Examining the Month of the Year Effect in Value Growth Portfolios: Empirical Evidence from the Pakistan Stock Exchange (PSX)

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Farah Naz[1], Veera Salman[1], Kanwal Zahra[2]

Abstract

This research analyzed the calendar anomalies context in the value premium portfolios to identify the month of the year (MOY) effect in the Pakistan stock market. To evaluate the MOY effect in 6 value premium portfolios, 120 listed firms have been considered. The data of these firms have been taken from the financial statements of the annual reports of the firms for the period 2009-2019. The sample was divided into two sections, that are 2009-2014 and 2015-2019, to identify the proper trends in the closing prices of the stocks using OLS regression, GARCH, TGARCH, and EGARCH models. These models are used due to the heteroskedastic nature of the data. The results indicate negative January, June, and August and positive March, July, November, and December for predictability. The results of this research are useful to the local and foreign investors in making proper investments. Moreover, the market analysts can enhance their work for the proper analysis of the portfolios when calendar anomalies exist in the markets.

Keywords: Month of the Year (MOY) Effect, value premium portfolios, Pakistan Stock Exchange (PSX), January effect (JE), TGARCH model

INTRODUCTION

Capital markets provide the dynamics for investors to make investments in diversified portfolios (Dai et al., 2022). However, these capital markets may be affected through the seasonal effects contained in the financial markets results in the abnormality of the returns thus affects the investor in making heavy investments (Khan et al., 2017). This abnormality in the markets, mainly known as calendar anomalies, cannot be illuminated through the traditional asset pricing models due to the existence of several calendar anomaly effects such as DOW, MOY, January, TOM effects (Calluzzo et al., 2019). The occurrence of calendar anomalies weakens the condition of capital markets because of the predictable calendar effect, the prices may not be random thus increases the abnormal profits for the investors (Wuthisatian, 2021). In order to prevent such abnormal profits, the investor needs to make strategies to control their loss and help in removing the factors impact the market performance and affects the market analysts analysis over the market conditions (Ahmad et al., 2022). The market performance affected due to the existence of factors such as the behavioral biases, imperfect competition, calendar effects which are referred as the market anomaly (Goodell et al., 2022). In this regards, the Efficient Market Hypothesis (EMH) theory provides the broader perspective of the markets that investors are unable to make abnormal profits when the equal information given to investors and market analysts (Kasidi & Banafa, 2022). However, the existence of calendar anomalies violates this theory because these anomalies generate because of the inefficiency of the markets that results in the appearance of calendar effect in the capital markets (Obalade et al., 2022). Moreover, the irregularities in the market occurs due to the calendar anomalies which affect the economic activities as well the stock markets (Rossi & Gunardi, 2018).

The calendar anomalies are associated with the small stocks that have the small capitalization in comparison to the large-capitalization stocks because of the effective fundamental analysis of the large-cap stocks easily identifies the abnormalities in the prices of stocks (Samaniego et al., 2022). Despite the companies proper check over the fundamental analysis, the existence of calendar anomalies is still unknown, which violates the market efficiency (Zhuravleva, 2022). The value premium portfolios testing enables the calendar anomalies, which helps in analyzing the variation of firm size, which is treated as the risk factor for companies (Fays et al., 2022). Thus, the small and large cap stocks were examined from different indicators to detect the calendar anomalies in the portfolios, which may be dissimilar on the first and last five trading days for January and non-January months in the calendar year (Holopainen, 2021).

This research is conducted to fill the gap in the previous literature concerning the value-premium portfolios. Previous studies in Pakistan stock market exhibits Gregorian and Islamic calendar effect. The study contributes in identifying the growth of the calendar anomalies over time across weighted returns based on size percentiles. Further, an analysis of the effect in two sub periods suggests that the magnitude of the effect has shown very diverse behavior over time. Finally, the divergence in the extent of the effect is inversely associated to size, which is the validation of seasonality in return patterns, confirming the role of value premium indicators in weighted returns. It is essential to highlight how the present state of market efficiency; in individual stocks and value growth portfolios, affects trading patterns. This study aims to examine the effect of calendar anomalies in different portfolios, form based on value and growth indicators, i.e., book to market,

[1] Department of Accounting and Finance, Kinnaird College for Women, Lahore. Corresponding Email: farah.naz@kinnaird.edu.pk
[2] Faculty of Management Sciences, University of Central Punjab

earning to price, dividend to price, cash flow to price, gross profit to total assets, sales to price ratio.

LITERATURE REVIEW

Distinctive features categories seasonal effects based on industry and size (Fays et al., 2022). It appears neither aftermath of stock characteristics or mere proxies for uncertainty, nor does it attribute to inherent contenders for yearly seasonal news, for example, earnings releases, dividends, or fiscal year-end (Sarria-Allende, 2022). Even though seasonal stock strategies make a profit for almost every month annually, recording these returns mostly calls for a 100% turnover per month across spells of presumed illiquidity (Forsberg & Sundqvist, 2022). Many studies have recognized the existence of several calendar anomalies which intrude upon the principles of renowned asset-pricing theories. Like, (Fields, 1931) was the first to find holiday effect later work done by (Ariel, 1990; Fields, 1934; Keef & Roush*, 2005; Marrett & Worthington, 2009; Vergin & McGinnis, 1999), identified monthly or January effect.

