 by the R-squared value.) Similarly, as compared to macroeconomic factors, X52w and XHH have a strong predictive capacity. For data processing, we have used the KSE-30 index to ensure that the findings were reliable. The findings, along with KSE-100 values, are presented in the tables below. There is no substantial gap between the KSE-100 and KSE-30 numbers, implying that investors use 52-week and historical highs as anchors for all indices without distinction.

Table 10: ***Empirical results NLS-ARMA for Pakistan Stock Exchange (Future returns on past returns, X_{52w}, X_{HH}, D_t, I_t, 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**	.18	.012
	-3.18	-2.57	(-3.38)	-1.58	(-1.18)	-2.88	(-1.737)	- .35	
Daily KSE-30	- .08*	.01*	- .00*	0	0	-3.7E-5*	0	.53	.013
	(-3.81)	-2.18	(-2.85)	-1.58	(- .88)	(-2.2)	(-1.05)	-1.1	
Weekly KSE-100	.05	- .00*	- .00*	.03***	- .00*	.00*	2.8E-05*	- .18	.0175
	-1.17	(-2.82)	(-3.55)	-1.58	(-2.55)	-3.58	-1.15	(-.71)	
Weekly KSE-30	0	- .00*	.00*	.05	.00*	1.3E-07*	8.30E-05	- .02	.013
	- .83	(-2.18)	(-3.03)	-1.33	(-2.33)	-3.18	- .85	(-.03)	
Monthly KSE-100	.02	- .00*	- .001*	.08***	0	- .12***	- .01	.18	.081
	- .23	(-2.78)	(-3.32)	-1.53	(- .22)	(-1.55)	(- .83)	- .35	
Monthly KSE-30	0	- .00*	- .02*	.03	- .002	-8.72E-05	-3.50E-05	.271	.081
	- .05	(-2.17)	(-3.33)	-1.2	(-.132)	(-1.12)	(- .15)	- .17	
QuartrlyKSE-100	-1.73	- .00*	- .00*	.011	-.00***	0	5.32E-5**	- .1	.1838
	(- .81)	(-3.23)	(-5.75)	-1.1	(-1.57)	-1.13	-1.82	(-.18)	
Quartrly KSE-30	- .17	0	.00*	.05	0	0	0	.31	.175
	(-1.12)	- .18	-2.53	- .53	(-1.23)	- .83	- .88	- .55	
Yearly KSE-100	.7	.00***	- .00*	.55	5.80E-05	0	-8.37E+05	- .88	.338
	-1.35	-1.87	(-3.05)	-1.15	- .5	- .88	(-1.37)	(-.82)	
Yearly KSE-30	.58	.00***	.01*	.18	0	.75	0	.7	.515
	-1.33	-1.58	-3.81	-1.1	- .38	- .57	(-1.10)	- .31	

5. Conclusion and Recommendation

The current study used two anchors, 52 week high and historical high, along with lagged returns, a dummy variable representing when 52w high equals historical high, a dummy variable for historical high indicator, and some macro-economic variables, such as inflation rate, interest rate, and exchange rate, to examine the effect of anchoring on stock market at different frequencies of time. The anchoring impact in the KSE-100 and KSE-30 has been confirmed using two anchors: proximity to 52-week high and proximity to historical high. The index is under reaction if it is close to its 52-week peak, whereas it is above reaction if it is close to its historical high. As a result, investors appear to underreact to short-term positive news (closeness to 52-week high), thus overreacting to long-term positive news (nearness to historical high). The time series study revealed that proximity to a historical high (anchor) predicts future returns negatively, whereas proximity to a 52-week high predicts future returns positively. When using the 52-week high anchor, the Pakistani stock market underreacts to new facts, whereas when using the historical high anchor, the Pakistani stock market overreacts. In comparison to macroeconomic indicators, these two anchors have a higher predictability. The total model, which includes macroeconomic factors, has about 62 percent accuracy in predicting projected returns. Similarly, the findings reveal that when the study's individual variables are moved from every day to annual horizons, their predictive capacity decreases. In addition, the findings indicate that after integrating the risk factor into the model through GARCH (1,1), the model's prediction capacity drops to.41 and.33 on regular horizons. It was also discovered that although there is no statistically meaningful gap between the KSE-100 and KSE-30 performance, the KSE-100 has slightly better results than the KSE-30, meaning that it is more common with investors. For greater robustness, future studies would likely require broader annual, biannual, and quarterly samples. Cross-sectional analyses are therefore recommended to test the findings of this research. This research aims to examine and assess the stock market indices KSE-100 and KSE-30 in terms of firm-specific factors as well as macro-economic factors that may be important for investment purposes.