Wachtel (1942) was the first who analyses US stocks and detect abnormal stock returns in January; afterwards (Rozeff & Kinney Jr, 1976) identified this effect based on the observation of equally-weighted indices, which resulted in higher January returns than in non-January months. Many researchers claim that a stock's performance at the start of the year, especially in the first month, often forecasts the whole year's performance. As a result, several investors choose to sell their invested stocks before the year-end to assert capital loss instead of tax purposes. This fact has been recognized as a cause of the existence of the January effect (Fountas & Segredakis, 2002; Grinblatt & Moskowitz, 2004; Reinganum, 1983).

Madureira and Leal (2001) selected the most liquids IBOVESPA stocks for individual stock analysis from the Brazilian equity market to investigate the twist-of-the-Monday effect. The index results recommended the existence of the tested seasonality. Nevertheless, analysis of multiple sub periods showed that anomalies appeared in the prior period and vanished later. Similarly, the analysis of the individual stocks specified that out of the 44 securities studied, only 3 pronounced the presence of the anomaly and obviously, this smaller proportion of individual stocks was not responsible for the twist-of-the-Monday effect in the indexes.

Athanassakos (2002) analyzed the data of low-risk Canadian firms in safe industries. The findings of the study supported strong evidence of seasonality in highly scrutinized firms. After controlling risk variations amongst the stocks, seasonality persists. Results exhibited that the January effect was not established in asset classes and industry sectors, as mentioned in earlier literature. When the JE was examined, sampled firms showed a weak January effect in the last quarter, which experienced a strong January effect earlier. Thus, it supported the gamesmanship hypothesis but not the tax-loss selling hypothesis.

Haug and Hirschey (2006) study reaffirmed the presence of the JE in the stock market. The effect is most heavily evident in the small-cap companies. The study proved that despite introducing the Tax Reform Act of 1986, the JE persists in small-cap companies largely. Therefore, tax loss cannot be attributed to this JE. The study indicated that behavioral factors should be considered to determine the actual causes behind the JE, specifically in small-cap companies.

Fink et al. (2008) conducted a significant study on the January effect in the US market by taking a vast sample of data from the NYSE (The New York Stock Exchange), NASDAQ (National Association of Securities Dealers Automated Quotations) and American Stock Exchange (AMEX). The stock returns of all domestic firms were taken into consideration. Furthermore, it emphasized a unique perspective of the January effect, i.e. it tried to find out whether the January effect is related to the age of the company or not. At the same time, most of the studies concluded that the January effect is most prevalent in small-cap companies. Empirical findings determined that the JE is most evident in younger firms compared to the older ones. The study established that younger companies tend to show a robust and sustainable trend of January effect as compared to the old companies. The results remained robust even when the size and systematic factors were controlled. The reason for this trend is yet to be investigated.

Bohl and Salm (2010) explored stock market seasonality, tested January stock market return's predictive power for the non-January months across 19 countries, and rejected the January effect as an international phenomenon because only 2 out of 19 countries' displayed a robust other January Effect. Depenchuk et al. (2010) scrutinized the Ukrainian stock and bond market returns and found no indication of a weekend or January effect in the Ukrainian bond and equity markets.

Similarly, P. M. Silva (2010) scrutinized calendar anomalies in the Portuguese equity market without indicating the Weekday or the January effect. Mehdian and Perry (2002) considered three market indices (i.e., NYSE Composite, Dow Jones Composite, and the S&P500) to explore the January effect in US stock markets, taking data from 1964 to 1998 and found unbalanced monthly seasonal effects in the equity market. Easterday (2015) followed the logical basis of (Feltham & Ohlson, 1995) and (Ohlson, 1995), comprising the description of earnings as a function of present and future accounting earnings with a segregation of the companies exhibiting January effect in return premiums and those with no emphasis on this anomalous feature. For this purpose (Fama & MacBeth, 1973), the methodology was applied and concluded an unexpected and noteworthy negative connection between first-quarter earnings and January returns.

Raj and Thurston (1994) employed New Zealand stock data to validate the tax-loss selling hypothesis with the basis of investigation that there would be no January effect because financial year-end in March. Thus, there should be an abnormal return in April instead of January if the tax-loss selling hypothesis is true. Similarly, Ahsan and Sarkar (2013) investigated the tax-loss selling hypothesis in Bangladesh, where tax ends on June 30th. To explain the "June effect", which ultimately leads to detecting any tax-driven sales in the Dhaka stock exchange headed for the end of June and if that tends to a substantial price upsurge in July.

Still, the tax-loss selling hypothesis cannot describe the January effect anomaly in several situations because Gultekin and Gultekin (1983) have not confirmed the tax-loss selling hypothesis. The

results showed July seasonality in Australia and April seasonality in the UK. Whereas, in most major industrial countries, the January effect exists. Brown et al. (1983) marked seasonality in July and January, even though the tax year beginning in Australia is in July. Keong et al. (2010) determined a optimistic December effect in most Asian stock markets except for Hong Kong, Japan, Singapore, China, and India, which showed the best returns in February, July and August. In comparison, Indonesia is the only country that displays a negative August effect.

The bond market was also being examined to find out the existence of the January effect. Heston and Sadka (2008) demonstrated that a recurring trend in the cross-section of average stock returns indicates a positive correlation: stocks with above-average returns in a specific month are likely to reflect above than average returns at year-long stretches for up to two decades. This correlation was taken as a symbol of seasonal discrepancy in stock returns. The (Conrad & Kaul, 1998; Jegadeesh & Titman, 2002) approach was used to approximate the calendar anomalies in the cross-section of stock returns. The effect was considerably concrete to be measurable via return data alone. While previous findings do not affect returns over entire months, calculating the cross-section of expected stock returns past seasonal months shows signs of a notable economic effect. The findings of this study are solidly built, constituting a range of seasonal plans while simultaneously working out the decile-spread performance that surpasses 50 basis points per month and carries on for almost two decades. This outcome gives the impression of being a substantial and durable seasonal effect, with the results exhibiting complete harmony with individual stocks that continuously draw disparate returns across calendar months. Apart from returns, trading volume and intra-month volatility show seasonal variation but do not include or absorb the seasonal effect of historical return.

Halari (2014) presented a comprehensive examination of the influence of the Islamic and the Gregorian calendar in describing the variability of stock returns in the Karachi Stock Exchange (KSE). The study also endeavored to address whether any discrepancy in stock returns was associated with the firm size, the sector location, or a specific year during the sample period. The research outcomes were based on 106 companies listed on the KSE employing stock prices data daily. Investment based on size or industry specification was least impactful compared to funds apportionment of firms in varying calendar months. The quantitative analysis demonstrated that investors might take advantage by regulating their portfolio strategy following the monthly Gregorian calendar trends contrary to the Islamic calendar months. The later was least persuasive in describing the KSE returns. Also, the results emphasized a significant variation in stock returns across years, which is an indicator of the impulsive type of the stock market.

Ching et al. (2016) applied the methodology suggested by Lluís Carrion-i-Silvestre et al. (2005). They proposed robust panel stationarity tests that permitted the existence of multiple essential breaks and utilized the cross-sectional disparity of the bank prices series. Findings of the study suggested that bank stocks were weak-form efficient because all series exhibited a random walk process. Also, the banking stocks series displayed structural breaks and cross-sectional dependence (CSD), and it was recommended that overlooking it could lead to biased approximations and spurious inference. The study results have prominent inferences about stock price forecasting, estimation methods, capital allocation, and the effect of price shocks on securities prices.

Following (Munir & Sook Ching, 2018; Narayan et al., 2015) further investigated finance stocks in the Malaysian equity market. A detailed firm-level empirical evidence of calendar anomalies was provided, including DOW and the MOY effect. Twenty-one finance stocks showed predictable patterns in daily seasonality, whereas monthly seasonality was observed in 19 finance stocks. The observed outcomes of the TGARCH (threshold GARCH) model recommended asymmetric news effect and the significant daily and monthly seasonality. It showed the evidence of a weak form of inefficiency, inferring those investors may be able to gain the detected abnormal returns by employing timing strategies.

METHODOLOGY

This research investigated the MOY effect in the 6 portfolios returns for the listed companies on Pakistan Stock Exchange (PSX) for the period of 2009-2019 where the sample was divided in two periods that is 2009-2014 and 2015-2019. The models that are used in this research are OLS regression, GARCH, TGARCH and EGARCH due to the presence of heteroscedasticity in the data. The data to evaluate the portfolios have been taken from the financial statements via annual reports for the non-financial firms. The firms that thinly traded have been excluded from the sample as the reliability of the portfolios for the thinly traded firms may be affected (Boudry et al., 2019). Moreover, the firms that delisted during the sample period have also been excluded in order to get the accurate results (Gaunt, 2004). Only non-financial firms have been taken into consideration due the different debt and equity structure of financial firms which leads to only include one of them (Yen et al., 2004).

The 120 non-financial firms by largest market capitalization are graded at the end of the period based on their book-to-market ratio and assigned to one of five book-to-market portfolios. Each portfolio comprises an equivalent number of stocks. The first (growth) portfolio holds 20% of stocks and contains the lowest book-to-market ratio. The second group includes of next 20% of stocks. The method lasts through the last (value) portfolio covering the highest book-to-market ratio with the previous 20% of the stocks. These cutoff points are, at that point, stored and used to allocate all other listed firms into five book-to-market portfolios.

OLS regression

The OLS regression have been performed initially to check the regressed terms. Therefore, the mean daily returns obtained from the descriptive statistics. Then, OLS regression will examine the existence of MOY effect in the capital market in order to check the efficiency of Pakistani capital market. The regression to identify monthly effects will include 12 dummy variables as independent variables, the lagged return on the index will be added again, so the model becomes:

$$R_t = \sum_{i=1}^{12} \beta_1 D_{it} + \beta_{13} R_{t-1} + \varepsilon_t$$

R_t is the index return in period (day) t, ε_t is the error term, D_{it} is the dummy variable for January (D_{it} = 1 if the observation t belongs to January and 0 otherwise), D_{2t} for February, and so on (Hussain et al., 2011; P. Silva, 2010).

GARCH Model

The features of time varying volatility and clustering of volatility in return series of any stock cannot be captured by the OLS regression model, leaving it to an insufficient model. Thus, we will additionally utilize the GARCH models to consider this perspective(Parikh, 2009). The GARCH model introduced by Engle (1982) and its extension made by (Bollerslev, 1986) in order to analyze the historical data that may affect future data that termed as autoregressive. The conditional variance determines through squared errors by its own lagged values. The Unit root test helps in analysis of GARCH and its family models using empirical and theoretical literature. The MOY effect can be examined from the GARCH model through equation:

$$\sigma_t^2 = w + \sum_i^q \alpha_i \, \varepsilon_{t-i}^2 \sum_j^p \beta_j \, \sigma_{t-i}^2 + \gamma h_{t-j}^2$$

Diagnostic tests by Engle and Ng (1993) are conducted to test the asymmetric response in volatility to negative shocks. Basically, three tests are premeditated to define if a particular dataset require an asymmetric model to the residuals of a standard GARCH model with a constant in the mean equation. These tests scrutinize the predictive power of variables detected earlier which are not part of a GARCH model. If the squared normalized residual can predict these variables, then the variance model is misspecified.