We suggest two predictors for aggregate market excess returns in this article, inspired by minimal investor attention and anchoring. We prove that proximity to the 52-week high positively predicts future returns, whereas proximity to the historical high negatively predicts future market returns using time-series regression analysis. In general, these two variables have a higher predictive capacity than conventional macroeconomic variables, and they collect knowledge regarding possible aggregate stock returns that other macroeconomic variables do not. Our findings show that behavioral preferences may influence not only individual stock values, but also the overall economy. Our reports further emphasize the significance of taking into account both the 52-week and historical high anchors. On the cross-sectional line, we demonstrate that the momentum impact is three to six times higher for stocks where overreaction was less possible in the past. In a clear one-way sorting dependent on proximity to the 52-week peak, though, the momentum impact is no longer important for stocks where underreaction was less possible. The momentum impact, however, resurfaces dramatically after controlling for the second anchor, namely the historical peak. Our results show that models in which agents' focus is constrained and agents' valuations are based on anchors/reference points (e.g., Peng and Xiong, 2006; Grinblatt and Han, 2005) are likely to be effective in describing market movements.

The results of this report have implications for investors and policymakers. Since volatility is priced, including the sentiment-driven portion, investors may use a sentiment element when calculating overall risk in their strategies. With the large positive risk premium, investors must keep well-diversified portfolios in order to be compensated for the risk component according to CAPM. Volatility persistence can have a detrimental effect on market functioning and asset prices for policymakers. Changes in investor sentiment can amplify this impact, resulting in capital outflows and financial uncertainty as investors seek higher-quality markets. As a result, policymakers must consider all proven underlying factors of uncertainty and market sentiment. If uncertainty increases, policymakers must pay greater heed to negative surprises and shifts in market sentiment due to the major leverage implications. Understanding the importance of cognition and knowledge processing in influencing investor sentiment encourages asset market regulators to be more constructive. They will aid investors in making better choices by enhancing impartial knowledge gathering by strengthening investor knowledge and information disclosure laws. The importance of valuing market sentiment cannot be overlooked.

Overall, these robustness findings for a variety of requirements provide industry practitioners with valuable insights into the price creation phase. They prove that, unlike in the traditional paradigm of asset pricing theory, sentiment-driven buyers are not unreasonable. Rather, they understand when to trade against the herd and earn profits, and they may also act as a liquidity provider by purchasing unnecessarily sold stock during times of deteriorating sentiment and bear market conditions. The trading policies of sentiment-driven investors are influenced by a broad variety of factors in financial markets. In upcoming behavioural research, it's time to rethink this pattern. The application of the sentiment-driven trading theory can yield more precise results. Our research has several drawbacks, which we agree. We had some difficulties obtaining information. On the one side, due to calculation difficulties and data, there is a lack of validity for other consequences. The sample size, on the other hand, and the lack of knowledge about specific times of the exercise have reduced the precision of our estimates. Future studies in this field should expand on the findings and draw guidance from current events and news to reduce these limitations and mistakes. Investors' propensity to focus their trade terms in a particular range of prices is referred to as price clustering. It has been well documented, and many plausible theories that are compatible with the facts have been suggested. A new hypothesis called "reverse clustering" tries to understand clustering as investors' desire to exchange around focal numbers rather than on focal numbers (see Bhattacharya et al., 2012). We link this principle to Tversky and Kahneman's (1974) "anchoring-and-adjustment" heuristic bias, and extend it to the context of the London Stock Exchange.

We believe that the tacit interaction between the upstairs and downstairs markets changes the price process in the upstairs sector. As a result, the minimum tick size rules that exist in the order-book sector but are not needed while trading at the upstairs market have a significant impact on the probability distribution of prices quoted/traded at the upstairs market. The “price anchoring effect” is how we refer to this theory. Liquidity suppliers consistently purchase below the tacit minimum price increment and consistently offer over it, according to our findings. Stock-price momentum and times of elevated trading intensity are closely linked to the likelihood of purchasing below the tick or selling above it. As a result, we affirm the hypothesis that market players will use the implied minimum tick as a threshold price in the upstairs market due to the institutional environment and the lack of minimum tick size regulations.

We often look at the economic effect of concentrated transactions at the upstairs market, utilising transaction cost indicators to determine the ex-ante cost of trading and price impact measures to determine the ex-post benefit consequences of trades. We propose that buyers in the upstairs business time their trades depending on two criteria: the knowledge content of trades and the economic rents that can be derived. This theory is known as the "adjustment impact." We found that market participants who sell below the tick and purchase above it at the upstairs market have lower execution costs. Market makers' decisions are partially clarified by disparities in educated trading, but they are mostly linked to the notional price hurdles and resistance thresholds introduced by the order book's minimum tick scale.

Overall, our findings suggest that "cluster undercutting" (Bhattacharya et al., 2012) has significant repercussions for the LSE's upstairs business architecture. Previous research has concentrated on market participants' proclivity to limit their trade terms to a single collection of numbers. This research looks at the pricing activities of liquidity providers, and how market makers use the institutional environment to get a leg up on the competition. Market members at the LSE may be interested in the findings.

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