TGARCH model

The threshold-GARCH model helps in identifying the good and bad news effect which are mainly the market shocks or volatility that impacts the analysis of market analysts. The TGARCH model comes up with the addition of asymmetric threshold effect from the standard GARCH model.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \, \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \, \varepsilon_{t-1}^2 I_{t-1}$$

The TGARCH model condition undertakes unanticipated changes in the market returns or ε_t will have diverse effect on the unpredictability of stock return$\boldsymbol{\sigma_t^2}$. $\boldsymbol{\gamma}$ indicates the asymmetric effects in the return's volatility. Good news will central to higher return, hence it is associated with higher variance through.

EGARCH model

The exponential-GARCH model is further an extension of GARCH model that captures the external unanticipated shocks upon the predicted volatilities in the market and thus helps in identifying the conditional variance with a broader analysis.

$$\log\sigma_t^2 = \acute{\eta}_0 + \sum_{i=1}^p \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \sum_{j=1}^q \beta_j \log\sigma_{t-j}^2 +$$

$$\partial_{MON} D_{1t} + \partial_{TUE} D_{2t} + \partial_{THU} D_{3t} + \partial_{FRI} D_{4t}$$

$$\ln\sigma_t^2 = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln\sigma_{t-1}^2$$

This model also analyzes the asymmetric effect and in the equations of EGARCH model, the γ represents the asymmetric shocks of volatility as represents in the TGARCH model.

RESULTS AND DISCUSSION

Descriptive Analysis Monthly Portfolio Weighted Returns

The growth firms displayed positive monthly returns in January, while the value firms have positive but very low returns in the first sample period. Overall return patterns are similar in both sample periods with negative January, June and August and positive March, July, Nov and Dec.

Figure 1 (**Annexure 1)** shows that the book-to-market portfolio weighted returns outperform in November, but negative return trends can be seen for January, June, and August in both sample periods.

Figure 2 (**Annexture 1**), Div./ Price portfolio has negative returns in first sample period in January, but the opposite trend is found in the second sample period; also, a positive trend is found in first sample period while a downturn is observed in the second sample period which may be due to the global financial conditions in that time. Although August showed negative returns in both periods, Feb has the highest returns during 2015-2019.

Figure 3 (**Annexture 1)** showed that in earning to price monthly weighted returns, value firm's percentage of returns is dissenting in January, but they outperform in March for the first sample period.

The GP/Total Assets returns presented in figure 4 showed that average returns of value firms in the second subsample proved the fact claimed by (Novy-Marx, 2013) that value firms makes expressively higher returns than growth firms, regardless of having expressively higher valuation ratios. Steadily, high average returns are observed in Feb along with negative returns in August.

Price to cashflow monthly weighted returns in figure 5, followed positive returns though lower returns except for negative August in first sample period which is altered in the second subsample with negative March, May, June, July and August. The most exciting finding is the rise of returns in February with maximum returns by growth firms.

In Sales to price-weighted monthly returns presented in figure 6, growth firms displayed negative whereas value firms positive but low returns in first sample period with July and November positive thereby significant share of growth firms. While, in the second subsample, growth firms have shown higher returns than value firms in January and April, with negative returns in February and March. At the same time, the value firms return transcend in February. As suggested by (Vruwink et al., 2007), over time, a company's more considerable intangible assets, particularly intellectual capital, should be contemplated in accelerated sales growth. Accordingly, the actual market value of the firm can be best described by the firms' sales; thus, the P/S ratio is theoretically leading to the P/B ratio.

Month of the Year Effect in Portfolio Weighted Returns

Table 1: Summary of Results of MOY effect (Regression, GARCH, TGARCH, and EGARCH)

	Sample period (2009-2014)			Sample period (2015-2019)		
Value Weighted Returns						
KSE-100 Index	September (+)	-	-	August (-)	-	-
KSE-30 Index	-	-	-	-	-	-
Equal Weighted Returns (On the basis)						
Book to Market						
Small	January (+)	July (+)	August (-)	January (-)	August (-)	November (-)
2	January (-)	July (+)	August (-)	January (+)	August (-)	November (+)
3	January (-)	August (-)	November (+)	January (+)	August (-)	November (+)

4	June (-)	August (-)	September (+)	January (+)	February (-)	August (-)
Big	January (+)	July (+)	August (-)	February (-)	July (-)	August (-)
Earning to Price						
Small	September (+)	-	-	August (-)	-	-
2	September (+)	-	-	February (-)	August (-)	-
3	August (-)	-	-	June (-)	August (-)	-
4	August (-)	September (+)	-	January (+)	August (-)	-
Big	March (+)	-	-	February (-)	August (-)	September (+)
Dividend to Price						
Small	January (-)	February (-)	June (-)	January (+)	September (-)	November (+)
2	January (-)	February (-)	September (+)	January (+)	September (+)	November (+)
3	January (-)	October (-)	September (+)	January (+)	February (-)	September (+)
4	February (-)	October (-)	September (+)	January (+)	August (-)	September (+)
Big	January (-)	-	-	February (-)	August (-)	September (+)
Cashflow to Price						
Small	August (-)		September (+)		August (-)	September (+)
2	August (-)		September (+)	February (-)	June (-)	September (+)
3	February (-)	August (-)	September (+)		August (-)	September (+)
4	June (-)	August (-)	September (+)	February (+)	May (-)	September (+)
Big	-	-	-	February (+)	June (-)	September (+)
GP/Totall Assets						
Small	February (-)	August (-)	September (+)	February (-)	August (-)	September (+)
2	February (-)	August (-)	September (+)	February (-)	August (-)	September (+)
3	February (-)	August (-)	September (+)	February (-)	August (-)	September (+)
4	June (-)	August (-)	September (+)	February (-)	June (-)	August (-)
Big	-	-	-	February (-)	July (-)	August (-)
Sales to Price						
Small	August (-)	-	-	February (-)	July (-)	August (-)
2	August (-)	October (-)	November (+)	June (-)	-	August (-)
3	August (-)	October (-)	September (-)	August (-)	-	-
4	February (-)	August (-)	September (+)	January (+)	-	August (-)
Big	-	-	-	February (+)	-	August (-)

Seasonality is evident in expected returns and volatility (based on significant p-values of variance equation of all GARCH models employed), as concluded by the MOY effect results presented in the above table. September is marked off as the month with the most seasonality in volatility and the returns patterns than all other trading MOY, which is consistent with the findings of (Akash et al., 2020).

Table 1 showed that in the first sample period, growth and value firms in Book/Market weighted returns displayed positive January keeping higher and significant coefficient which turned into an inverse pattern in the second subsample. Earning to price-weighted returns in the first sample period showed positive September returns and negative August; this is a common returns pattern found in all indicators returns.

Approximately 77% of the results showed 5% significance for these two months. Thus, big firms in all indicators provided market efficiency with no or very less (in few cases) significant signs of seasonality in the first sample period. At the same time, small firms have shown January and February seasonality in most of the indicators results simultaneously.

CONCLUSION

The study examines the calendar anomalies' existence and its effect on the historical prices pattern using the value-premium portfolios analysis using 6 portfolios for the period 2009-2019. The sample divided over the two periods that is 2009-2014 and 2015-2019 in order to analyze the patterns of prices over two sample periods. The results show similar return patterns in both sample periods with negative January, June and August and positive March, July, Nov and Dec. The study provides the supporting evidence for the contradictions with EMH theory by observing the broader view after the financial crisis. This research depicts that the stock market efficiency is linked to the scarce capital resources allocation thus effective informational efficiency is required by the markets to achieve the efficient pricing mechanism in order us resources productively.

This research would be helpful for the local and foreign investors as well as the traders who articulates the trading approaches. The study provides the view about the predictability of stock behaviors when analysts are able to understand anomalies properly. The detailed analysis of the calendar anomalies over the value premium portfolios helps the stakeholders around the world in planning their investments. Moreover, this research extends the empirical literature of the calendar anomalies in Pakistan in term of value premium portfolios.

The limitation of this study include for the validity of results, no supportive evidence is found to validate the results like the September effect, as there is no affirmative disposition available in this regard. Thus, further investigation is required to corroborate these findings. During the COVID-19 period, four new indices are launched by the Pakistan stock market; MZNPI (Meezan Pakistan Index), NITPG (NIT Pakistan Gateway Index), NBPPGI (NBP Pakistan Growth Index) and UPP9 (UBL Pakistan Enterprise Index). Thus, these can also be utilized to recognize abnormal returns and seasonality from the perspective of the pandemic in the Pakistan stock market. Further researches can be examined again by including intraday data of individual stocks to addition the indices and industry returns analysis to test the calendar anomalies.

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Annexture 1

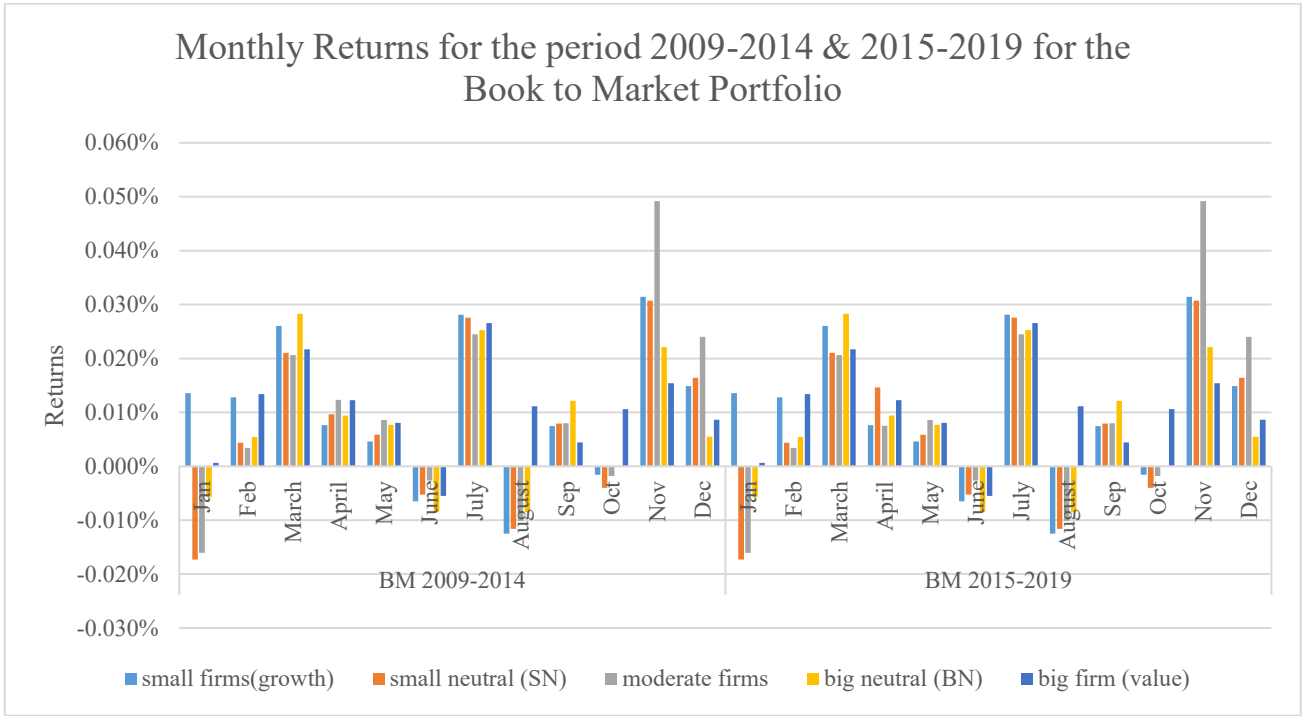

Figure 1: Book to Market Portfolio

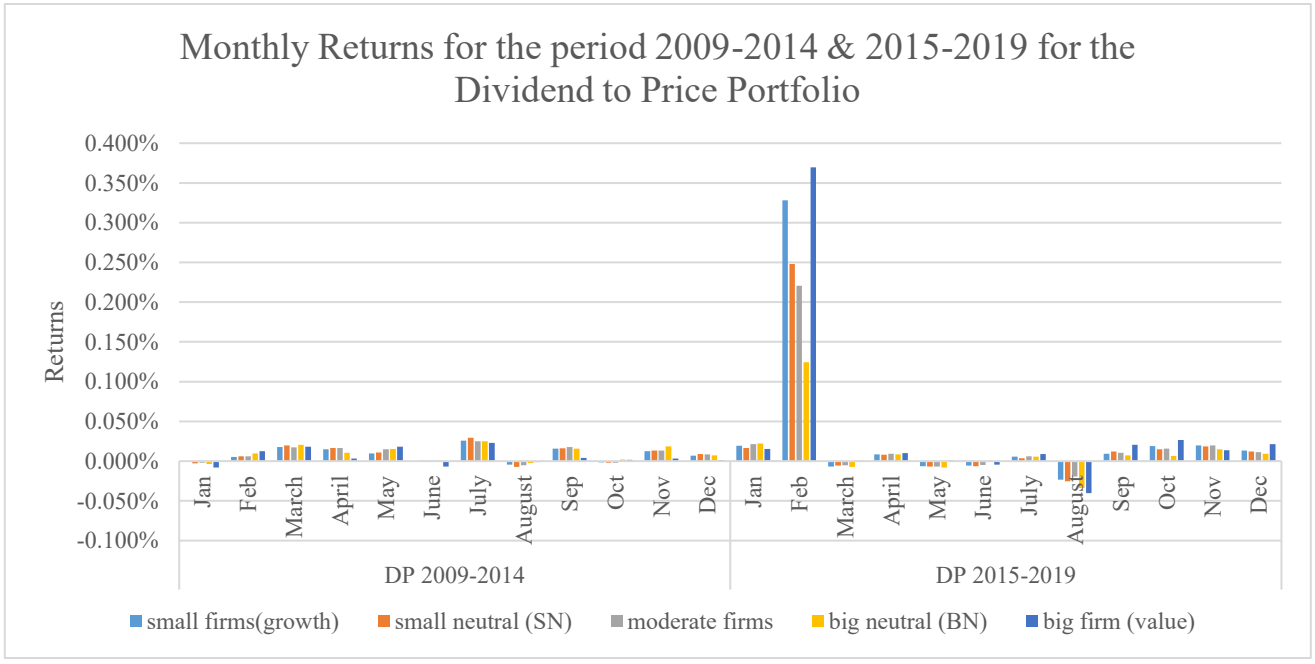

Figure 2: Dividend to Price Portfolio

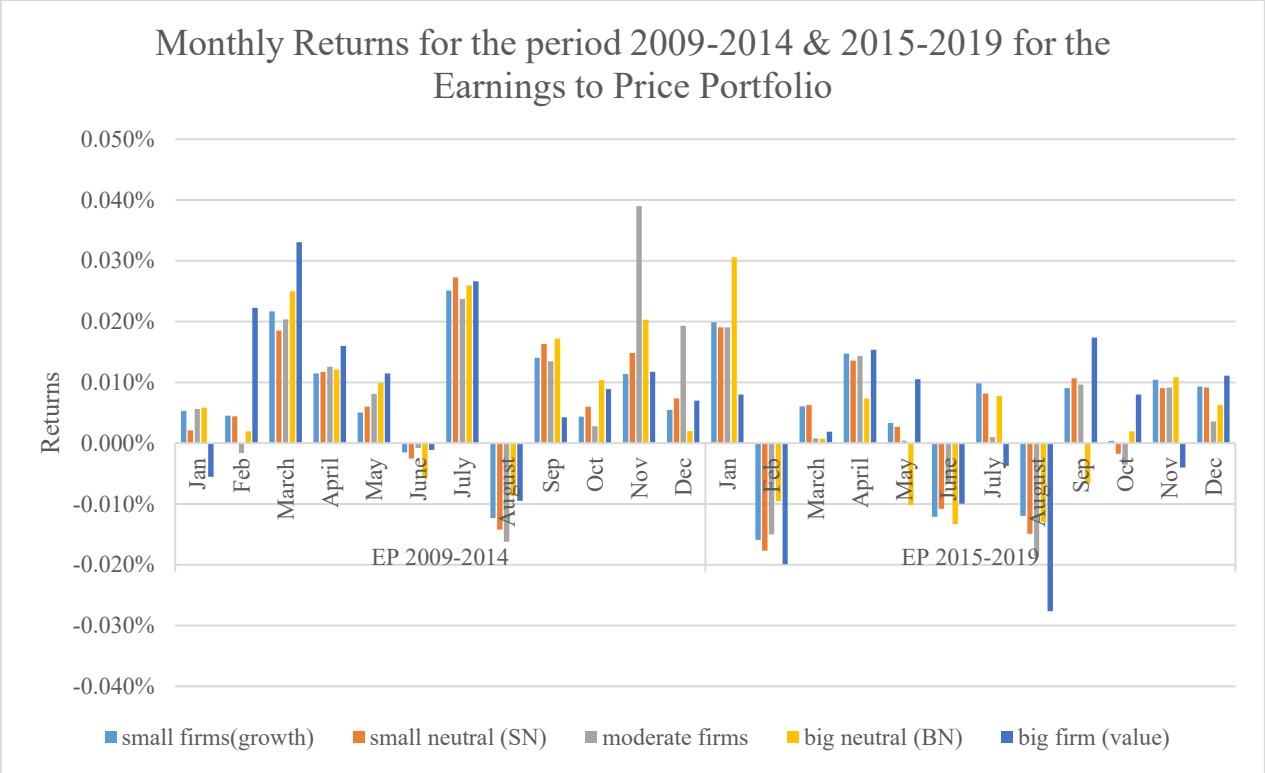

Figure 3: Earnings to Price Portfolio

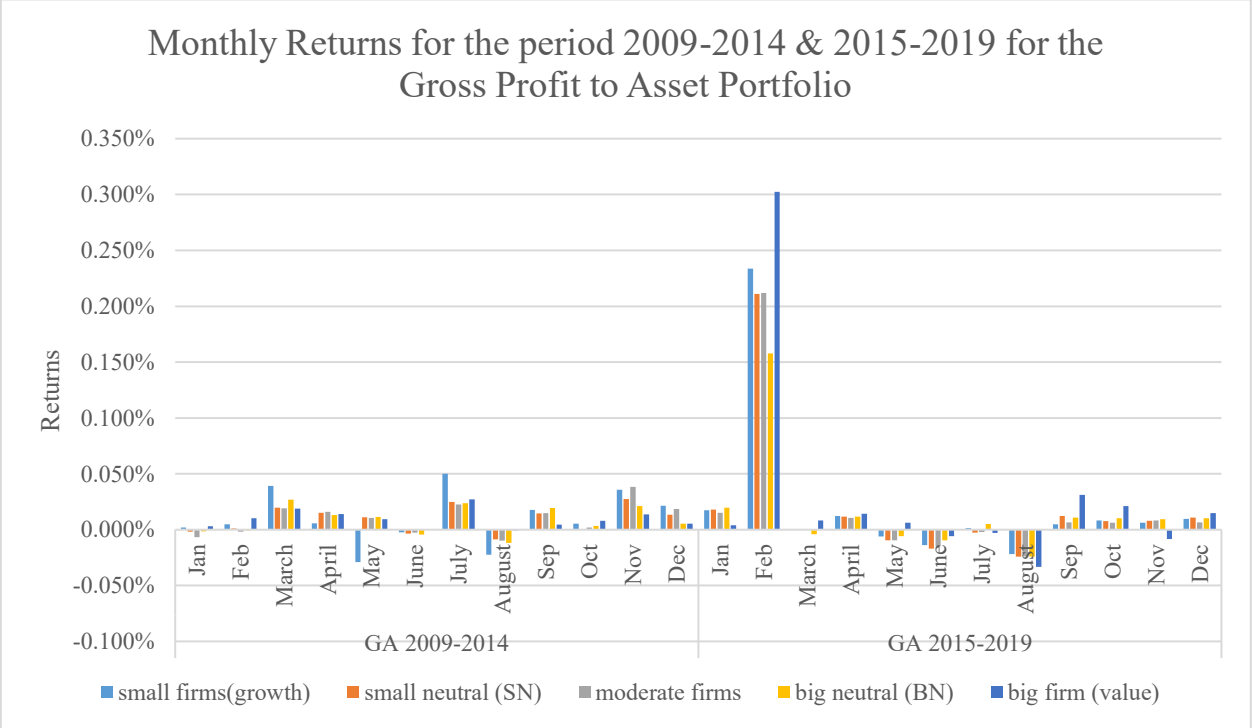

Figure 4: Gross Profit to Asset Portfolio

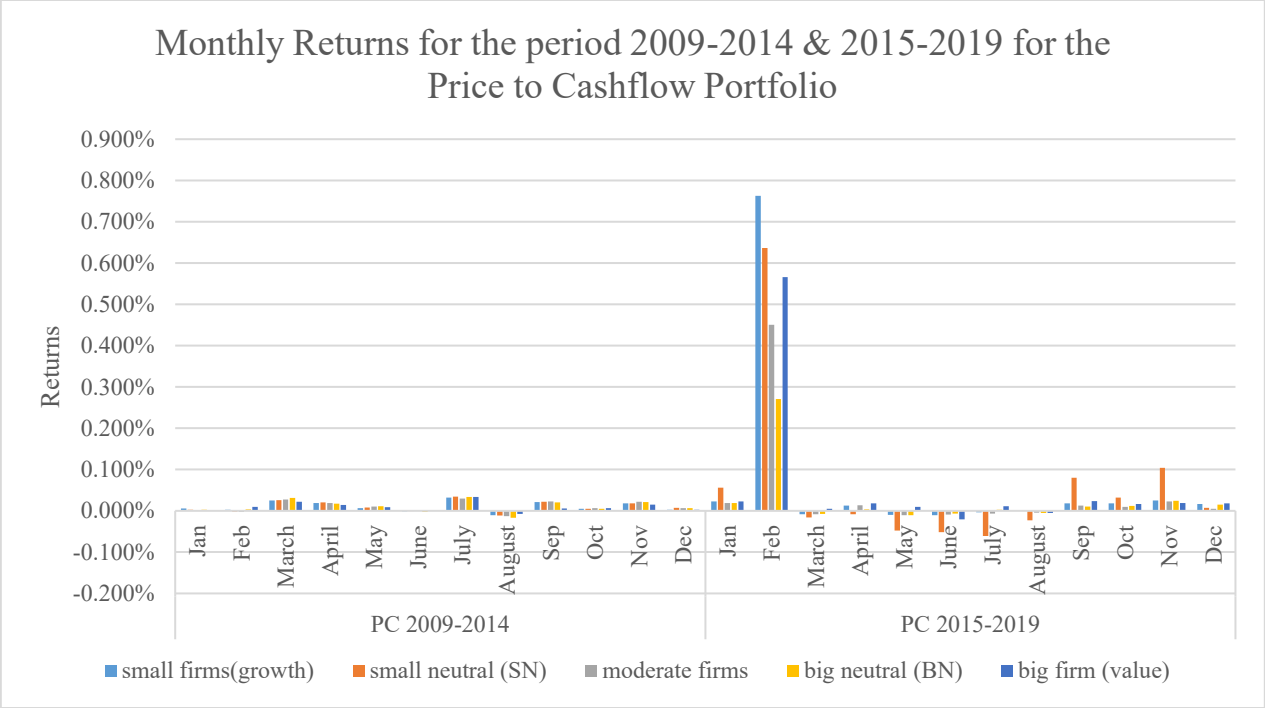

Figure 5: Price to Cash Flow Portfolio

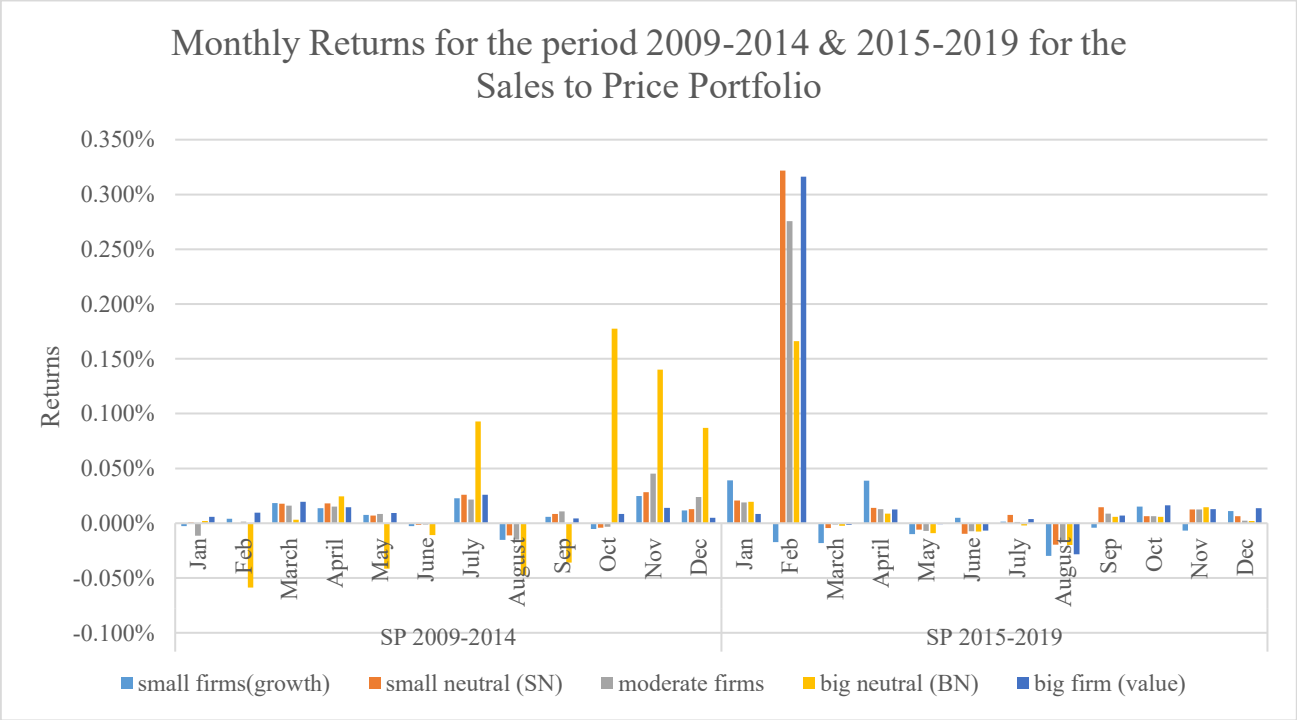

Figure 6: Sales to Price Portfolio